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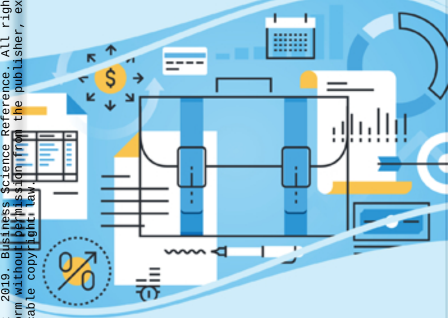
Metaheuristic Approaches to Portfolio Optimization



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Metaheuristic Approaches to Portfolio Optimization

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A volume in the Advances
in Information Quality and
Management (AIQM) Book Series

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Published in the United States of America by
IGI Global
Business Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Names: Ray, Jhuma, 1980- editor.
Title: Metaheuristic approaches to portfolio optimization / Jhuma Ray [and three others], editors.
Description: Hershey, PA : Business Science Reference, 2019.
Identifiers: LCCN 2018047357| ISBN 9781522581031 (hardcover) | ISBN 9781522581048 (ebook)
Subjects: LCSH: Portfolio management--Mathematical models. | Portfolio management--Data processing. | Metaheuristics.
Classification: LCC HG4529.5 .M476 2019 | DDC 332.6--dc23 LC record available at https://lccn.loc.gov/2018047357

This book is published in the IGI Global book series Advances in Finance, Accounting, and Economics (AFAE) (ISSN: 2327-5677; eISSN: 2327-5685)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Advances in Information Quality and Management (AIQM) Book Series

ISSN:2331-7701
EISSN:2331-771X

Editor-in-Chief: Siddhartha Bhattacharyya, RCC Institute of Information Technology, India

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Detailed Table of Contents

Portfolio optimization stands to be an issue of finding an optimal allocation of wealth to place within the obtainable assets. Markowitz stated the problem to be structured as dual-objective mean-risk optimization, pointing the best trade-off solutions within a portfolio between risks which is measured by variance and mean. Thus the major intention was nothing else than hunting for optimum distribution of wealth over a specific amount of assets by diminishing risk and maximizing returns of a portfolio. Value-at-risk, expected shortfall, and semi-variance measures prove to be complex for measuring risk, for maximization of skewness, liquidity, dividends by added objective functions, cardinality constraints, quantity constraints, minimum transaction lots, class constraints in real-world constraints all of which are incorporated in modern portfolio selection models, furnish numerous optimization challenges. The emerging portfolio optimization issue turns out to be extremely tough to be handled with exact approaches because it exhibits nonlinearities, discontinuities and high-dimensional, efficient boundaries. Because of these attributes, a number of researchers got motivated in researching the usage of metaheuristics, which stand to be effective measures for finding near optimal solutions for tough optimization issues in an adequate computational time frame. This review report serves as a short note on portfolio optimization field with the usage of Metaheuristics and finally states that how multi-objective metaheuristics prove to be efficient in dealing with portfolio selection problems with complex measures of risk defining non-convex, non-differential objective functions.

Optimization is discovering an alternative with the most cost-effective or highest-achievable performance under the given constraints, by maximizing desired factors and minimizing undesired ones. Portfolio optimization in finance depends on selecting assets from an opportunity set which yields highest expected return on each level of portfolio risk. Optimization algorithms based on natural events are called heuristic algorithms. The particle swarm optimization (PSO) is a population-based heuristic optimization technique. The technique is inspired by the ability of animals such as birds and fish to adapt to their environment by applying a "sharing of knowledge" approach, to find rich food sources and to avoid hunting. This chapter focuses on portfolio selection problems and shows how to manage financial portfolios using a particle swarm optimization (PSO) technique which is a heuristic algorithm. In order to better understand the subject, the technique has been evaluated in Istanbul Stock Exchange for three transportation sector stocks.

This chapter will propose solution how to recognise important factors within portfolio, how to derive new information from existing data and evaluate its importance factor. The chapter will also propose methodology for sensitivity evaluation between factors recognised as important. This information has valuable factors for Bayesian network construction. Such created Bayesian network can be used as simulation tool, as well as tool for portfolio optimization. As a simulation tool, such Bayesian network can be for output analysis regarding potential decisions via decision graphs. Also, as an optimization tool, Bayesian network can be used in way of finding optimal value of decision factors upon expected outputs from portfolio. For achieving this aim, evolutionary algorithms will be used as optimization tool.

Over the past few decades, an extensive research on the multi-objective decision making and combinatorial optimization of real world's financial transactions has taken place. The modern capital market theory problem of portfolio optimization stands to be a multi-objective problem aiming at the maximization of the expected return of the portfolio in turn minimizing portfolio risk. The conditional value-at-risk (CVaR) is a widely used measure for determining the risk measures of a portfolio in volatile market conditions. A heuristic approach to portfolio optimization problem using ant colony optimization (ACO) technique centering on optimizing the conditional value-at-risk (CVaR) measure in different market conditions based on several objectives and constraints has been reported in this paper. The proposed ACO approach is proved to be reliable on a collection of several real-life financial instruments as compared to its value-at-risk (VaR) counterpart. The results obtained show encouraging avenues in determining optimal portfolio returns.

In the last two to three decades, use of credit cards is increasing rapidly due to fast economic growth in developing countries and worldwide globalization issues. Financial institutions like banks are facing a very tough time due to fast-rising cases of credit card loan payment defaulters. The banking institution is constantly searching for the perfect mechanisms or methods to identify possible defaulters among the whole set of credit card users. In this chapter, the most important features of a credit card holder are identified from a considerably large set of features using metaheuristic algorithms. In this work, a standard data set archived in UCI repository of credit card payments of Taiwan is used. Metaheuristic algorithms like particle swarm optimization, ant colony optimization, and simulated annealing are used to identify the significant sets of features from the given data set. Support vector machine classifier is used to identify the class in this two-class (loan defaulter or not) problem.

Twitter-based research for sentiment analysis is popular for quite some time now. This is used to represent documents in a corpus usually. This increases the time of classification and also increases space complexity. It is hence very natural to say that non-redundant feature reduction of the input space for a classifier will improve the generalization property of a classifier. In this approach, the researchers have tried to do feature selection using Genetic Algorithm (GA) which will reduce the set of features into a smaller subset. The researchers have also tried to put forward an approach using Genetic Algorithm to reduce the modelling complexity and training time of classification algorithm for 10k Twitter data based on GST. They aim to improve the accuracy of the classification that the researchers have obtained in a preface work to this work and achieved an accuracy of 87% through this work. Hence the Genetic Algorithm will do the feature selection to reduce the complexity of the classifier and give us a better accuracy of the classification of the tweet.

The portfolio optimization is an important research field of the financial sciences. In portfolio optimization problems, it is aimed to create portfolios by giving the best return at a certain risk level from the asset pool or by selecting assets that give the lowest risk at a certain level of return. The diversity of the portfolio gives opportunity to increase the return by minimizing the risk. As a powerful alternative to the mathematical models, heuristics is used widely to solve the portfolio optimization problems. The genetic algorithm (GA) is a technique that is inspired by the biological evolution. While this book considers the heuristics methods for the portfolio optimization problems, this chapter will give the implementing steps of the GA clearly and apply this method to a portfolio optimization problem in a basic example.

Selection of weights of the selected securities in the portfolio is a cumbersome job for any investor. The famous nonlinear Sharpe's single index model has been simplified with a linear solution and the risk-taking propensity of the investors have been taken into consideration in the simplified formulation. The coefficient of optimism is included to observe the effect of risk-taking propensity in the portfolio selection. After the empirical analysis it is found that heuristically an investor can reach near to the optimum solution. For empirical analysis 126 months data have been

Foreword

I am delighted to write the foreword for this edited book, which is integrating two very diverse and mature fields of financial portfolios and metaheuristics. This work would help future researchers and interested readers in understanding and appreciating the interdisciplinary field.

This book will help them in undertaking research in the areas of metaheuristics, financial portfolio and the interdisciplinary area which lies at the cusp of the two. The book exposes them to the modeling of the financial portfolio, which is required for reaching to a resolution in investment opportunities involving high-risk addressing the risk-reward tradeoff by maximizing returns or minimizing risks within a given investment period for a variety of assets. These models are often very complex and lead to computationally expensive solutions. In fact, they cannot be solved by using deterministic algorithms given limited resources within a reasonable amount of time. However, most such problems often need a good enough solution in quick time. Thus, metaheuristics should be applied to solve such complex problems like financial portfolio optimization, which are characterized by large search spaces, multiple conflicting objectives and is looking for better than existing solutions.

Metaheuristics are search and optimization techniques and belong to the broad area of Advance Computer Science / Artificial Intelligence and Applied Mathematics. In last three decades, several metaheuristics have been designed by mimicking natural metaphors (e.g., evolution of species, physical processes, swarming, foraging, immune system, and quantum, etc.) to successfully solve complex optimization problems like financial portfolio optimization and assets management. This book has dedicated chapters on the application of metaheuristics like Genetic Algorithms and PSO for solving portfolio optimization problems, which would help researchers in understanding and undertaking the designing of such algorithms as a solution.

Financial portfolio management is an important real-world problem and has been widely studied from different perspectives like in mathematics, statistics, financial and computational sciences. This book has explored both popular and emerging models of representing portfolio optimization problems. In real life applications, portfolio optimization is challenging due to the complexity of mathematical formulations, parameters, business constraints, varying nature of different types of financial instruments and the continuous interaction with the social environment brought by ubiquitous networking technology. This book has thrown light on the emerging impact of social media on financial portfolio management also.

I wish good luck for the success of the book to all the contributors and future readers.

Ashish Mani
Amity University Noida, India

Preface

In today's business world every financial move or decision is backed by classified market information, calculated risk factor and assured return rate within the ambit of investment opportunities and resources at hand (portfolio). Portfolio management has become very important for assessing investment opportunities involving high-risk while addressing the problem of risk-reward balance - by maximizing returns or minimizing risks within a given investment period for a variety of assets. The general purpose of portfolio optimization is to discover an efficient frontier that yields the highest expected return on each level of portfolio risk. Portfolio selection is the decision of forming the optimum portfolio from a number of assets under certain expectations and constraints. Thus proper selection, combination and optimal utilization of financial instruments within a portfolio can reap the benefit of net financial gains.

Metaheuristic approach is meant to create or develop a heuristic (partial search algorithm) which may present an adequately satisfactory answer to an optimization problem, especially problems with high dimensionality, inadequate information or restricted computational scope. Metaheuristic output pattern is usually a set of solutions over a number of iterations thereby yielding an array of optimal choices. Such metaheuristics include but are not limited to Simulated Annealing (SA), Ant Colony Optimization (ACO), Evolutionary Computation (EC), Particle Swarm Optimization (PSO), Differential Evolution (DE) and Genetic Algorithms (GA). These metaheuristics are not at all restricted to local search but optimizes through global search as well.

Owing to the discrete and multidimensional nature of the portfolio optimization problem, the classical or statistical methodologies could not yield assured solutions. In this context, the metaheuristics as mentioned above are quite effective and handy tool to give an easy, near accurate and faster solution. The dynamism of the heuristic portfolio optimization give managers and inventors the scope for proper selection of asset in portfolio, asset diversification and proportion of investment of selected asset in portfolio that in turn controls risk beyond VaR and maximizes return.

As the classical models of portfolio optimization are difficult to understand and require expert knowledge. Heuristic optimization can give an easy, near accurate and faster solution which can be comprehensible without having to be expert in the subject. Therefore, the dynamism of heuristic portfolio optimization has an appeal to the researchers.

This book is a collection of nine chapters including one that depicts state-of-the-art in this field of portfolio optimization and other relevant research work with potential impact. The chapters are very focused to the theme of the book and have been carefully selected out of several submissions following a rigorous review, revision and editing process. It is indeed encouraging for the editors to bring out this collection under IGI Global edited book series and the book is expected to evoke interest of researchers of different backgrounds owing to its cross-platform characteristics. The chapters of the book are organized as follows:

The first chapter titled 'Portfolio Optimization and Asset Allocation With Metaheuristics: A Review' is an introductory chapter that sets the context of the book. It explains the inherent challenges in solving the highly sensitive non-linear multi-dimensional portfolio optimization problems of real-life scenario and establishes the effectiveness and practical significance of the metaheuristics in adequately handling such problems. Though research in this field is quite old, the classical mathematical approaches have been outmoded over the years by the evolving metaheuristics that has brought about a revolution in optimization. This chapter gives an extensive account of mono and multi-objective metaheuristic approaches dealing with portfolio selection problems with complex non-convex, non-differential objective functions. The principal methods and the knowledge realm of application of the methods have been outlined by the authors quite aptly.

Markowitz's theory for portfolio selection says that as you add new assets to an investment portfolio the total risk of that portfolio decreases continuously depending on the correlations of asset returns, but the expected return of the portfolio is a weighted average of the expected returns of each asset. An experiment on application of this theory in portfolio selection and optimization using PSO has been reported for the first time in the second chapter titled 'Particle Swarm Algorithm and an Application on Portfolio Optimization'. Using transportation stock data of one year PSO algorithm is run in MATLAB to evaluate the optimal portfolio (having the best performance value) within the created portfolio types differing by the stock diversity and their weights.

The third chapter titled 'Bayesian Networks and Evolutionary Algorithms as a Tool for Portfolio Simulation and Optimization' presents the methodology of using PSO algorithm, as a tool for finding the riskiest profiles, based on a previously developed Bayesian network model. The proposed methodology is illustrated through a real-life case study from insurance industry, evaluating risk levels for each of the existing members of selected insurance portfolio. Finding optimal combination of nodes with corresponding evidences, which will maximize final output, is not a trivial task – PSO has been deployed to achieve this quite effectively. Presented methodology has a practical significance from business point of view where information about customer's risky profiles is valuable for future portfolio planning. The authors also highlight how the methodology is useful in profile similarity calculation and periodic determination of changes in risk profiles that implies changes in customer behavior or preferences over time.

ACO is another useful population-based metaheuristics which has been effectively used to evolve optimized portfolio asset allocations pivoting on optimizing the Conditional Value-at-Risk (CVaR) measure in the fourth chapter titled 'Conditional Value-at-Risk-Based Portfolio Optimization: An Ant Colony Optimization Approach'. Comprehensive experiments have been carried out in this article to evaluate how well ACO has behaved in extracting the salient features on different datasets. A comparison of the proposed CVaR approach vis-a-vis VaR approach is demonstrated on a collection of portfolio data of TATA Steel industry – it shows how CVaR is able to quantify risk beyond VaR. The modeling flexibility of ACO under different risk structures, its consistency and reliability proves the effectiveness of ACO towards finding risk minimization solution of different financial portfolio.

In the fifth chapter titled 'Metaheuristic-Based Feature Optimization for Portfolio Management' different features or parameters of portfolio dataset collected from UCI repository are optimized with metaheuristic method like SA, PSO and ACO and then the optimized feature set is used to classify the data with different supervised and unsupervised machine learning technique. It has effectively reduced the problem of data over fitting and inaccuracy in classification arising due to redundant feature set. In this work authors have also tried to find whether increase in selection of number of features also have some influence on the accuracy of determining defaulters of financial institutions.

In the sixth chapter titled 'Optimizing Social Media Data Using Genetic Algorithm' the authors have done the metaheuristic-based analysis of the reaction of the investors and Indian Stock Market (influenced by different share values of industries such as IT, manufacturing, automobile, agriculture, healthcare, banking, FMCG and textile industries) in view of the Goods and Service Taxs (GST) - a major economic reform in India in recent times. Using GA as a metaheuristic tool for feature selection, the space complexity and time of classification of features of opinion dataset have been reduced considerably. In effect 87% accuracy of classification has been achieved which in turn has facilitated the job of a portfolio manager in taking informed decision for portfolio selection and optimization. This work can be treated as one of the first optimization work on such a large-scale economic reform having potential impact on the current trend of portfolio analysis.

Another experiment on generating the optimum portfolio for the selected stocks has been reported in the seventh chapter titled ‘The Genetic Algorithm: An Application on Portfolio Optimization’. In this chapter, daily price movement of 6 shares traded in Borsa Istanbul over 3 years have been considered as dataset. Returns calculated by the logarithmic function are used in order to achieve the optimum risk by using GA based on Markowitz mean variance model. The results showed that the GA method generally yielded near optimum results in terms of Sharpe Ratio, return and variance of portfolio. The author suggests that GA can be safely used to reduce unsystematic risk of a portfolio in a portfolio selection problem.

