RESEARCH ARTICLE

PORTFOLIO OPTIMIZATION USING NATURE INSPIRED COMPUTING TECHNIQUES: A REVIEW

Kshma Kaushal[1] and Sukhdev Singh[2].
1. Research Scholar, IKG Punjab Technical University, Kapurthala, State-Punjab, india
2. Department of Business Administration, Guru Nanak Dev Engineering College, Ludhiana, State-Punjab, india

……....

Manuscript Info	*Abstract*
……………………. *Manuscript History* Received: 16 July 2016 Final Accepted: 16 August 2016 Published: September 2016	……………………………………………………………………… A portfolio of is a collection of different types of stocks. This diversification is necessary to reduce investment risk. This paper presents a state of art review of various nature inspired techniques used for portfolio optimization. There are various nature inspired techniques like Genetic Algorithm etc., which are successfully used in many areas of science, engineering and management. This paper looks for applications of these for portfolio optimization. This also presents the gaps, which are present in this research area, and can be surveyed further.

……....

Introduction:-

An investment is a commitment of funds made in the expectation of some positive rate of return   (Fischer and Jordan, 2009). There are three basic elements of investment (Singh et al., 2010).

1. Return: Expectation of reward motivates the investor to part with his money and take risk. Return is the gain or profit which accrues to an investment.
2. Risk: Investors' actual returns may be different than expected. Risk is usually measured by calculating the standard deviation of the historic returns. Risk can also be measured using a parameter beta. Beta is calculated by relating the returns on a security with the returns for the market (Fischer and Jordan, 2009).
3. Time: The different investments are examined over the period of time, and risk and return are measured. Thus investment time will dramatically affect the investment vehicle.

The saving of a company will remain under utilized in the absence of stock exchange. Stock exchanges are the markets which exist to facilitate purchase and sale of securities of companies or bonds issued by government in course of its borrowing operations. In Indian stock market, most of the trading takes place on its two stock exchanges: the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE).

A fundamental principle of investments is diversification, where investors diversify their investments into different types of assets. The different stocks can be clubbed in one portfolio. Portfolio diversification minimizes investors' exposure to risks, and maximizes returns on portfolios. Since it is rarely desirable to invest the entire funds of an individual or an institution in a single security, it is essential that every security be viewed in a portfolio context. Thus it seems logical that the expected return of a portfolio should depend on the expected return of each of the security contained in the portfolio. The aggregate characteristics of the constituent securities may or may not be accommodated in a portfolio (Bhalla, 2008).

Corresponding Author:- Kshma Kaushal.
Address:- Research Scholar, IKG Punjab Technical University, Kapurthala, State-Punjab, india.

The most important investment decision which the owner of a portfolio must make is the portfolio's asset allocation. Asset allocation refers to the percentage invested in various security classes. Designing of a best portfolio that meets the needs of the investors can be modeled as an optimization problem (Fabozzi et al., 2007).   In case of portfolio optimization, the optimal weights of the securities have to be found in order to meet the satisfaction of the investor. The satisfaction of the investors lies in maximizing return and minimizing risk. Constructing an optimal risky profile is a high dimensional constrained optimization problem where financial investors look for an optimal combination of their investments among different financial assets with the aim of achieving maximum reward to variability ratio. In these days, various nature inspired optimization techniques are being applied in this area (Anagnostopoulas and Mamanis, 2011).

Optimization is a term used to refer to a branch of computational science concerned with finding the "best" solution to a problem. Here, "best" refers to an acceptable (or satisfactory) solution, which may be absolute best over a set of candidate solutions. Optimization algorithms are search methods, where the goal is to find a solution to an optimization problem, such that a given quantity is optimized, possibly subject to a set of constraints. Optimization provides an elegant blend of theory and applications. The theory uses elements beginning with elementary calculus and basic linear algebra and continues with functional and convex analysis. The applications of optimization involve science, many areas in engineering, economics, and industry (Goldberg, 1997).

An optimization algorithm searches for an optimum solution by iteratively transforming a current candidate solution into a new, hopefully better solution. An optimization problem can be single or multi-objective depending upon the number of objectives to be fulfilled. Further, optimization methods can be classified as deterministic or stochastic. Stochastic method make use of random values and probability theory, whereas deterministic do not. The nature inspired optimization methods belong to the category of stochastic methods. The nature inspired optimization algorithms are optimization algorithms which are inspired from natural processes (Engelbrecht, 2005).