The eighth chapter titled ‘Heuristic Optimization of Portfolio Considering Sharpe’s Single Index Model: An Analytical Approach’ presents construction of a near optimum portfolio based on the Sharpe’s Single Index Model which is a simplification of the Markowitz mean variance model. The problem of weight generation of assets in portfolio and proportion of investment of the selected assets in the portfolio are resolved effectively following heuristic methods. The beauty of the method presented is its simplicity and it remains interesting to see how it is accepted to investors with less technical knowledge.

The work presented in the last chapter titled ‘Role of Metaheuristic Portfolio Optimization in Banking Sector: A Case Study’ is a typical example of portfolio management where a probability of taking personal loan of a customer from a bank can be near-accurately computed from the initial database of the client and his/her behavioural pattern with the bank. The classification work is carried out using Decision Tree (DT), Support Vector Machine (SVM) and k-nearest neighbour (k-NN). Feature optimization is done with GA and results reflect 91.5% accuracy for predicting the outcome. In view of portfolio management, bankers can safely take decisions based on the selective 5 crucial features only instead of all - it doesn’t compromise with the accuracy but saves time, and decision making becomes faster. Thus the work has potential impact on the financial growth of banks by selectively removing the probability of bad debt.

The authors of different chapters share some of their latest findings that can be considered as novel contributions in the present domain. It is needless to mention that the effort of the editors to come out with this volume would not have been successful without the valuable contribution and the effort and cooperation rendered by the authors. The editors take this opportunity to express their thanks to IGI Global, an international publishing house of eminence, to provide the scope to bring out such a concise and quality volume on a theme on which not many titles are available, The editors would also like to express their heartfelt thanks to Josephine Dadeboe, Assistant Development Editor, IGI Global and Jan Travers, Director of Intellectual Property & Contracts, IGI Global for their support and guidance right from the proposal phase. Last but not the least the editors gratefully acknowledge the contribution of the reviewers who have shared their valuable expertise and time in meticulously reviewing the chapters included or excluded in this volume. We sincerely hope that this book volume becomes useful to the young researchers, academicians and industry experts working in relevant domain. We invite any suggestion and criticism of this treatise from the readers with an open mind to enrich our future work in relevant domain.

Chapter 1

Portfolio Optimization and Asset Allocation With Metaheuristics: A Review

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ABSTRACT

Portfolio optimization stands to be an issue of finding an optimal allocation of wealth to place within the obtainable assets. Markowitz stated the problem to be structured as dual-objective mean-risk optimization, pointing the best trade-off solutions within a portfolio between risks which is measured by variance and mean. Thus the major intention was nothing else than hunting for optimum distribution of wealth over a specific amount of assets by diminishing risk and maximizing returns of a portfolio. Value-at-risk, expected shortfall, and semi-variance measures prove to be complex for measuring risk, for maximization of skewness, liquidity, dividends by added objective functions, cardinality constraints, quantity constraints, minimum transaction lots, class constraints in real-world constraints all of which are incorporated in modern portfolio selection models, furnish numerous optimization challenges. The emerging portfolio optimization issue turns out to be extremely tough to be handled with exact approaches because it exhibits nonlinearities, discontinuities

DOI: 10.4018/978-1-5225-8103-1.ch001

and high-dimensional, efficient boundaries. Because of these attributes, a number of researchers got motivated in researching the usage of metaheuristics, which stand to be effective measures for finding near optimal solutions for tough optimization issues in an adequate computational time frame. This review report serves as a short note on portfolio optimization field with the usage of Metaheuristics and finally states that how multi-objective metaheuristics prove to be efficient in dealing with portfolio selection problems with complex measures of risk defining non-convex, non-differential objective functions.

INTRODUCTION

Portfolio optimization or asset allocation is found to be of immense importance within classical investigation issues within financial philosophy along with operations research. Managing funds and their optimum allocation by selecting an optimal portfolio is an all-time problem been faced by the financial organizations like Banks, insurance companies, and fund management organizations. Markowitz (1952) is the pioneer in this research domain propounding the mean-variance portfolio model established over quadratic optimization issue based on linear restraints. Numerous theoretical progresses been tried for developing Markowitz model and resolving it, alluding to mathematical modeling techniques. Researches done by Nishimura (1990), Figueroa-Lopez (2005) and Bolshakova et al., (2009) furnish elaborate information on these advances. The model still experienced efficiency in its applicability to real life scenarios. Actually, the progress been done to this model with the usage of transaction costs, complex constraints and by the usage of alternative objective function creates more complexities to the model thereby making it much more computationally improbable. Thus by the usage of numerous classical optimization techniques for solving similar pattern of issues some mathematical conditions can be executed. If any objective function and restraints are indicated by a linear function of conclusion variables then, linear programming proves to be feasible in that case. Further, applicability of non-linear programming can be done in the case of nonlinear objective function and constraints. To a matter of regret these classical methods become outmoded in any situation experienced which usually involve single or additional complications. Viz. the objective function can become non-homogeneous, or is impossible to be expressed analytically in terms of the specifications, or else the issues may desire further cogitation of dual or numerous conflicting purposes which in turn is defined as multi-objective optimization procedure.

The evolution of an advanced category of optimization techniques, named as Metaheuristics, imprint a tremendous revolution in the terrain of optimization. The approaches are pertinent in every category of combinatorial issues, and even proving to be suitable to continuous issues or problems. They let on researchers in finding an adequate result customarily along with a legitimate computational time frame, in spite of assuring the optimality of acquired resolution. Metaheuristic techniques happen to be most fortunately utilized for resolving huge issues. These techniques can be prorated within dual categories. At the begining, the particular algorithms are outlined by the usage of understanding realm for a stated problem. Next, the common or accepted algorithms can be utilized for far-reaching sort of problems. Subsequently, numerous research studies targeted on the portfolio optimization problem have been initiated for the application of the meta-heuristics in determining practical solutions and conquering the complications of the stated problems.

This chapter targets in acquiring the knowledge about the practice of Metaheuristic optimization approaches meant both for the single-objective as well as the multi-objective issues altogether and its utilization within the portfolio optimization. This review work is fragmented into three sections exploring the principal methods of mono-objective Metaheuristics and their usage in portfolio optimization domain, investigating the principal system of multi-objective Metaheuristics and its utilization within portfolio optimization problem and finally concluding.

Portfolio Optimization with Metaheuristics

Within the domain of finance, Portfolio optimization stands to be very vital area of investigation. Commonly, the problem dwells for probing an optimal allocation of the accessible capital within numerous assets. An important explanation for this issue is provided by Harry Markowitz who has suggested the mean–variance model for any portfolio selection (Markowitz, 1952; Markowitz, 1990). The mean–variance model states resolution to the issue of portfolio selection in finding out the best trade-off portfolios amidst the expected return or the mean along with the risk which in turn is determined by the variance. The return expected is maximized and variance is minimized simultaneously. For analyzing these trade-off portfolios, solving a multi-objective nonlinear optimization problem is required. These portfolios delineate an appropriate solution set which in turn stands to be very vital in the theory of portfolio management. The stated set is known to be very efficient in the vocabulary of portfolio's theory. The representation of the stated set within mean–variance area construes a simulated competent frontier (Elton, Gruber, Brown, *et al.* 2014). Creating the accurate competent set and the efficient frontier for any mean–variance portfolio optimization model, rare techniques exists, which are able to deal with instances involving greater than 2000 assets (Hirschberger, Qi, Steuer, 2010). Moreover, a distinct definite approximation which can be a dotted representation for a continuous efficient boundary can exist with the usage of quadratic programming algorithms which are incorporated within numerous commercial software as a whole (Qi, Hirschberger, Steuer, 2009). Nevertheless, quadratic programming algorithms desire the covariance matrix to be positive for its application. The stated necessity may be contravened when vast real time data set is put under consideration (Schlottmann, Seese, 2004).

The portfolio optimization research at present is being concentrated on the following three directions:

- For introducing the alternative risk techniques (Righi, Borenstein, 2017),
- For incorporation of any new additional criteria, and
- For inclusion of further practical restraints (Anagnostopoulos, Mamanis, 2010).

The establishment of higher array moments within portfolio choice is of vital importance. Particularly within the mean–variance portfolio selection model skewness can be applied. Skewness stands to be an alternative measure of risk in portfolio choice. Number of research studies is found to consider multiple objective portfolio choice models involving dual risk techniques (Roman, Darby-Dowman, Mitra, 2007). These models are considered to be as mean–variance–skewness along with mean–variance–CVaR multi-objective portfolio optimization models.

Furthermore, number of constraints is considered as objectives within the portfolio selection modeling. Multi-objective optimization always defines about a line between what is to be considered as an objective as well as stating about the more suitable options to be modeled as a constraint. Usually within multi criteria optimization any objective is acclaimed from a restraint if not proved to be easier for fixation of the right side of the constraints for not having proper knowledge of the levels of the other objective functions (Steuer, Qi, Hirschberger, 2007). Relying on these stated facts, Anagnostopoulos and Mamanis (Crama, Schyns, 2003) handled the cardinality constraint as an additional objective function that requires to be minimized.

If been considered a few or all of the stated issues results in portfolio optimization problems which are very complicated to be handled with the usage of existing mathematical programming algorithms because of the involvement of huge multi-modal search areas, nonlinearities, non-convex functions, multiple objectives, discontinuities and high dimensional efficient frontiers (Crama, Schyns, 2003; Jobst, Horniman, Lucas, et al. 2001; Mitra, Kyriakis, Lucas, et al. 2003). Numerous lengthened portfolio models are being stated to be a part of the classification of NP-hard issues like the conclusion drawn for problems in portfolio optimization (Bienstock, 1995; Shaw, Liu, Kopman, 2008). Several research papers are found to resort Metaheuristic algorithms which in turn are proved to be more appropriate for handling them (Chang, Meade, Beasley, 2000; Crama, Schyns, 2003; Cura, 2009;

Fernandez, Gomez, 2007; Maringer, Kellerer, 2003; Schaerf, 2002; Soleimani, Golmakani, Salimi, 2009).

Usually, researchers in the domain of heuristic portfolio optimization are only engaged in proposing heuristics in financial industry. The advantage of heuristics lies in tackling practical portfolio optimization models at the time of failure of all other proper optimization algorithms. Another option is simplifying the model for getting it controlled by appropriate measures (Gilli, Maringer, Winker, 2008). Almost all models for optimization of a portfolio, believe markets as frictionless for making them approachable. The compulsion of these models are restrictions regarding the budget which designates that the weight of an asset within the portfolio add up to one and the short selling restriction signifies that the relative amount invested within any asset is non-negative. Heuristic optimization measures provide an advanced technique for consideration of more practical and complex situation without simplifying any assumption (Maringer, 2005). For reliable, powerful and effective optimization measures which can solve practical large-scale portfolio optimization issues, there is a constant increase in demand from finance corporations. Heuristics are able to provide a beneficial trade-off amidst the required computational time frame and trait of the consequence.

Metaheuristics prove to be suitable for practical portfolio optimization problems because of its characteristics to be of non-convex objective function and search spaces. Moreover, Multiobjective Metaheuristics (MOMHs) are efficient in handling problems with multiple objectives in a natural way. MOMHs administers as a natural framework for resolving portfolio optimization issues along with added objective functions and practical constraints although been little explored in the specialized literature (Macedo, Godinho, Alves, 2017; Kumar, Mishra, 2017). The main advantage of MOMHs, while being compared to classical or single objective Metaheuristics, lies in generating the efficient set along with the specific efficient frontier within single application of the algorithm. Single objective Metaheuristics desires numerous optimization issues for generating an approximation of the correct effective frontier. This can generally be achieved by the alliance of the objective functions along with the usage of weights which define the relative significance of the stated objective function in terms of weighted sum approach. The effective frontier can be drawn out by changing appropriately the weights and resolving every single objective optimization issue. The stated procedure however does not prove that a well-proportioned diversity of weights will lead to consistent variety of results over the efficient frontier. Diversity of results along the efficient frontier stands to be vital in multiple objective optimizations because it is not capable of holding numerous trade-off solutions with huge value for the decision making choice.

Anagnostopoulos and Mamanis (Anagnostopoulos, Mamanis, 2011) have done comparisons between the performance of five different state-of-the-art multi-objective evolutionary techniques (MOEAs) with the mean-variance cardinality restricted portfolio optimization issue along with a traditional single objective evolutionary technique suggested within Chang et al. (2000). The factual result states that every MOEA can produce better quality of efficient and effective frontiers rather than the single objective evolutionary technique within lesser computational time frame. In fact requirement of good optimization algorithms or a vast spectrum of algorithms is vital since considering the later to provide opportunity for better portfolio modeling.

The authors in Steuer et al (Steuer, Qi, Hirschberger, 2008) have stated a distinct picture with a dotted representation of the appropriate efficient frontier which is possible for construction, when been added to the objective functions beyond the bound of mean and variance of the Markowitz's model, and/or constraints assumed to be linear. Nevertheless, it is also stated that if in any way one of the objective functions is non-linear, substitute techniques for solutions to be achieved are required.

Single-Objective Metaheuristics Approaches: Implication on Optimal Portfolio Selection

Advancement of Metaheuristic techniques inclusive of huge performance of computational foundation contributes to the wider sphere of resolutions to complicated issues.

Eddelbuttel (1996) probes among the initial researcher seeking interest for the appliance of mono-objective Metaheuristics within portfolio optimization issues. The study deals with the index-tracking problem, which describes about emulating the practice of a benchmark index within a target portfolio. The objective of the research work is nothing else than to minimize the variance of return divergence amidst the benchmark index along with apprehending the portfolio. However analytically, the anticipated return distinctness is described beforehand and the portfolio is found to be selected referring to a lesser number of stocks. The stated situation's resolution is computationally tough for which the researcher has applied a hybrid Genetic Algorithm. Initially at the beginning of every generation, assets incorporated within the portfolio been chosen by the usage of genetic algorithm. Afterwards, optimal weights of the chosen stocks been outlined by a quadratic programming solver. Similar model is analytically practiced on "Deutscher AktienInde X" (DAX) by the usage of every day's closing prices. Chang et al. (2000) targeted for solving the Mean-Variance portfolio optimization issue counting cardinality restrictions along with the weights restrictions. To achieve this target, authors have utilized three different types of techniques: Gentic Algorithm along with Taboo Search and

Simulated Annealing. The outcome of the research work depicts that the occupancy of cordiality restrictions administer a desultory effective borderline. Therefore, effective borderline is built up by a mathematical programming technique and established over every combination of dissipated scenarios. The researchers have demonstrated the few fragments of effective borderland is secluded and the utilization of projected Methaheuristics exhibit that Genetic Algorithm is the much more effective when been compared to the other algorithms. Chan et al., (2002) researched a multi-stage portfolio optimization issue by the usage of genetic techniques. By the application of Simulated Annealing algorithm Crama and Schyns (2003) have solved portfolio optimization problem along with specific inclusion of constraints. Lin et al., (2005) summated transaction expences within the issue of portfolio optimization and have used a Metaheuristic technique to solve the problem of optimization within a portfolio. Chen et al., (2006) developed a constrained portfolio optimization issue and have resolved it with the usage of particle swarm optimization technique. Still, Thong (2007) has applied an Ant Colony algorithm for an identical sort of issue. Ruiz-Torrubiano and Suarez (2007) have targeted on Mean-Variance exemplary along with cardinality restrictions inclusive of weight restrictions on every asset or classification of assets. The researchers have used combination of techniques for the stated purpose. Thus, during the initial start, they desired the optimal distribution of assets within the portfolio targeted by the means of an evolutionary algorithm. During the next step, they have used a quadratic programming solver for defining the optimal weight associated for every selected asset. Adding to the conventional objectives desired by any other applications for increasing the returns along with decreasing risks, Aranha and Iba (2007) have dealt with another objective which is able to minimize transaction expences within dual consecutive time frames. For factual operation the researchers have used monthly recorded returns of NIKKEI and NASDAQ indexes along with the usage of Genetic Algorithms. Relying over stochastic programming, Hochreiter (2008) has applied ambiguity within the portfolio miniature. For solving the issue of optimization, practical application for a week is established on weekly report of fourteen varieties of assets enlisted within Dow Jones Index. Four different risks are accepted within empirical simulation of theresearch, specifically, standard deviation, Value at Risk, mean absolute downside semi deviation and wonted shortcoming. A stochastic programming technique is been approved by Geyer et al., (2009) for optimizing a multi-period natured portfolio. Chang et al., (2009) researched a portfolio optimization issue with a view of risk-aversion. Within the research work, four different breeds of risk measuring technique are approved, particularly the variance measure, semi-variance technique, mean absolute deviation measure and variance technique along with skewness. For solving the optimization problem, authors of this research work have used the Metaheuristic in the form of

Genetic Algorithm. Here, in this research Genetic Algorithm is represented with a binary tournament election, uniform crossover and then a replacement procedure associating the replacement of worst fitter individuals with the usage of offspring chromosomes. Empirical significance of the research study states that any enrichment of cardinality indicates an improvement on computational time. Further, effective borderline with lower cardinality prevail those with higher cardinality. Thus for achieving a potent portfolio authors have suggested a restriction to the cardinality for being at least one-third of total number of assets. Soleimani et al. (2009) have suggested for the sector capitalization restraints within any portfolio optimization issue. The mentioned constraints within the research work are advantageous for reduction of overall risk. But yet, the stated constraints make any problem much more complicated. Authors have used Genetic Algorithm as the Metaheuristic approach for solving the suggested issue. Yu et al. (2010) have applied a simulation miniature for searching the optimal asset apportionment which can maximize shareholders' utility function in consideration of non-life insurance organizations. The researchers have developed a latest form of evolutionary technique by considering the multi-periodic situation within the asset allocation issue. They have stated that their model is much more efficient than any other approaches which can optimize mono-periodic issues.