Application of various nature inspired techniques for portfolio optimization:-
Byrne and Lee (1994) have used modern portfolio theory (MPI) as a more rational approach in the construction of a real estate portfolio. This is a process which can be achieved using powerful facilities found in spreadsheets. The use of relatively sophisticated analytical methods such as Solver is too easy to use on the problem. Leinweber and Arnott (1995) have used Genetic Algorithm for predicting the forecasting performance of financial models. Many studies in finance (Colin, 1996; Nelly et al., 1997; Allen and Karjalainen, 1999) use GA particularly in developing trading strategy patterns.

Ostermark (2001) has applied Genetic Hybrid Algorithm (GHA) for complex nonlinear programming problems. The algorithm combines features from parallel programming, classical non linear optimization and techniques of numerical calculus. The test results add significant evidence in solving complicated optimization problems successfully.

Kendall and Su (2005) have applied Particle Swarm Optimization for the construction of optimal risky portfolios. A particle swarm solver is developed and various restricted and unrestricted risky investment portfolios are tested. The particle swarm solver has shown high computational efficiency in constructing optimal risky portfolios of less than fifteen assets.

Marinakis et al. (2009) have proposed ant colony optimization and the particle swarm optimization algorithm to solve the feature subset selection problem. The proposed algorithm was tested in two financial classification tasks, involving credit risk assessment and audit qualifications. This algorithm was found to provide the best results in terms of accuracy rates.

Chang et al. (2009) have employed genetic algorithm for solving difficult portfolio optimization problems with different risk models and compares its performance to mean-variance model in cardinality constrained efficient frontier. Three different risk measures based upon mean-variance by Markowitz, semi-variance, mean absolute deviation and variance with skewness are used. Three data sets are collected from main financial markets and solved by a genetic algorithm.

Anagnostopoulos et al. (2010) have used a greedy randomized adaptive search procedure (GRASP) to solve the mixed integer portfolio optimization problem. GRASP is a powerful metaheuristic approach to solve many hard optimization problems.

Uryasev et al. (2010) have analyzed that risk aggregation in Internal Capital Adequacy Assessment Process (ICAAP) is based on risk adjusted aggregation approaches. It is possible to obtain optimal portfolios with similar properties by using different values of confidence level α and variances.

Gazioglu and Hayfavi (2010) have used stochastic optimization technique to optimize the consumer-investor function subject to a self-financing constraint. Bequest is included in the model. The main contribution of this article is that the assumption of constant-consumption-wealth ratio, which was assumed in the literature, was dropped. The Stochastic optimization model with a self-financing portfolio has been simulated which distinguishes risk neutral investors (Y-low) from high risk averse investors (Y-high), both with and with no bequest.

Golmakani and Fazal (2011) have presented a heuristic approach to solve an extended Markowitz mean-variance portfolio selection model. The extended model includes four sets of constraints; bounds on holdings, cardinality, minimum transaction lots and sector capitalization constraints. A heuristic based on Particle Swarm optimization (PSO) method is compared with GA and PSO effectively out performs GA especially in large scale problems.

Anagnostopoulos and Mamanis (2011) have presented a computational comparison of five state of the art multi objective evolutionary algorithms (MOEA's) on the mean-variance cardinality constrained portfolio optimization problem (MVCCPO). The MOEA's which are considered in this model are the Niched Pareto genetic algorithm2 (NPGA2), Non-dominated sorting genetic algorithm II (NSGA-II), Pareto envelope based selection algorithm (PESA), strength Pareto evolutionary algorithm 2 (SPEA2) and e-multiobjective evolutionary algorithm (e-MOEA). The computational comparison was performed using data sets which contain up to 2196 assets.

Kremmel et al. (2011) have proposed an algorithm to describe software project portfolios with a set of multiobjective criteria for portfolio managers using the constructive cost model (COCOMO II) and introduced prototype optimization with improvement steps (POEMS) which has performed comparatively even better than the state of the art multiobjective optimization evolutionary algorithms.

Zu et al. (2011) focuses on solving the portfolio optimization problem with particle swarm optimization method, where the objective functions and constraints are based on both the Markowitz model and the Sharp Ratio model. PSO has become a popular optimization method as one finds the best optimum as compared to other common optimization algorithms. PSO model is considered superior as it demonstrates high computations efficiency in constructing optimal risky portfolio in comparison to GA.

Lin (2012) introduces a PONSGA model by applying the non-dominated sorting genetic algorithm (NSGA-2) on portfolio optimization problems. NSGA is the well known non-linear optimization method. A PONSGA model has introduced for portfolio optimization to get the maximum return at minimum risk under different risk measures such as mean-variance, semi-variance, mean-variance skewness, mean-absolute-deviation and lower-partial moment. The experimental results indicated that the PONSGA is superior to GA in all performances, as it had a lower coefficient of variation, a higher sharp index, sortino index and PPI index and relatively higher return with low risk.

Vazhayil and Balasubramanian (2012) have formulated Hierarchical multi-objective policy optimization for the planning and design of energy strategy framework and applied to the energy sector planning for India's 12th five year plan for which the objectives of faster growth, better inclusion, energy security and sustainability have been identified.

Niu et al. (2012) have proposed a new model using VAR measuring both market and liquidity risk and then employed a new swarm intelligence based method, Bacterial foraging optimization (BFO) to solve this model.

Kabundi and Mwamlia (2012) have used genetic algorithm (GA) approach for a South African investor who wants to maximize his return but facing exchange rate risk. The performance of GA is compared with the non-linear models, namely the quadratic mean-variance (QMV) and the quadratic variance minimization.

Ha (2013) has conducted a numerical experiment to see the performance of two well established optimization methods-steepest ascent and genetic algorithm , in the solution of an optimal risk-allocation problem in primary-insurance portfolio management. The steepest-ascent method was found to be functionally dependent on the initial starting policy that is chosen. The genetic algorithm produced superior results as compared to steepest ascent method.

Stchedroff (2013) have examined the effects of evaluating large numbers of proposed solutions in parallel for use with direct search optimization. This leads to a method that has considerable performance increase. Zheng and Liang (2013) have presented a robust mean-variance portfolio selection model of tracking error with transaction cost that only risky assets exist and expected returns of assets are uncertain and belong to a convex polyhedron.

Conclusions and Future scope:-

From the present review, the following research gaps have been identified. The optimization of constraint portfolio optimization has been done using Genetic Algorithm (GA), different variants of GA, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Bacterial Foraging Optimization (BFO) algorithms. The new computationally efficient nature inspired optimization algorithms like Wind Driven Optimization, Biogeography Based Optimization (BBO), Invasive Weed Optimization (IWO), Differential Evolution (DE) optimization, which are very effective in solving the optimization problems, are not applied in portfolio optimization. These techniques can be used for portfolio optimization.

Portfolio optimization can yield substantial benefits in terms of risk reduction. The recent interest in asset allocation methods, including international diversification, has also spurred interest in portfolio optimization. Another factor is the increased use of sophisticated nature inspired computing methods in the investment industry, together with increased computing power. There is an increased emphasis on risk control in the investment management industry. Thus there is a strong requirement of application of a recent nature inspired technique on the portfolio optimization problem.

Acknowledgement:-

References:-

1. Allen, F. and Karjalainen, R. (1999), "Using genetic algorithms to find technical trading rules", Journal of Financial Economics, 51, pp. 245-271.
2. Anagnostopoulas, K.P., Chatzoglou, P.D. and Katsovounis, S. (2010), "A reactive greedy randomized adaptive search procedure for a mixed integer portfolio optimization problem", Managerial Finance, 36(12), pp.1057-1065.
3. Anagnostopoulas, K. P. and Mamanis, G. (2011), "The mean-variance cardinality constrained portfolio optimization problem: An experimental evaluation of five multiobjective evolutionary algorithms", Expert Systems with Applications, 38, pp. 14208-14217.
4. Bayraktar, Z., Komurcu, M. , Bossard, J.A. and Werner, D. H. (2013) , " The wind driven optimization technique and its application in electromagnetics," IEEE Trans. On Antennas and Prop., 99.
5. Byrne, P. and Lee, S. (1994), "Real Estate Portfolio Analysis Using a Spreadsheet Optimizer", Journal of Property Finance, 5(4), pp.19-31.
6. Bhalla, V. K. (2008), *Investment* Management: Security Analysis and portfolio management, S. Chand.
7. Chang, T. J., Yang, S. C. and Chang, K. J. (2009), "Portfolio optimization problems in different risk measures using genetic algorithm", Expert Systems with Applications, pp. 10529-10537.
8. Colin, A. (1996), "A genetic programming based approach to generation of foreign exchange trading models", Proceedings of the conference on Commerce, Complexity and Evolution, University of New South Wales.
9. Engelbrecht, A. P. (2005), Fundamentals of Computational swarm intelligence, John Wiley & Sons.
10. Fabozzi, F. J. , Kolm, P.N., Pachamanova, D.A., Focardi, S. M. (2007), " Robust portfolio optimization", The Journal of portfolio management, pp. 40-48.
11. Fischer, D.E. and Jordan, R. J. (2009), Security Analysis and Portfolio Management, Prentice Hall.
12. Gazioglu, S. and Hayfavi, A. B. (2010), "Stochastic Optimization applied to self-financing portfolio: does bequest matter?" Applied Economics, 42, pp. 3831-3838.