Above mentioned research works are only a few among the Metaheuristic applications over portfolio optimization issues and asset apportionment issues. A researcher should possess the minimum level of skill in the domain of Metaheuristics for overcoming the already treated optimization issues. Moreover, the research works are implications of a few Metaheuristics for optimization of a portfolio or asset distribution issues.

The following sections will be stating about some important algorithms along with their main characteristic:

Portfolio Optimization Based on Evolutionary Algorithms

Fraser (1957) is known to be the pioneer of evolutionary approaches, representing the classification of research techniques exhilarated by any species' biological evolution. An evolutionary algorithm emerges slowly, through consecutive iterations or generations along by retaining a consistent size of population composition. The aim is an overall advancement of individuals' performance by the way of generations. Within every generation one put into use a series of operator, namely, selection operator, mutation operator and crossover operator for population individuals which creates a current population. Every operator utilizes single or numerous population individuals known as parents for generating fresh candidates known as offspring. An entire record of all existent techniques for describing the operators can be found in Eiben and Smith (2003). Evolutionary algorithm incorporates dual outstanding techniques: Genetic Algorithm (GA) and Evolutionary Strategy (ES). This technique was originally been suggested by Rechenberg (1965), which is accepted as the earliest authentic Metaheuristic and the primary evolutionary algorithm. Within its primitive version the algorithm maneuver iteratively a class of original variables vector by the usage of mutation and selection operators. The mutation is usually accomplished within a normal distribution by summing up a random value. The selection is done by selecting the best individuals bestowed on the fitness function.

According to Schoenauer and Michèle (1987) Evolution Strategies uses a class of parents for production of offspring, and for doing such parents are recombined. After that the already produced offspring undergoes through the process of mutation. Selection step is applicable either only for offspring or for parents and offspring altogether. The latest actual approaches use crossover operator for avoiding being captured within the local optima.

Application of Genetic Algorithm (GA) in Portfolio Optimization

Genetic algorithms are stated to be the stochastic search approaches and its theoretical foundations are drawn by Holland, (1975). This was originally been inspired by Charles Darwin's theory articulating the concept of natural evolution of living species. There exist dual mechanisms permitting emergence of living species either through natural selection or reproduction procedure. Natural selection approves the well accepted population individuals within their environment. The election procedure is pursued by reproduction procedure which is accomplished by crossovers and mutations in individuals' genes. Thus transition of some of the genetic heritage to happen from the parents to their offspring is due to intersection. Along with this some individuals' genes can possibly mutate within the phase of reproduction. The association of these two techniques led to much more accepted population within its environment. Generally, Genetic Algorithms undergo slow convergence or premature problems.

Implication of Taboo Search Algorithm in Portfolio Optimization

Glover (1986) has introduced the Taboo search algorithm. It is a mathematical technique approach utilized for solving combinatorial issues. This algorithm has the capability for improvement for local search efficiency in terms for adjoining the memory construing inspected solutions to a research procedure. Within an environment, Taboo search algorithm is able to analyze any neighborhood and can pick out a fresh one that can in turn optimize the stated objective function. The process is iteratively been repeated until and unless criterions been intended are fulfilled. In this manner, each potential result is noted as Taboo and combined with the memory, which in turn is known to be Taboo list. The stocked list of results can be visited during the forthcoming iterations. The major benefit of the stated technique bearing a lesser criterion over the below mentioned simulated annealing algorithm. Nevertheless, Taboo search algorithm may not always be efficient enough, without adding up an appropriate intensified and/or diversified process that may draw a new parameter according to Glover and Laguna (1997).

Simulated Annealing Algorithm for Portfolio Optimization

This Metaheuristic technique is being heartened because of the physical system of annealing of the crystalline components. It is nothing else than heating an item at a higher rate of temperature and then getting it cooled for increasing the magnitude of crystals. For implementation of this technique with any optimization approach, random movements of every point are correlated by a probability of dependent variables by the representation of the temperature of the stated material. The connection amidst the Simulated Anneling algorithm and optimization issues has been suggested initially by Pincus (1970), then by Kirkpatrick et al. (1983) and again by Cerny (1985), within their different research studies. They are thus considered as the pioneer within the advanced mode of simulated annealing technique. The approach stands to be a popular approach because of its smooth and easier nature of adapting to different issues and its effectiveness. Still, the disadvantage lies within the huge number of parameters viz: initial temperature, temperature lessening regulation, temperature phases' time duration, etc. which makes it quite factual.

Algorithms Based on Swarm Intelligence in Portfolio Optimization

Collective intelligence indicates innates intellectual capabilities happening from diversified communications within community representatives also known to be as agents. From a simple action, agents are able to perform complicated assignments owing a basic system called to be synergy. Within a particular situation, constituted synergy over collaboration within individuals materializes few opportunities for depiction, creation and education excelling over confined individuals. The intelligence as a whole is of different types according to association type and representative which are met. These types of intelligence are visible within social insects such as ants, bees, and other animals in motion like migrating birds and fish schools. Depending over such activities numerous techniques are created such as ant colonies and particle swarm algorithms.

Ant Colony Algorithm (ACA) based Portfolio Optimization

Ant colony optimization techniques are innate from clear investigations. Insects, specifically ants, resolve usually complicated issues. The dominant factor facilitating the stated pattern of behavior is the communicating pattern of the ants within themselves diffusely owing secretions of chemical elements known to be as pheromones. This pattern of communication indirectly is known to be as Stigmergy. Goss et al. (1989) stated that if a barrier is brought intothe paths of ants, they all tend to follow the abridged technique to move between home place and the obstacle. Their attraction is more towards the field in which the rate of pheromone is the highest. Initially, algorithms encouraged from this homology were suggested by Colorni et al. (1992) and Dorigo et al. (1996) for resolving the issue of any business traveler. Within the stated approaches every resolution is being agreed to be an ant moving within the search area. Ants characterized to be of excelling solutions and prevailing the markings given before for optimizing their research. This algorithm uses an absolute probability distribution for performing the transition within iterations.

These algorithms are extended for resolving numerous discrete and unending optimization issues been described by Dorigo and Blum (2005) and Siarry et al. (2006)).

Particle Swarm Optimization (PSO) for Optimization of Portfolio

Kennedy and Eberhart (1995) proposed Particle Swarm Optimization as another Metaheuristic approach being inspired by the movements of swarms. The best example is stated on the behavioral pattern of fish school described by Wilson (1975) and Reynolds (1987). However, these animals are recognized by comparably complicated along with dynamic movement having restricted intelligence and regional knowledge targeted on the situation within the swarm. Thus, every individual possess knowledge only regarding the situation along with the speed of the adjacent neighbors. As an outcome, every individual's intrinsic movement is been altered by both the memory as well as local facts of nearest neighbors. Simple principles, like moving in the similar pattern as others having the similar speed or motion, speeding towards the similar direction or remaining close towards the neighbors are namely the basic behaviors maintaining cohesion of swarm and allowing the application of complicated and adaptable behavioral pattern. Local communication within various particles constitutes the global intelligence pattern of behavior of swarm. Potential results of this approach are represented by particles scattered over the area of search for seeking universal optimum. Particle's motion is been influenced by different three elements: Firstly, the particle following the present direction, Secondly the particle moving towards its best area by which it has already gone through and thirdly, the particle relies on congener's experience, moving towards the already best proved area by the neighbors. Alike other Metaheuristics, PSO bears numerous control settings like the size of swarm, maximum extent of particles within a neighborhood, maximum amount of velocity which stand to be the limit for setting a long as well as tough and complicated procedure. Because every parameter bears strong authority on the pattern of algorithm, it becomes very important for understanding for every problem the acceptable and suitable assortment of parameters.

Multi-Objective Metaheuristics and Optimal Portfolio Selection

All Metaheuristics are basically been accepted for resolving single-objective issues. Single-objective optimization approaches are been established on minimizing or maximizing an individual objective function which without reflecting the original coordination needs to be optimized. However, multi-objective optimization permits optimization of complicated issues recognized by the existence of two or more than two objective function. When been compared to single objective optimization issues, multi-objective optimization issues are complex to be resolved because they don't provide any single resolution but numerous resolutions are obtained.

Amidst the initial research works concerned with the utilization of multi-objective Metaheuristics for portfolio optimization issue the research work done by Doerner et al., (2001) has been considered here in this literature review. Within the study, multi-objective portfolio selection is done by the usage of Ant Colony Optimization Algorithm as a Metaheuristic approach. During the similar period another study done by Lin et al.,(2001) states about the multi-objective portfolio selection problem associated to the considerations related to fixed transaction costs along with linear constraints within the capital invested. For solving this constrained issue authors have used "Non-dominated Sorting Genetic Algorithm" (NSGA-II) as Multiobjective Metaheuristic approach. The acceptance of an integer encoding rather than the originally admired encoding, compelled the authors for making radical conversion on the genetic operators by the usage of the NSGA-II. The principal perception of this research work was for the introduction of the superior variance including an excelling rate of return within the population given with a reduced range of dependency amidst the non-dominated result set. Fieldsend et al., (2004) has researched the mean-variance structure for portfolio optimization issue with the existence of cardinality restraints. Other referred studies within the research work, has stated that the cardinality hasn't been described ahead. The cardinality of the portfolios has been described as the additional objective function which is required to be minimized. Thus the selection has been explained as the probability for finding dual portfolio equivalent in nature, one among which is been characterized by an inferior cardinality and the other one with a superior cardinality. Hypothetically, it has been stated that a portfolio having superior cardinality involves an abundant number of assets possessing zero-weight. For resolving such problem the "Multiple Objective Evolutionary Algorithms" (MOEA) is been used. Streichert et al., (2004) has utilized the "Non-dominated Sorting Genetic Algorithm" (NSGA-I) approach as a Metaheuristic for the determination of a mean-variance miniature within a portfolio optimization issue. The approach been used is recognized by the usage of binary encoding system including with the real-value encoding system. This distinctive character has been recommended with the radical conversions on the genetic operators of the utilized Metaheuristic approach. Subbu et al., (2005) has treated the portfolio optimization issue by the adaptation of a hybrid evolutionary multi- objective optimization approach. The stated approach is established on linear programming along with the evolutionary computation and is based on "Pareto Sorting Evolutionary Algorithm" (PSEA). This model stated in the research accounts the different characteristics of portfolio risks chiefly associated with asset and its liability management. Thus, PSEA is been boot up by Random Linear Programming technique. The principal advantage of the stated algorithm is determining basic solutions likely for meeting the constraints proposed within the problem. Thus, the stated algorithm is able to provide an extreme limit sampled from the search area. Tsao and Liu (2006) have applied a modified form of NSGA-II within a Mean-VaR portfolio and have considered a budget restriction within the model. The characteristic of non-convexity of the VaR function makes it much more complex which requires a huge amount of time for simulating it. Authors have proposed a magnitude to be maintained for the primary generation which is been inconsistently generated. Vassiliadis and Dounias (2008) have investigated the issue of constrained portfolio optimization during the application of bee colony optimization technique. Mishra et al., (2009) however preferred for a multi-objective particle swarm optimization technique for solving the similar stated problem. Again, Branke et al., (2009) has added a variety of non-convex restraints to the issue and has solved it based on "Envelope-based Multi-Objective Evolutionary Algorithm" (EMOEA) approach. All the constraints have been encouraged from a specified rule within German investment law. The rule states firstly, the total holdings if been exceeded by five percent are granted to be as lesser than fourteen percent of the total net asset value of the fund. Secondly, the shares of every asset will not be more than ten percent of the net asset value of entire amount of fund. Thirdly, share of asset of a similar issuer will not be more than five percent of the net asset value of the entire fund. Latterly, Ardia et al., (2010) and Krink and Paterlini, (2011) have researched multi-objective portfolio optimization issue with the help of realistic restraints and have solved the issue based on a differential evolution relying upon stochastic-search heuristic approaches.

The best conception within the multi-objective issues differs from any of the mono-objective issue. So a global optimum is not only pursued solely, rather a solution area which provides a superior compromise within objectives is always been desired (Pareto,1896)

Evolutionary Algorithms as Multi-Objective Approach

Evolutionary algorithms are extensively utilized for solving the multi-objective issues. A comparative literature study of evolutionary algorithms in the field of multi-objective optimization can be viewed within Zitzler et al. (1999). The techniques are established on Pareto approach which in terms can be categorized into two primary sorts of algorithms: the non-elitist approach and the elitist approach.

The initial technique known as "Multiple Objective Genetic Algorithms" (MOGA) has been suggested by Fonseca and Fleming (1995). The starting step of this approach targets to rank every individual in accordance to the figure of individuals which governs it.

This approach provides superior quality of results and its application is easier, but the actual accomplishment provided is dependent over the criterion targeted over the sharing function.

The next approach known as "Non-dominated Sorting Genetic Algorithm" (NSGA) is been suggested by Srivinas and Deb (1993). Within the algorithm the computation of the fitness is done by subdividing the overall population into numerous groups by considering the degree of individual dominance.

The stated approach is less effective within computational time frame than the MOGA approach. But by the usage of giving in the stated space and distributing solutions within various domains seems to be more perfect for maintaining population diversification and higher effective distribution of results on the Pareto frontier. Adding up to the stated approach it is applicable to issues with any sum of objectives. However, it is appealing for the usage of population sort heuristic for distribution of the population over the Pareto frontier. Nevertheless, the stated approach proves to be sluggish along with the concurrence of the algorithm.

Hornand Nafpliotis (1993) stands to be the pioneer for suggesting the third category of algorithm called "Niched Pareto Genetic Algorithm" (NPGA) depending on the Pareto dominance assumption. This approach targets on selecting randomly two individuals and comparing them with a sub-population randomly been selected having a size stated as t. This technique is proved to be faster than prior mentioned techniques bearing superior quality solutions due to the sharing been only applied within a portion of the population.

The represented techniques within the prior category are been considered to be non-elitist. Firstly, they don't maintain Pareto-optimal individuals found within the time frame which has also been stated. Secondly, they can hardly maintain any variety within the Pareto frontier. Finally, the results' convergence against the Pareto frontier is sluggish in nature.

For resolving the above mentioned issues, few techniques have emerged recently. Zitzler and Thiele (1998) suggested a new multi-objective optimization known as "Strength Pareto Evolutionary Algorithm" (SPEA which in turn is dependent on Pareto concept for comparing the solutions. The method is able to distribute solutions efficiently within the Pareto frontier. The technique of rating permits sampling individuals within the space. The principal drawback of this of this technique stands to be the rating depending on the external population size selected by user.

"Pareto Archived Evolution Strategy" (PAES) originally been suggested as a local search technique within an off-line routing information issue. Knowles and Corne (1999) have proved this algorithm to provide superior results than research methods based on population. The used algorithm is very simple and been inspired from an evolution strategy. Rechenberg (1973) and utilized this approach of crowding established on a distribution into hyper-cubes within the objective space. This approach is relatively simple for usage. It is also able to avoid the settings of algorithms as it is not based on a genetic algorithm. Still the effectiveness lies on the new parameter selection permitting the disorganization of objective space. Knowles et al.,(2000) proposed the "Pareto Envelope based Selection Algorithm" (PESA) which is based upon the crowd principle originated within PAES and defines a parameter known as squeeze_factor representing the space congestion.

Deb (2000) suggested another latest version of NSGA known as (NSGA-II) which resolves few criticisms within the initial technique like complexity, non-elitism and the usage of sharing. The complicatedness of this approach, NSGA is primarily due to creating procedure of various borders. For reduction of this computational complexity of NSGA, Deb again proposed an alteration of the sorting technique of population within several borders.

Corne (2001) also has suggested another modified version of PESA known as PESA-II. It is the latest selection method based on the usage of hyper-cubes within the objective space. Inspite of selecting based on the fitness of individuals within PESA, this approach makes a choice of hyper-cubes inhabited by single individual. This approach is much more effective for spreading the solutions over the Pareto frontier. This is because of the ability to select individuals situated within desert areas having a probability superior than the classic tournament. PESA-II enables progressing positively the selection, favoring lesser congested space field.

Simulated Annealing as a Multi-Objective Algorithm

The simulated annealing approach within multi-objective optimization was first directed by the usage of an aggregation outlook (Serafini (1992) and Friesz (1993)). Afterwards, the next two techniques came into popularity:

1. Multiple Objective Simulated Annealing (MOSA)

This approach was suggested by Ulungu et al. (1999) which utilizes the simulated annealing features for finding the non-dominated resolutions.

2. Pareto Archived Simulated Annealing (PASA)

This approach was proposed by Engrand (1997) which utilizes the aggregate function of every objective function correlated to an archived technique of non dominated resolutions.

Multi-Objective Algorithms Based on Swarm Intelligence

Ant Colony Algorithm

Within the single-objective optimization function, ant colonies algorithms remain very popular for resolving combinatorial issues. Very few researches prevail within the situation of multi-objective. Doerner et al. (2006) suggested another algorithm known to be P-ACO committed for solving the portfolios allocation issues. This algorithm interprets superior results as compared with NSGA and simulated annealing. The OCF technique as suggested by Gagné et al., (2004) is established on the similar principle like P-ACO. On every iteration, ants alter their objective function for optimization. During the end of the iteration procedure, the ant giving the best performance renovates the pheromonetrail.

Particle Swarm Optimization Algorithm

Ray and Liew (2002) suggested an algorithm by the usage of Pareto dominance, combining methods from PSO along with evolutionary algorithms. Coello et al., (2002, 2004) developed an algorithm based on the usage of an external archive. A mutation operator is also utilized. Srinivasan and Seow (2003) have suggested a hybrid approach PSO-evolutionary algorithm with an objective for application of the operators of evolutionary algorithms for making the mechanisms of the PSO more efficient. A selection operator is also utilized for ensuring the convergence of non-dominated solutions. The authors did not utilize an external archive. Bartz-Beielstein et al., (2003) have introduced an elitist approach to the PSO. Various operators for selecting and eliminating are framed for finding the combination which can produce the superior approximation within the Pareto front. The methods of disposal are structured on the contribution of particles to the swarm's variations. If been compared, the selection operators are established on the values of objective functions. Li, (2003) adapted the main techniques of the NSGA-II for the multi-objective PSO approach. Raquel and Naval (2005), within the space distance or the crowding distance, already been utilized within NSGA-II, serves as a criterion for maintaining the recorded diversity.

CONCLUSION

The issue of fund management field is extensive and involves several techniques to be investigated. The leading issue is the combination of assets to be identified which is known as either an asset allocation or portfolio optimization problem. Due to the challenging attributes and increasing intricacies of markets, demand a few financial and statistical methodologies which prove to be very important from diversified asset management outlook. Putting under consideration the complicacies, mathematical approaches become incapable of providing solutions meant for the advanced models within this area involving higher number of constraints and objectives. Nevertheless, the theoretical advancements appearing within Metaheuristic techniques administered turmoil within the field of portfolio optimization.

Metaheuristics are proved to be the stochastic approaches targeting for solving a huge jury of issues not being intervened by the users. These approaches are encouraged and developed from a likeness with other domains such as physics, field of genetics, or even ethologic. Metaheuristics have boomed quickly due to the essence of simplicity in nature along with elevated modularity. They are readily malleable for obtaining the best believable accomplishment meant for a defined time frame.

Here in this introductory chapter, investigations done are associated to the portfolio optimization issue with the usage of Metaheuristics. The chapter is segmented into different sections, initially describing the applications of mono-objective Metaheuristics to portfolio optimization issues, next focusing on researches on application of multi-objective Metaheuristics, along with Metaheuristics approaches described as peroration. This chapter admits for confining the deep array of available research works.

As concisely stated in this literature study, any investor within a real-world portfolio decision making process experiences complications for optimum allocation of assets targeting an optimal portfolio by the usage of efficient computational techniques. During the previous two decades numerous researchers have suggested different constraints and objective functions requiring discrete decision variables recommending the efficient frontier for such issues. Metaheuristic algorithms are proved to generate an acceptable solution or even the real optimum within feasible computational time frame. At the outset portfolio optimization issue being multi-objective in nature, multi-objective Metaheuristics administer portfolio selection problems involving complicated measures of risk.

It has been investigated that a parallel study of various approaches seems particularly appealing and of immense importance. Most of the research studies acknowledge formal single-period portfolio optimization issue. Research studies also exist in view of the multi-objective portfolio models employing dual risk measures. multi-objective Metaheuristics administer a pleasant recognition within legitimate multi-objective issues over the single-objective techniques often been applied in mean-risk portfolio problems.

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Chapter 2
Particle Swarm Algorithm:
An Application on Portfolio Optimization

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ABSTRACT

Optimization is discovering an alternative with the most cost-effective or highest-achievable performance under the given constraints, by maximizing desired factors and minimizing undesired ones. Portfolio optimization in finance depends on selecting assets from an opportunity set which yields highest expected return on each level of portfolio risk. Optimization algorithms based on natural events are called heuristic algorithms. The particle swarm optimization (PSO) is a population-based heuristic optimization technique. The technique is inspired by the ability of animals such as birds and fish to adapt to their environment by applying a "sharing of knowledge" approach, to find rich food sources and to avoid hunting. This chapter focuses on portfolio selection problems and shows how to manage financial portfolios using a particle swarm optimization (PSO) technique which is a heuristic algorithm. In order to better understand the subject, the technique has been evaluated in Istanbul Stock Exchange for three transportation sector stocks.

INTRODUCTION

This chapter focuses on the heuristic optimization technique that proceeds from the inspiration of Swarm Intelligence: Particle Swarm Optimization (PSO). The PSO is mostly used in multicriteria optimization problems. In recent years artificial intelligence techniques are mostly used in portfolio optimization. Optimization is the process of obtaining the best solution when performing certain operations

DOI: 10.4018/978-1-5225-8103-1.ch002

for a given purpose. Before, optimization problems used to be defined by the mathematical functions. Due to the lack of flexibility and disadvantages of such methods, new methods have been developed and inspired by events in nature. Optimization algorithms based on natural events are called Heuristic algorithms. Heuristic algorithms are the algorithms that are inspired by natural phenomena to accomplish any purpose or goal. There is a convergence to the optimum solution in the solution space, but no definite solution can be guaranteed in these algorithms. With the rise of the use of heuristics based methods in problem solving in science, heuristics based methods are widely used in quantitative decision making. PSO, one of a heuristic method, was first introduced by Russel Eberhart and James Kennedy in 1995. It is inspired by simulating the behaviours of the bird and fish swarms. Collection of something such as birds and fish flocks that move somewhere in large numbers is called Swarm Behaviour (Mishra et al. 2013). PSO is a technique that is developed by taking advantage of the collective action of particles in the swarm. Each of the particles represents a solution candidate and forms the ideal solution space of an optimization problem (Cura, 2009).

As the Portfolio Optimization Problems are considered in this book, in this chapter it is aimed to give an explanation about the theorical structure of Particle Swarm Optimization and application of PSO for the portfolio optimization problem is set.

Portfolio optimization is a crucially important problem in modern finance. Portfolio selection is the decision of forming the optimum portfolio from a number of assets under certain expectations and constraints. Solving this kind of problem is quite difficult because of the large amount of complex data and other constraints. The general purpose of portfolio optimization is to discover an efficient frontier that yields the highest expected return on each level of portfolio risk. If a portfolio consists of funds in various kind of assets, then we can say that the portfolio is well diversified. Such portfolios may support a higher return at the lower possible risk. H. Markowitz's Portfolio Theory for portfolio selection indicates that as you add new assets to an investment portfolio the total risk of that portfolio decreases continuously depending on the correlations of asset returns, but the expected return of the portfolio is a weighted average of the expected returns of each asset (Markowitz, 1952). Put it another way, inverstors may decrease their risk by investing in portfolios rather than in individual assets. In time, some additions are made to the Markowitz model and it was attempted to improve the solution process by different algorithms. The literature indicates that there are so many papers on portfolio optimization problem that studied the Markowitz optimum portfolio using heuristic techniques. These techniques could be more suitable for solving problems in portfolio management than others. However, the studies that deal with this problem by using particle swarm optimization (PSO) approach are quite rare. In this chapter, a heuristics model of PSO has been explained in detail and presented how to implement Markowitz portfolio optimization using PSO technique.

In order to better understand the subject, the technique has been evaluated for three transportation sector stocks listed on the Istanbul Stock Exchange by using daily stock returns for one year between June 30, 2017 and June 30, 2018. The Markowitz Mean Variance model is solved using the PSO technique providing with constraints that sum of weights is 1 and each stock weight in the portfolio is equal or more than zero, which preserves the budget constraint and no short sale. The remainder of this chapter is organized as follows. First, the background about PSO is given and especially PSO for portfolio optimization literature is explained in detail. After giving general properties of Swarm Intelligence concept, the characteristics, model, geometrical illustriation, implementation steps and algorithm of the proposed PSO is explained in detail. The information about portfolio optimization is given in the next section and the Markowitz Mean-Variance model for Portfolio Selection is explained. Then the portfolio selection problem and the mathematical model that is based on Markowitz's portfolio selection theory are described. Finally, empirical experiments are executed, and the results are discussed to explain PSO in more detail. The results obtained by PSO algorithm are compared with the results obtained using Nonlinear GRG to solve the Markowitz Mean-Variance model for portfolio optimization problem.

BACKGROUND

PSO has been developed based on simulations of the social behaviour of birds or fish. It was first described by Eberhart and Kennedy as "*The algorithm that is an adaptive algorithm based on a social-psychological metaphor; a population of individuals (referred to as particles) adapts by returning stochastically toward previously successful regions."* in 1995. This simple and powerful algorithm is successfully applied to enormous applications in various fields of science. PSO is widely used in various optimization problems in different areas of interest. In this section a brief summary is given for PSO algorithm application areas.

The algorithm is mostly used in dynamic problems (Hu & Eberhart, 2002; Eberhart & Shi, 2001). Moore and Chapman used PSO algorithm for solving Multi-Objective Problems first time in 1999, then many scholars have proposed a lot of new method to promote the performance of PSO for Multi-Objective Problems (Fieldsen & Singh 2002; Hu & Eberhart 2002). Salman et al. (2001), used PSO Algorithm to solve an assignment problem, Onwubolu & Clerc (2004), Pang et al. (2004), Surekha et al. (2010) and Wang et al. (2003) used PSO to find out the optimal path in a traveling salesman problem. Cao (2009) used PSO in clustering analysis, he analysed the bahaviour of the internet users. There are also some applications of PSO with fuzzy sets in the literature. Abdelbar et al. (2005) proposed the fuzzy PSO with a fuzzy variable.

There are also more recent studies about PSO. Yu et al. (2016) proposed a model for multi-period cross-docking distribution problem. Fathia et al. (2016) modified PSO algorithm to solve the assembly line part-feeding problem. Asla et al. (2016) used PSO for facility layout problem. Alagulaskhmisubha and Mohanapriya (2016) used Discrete Multi-Valued Particle Swarm Optimization (DPSO) to maximize the willingness for social activity planning. Zhang and Yang (2018) aimed to develop an accelerated particle swarm optimization (APSO) to optimize the large- scale network and make a resourse levelling with different constraints. Yang et al. (2018) proposed a multi-objective particle swarm optimisation (MOPSO) algorithm with non-dominated relative crowding distance.

The literature referenced above shows that the areas where the PSO technique is used, are very broad and common. However, the number of studies in portfolio optimization is very limited. Cura (2009), Zhu et al. (2011), Sun et al. (2011), Golmakani & Fazel (2011), Deng et al. (2012), Corazza et al. (2013), Kamali (2014), Abuelfadl (2017) used PSO algorithms in portfolio optimization. The results of this kind of studies are set out below.

Cura (2009) applied the PSO technique to a portfolio optimization problem. He compared the results with the results of Genetic Algorithm, Simulated Annealing and Tabu Search Algorithms. He found out that the PSO algorithm is more successful in portfolio optimization. Mishra et al. (2009) also compared the results of Multi-Objective Particle Swarm Optimization (MOPSO) and those of Non-Dominated Sorting Genetic Algorithm-II, NSGA-II of a portfolio optimization problem without investment constraints. The results show the superiority of MOPSO over NSGA-II.

Zhu et al. (2011) presented a meta-heuristic approach to portfolio optimization problems using the Particle Swarm Optimization (PSO) technique in their paper. The model was tested on different limited and unlimited risky investment portfolios. They compare the results with the genetic algorithm results. The PSO model showed high computational productivity in creating optimal portfolios. They have recommended the development of hybrid techniques for the development of PSO performance.

Sun et al. (2011) in their paper, proposed a novel variant of particle swarm optimization (PSO), called drift particle swarm optimization (DPSO), and applied it to the MSPO problem solving. The objective function of their study was the classical return variance function. The productivity and the performance of the different methods used in their study are compared in terms of efficient frontiers, fitness values, convergence rates and computational time consumption. In his study, his findings showed that DPSO is a better problem-solving technique than other methods studied in that kind of problems.

Golmakani & Fazel (2011) presented a novel heuristic method for solving an extended Markowitz mean–variance portfolio selection model. The extended model was a quadratic mixed-integer programming model with the use of heuristics. In their paper, they proposed a heuristic method based on Particle Swarm Optimization (PSO). They compared this approach with the Genetic algorithm. At the end their proposed algorithm performed more effective that genetiz algorithm especially in large-scale problems. Deng et al. (2012) also obtained better results for PSO technique for portfolio optimization.

Corazza et al. (2013) considered a non-linear mixed-integer portfolio selection model with several constraints used in fund management practice. They applied PSO reformulating a mixed-integer model.

Kamali (2014) used PSO and GA algorithm for a Markowitz mean–variance model for portfolio selection problem and the results showed that a PSO approach is suitable for portfolio optimization.

Abuelfadl (2017) investigated optimization techniques based on historical data and the use of individual investors' trading data as the training points in the Quantitative Partide Swarm Optimization (QPSO) algorithm. They declared that the latter produced better optimization results for short-term investment horizons.

As can be gleaned from the results of the studies using the PSO algorithm in portfolio optimisation problems, the PSO gives good results as a heuristic method.

SWARM INTELLIGENCE CONCEPT AND FEATURES

Swarm intelligence (SI), is an advanced section of the Artificial Intelligence (AI) discipline that is interested in designing intelligent systems inspired from the natural behaviour of social animal swarms (Blum & Li, 2008). Therefore, swarm intelligence models are called computational models inspired by natural swarm systems (Srikanth & Geetha 2018).