13. Goldberg, D. E. (1997), Genetic algorithms in search: Optimization and machine learning, Addison –Wesley, Longman, Inc.
14. Golmakani, H.R and Fazel, M. (2011), "Constrained Portfolio Selection using Particle Swarm Optimization", Expert Systems with Applications, 38, pp. 8327-8335.
15. Ha, S. (2013), "Optimal insurance risk allocation with steepest ascent and genetic algorithms", The Journal of Risk Finance, 14(2), pp.129-139.
16. Kabundi, A. and Mwamba, J. M. (2012), "Applying a Genetic Algorithm to International Diversification of Equity Portfolios: A South African Investor Perspective", South African Journal of Economics, 80(1).
17. Kendall, G. and Su, Y. (2005), "A Particle Swarm Optimization Approach in the construction of Optimal Risky Portfolios", Proceedings of the 23rd IASTED International Multi-Conference Artificial Intelligence and Applications, pp. 100-453.
18. Kremmel,T., Kubalik, J. and Biffl, S. (2011), "Software project portfolio optimization with advanced multiobjective evolutionary algorithms", Applied Soft Computing, 11, pp. 1416-1426.
19. Leinweber and Arnott, R. (1995), "Quantitative and computational innovation in investment management", Journal of Portfolio Management, 21(2), pp. 8-15.
20. Lin, P. C. (2012), "Portfolio Optimization and Risk Measurement Based on Non-Dominated Sorting Genetic Algorithm", Journal of Industrial and Management Optimization, 8(3), pp. 549-564.
21. Marinakis, Y., Marinaki, M., Doumpos, M. and Zopounidis, C. (2009), "Ant Colony and particle swarm optimization for financial classification problem", Expert Systems with Applications, pp. 10604-10611.
22. Nelly, C., Weller, P. and Dittmar, R. (1997), " Is technical analysis in foreign exchange market profitable ? A genetic programming approach", Journal of financial and quantitative analysis, 32(4), 405-426.
23. Niu, B., Fan, Y., Xiao, H. and Xue, B. (2012), "Bacterial foraging based approaches to portfolio optimization with liquidity risk", Journal of Neurocomputing.
24. Ostermark, R. (2001), "New tests with a multipurpose parallel genetic hybrid algorithm", www.emerald-library.com\ft, 30(2), pp. 193-203.
25. Stchedroff, N. (2013), " Portfolio optimization", Financial Engineering, 63, pp.
26. 52-57.
27. Singh, D. R., Gupta, M., Jain, R. (2010), Security Analysis and Portfolio Management, Kalyani Publishers.
28. Uryasev, S., Theiler, U.A. and Serraino, G. (2010), "Risk-return optimization with different risk-aggregation strategies", The Journal of Risk Finance, 11(2), pp. 129-146.
29. Vazhayil, J.P. and Balasubramanian, R. (2012), "Hierarchical multiobjective optimization of India's energy strategy portfolios for sustainable development", International Journal of energy Sector Management, 6(3), pp.301-320.
30. Zheng, D. and Liang, X. (2013), "Optimization of Tracking Error for Robust Portfolio of Risk Assets with Transaction Cost," *iBusiness*, 5 (1B), pp. 23-26.
31. Zhu, H., Wang, Y., Wang, K. and Chen, Y. (2011), "Particle Swarm Optimization (PSO) for the constrained portfolio optimization problem", Expert Systems with Applications, 38, pp. 10161-10169.