Sometimes, the individuals who cannot do anything by themselves can behave intelligently when they act collectively. The basic idea underlying the concept of swarm intelligence is that the individuals within a group will exhibit complex and intelligent behaviours. For this purpose, strategies were developed inspired by the behaviour structure of observed groups in nature and these strategies were turned into theoretical, mathematical bases for solving engineering problems (Kucukdeniz, 2009). Bird and fish swarms show natural movements. For instance, the birds leave a certain distance between their neighbours when flying or the fish swim away from their neighbours when they swim underneath. Furthermore, they become intensive groups when they realize a threat. These groups can be changed, separated, or reassembled when any threat emerges (Hemelrijk & Hildenbrandt, 2012). This is called intelligence.

In literature, several swarm intelligence medhods based on various natural swarm systems have been suggested, and successfully implemented in numerous real-life applications. Ant Colony Optimization (Macro, 1992), Particle Swarm Optimization (Kennedy & Eberhart, 1995), Artificial Bee Colony (Karaboga, 2005), Gravitational Search Algorithm (Rashed et al. 2009), Glowworm Swarm Optimization (Suruthi & Gomathi, 2013). Intelligent Water Drops (Hamed-Shah, 2009), River Information Dynamics (Mishra et al., 2013) can be considered as some examples of swarm intelligence methods.

SWARM INTELLIGENCE AND PARTICLE SWARM OPTIMIZATION

PSO is one of the techniques covered under swarm intelligence algorithm. Typical swarm intelligence systems have common characteristics, as defined by Sumathi and Surekha, and are listed below (Kutlu 2012, from Sumathi & Surekha 2010:655-656). PSO has the common characteristics of a typical swarm intelligence system defined by Sumathi & Surekha (2010).

PSO offers the advantages of simplicity and easy implementation. For instance, PSO has no overlapping and mutation calculation. It can be completed easily and is a powerful tool for optimization as against the other developing calculations. The speed of the particle carries out the search. Only the particle that has the best value can deliver information to the other particles during the search. In other words the PSO algorithm has a powerful efficiency to find global optimal results. Its searching speed is also very high compared to the other heuristic methods. In addition, it offers fast biological convergence (Walker, 2017) and it is based on intelligence. PSO has many other advantages. It can be scaled, its error tolerance is lower, it is easy to adapt, so on. The failure of some individuals does not affect the swarm directly in PSO. It is an algorithm that is gradient-free, easy to parallelise and simple to implement (Wilke, 2005). It benefits from the corporate movements of the particles under a swarm (Cura, 2009). According to Mishra and Das (2013), the PSO gives the near results compared to the other optimization methods.

BASICS OF PARTICLE SWARM OPTIMIZATION

It has been observed that the movements of animals in flocks for searching food or meeting their safety needs lay out the other individuals in the flock and provide

Table 1. Definition of common charecteristics of intelligence systems

Charecteristics	Definitions
Combination	A particle is a combination of individuals. The individuals are relatively homogeneous. They can be identical or they can belong a typologie. The ability of acting in a coordinated way without any controller is a characterizing property of a swarm intelligence system. It is mostly observed that swarms shows collective behavior without any external control.
Fault Tolerance	Particle Intelligence Process is not depending on a central control mechanism. For this reason, the loss of few nodes or relations does not cause important failures. The failure of some individuals does not affect the swarm directly.
Rule Based Behaviour	Only individuals who use local information monitor exact rules. Individuals change directly or over the environment. Individuals in the swarm can only have a limited information abour their environment in local level.
Autonomy	All behaviours of a particle system are organised by the system, and do not rely on a foreign layout. No human supervision is required. The behavior of each individual of the swarm is displayed a stochastic behaviour. This stochastic behaviour depends on his local perception of the environment.
Scalability	The population of representatives is able to accommodate variances in the size of the swarm.
Adaptation	There are multiple interactions between individuals. Changes like ending or reproduction is according to all network changes.
Velocity	Individuals in a community change their behaviours quickly according to their neighbours. They create a decentralized structure. There is no central control in decentralized structure. This efficient structure helps the swarm to survive in many different conditions.
Modularity	The behaviours of individuals are independent from others in community. There are simple rules that set up the interactions among the individuals. These rules utilise when the individuals faced with an exchange situation (Andreea, xx). This innovative ways of problem solving method by swarms is used in many cases.
Parallelism	Activities of individuals are naturally parallel. The interactions of individuals each other and their environment cause the behaviour of a system (Lakkakula et al. 2014). In case of a lack of an individual liable of the group, swarm can show intelligent behaviour (Goel et al. 2011). Obeying basic rules and interacting with the neighbours' of the individuals, results with intelligence behaviour of the swarm.

easier access for the purpose of the flock. Each individual is called a particle, and the population that these particles form is also called the swarm in PSO. The aim is to determine the particle with the best position in the swarm and provide the other particles to move in that direction. The particles aim to improve their next position by using the information of the particle that has the best position in the swarm.

The basic criterion of a problem suitable for solving by a PSO algorithm is that the value of the selected system needs to be measurable at any time (Kucukdeniz, 2009). The PSO first constructs particles, each of which presents the candidate solution to find an optimal or near optimal solution. Every particle in PSO provides a solution. PSO starts randomly with the determined number of particles. These particles are updated for investigating the best possible solution value (Pedersen, 2010). The solutions are iterated by using pbest and gbest values. Pbest and gbest values refer to the best value of the particle and the best value of all particles in the swarm respectively. These values are kept in mind. PSO begins with a random number of solutions with particles and the best solution value is searched by iterating the particles. The swarm for the solution is obtained from the combination of the individuals. The PSO is dependent on sharing information between individuals. Each particle also benefits from its previous experience, when setting its position to the best position. In a swarm that is consisting of "n" particles and every particle have a position in d dimensional space. The particles change its condition according to three principles as follows (Bai, 2010):

1. Keep the inertia,
2. Change the condition according to its most optimal position,
3. Change the condition according to the swarm's most optimal position.

Gbest and pbest are neighbourhood topologies and before introducing the algorithm of PSO, gbest and pbest terminologies are explained as neighbourhood topologies below.

Global Best PSO- Gbest

In Global Best (gbest) PSO, whole particles are neighbours of each other. Therefore, the neighbour with the best possible value in the swarm is taken into consideration while updating the particles' velocity. The disadvantage of this topology occurs when the global optimum point is not similar to the best particle. Because, in case of global optimum point is not near the best particle, other particles will not stray far from the best particle and the swarm will get stuck on the local optimum point (Kaur & Saini, 2018).

Personal Best PSO- Pbest

In the swarms that can be named as Personal Best, the neighbours of a particle are defined as a certain number of particles. Thereby, not the best particle in the swarm is used to update the velocity, but the best of the subgroup is considered. It goes slowly to the solution but the chance of tendency to the global optimum is high.

GEOMETRICAL ILLUSTRATION OF BASIC PSO MODEL

The geometrical illustration is a useful tool to explain how the changes in position and velocity of the particles occur. Initially PSO starts with a group particles randomly selected. By updating the generations it searches for the optimal value. In practice, a lot of 20 particles work quite well for most real problems at sizes between 2 and 100. As it is mentioned before; the initial position and the velocity of a particle starts with a random value. These values are the values of variables defined within a defined range. Particles are learning from each other. In addition to their position and velocity, every particle has a memory of its best position. All particles are updated by using two "best" values in each iteration. The first one is the best solution (that is the value of fitness) the particles achieved. (This fitness value is also stored.) This value is called 'Personal Best' (pbest) (Kaur & Saini, 2018) and refered by $p_i(t)$. The second one is the Global Best (gbest) value. The best position based on a shift of neighbouring particles is called as gbest. g(t) is the global best that belongs to the whole swarm.

Before starting the algorithm, the fitness function should be defined. It can be maximization or minimization. Fitness function is a critical factor in the PSO method. According to the objective of the problem, the researcher can determine the fitness function. For every particle in the swarm fitness value is calculated. A particle moves in a solution space by taking into account its previous position and the neighbour's previous position. (pbest and gbest respectively.)

Particles make their moves according to the velocity of themselves and also the velocity of the swarm. The position of each particle is updated according to the best position faced by them and their neighbours. In every iteration of PSO, the position and velocity of every particle is updated according to the algorithm. The geometrical illustration of first position and the new velocity with new position of a particle (i) is simply illustrated in Figure 1 and Figure 2 respectively.

$\overrightarrow{x_i}$ (t): The initial value of particle i at t time.

$\overrightarrow{P_i}$ (t): Pbest value of particle i at t time.

$\vec{g}$ (t): Gbest value of the swarm at t time.

Figure 1. First position of the particle i

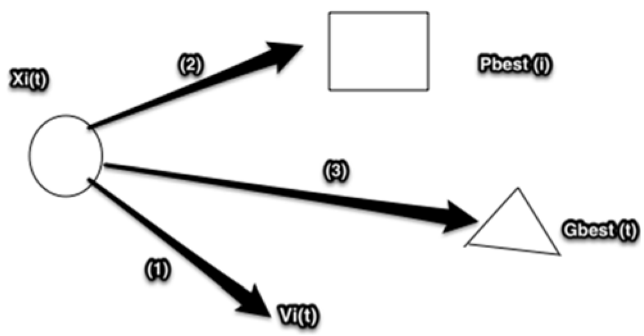
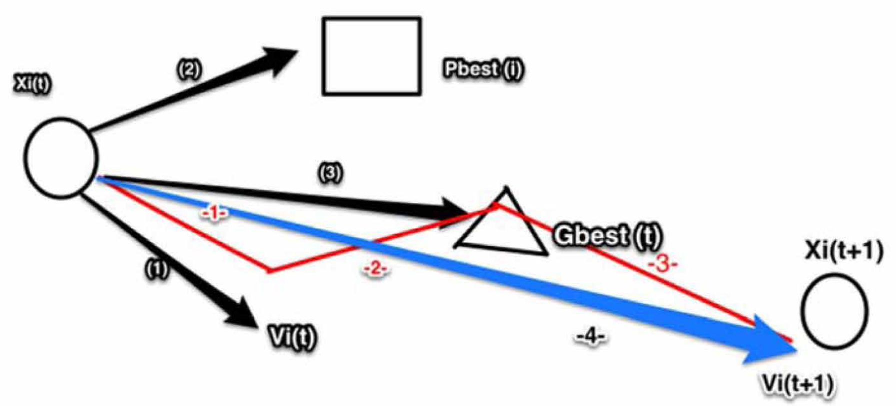


Figure 2. New velocity and the position of the particle i



$\vec{v}_i$ (t): The velocity of particle i at t time.

$\vec{v}_i$ (t+1): The new velocity of the particle i at time (t+1).

$\vec{x}_i$ (t+1): The new position of particle i at time (t+1).

Every particle uses 3 vectors shown in the Figure.1 as (1), (2) and (3) to determine its new vector. The calculation of the vectors are given below respectivlely:

$$\overrightarrow{Pbest_i}(t) - \vec{x}_i(t) \tag{1}$$

$$\overrightarrow{gbest}(t) - \vec{x}_i(t) \tag{2}$$

$$\vec{v}_i(t)$$

The particle uses these 3 vectors when moving. The sum of these 3 vectors creates the new velocity vector. The new position of the particle is calculated by taking into account these three vectors. The sum of these three vectors is the new velocity of the particle i. $\overrightarrow{v_i}$ (t+1) has its own updating equation as follows:

$$\overrightarrow{v_i}(t+1) = \overrightarrow{P_i}(t) - \overrightarrow{x_i}(t) + \vec{g}(t) - \overrightarrow{x_i}(t) + \overrightarrow{v_i}(t)$$

Iteration for updating the position of particle is as follows:

$$\overrightarrow{x_i}(t+1) = \overrightarrow{x_i}(t) + \overrightarrow{v_i}(t+1)$$

Based on this model obeying the rules by every particle in the swarm, the particles will coorporate to find the best location and the best solution of the optimization problem. At the end of each iteration, particles come closer to the optimal solution.

BASIC COMPONENTS AND PARAMETERS OF PSO

As it is mentioned above, PSO is a simulation of behaviours of animals like bird and fish swarms. Birds and fish follow the neighbour that is nearest to the food, when they search for food. All the individual solutions that are named by ‘particle’ are a bird or a fish in the search space. When the particle moves, it sends its coordination to a function and consequently, the fitness value of the particle is measured.

The Algorithm of PSO

Each solution in a PSO algorithm is expressed in terms of ‘Particle’ in the search space. Each particle has a position, velocity and fitness value. The particles aim to improve their next position based on their past experience and the best position in the swarm. Particle Swarm Algorithm has simple components named as the particles. They are placed in the search space and each calculates the objective function at its current location. Each particle identifies its movement through the search space by taking into account its own current and best locations. After all particles have been moved, the next iteration starts. Sooner or later, the swarm moves collectively close to an optimum value of the fitness function. To mathematically express the algorithm the equations are given below. According to equation (1); particle swarm include N particles, $X_i = (x_{i1}, \dots, x_{in})$ and $V_i = (v_{i1}, \dots, v_{in})$ expresses the location and velocity of particle i respectively in n-dimensional search space. "Pbest" expresses the personal optimal location of each particle and "gbest" expresses the global optimal location of all particles.

Velocity update formula of each particle is given in equation.1.

$$v_{ij}^{t+1} = w * v_{ij}^{t} + c_1 r_1^t \left[pbest_{ij}^t - x_{ij}^t \right] + c_2 r_2^t \left[gbest_j^t - x_{ij}^t \right] \tag{1}$$

for i = 1, … , N and j = 1, … ,N.

After updating particle velocity, the algorithm uses the formula expessed in equation. 2 to update the location of each particle:

$$x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1} \tag{2}$$

The new location of each particle should be compared with the objective value of personal optimal location (pbest). If the new location of the particle is better than the pbest value, then the pbest is updated for the new location. In other case, the original value of pbest is stored unchanged. The new global optimum solution (gbest) is updated according to the gbest of the new particle swarm. Continue to compute the values for the next generations. After the maximum number of iterations has been done, the particle swarm will converge to the global optimum solution (Kamali, 2014).

Parameters and Implementation Steps of PSO

The parameters of the PSO algorithm are summarized in Table. 2.

The process of Particle Swarm Algorithm defined in Eberhart & Shi (2001) is as follows:

Step 1: At this stage the parameter that is needed to be determined is the swarm size. The swarm size is the number of particles in the swarm. Also there should be an upper and lower limit for the swarm size. The swarm is defined in the search space within the lower and upper limits. Initial population of particles is defined randomly.

Table 2. The parameters of PSO

Parameters	Definitions
Swarm Size	The number of particles in the swarm. Swarm size is the number of rows in the swarm matrix. It can be refered by 'n'. There is an upper and lower limit for the swarm size.
Dimension of Particles	The number of variables in the problem. The dimension of the swarm is the number of columns in the swarm matrix. This parameter shows the number of variables in the problem. It can be refered by 'd'.
Range of Particles	The maximum number of iterations the PSO execute and the minimum error requirement. The range of the particles depends on optimization problem. In general, the range of the most optimization problem is selected between 20 and 40. Also 10 particles is large enough to get good results.
The Stop Condition	The maximum number of iterations the PSO execute and the minimum error requirement. The stop condition of the problem is determined according to the optimization problem.
Iteration Number	The iteration number is an important problem dependent used to reach a good solution. Small number of iterations may exhaust the search early. A large number of iterations will cause unnecessary computational complexity.
Velocity Components	The velocity of particle i denoted in equation 1. This parameter provides a memory of the previous flight direction and also the new directon is determined by using this parameter. Also it is updated in every iteration. The velocity components are crutial in updating a particle's velocity (Talukder, 2010).
Accelation Coefficients	Learning coefficients. The acceleration coeficients are represented by c_1 and c_2. They are called as "learning factors". c_1 denotes the level of confidence value that the particle has itself. c_2 denotes the level of confidence value that the particle has in its neighbors. Assume that there is no inertia, c_1 and c_2 will be both equal to 0, and then the particles will keep flying at their current speed until they hit a boundary of the search space. In case of $c_1 > 0$ and $c_2 = 0$ then all particles flies independently. (Engelbrecht, 2007). This means particles execute a local search. In general they are taken as equal to 2. They are ranged between 0 and 4 in different applications. They are also used with the random vectors r_1 and r_2.
V_{max}	V_{max} is the maximum value of a particle that can change during one iteration. It is neede to be limited. Taking the determining of V_{max} too large, the particle may miss out the good solution. Conversely, determining the value of V_{max} too small, the particle may not explore the space outer local best area. So it easily gets into local best. Determining the value of velocity too big or too small may decrease the computational efficiency of algorithm (He et al. 2016).
Velocity Update	The process of chaging the particle position. At each iteration, every particle updates its velocity according to its current velocity, its previous best position and the global best position of the swarm (Bhattacharyya, S. 2015). The velocities may become too high and the particles may go beyond the search space. For this reason, it is needed to define a parameter to prevent the velocity from exceeding the search space. Velocities are bound to a maximum value V_{max}. V_{max} is calculated from the range of the particle. It is the maximum value of a particle that can change during one iteration. If the range of a particle is defined as [-5, 5], then V_{max} equals to 10.
Position Update	The process of chaging the particle position. N number of solution will get of out n number of particles. In all iterations, pbest is evaluated and the best position of all particles within the swarm (gbest) is evaluated. In all itarations for a PSO algorithm having n number of particles, there are n numbers of pbest values, while; there is only one gbset value for every iteration. At the beginning of the algorithm, the starting value of all particles is the pbest value of them at the same time. After the next iterations, the particle's position is updated according to other particles' positions and compared with the last pbest value of the particle. In case of a better value, new solution assigned as pbest.
Inertia Weight	Inertia weight is a parameter that is multiplied with the velocities of particles in a previous time step. In the constant inertia weight strategy, it is taken constant between 0 and 1. If the inertia weight is determined small, the exploration capability of PSO will ascend (Jordehi et al. 2012).

Step 2: Determine the fitness function. The values of objective (fitness) function are obtained. For each particle, evaluate the value of the fitness function. Initialize the positions and the velocities for all the particles randomly.

The fitness function for particle *i* is given in equation.3.

$$f_{fitness} = (x_{i1}, x_{i2}, \ldots\ldots, x_{id}) \tag{3}$$

The function is written in matrix form in equation 4.

An initial solution with n particles for calculating the fitness function of a problem with d variables (d-dimensions) is illustrated in equation.4 (Erdogmus & Yalcin, 2015). Each of the rows named as particles in the matrix given in the equation.4, expresses a solution.

$$\begin{pmatrix} x_{11} & \cdots & x_{1d} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nd} \end{pmatrix} \begin{pmatrix} \cdots \\ \cdots \\ \cdots \end{pmatrix} \tag{4}$$

The first (n*d) matrix shows the particles in the swarm. Each row shows a particle in the swarm. The dimension (d) of the swarm is the number of columns in the matrix. This parameter shows the number of variables in the problem. Swarm size is the number of rows in the matrix, which shows the number of particles (n), and the second matrix shows the fitness function value of each particle in the swarm.

The algorithm starts with the initial swarm.

Step 3: There are two main operators of PSO named as velocity update and position update as mentioned above. To generate the new position each particle accelerate towards the particle's previous best position and the global best position. Particle's fitness value is compared with particle's pbest value. If the current value is better than pbest, then the pbest value is set equal to the current value, and the pbest location is set equal to the current location in the d-dimensional space (Behera, 2016).

Step 4: Fitness value is compared with the population's overall previous best. If current value is better than gbest, then change gbest to the current particle's array index and value.

Step 5*:* Change the velocity and the position of the particle according to the equation.1 and equation.2, respectively:

Step 6: Back to Step.2 until a criterion is met, usually a sufficient good fitness or a maximum number of iterations.

MODERN PORTFOLIO THEORY AND THE MARKOWITZ MEAN-VARIANCE MODEL FOR PORTFOLIO SELECTION

Portfolio optimization is a problem that arises from the desire to minimize risk while maximizing the investor's returns. The concept of optimal portfolio comes from the Modern Portfolio Theory (MPT). MPT assumes that rational investors focus on minimizing risk when striving to get the highest possible return. And also, rational investors make decisions with the goal of maximizing return for a given acceptable level of risk. The investors, who want to get high profits, take great risks. An investor who avoids arbitrary money will settle for low earnings. In the stated balance, the best solutions or solutions are tried to be reached. The basis of financial investments is diversification. Investors can choose different types of assets to diversify their investments. Investors can minimize their risks and maximize returns on their portfolio by Portfolio diversification.

Portfolio managers are expected to create a portfolio of assets that provides the highest possible rate of return at the lowest posible risk level. In other words, they are to create a portfolio that allocates funds in different assets to well diversfy the portfolio and to provide the highest return at the lowest possible risk. The concepts of risk and return represent the core of financial decision-making (Kulali, 2016).

The total return includes both current income and capital gain or losses arising from the increase or decrease of the asset price. Risk is a concept that represents a potential negative impact on an asset or some characteristic value that may arise from some present process or future event. In daily usage, risk is often used synonymously with the probability of a known loss. Risk is uncertainty of the income or capital appreciation or loss of the both (Bodie et al. 2010).

H. Markowitz (1952) developed his portfolio selection technique called Modern Portfolio Theory (MPT). Portfolio optimization models were centered on returns that are produced by investment opportunities prior to the Markowitz's work. Optimal portfolios were generated from the stocks that gave the best opportunity with minimal risk. The importance of return in MPT retains its importance but also with the same level of risk. Thus, the risk of the portfolio concept has blown up. While the risk has been cogitate as a major factor and measured by standard deviation, Markowitz introduced his model to reduce the standart deviation of a portfolio by different stocks (Markowitz, 1959). According to MPT, by increasing the number of stocks within the portfolio, the total risk of the portfolio can be decreased. And the expected return of the portfolio is calculated as the weighted average of the expected returns of each stock (Marlin and Emanuelsson, 2012).

In Markowitz mean-variance model, increasing variety of stocks can cause a decrease in the risk of the portfolio for a determined return level. The investors are assumed as risk averse. Therefore, in case of higher expected return, they will prefer increased risk. Indeed, for willing higher returns the investors must accept more risk. The exact trade-off will accord to individual risk avoidance characteristics of the investors (Chen et al., 2010).

In line with these objectives, optimal portfolio solution requires nonlinear mathematical programming. The Markowitz Mean-Variance model is a traditional nonlinear mathematical approach for portfolio selection problem. The Markowitz Mean-Variance model for asset selection of risky portfolio construction is described as below.

Using a portfolio (R_p) with two risky assets, R_A and R_B, as an example, assume the expected returns of the two risky assets are $E(R_A)$ and $E(R_B)$. The standard deviations of the two risky assets are σ_A and σ_B. The covariance between A and B is $Cov(R_A, R_B)$. The expected return of the risky portfolio $E(Rp)$ is calculated using equation (5) below:

$$E(R_p) = W_A * R_A + W_B * R_p \tag{5}$$

Where W_A and W_B are the weights of A and B in the risky portfolio respectively. The variance of the two asset risky portfolio is calculated as shown in equation (6).

$$\sigma_P^2 = W_A^2\sigma_B^2 + W_B^2\sigma_B^2 + 2W_A W_B Cov(R_A, R_B) \tag{6}$$

The simple two-asset risky portfolio is described in equation 6. It can be enlarged for the portfolios with several numbers of risky assets. The calculation of expected return $E(R_p)$ of a multiple-asset risky portfolio is similar to equation (7). The border-multiplied covariance matrix is used to calculate the standard deviation (σ_P) of a risky portfolio with multiple-asset. The general formula of expected return for n assets can be seen from the equation. 7 below:

$$Var(r_p) = \sum_{i=1}^{n} w_i E(r_i) \tag{7}$$

Where; n is the number of securities, calculating the return is the same thing as finding the weighted average return of the securities included in the portfolio.

Portfolio Risk can be calculated using the weights and covariances of individual assets making up the portfolio:

$$Var(r_p) = \sigma_p^2 = \sum_{i=1}^{n} \sum\nolimits_{j=1}^{n} w_i w_j Cov(r_i, r_j) \tag{8}$$

The mathematical formulation of the portfolio optimization problem using Markowitz Mean-Variance model is given in the following nonlinear programming model.

Objective Function:

$$\min Var(r_p) = \sigma_p^2 = \sum_{i=1}^{n} \sum\nolimits_{j=1}^{n} w_i w_j Cov(r_i, r_j)$$

such that;

$$\sum_{i=1}^{n} W_i = 1 \; 0 \le W_i \le 1 \text{ i=1,2.....n}$$

The constraints simply imply that the assets cannot be in short positions.

APPLICATION: PORTFOLIO OPTIMIZATION PROBLEM BY USING NONLINEAR PROGRAMMING AND MARKOWITZ BASED PSO

In order to better understand the subject, a basic application using the PSO tehcnique by Mean-Variance model has been made with transportation sector stocks that are trading on the Istanbul Stock Exchange. In this chapter, the results were obtained by using Nonlinear GRG and PSO algorithms are compared. MS Excel solver tool is used to calculate the optimum portfolio of Markowitz Mean-Variance model by using nonlinear GRG model. MATLAB is used for coding and running PSO.

Problem Definition

Minimizing the portfolio risk, which is calculated using the weights and covariances of each individual asset making up the portfolio, is the main problem. Thus, the aimed problem is to minimize portfolio risk, consisting of transportation stocks, while maximizing the portfolio return.

There are eight transportation stocks traded on the Istanbul Stock Exchange. Three of them are choosen in order to show a basic example.

One-year daily data between June 30, 2017 and June 30, 2018 is used for these three transportation stocks. The data set has been obtained by using the logarithmic differences of last price series with 273 daily observations using equation 9. In Quantitative Finance, log returns are widely used rather than arithmetic returns. Because log returns are not impacted by the compounding frequency, they are time-additive, with small returns, log returns are approximately equal to arithmetic ones and lastly log-returns can be considered as normally distributed. Therefore, logarithmic returns are calculated. The logarithmic historical returns are calculated by using the equation.9.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{9}$$

The average log return, variance and standard deviation of the three stocks are shown in Table.3.

It can be seen from Table.3 that all the stocks have a positive average return that are calculated from the one-year daily data between June 30, 2017 and June 30, 2018.

Variance-Covariance Matrix is calculated and can be seen in Table 4.

Table 3. Return, variance and standart deviation of three transportation stocks

	Stock.1	**Stock.2**	**Stock.3**
Average log return	0,005534	0,001435	0,00048
Variance	0,005604	0,00048	0,000546
Standart deviation	0,074863	0,021901	0,023368

Portfolio Optimization by Using Mathematical Model and the Results

To draw a comparision of PSO algorithm, the problem is solved with a mathematical model. The Markowitz Mean-Variance model is also a nonlinear model, thus it is solved by using MS Excel solver as a nonlinear programming and the results are shown in Table.5. The results showed that the Stock.2 stock has the biggest weight within the potfolio with the ratio of 51,71%. Stock.1 has as the smallest weight within the potfolio with the ratio of 4,5%.

According to the calculated weights; the return, variance, and the standart deviation of the portfolio is calculated and the results are illustrated in Table.6. The return of the optimal portfolio is calculated as 0,12%.

Portfolio Optimization by Using PSO Algorithm and Results

The same problem is solved by using the Markowitz Mean-Variance model Based PSO algorithm. The implementation steps of PSO have logical meanings. The steps of PSO while running in MATLAB is illustrated in Figure.3. The first step is problem definition and defining the fitness function (Objective Function): The fitness function in the application is the objective function used in Markowitz model.

Table 4. Variance-Covariance matrix of there transportation stocks

	Stock.1	**Stock.2**	**Stock.3**
Stock.1	**0,005625**	- 0,000104	0,000099
Stock.2	- 0,000104	**0,000481**	- 0,000001
Stock.3	0,000099	- 0,000001	**0,000548**

Table 5. Weights of the stocks in optimal portfolio calculated by non-linear GRG

	Weights
Stock.1	0,04518
Stock.2	0,51711
Stock.3	0,43771
TOTAL	1,00000

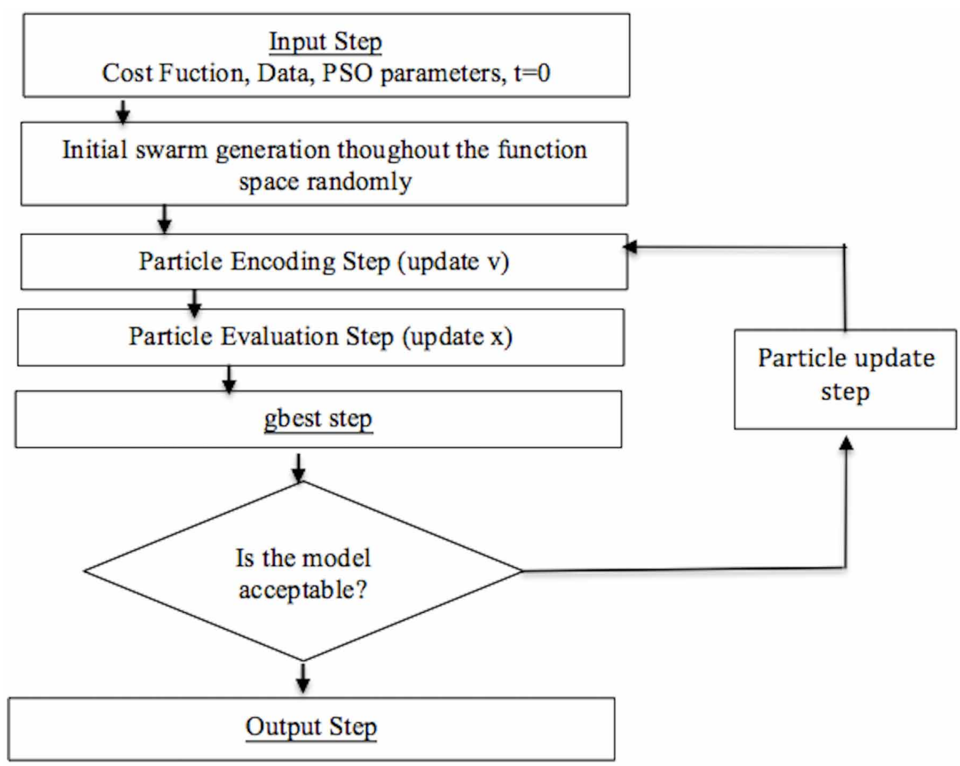
Table 6. Return, variance and standart deviation of optimal portfolio calculated by non-linear GRG

	Optimal Portfolio
Portfolio Return	0,001202180
Portfolio Variance	0,000243755
Portfolio Std Dev	0,015612641

Problem Coding

In the Problem definition step the optimization problem that is being solved by PSO is defined. The main component of the problem is the fitness function. The name of the fitness function is determined as "MarkowitzObj". In the first step of coding, the objective function is determined and the codes are written in a script as

Figure 3. Implementation steps flow chart of basic PSO



can be seen in Figure.4. The algorithm for the objective function that was given in the equation.8 is coded in MATLAB as seen in Figure 4.

The aim of the problem is to minimize the risk. The objective fuction is written as a fitness function. The code can be seen in Figure.5.

In the problem definition step some variables such as nVar, SizeVar, MinVar and MaxVar should have been determined. nVar is the number of variables that show how many decison variables exist in the problem. As 3 stocks are considered, there are 3 variables in the problem. In another words, the matrix is 3 dimensional, which represents 3 transportation stocks. SizeVar represents all the searching space in the problem; it shows all searching space and all solutions. It represents the horizontal particles of the matrix. This is the matrix size of decision variables. MinVar represents the minimum value of variables. MaxVar represents the maximum value of variables. For the portfolio probem explained in this chapter, the weights can at least be 0 and maximum 1. The codes are written as in Figure.6.

After defining the cost function and main variables, the next step is determining the parameters. The success of the PSO depends also on the parameters defined.

PSO is an iteration based optimization model. Therefore, the iteration number should be defined. MaxIt shows the maximum iteration number, in other words it shows how many times the PSO iterates while running. In this problem, the iteration number has been defined as 100. An unnecessary high number of iterations lead to extended problem solution time. Therefore, there is no need to select very high iteration numbers. nPop show the number of the population or swarm size

Figure 4. Codes for fitness function of PSO algorithm

```
function sum = MarkowitzObj(x,cov_matrix)
sum=0;
for i=1:3
    for j=1:3
        fit = x(i)*x(j)*cov_matrix(i,j);
        sum = sum + fit;
    end
end
end
```

Figure 5. Codes for Fitness Function of PSO Algorithm

```
FitnessFunction = @ (x) MarkowitzObj (x,cov_martix);
```

Figure 6. Codes for defining main variables of PSO

```
nVar = 3;
SizeVar = [1 nVar];
MinVar  = 0;
MaxVar = 1;
```

in the problem. Swarm size is the number of particles in the swarm. 30 is used in this application as the swarm size. It is the number of rows in the swarm matrix. The intertia weight coefficient was developed to control the algortihm better. In general, it is taken constant between 0 and 1. For more exploration capability of PSO algorithm, the inertia weight is determined less and vice versa. To provide a balance between global and local exploration and exploitation, inertia weight need to be determined suitable for the problem. In this application, intertia coefficient (w) has been set equal to 0.98. The acceleration constants c_1 and c_2 represent the weighting of the stochastic acceleration terms. Each particle is taken toward pbest and gbest positions by using these coefficients. Thus, adjustment of these constants changes the amount of tension in the system. Determining these value low will cause the particles get away from the target regions, while determining them high will cause sudden movements toward or past the target regions. They are set equal to 2.0 in this application. The coding of these parameters can be seen in Figure.7.

For storing the data for the particles, the codes written can be seen in Figure 8. If the swarm initializes neatly, this will provide PSO to inquire efficiently the search space.

To create the swarm, the template in Figure 8 is needed to be repeate; the code for repeating the codes in Figure 8 is written in Figure 9.

To initialize the global best and the population members, it is important to generate random solutions according to the sum constraint. In this case, the sum of weights should be equal to 1. Thus the sum of the generated numbers is needed to be equal to 1. To generate random solution we need to generate numbers between 0 and 1 with uniform distribution. The numbers generated by uniform distribution is

Figure 7. Codes for parameters of PSO algorithm

```
MaxIt = 100;

nPop  = 30;
w = 0.98;
c1 = 2;
c2 = 2;
```

Figure 8. Codes fot particle template of PSO algorithm

```
initial_particle.Position = [];
initial_particle.Velocity = [];
initial_particle.Cost = [];
initial_particle.Best.Position = [];
initial_particle.Best.Cost = [];
```

Figure 9. Codes for creating the swarm of PSO algorithm

```
particle = repmat (initial_particle, nPop, 1);
```

normalized and these normalized numbers are used to generate particle (i) position. The codes are shown in Figure 10.

For holding the best value of each iteration in the algorithm, the code in Figure 11 is written.

Figure 10. Codes for initializing the global best and population members of PSO algorithm

```
GBest.Cost = inf;

for i=1:nPop

    swap = unifrnd(MinVar, MaxVar, SizeVar);
    swap = swap /sum(swap);
    particle(i).Position = swap;

    particle(i).Velocity = zeros(VarSize);

    particle(i).Cost = FitnessFunction (particle(i).Position);

    particle(i).Best.Position = particle(i).Position;
    particle(i).Best.Cost = particle(i).Cost;

    if particle(i).Best.Cost < GBest.Cost
        GBest = particle(i).Best;
    end

end
```

Figure 11. Codes for holding the best value of each iteration os PSO algorithm

```
BestCosts = zeros(MaxIt, 1);
```

For updating the velocity and the position, storing the Best Cost Value, displaying iteration information and identifying the damping inertia coefficient, the codes seen in Figure 12 is written.

After coding and defining the parameters of PSO, it has been run for the results in MATLAB. Portfolio optimization results by using PSO Algorithm are given in Table 7 and 8.

The results of optimal weights calculated by using the PSO algorithm can be seen in Table.7. It is very close to the weights calculated by non-linear GRG. Stock.2 has the biggest weight within the optimal portfolio calculated by PSO with the ratio of 51.71% of the portfolio. Stock.1 has the least ratio of weights within the portfolio like the ratio calculated by using Non-Linear GRG method.

Portfolio return has been calculated according to the weights that minimize the risk level. Optimal portfolio return, variance and standard deviation are calculated and shown in Table.8.

The return of the optimal portfolio is calculated as 0,12%. Also as can be seen from the Figure 13, the weights are nearly the same with the weights calculated by Non-linear GRG method. The results show that PSO method gives similar results with the Non-linear GRG model.

FUTURE RESEARCH DIRECTIONS

Due to the lack of flexibility and disadvantages of the mathematical methods, “Metaheuristics” have been developed by inspiring from the events in nature. They are widely used in all area of science because of its simplicity. Indeed, in some cases it is difficult to determine the variables with a crispy numbers. The Grey System theory and Fuzzy Theory can be useful to idendicate the variables in some cases. The grey numbers and the fuzzy theory can be included in these algorithms. For the future research, the algorithm can be improved by using fuzzy or grey numbers.

Figure 12. Codes for PSO algorithm

```
for it=1:MaxIt

    for i=1:nPop

        particle(i).Velocity = w*particle(i).Velocity...
            + c1*rand(VarSize).*(particle(i).Best.Position -
particle(i).Position)
            + c2*rand(VarSize).*(GlobalBest.Position -
particle(i).Position);

        particle(i).Position = particle(i).Position +
particle(i).Velocity;

        swap = max(particle(i).Position, MinVar);
        swap = min(particle(i).Position, MaxVar);
        swap = swap /sum(swap);
        particle(i).Position = swap;

       particle(i).Cost = CostFunction(particle(i).Position);

              if particle(i).Cost < particle(i).Best.Cost

              particle(i).Best.Position = particle (i).Position;
              particle(i).Best.Cost = particle (i).Cost;

                   if particle(i).Best.Cost < GlobalBest.Cost
                   GlobalBest = particle(i).Best;
                   end
              end
    end

    BestCosts(it) = GlobalBest.Cost;

end
```

Table 7. Weights of transportation stocks in optimal portfolio calculated by PSO

Stocks	Weights
Stock 1	0,045167599
Stock 2	0,517112364
Stock 3	0,437720037
TOTAL	1,00

Figure 13. Weights of optimal portfolio

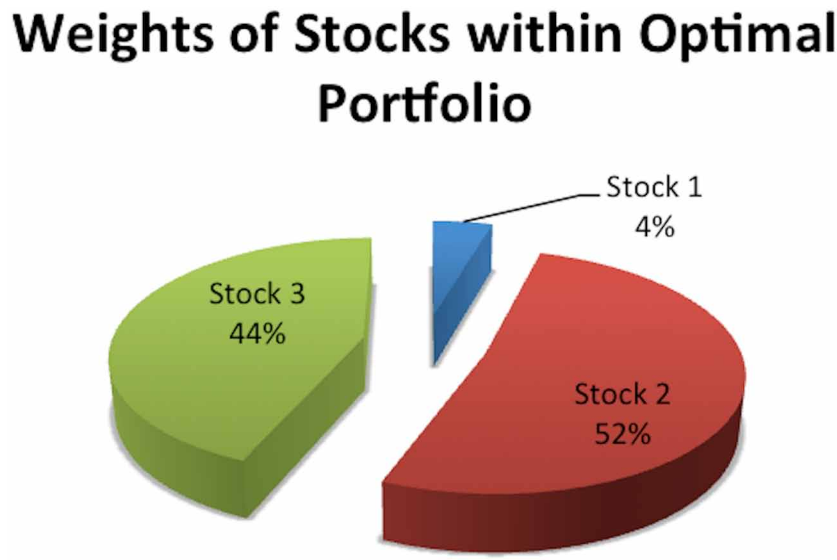


Table 8. Return, variance and standart deviation of optimal portfolio calculated by PSO algorithm

	Optimal Portfolio
Portfolio Return	0,001202119
Portfolio Var	0,000243755
Portfolio Std Dev	0,015612641

CONCLUSION

Various markets in the world provide lots of options to the people who want to invest. As a result of the studies done by using various methods, optimum portfolios have been created and presented to the investors. These portfolio types differ by the stock diversity and their weights in the portfolio. The portfolio having the best performance value is selected as an optimum portfolio within the created portfolios. PSO is one of the useful methods that can be used to identify the optimal portfolio. Optimization algorithms based on natural events are called Heuristic Algorithms. PSO is a population-based heuristic optimization technique. The technique is inspired by the ability of animals such as birds and fish to adapt to their environment by applying a “sharing of knowledge” approach, to find rich food sources and to avoid hunting. In this chapter, after giving the characteristics, model, geometrical illustration, implementation steps and algorithm of a proposed PSO in detail, the portfolio selection model, which is based on Markowitz's portfolio selection, is described. This chapter focuses on portfolio selection problems and shows how to select financial portfolios using a Particle Swarm Optimization (PSO) technique that is a Heuristic Algorithm. The data set used in this chapter is evaluated from contemporaneous data of three transportation stocks data for the period June 30, 2017, through June 30, 2018 that were obtained from www.bigpara.com.

In order to evaluate the optimal portfolio algorithm that requires obtaining the solutions, problem is coded in MATLAB. For the PSO algorithm, the number of iterations is set equal to 100, the population size set equal to 50, the minimum and maximum value of variables are between 0 and 1. The results from solving the PSO algorithm on the basis of the data set of transportation stocks are tabulated in tables 3 and 4. According to the results, the weights are 4%, 52% and 44% for Stock.1, Stock.2 and Stock.3 respectively. When using these weights, the portfolio daily return is found 0,12% and standard deviation is found 0,15%. The application of PSO in solving optimization problems could serve as facilitator in real financial life.

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KEY TERMS AND DEFINITIONS

Global Best: Whole particles are neighbours of each other. Therefore, the neighbour with the best possible value in the swarm is taken in to consideration in order to calculate the best.

Particle: It is a combination of individuals in the swarm. It is the potential solution in the PSO algorithm.

Personal Best: The neighbours of a particle are defined as a certain number of particles. Thereby, personal best is the best of the particle within a local area.

Portfolio Optimization Problem: A problem that arises from the desire to minimize risk while maximizing the investor's returns.

Swarm: For a community of animals such as fish flock or bee colonies that behaeive simultaneously is called "swarm".

Swarm Intelligence: That is interested in designing of intelligent systems inspired from the simultaneously behaviour of social animal swarms.

Chapter 3
Bayesian Networks and Evolutionary Algorithms as a Tool for Portfolio Simulation and Optimization

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ABSTRACT

This chapter will propose solution how to recognise important factors within portfolio, how to derive new information from existing data and evaluate its importance factor. The chapter will also propose methodology for sensitivity evaluation between factors recognised as important. This information has valuable factors for Bayesian network construction. Such created Bayesian network can be used as simulation tool, as well as tool for portfolio optimization. As a simulation tool, such Bayesian network can be for output analysis regarding potential decisions via decision graphs. Also, as an optimization tool, Bayesian network can be used in way of finding optimal value of decision factors upon expected outputs from portfolio. For achieving this aim, evolutionary algorithms will be used as optimization tool.

DOI: 10.4018/978-1-5225-8103-1.ch003

INTRODUCTION

Bayesian networks provide optimization in which the presumption of attribute independence is maintained, but with the exception of where it is usable in terms of final outcome efficiency. Exceptions are variables, i.e. sets of variables, which are declared dependent, and this dependence is defined by a common distribution of probability for this set. Bayesian network shows a common distribution of probable outcomes for attributes dataset presented by a collection of assumptions on conditional dependencies and sets of local conditional probabilities. Bayesian belief network hierarchy could be designed in different way using algorithm or node training, but from the business, value and general performance perspective, it is adviseable that Bayesian ruleset should be improved by industry experts. Bayesian logic is often used in probability space, due to its capabilities and fact that their structure often depends on industry expert knowledge. The Bayesian network can be used to evaluate the value of a target variable with the values given by other variables. In the general case, it will be necessary to estimate the probability distribution of any subset of network variables by the given values or the distribution of any subset of the remaining variables. The exact calculation of these probabilities in the general Bayes network is NPs difficult. Therefore, many methods have been developed that sacrifice precision for efficiency. In theory, even approximation of probability in Bayes' networks may be NP hard. But in practice, such methods have proved usable in many cases.

Learning Bayesian Network

There are several key concepts to be considered while in learning Bayesian networks: is the network paths known in advance, does the strucute must be learned, do any variables in each instance of learning really learn and are some instances may be invisible. The simplest case is, of course, learning the network if it is the default structure and if all the variables are always visible. Then we can apply a direct method, ie to estimate probability probability tables in average learning values, as in the Simple Bayesian Classifier. If, on the other hand, some variables are not visible the problem is similar to the problem of learning neural networks. One of the options is a gradual climbing technique in the space of a hypothesis corresponding to all the possible values in the probability probability tables. The objective function that is then maximized is the likelihood, the probability of the realization of the observed set with the condition of the hypothesis. Learning of Bayesian networks when the network structure is not known in advance is also difficult. There are developed metrics for dial-up between alternative networks and a heuristic search algorithm that learns the structure when the data is fully visible.

By participating in network structure, industry experts can not be a guarantee that the final network will be optimally designed but it will however be consistent with business expectations and environment. This chapter will present best practice taken from various projects combined into proposal for future hypothesize definition with goal to improve model robustness by using patters extension within the belief/probability network not only before but after network structure once take place. These actions have foundations in gain score for every node along the network, especially ones observed. Chapter methodology challenge expert knowledge on several levels with aim to to improve efficiency as well as to improve quality of hypothesis looking into impacts between nodes (impacts between nodes, objects and/or business valuation). As a result of such approach, final network recognizes greater predictive value, greater impact stability and improved robustness.

Evolutionary Algorithms Supported by Bayesian Belief Network

In research part, chapter will present a technique of using a swarm intellgince algorithm as a tool to look for and find complex information on the foundations of trained Bayesian structure. Meanning that the swarm intelligence algorithm will be used as a tool to look for and find optimal outcomes of input attributes (within trained data science models) as a reference code for probability improvement when looking for another risky event. The main advantage of the proposed solution is to automatically determine the most favorable details in a situation with mixture of cases is present, as result by node state for various nodes. The proposed methodology will be shown from perspective of actual research and real-life case from insurance industry. Research goal will be to asses adequate level of risk for each node in the network including existing members for the selected insurance coverage. The search route begins with the trining of Bayesian network using automated algorithms and by testing outcome performance. The next step will show the effects of incorporating expertise in the design of the Bayesian network, together with adjustments according to industry expert inputs. The final step will show the effect of the use of the proposed technique that takes the calculation of the evaluation of the profits for each node in the network, affecting the node that has seen the Bayes network. Final result will include warm intelligence algorithm to be used as a tool to look for and find optimal value of input variables within the trained predictive models together with reference metrics for the maximization of probability value that the buyer will choose/buy a product or service. Combining results with their business processes, insurance company can create and maintain profiles of the most vulnerable security users, even within numerous different combinations caused by heterogeneus nodes and their states within the trained Bayes belief Network and related model. This approach will help the company to better understand the cause of the risk of events in an environment where there are many factors and overlapping impacts.

Foudations behind the idea include holistic process that involves the development of a multinational predictive model and the use of this model developed on a sample of historical data for finding risk profiles using the swarm intelligence optimization algorithm. This problem is usually not expressed in the case of prediction models with various but ofter binominal, outputs, which is the probability of buying a product or service. Bayesian networks, by their definition, mainly relate to multinational outputs, not just the target variable. The reason for this lies in the fact that each linked variable within the model can be viewed as a target variable. That's why complexity of these models is different comparing to linear regression models and binomial variable output.

Background

Risk profiling in a case when models are trained to calculate the N-state probability has become a very difficult task that requires a lot of hand work with suspicious results. Unlike the binomial state of the output variables in the predictive model, the analysis of the attribute attribute for multinomial output overlapping in impact zones and combination expansion could not provide clear information for setting the input values of a risk-determining variable. In this case, the target variable within the predictive model should reach maximum likelihood criteria "be risky" using the swarm optimization algorithm. The final result will give optimal values of input variables for each product / service such as behavioral characteristics or socio-demographic characteristics, and models from which they develop on the basis of attribute relevance analysis. The results of this analytical approach are selected marks in space over many dimensions used for case-by-case-based scoring or grouping by means of distance measurements and customer risk profiling.

Biggest improvement of explained solution is the automatic profile detection originated from risk behavior of the user, in our case within insurance/finance industry, in the example where a model envisions many different products or services. Other benefits include ability to seek and find similar profiles using risk attributes. Proposed hypothesis is that a customer with target profile will act in a similar way and that we can detect their behavior using data science techniques and machine learning. The assumption of similar pattern in the corresponding problem space of detected nodes can be positive can also be misleading. This depends on the empirical behavior patters of targeted customer and requires additional testing during the implementation process. Those tests may also be interesting for determining the optimal distance between selected nodes within the input variables. The practical/ business model value is also derived in the phase that follows the calibration of the predictive model when the swarm intelligence optimization based on the analytical procedure is repeated for a each new node, while calculation is generated in a multi dimensional environment. The results may be useful for cross-sector profiling for various industries including insurance, when there is a need to understand clients conversion/migration trends of profile features within the portfolio.

RISK PROFILING AS PART OF PORTFOLIO OPTIMIZATION PROCESS

Methods and systems that support profiling and pattern filtering are not easy to implement. When browsing over the market evinroment, users often feel overwhelmed by the amount of data they are returning to. This could be especially important for portfolio optimization because those services could risk the ability of service providers to lose resources and users to leave their service with a bad impression and without value. Suggested approach combines user profiling and adaptable interface to help businesses meet their customers. User profiling has existed for some time in areas such as insurance, finance but also ecommerce, television, radio, and advertising (Arora, 2013, Nguyen, 2010, Taleizadeh, 2013). However, profiling users in global age can go beyond the reach of their predecessors because of the modern ability to collect data easily from global users. Compliancy with personal information security policies still keeps available data on purchases, the customers behavior patterns, how long the are using the service and other information. Once collected, this information can enable companies to analyze patterns, customize the models to meet optimization critera. These adjustments allow companies to better meet success score and increase the likelihood of creating business value. User profiling and optimization modeling can be done in three ways: use of stereotypes, use of questionnaire or use of "learned model" (Alexander, 1995; Zhang, 2000; Zuo, 2012). The first two are pretty simple approaches that use the information we already know, or the information we collect, so that we can then build the appropriate profiles. Third, however, using "learned models" is particularly interesting. This implies creating a system that does not know its users, but over time, while users communicate with the system, it learns from their trends and behaviors and creates profiles based on the experience they gain. It is also possible to create these profiles individually, per user or collaboratively, collecting all user data to form a general profile. As part of suggested approach, collaboration system with ability to d "learn" the overall user profile and test its usefulness on a typical portfolio optimization case (Giudici, 2003, Giudici, 2009).

As the finance and insurance market continues to grow and become increasingly commercialized, it will be increasingly important to improve its manageability of such systems. There are already a variety of tools and techniques that are used for this and we will explore a simple example of one of the latest developments. Suggested approach indicates anticipation of satisfactory amount of "intelligent" connections between observed nodes. The profiling system has improved the service and established the foundation for future improvements and ideas. More sophisticated profiling systems, data mining tools and other personalization methods will change the way we optimize portfolio sevices in the coming years. To be widely used, these improvements have to result in easier and more friendly use of systems that provide real information at the right time. The optimization system provides the basis for the extension. His general learning ability, which represents many users, is, in general, adequate, but there is something else that could be done. Most importantly, optimization can be tailored to individual desires. While the overall collaboration model is good for new or rare moels, as service increasingly communicate with data, it would be ideal for a service to be tailored to each individual. There are some similarities in the way systems behave, but each method has its own set of attributes and to achieve better results, the system should reflect these individualities. Portfolio optimzation enhancements can also be achieved by collecting additional information about each service using experimentation as well as the unlimited limitation of new ideas that are developed on a daily basis, which provide tremendous opportunities for portfolio optimization systems (Janecek, 2015) including particle swarm optimization models. Bayesian belief networks are complex in structure in comparison to other methods therefore using the suggested approach, each node in the Bayesian graph can be viewed as a target variable.

Customer Risk Profiling

Risk analysis implies analysis of strengths and weaknesses, and analysis of opportunities and dangers from the environment. In the research of strength and weakness judgment is divided into, on the one hand, the marketing mix of factors, which include product, pricing and conditions, promotion and sales promotion, concept and sales channels, and, on the other hand, on the company's business. Risk profiling is often related to the potential of sales, production, management, organization, development, finance and profitability. As part of the environment analysis, attention is paid to market analysis, which includes the procurement and sales market, industry and competition but, not less important, individual customers. Since it is impossible to systematically collect all the information, a conclusion is made on the collection and processing of only the information relevant to the profiling within the company. The second segment of the environmental analysis, which is usually carried out before the internal environment analysis itself, needs to assess the future development guidelines of general economic conditions, technology and ecology. Individual ratings within the marketing mix research of the factors and the factors of the company are valued as the strength, neutrality or weakness of the enterprise. When analyzing markets, economic development, technology and ecology, courts are presented as an opportunity, neutral or dangers. The mode of conducting the potential analysis by confronting the opportunities and dangers of wider and narrower environments, and the strength and weakness of the enterprise, is a creative process for detecting early signs of a business crisis. If a business opportunity comes to fruition, this is certainly a chance for business development. However, if the change of environment or the danger faces the company's weakness, it is a potential (potential) risk that may affect the company's long-term survival. As a conclusion of business analysis and business potential, considering a comprehensive analytical-diagnostic model for displaying results, an expanded SWOT matrix is used. The dynamic confrontation of the results of analysis of internal and external factors reveals the chances and risks of present and future business operations. Due to such results, potential analysis can be used as a system of early detection of a behavior pattern.

Being important technique in managing customer relationships, customer profiling can be very challenging to adopt to various scenarios. Various customer portfolio management activities are closely related to customer profiles. The same is the situation where we would like to measure the risk of the insurance company's clients. In today's mass and depersonalized business, personal access to a customer can only be achieved through adequate profiling. Contemporary marketing and sales mantra are personalized offering and targeted communication. But from the perspective of consumers, users are very rare opportunities when we get a personalized offer or when a company or brand is communicating with us personally. This is difficult because experiences with the nowadays and so rare small trade where our salesman serves over the counter and knows everything about us, in chains impossible. Personal experience can only be provided to the customer if we know him well and we see him every day. Through loyalty programs and customer relationship management strategies, we want to achieve their loyalty, but often without a detailed customer awareness and tracking their purchasing process, especially before making a purchase decision. The lack of relevant customer data remains a major problem for the company. According to the relevant market research (Agosta, 2000), more than a third of companies have a problem with lack of quality data when using marketing automation tools that should facilitate one to one marketing instead of creating difficulties. With the problem of data shortages, every marketing tool is ineffective. Habits of a particular customer and systematically record information on which we can predict his purchase and customize his offer are many. In a friendly and unobtrusive way, we can use all the points of contact with the customer. If we ask or follow only the relevant information that will allow us to tailor the offer to a particular client, this way is unobtrusive and even more - the client is motivated to share information with us, as this offers a better offer (and perhaps gifts for participation in the form of additional points of loyalty, discount and similar). Furthermore, digital channels and technologies allow us not to ask - through web analytics and other test and feedback tools, it is often enough to just observe the behavior of users. Technology successfully solves systematic data capture of individual clients in one place.

Profiling clients in insurance is a solution for faster achievement in the field of upsella and cross-selling of new products and package deals. To encourage the sale of these products by using new information about an individual customer, target group neds to be selected. If we already have existing target product users, we need to analyze their profile - what these insurers are and what their motive is for decision. Based on this information we get the target client profile. The profile consists of indicators that we collect through questions at different points of contact or interaction with clients: when visiting a branch office, when a policyholder logs into a user portal, a web shop or a mobile application (if we provide services through these channels), via e-mail messages or in a prize game. In the insurance field, there is often a problem with a limited number of contacts with the client because the existing insurer requires contact only when the contract (extension) of the insurance or contact exists only through the agent. But when we plan a sales campaign for a product, we need to profile as many potential customers in a limited time as possible. In that case, it is good to use a promotional contact gathering campaign, such as the email address below (certainly under license) we can use as a channel profiling. In the continuation of our profiling, we get responses that reveal the interest for the purchase based on which we can create a customer profile for the targeting. That profile then we look for a base of existing customers. If some of the indicators defining the target insurer profile already exist on a party basis, we can include them with analytics. This way we get accurately defined plaques with a higher probability of converting them into qualified leads, which reduces campaign costs (Aleksander, 1995). Long-term such profiling is used to enrich the profile in the CRM base to increase loyalty and increase the value of a particular customer.

To capture the data that we need to compile or fill in to make a customer profile, each company uses a channel that has the highest number of contacts and the way that the customer is the least intractable. In the classical store at the point of sale, the best way to table is in addition to cash registers. After the sales transaction the buyer is invited to participate in the table where the questions are still waiting for him with a simple data entry application. We always thank our customers for their participation with a gift or some advantage. In this way, a customized solution for an individual company enables optimization of marketing activities, especially direct marketing, as well as distribution of marketing budgets into different sales and communication channels. For sale, this means a reduction in acquisition and lead generation costs, as well as generating cross-sect and upsella. This way of pooling information on each customer in one place solves the IT problem in the area of CRM support, analytical CRM and campaign management automation. Insurance and trade are not the only sectors that use the value of customer profiling. Challenges to achieving better sales results by profiling can be solved by all service sectors that manage relationships with identified customers: e-commerce, financial, telecommunications, energy and the service sector, digital media and all other membership or loyalty clubs. This should be done with reference to the target variable that represents the use of some product or product group. Given the characteristics of customer behavior as part of profiling, profiling becomes more complicated. The first problem in a situation when a company chooses to include behavioral characteristics as an element of profiling refers to recognizing behavioral features, which is significant for profiling (Almeida and Sanots, 2014, Baksi, 2014). Behavioral characteristics are more powerful profiles than socio-demographic characteristics. The problem with this approach is the fact that it is not easy to identify key behavioral characteristics that will show a "typical" risk profile.

Being generative model allowing researcher to learn the joint distribution (opposed to logistic regression or Support Vector Machine (SVM), which model the conditional distribution) Bayesian Networks (BN) are commonly used in situations with lots of missing dana (e.g. portfolio data) and can be very effective since modelling the joint distribution (assertion on how the data was generated) reduces your dependency in having a fully observed dataset. BN are very powerful when there is a need to model a domain in a way that is visually transparent, having cause-effect relationships to be analysed. Although learning the joint distribution can be difficult task, modelling it for discrete variables (using conditional probability) is substantially easier than trying to do the same for continuous variables where BN not only allow observational inference but also causal interventions. This is often neglected and underappreciated advantage of this kind of approach. Using Particle Swarm Optimization (PSO) as chained technique, we are unlocking population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling. While PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA), concept here uses population of random solutions and searches for optimal approach by updating generations. Potential solutions are here called "particles", and they are "flying" through the problem space by following optimum particles. Compared to other techniques (e.g. GA,) the advantages of PSO are easy implementation with only few parameters to adjust. While PSO has been successfully applied in many areas like function optimization, artificial neural network training and fuzzy system control, our strategy provide powerful but easy to implement tool for portfolio simulation and optimization able to efficiently address several different research goals at the same time as part of same methodology.

PARTICLE SWARM OPTIMIZATION ALGORITHM AND PROFILING AS PART OF PREDICTIVE MODELING PROCESS

Organizations today are increasing their use of advance analytics and predictive modeling. The processes of generating predictive models involve data preparation, checking of data quality, reduction, modelling, prediction, and analysis of results. Generating high-quality predictive models is a time-consuming activity because of the tuning process in finding optimum model parameters and often required to redevelop, tweak or reuse the models in the future.

Feature relevance analysis has few important features:

- Identifying most important attributes that have impact on the target attribute,
- Understanding the relationship and correlation between the most important attribute and target variables including those between the most important predictors from the perspective of the target variable.

Functions and features are aligned with recognizing the customer profile, especially when we develop a predictive model for calculating the likelihood of buying a product or service. In addition to measuring relevance, attribute relevance analysis also evaluates attribute characteristics. Attribute Attribute Estimation includes the impact of attribute metrics on the target variables. It helps to understand the relationship and logic between the most important predictor and target variables, and to understand the relationship and logic between the most important predictors from the perspective of the target variable.

From the perspective of predictive modeling there are two basic types of predictive models relevant to the point of profiling:

- Predictive models with binomial target variables,
- Predictive models with multinomial target variables.

In the case of predictive models with binomial target variables, the usual approach to attribute relevance analysis is to use the weight of evidence and value values by using the following formulas:

$$WoE = \ln\left(\frac{\mathrm{Dnb}}{\mathrm{Db}}\right)$$

$$\text{IV}=\sum_{i=1}^{n}\left(\text{Dnb}_{\text{i}}-\text{Db}_{\text{i}}\right)*\ \ln\left(\frac{\text{Dnb}_{\text{i}}}{\text{Db}_{\text{i}}}\right)$$

The weight of evidence is calculated as the natural logarithm of the relation between distribution eg non-buyers (D_{nb}) and, for example, buyers (D_b) in the distribution range.

Information gain is then calculated as follows (Han, 2006):

$$Info\left(D\right)=-\sum_{i=1}^{n}\text{p}_{\text{i}}\log_2\left(\text{p}_{\text{i}}\right)$$

Equtation represents P_i as likelihood that random D belongs to the class C_i (Han, 2006). This measure is recommended when the output variable has more than two prediction states. Information gain is the amount of information that's gained by knowing the value of the attribute, which is the entropy of the distribution before the split minus the entropy of the distribution after it. The largest information gain is equivalent to the smallest entropy.

In formal way, risk probability can be expressed as:

$Pr[P_j] = Pr[\text{node parents}]$

Or more precisely as:

$$Pr\left[P_j\right]=\prod_{i=1}^{n}Pr\left[P_j\mid Y_i,\dots,Y_n\right]$$

Summary:

$Pr[P_j]$ – risk probability as per j insurance service

Y_i – trained Bayesian structure behavioral characteristics expressed through a network node state

Particle swarm optimization will be used as follows:

$v=v_c+c_1r_1(pbest- Y_i) + c_2r_2(gbest- Y_i)$

$Y_i= Y_i+v$

Where:

Y_i'- is particle position as given value from a Bayesian network generated in random way or by random data selection. Swarm size is generated as N randomly using uniform distribution. Values of particle are in range (0, 1), which represents normalized value in the Bayesian network.

gbest - best fit (swarm)

pbest - best fit (particular particle)

c_1, c_2 - acceleration factors range (0,4)

r_1, r_2 - random value (0,1); quick converging variety assurance

v - velocity

v_c - current velocity

Simple algorithm for each j-th product where criteria is maximization of P_j using a predictive model, using Y_1 to Y_n as particles and swarm of size N can be structured as follows:

1. Start
2. Initialize
3. Randomly assign initial values and evaluate fitness
4. Calculate pbest
5. Calculate gbest
6. Calculate v
7. Calculate particle position (new)
8. Repeat from 4 until reaching stopping criteria

In this way, the swarm intelligence optimization algorithm provides a powerful tool for automatically detecting risk profiles based on the predictiors and modelling attributes. The evolutionary approach integrated in the swarm optimization algorithm accelerates profile findings that best suits the specific state of the output variable. This approach gives companies opportunities for periodic and frequent profiling in the profile tracking service.

The described process was applied to the real data of an company. There are over hundred products and services in company's potfolio while its strategy was to produce predictive models at the product group level. Based on business logic and criteria of similarity, nine product groups were created. An individual client may be present in multiple groups in the data sample if he or she uses more than one insurance product. Based on this, the pattern of learning was divided into a development pattern and a sample sample at ratios 80:20. A Bayesian network model was developed, which was the basis for the application of the royalties optimization algorithm. The developed Bayesian model had ninth nodes (one output node) and this fact determines the number of particles in each case.

The criteria for stopping the PSO algorithm have made the suitability of each particle within the horn greater than or equal to 0.80 (on a scale of 0 ... 1 which is likely to buy the observed product), or retaining similar (6% change) or repetitive ability (recognized replicating samples similar, for example, 0.5, 0.6, 0.5, 0.6, 0.5) on the guard in the least 200+ epochs, with the fitness within the cave less than 0.80.

If the target was reached, where each particle within a hare is greater than or equal to 0.80, the algorithm memorizes score and look to improve results with convergence.

Results by using PSO algorithm are shown in Table 1.

The rate of success for profiling was 55.55% (5 successfully recognized profiles of 9). From the results it can be seen that successful profiles have fewer epochs. One of the reasons was the successful recognition of the profiles previously associated with the stoppage criteria. In case of unsuccessful profiling, the number of epochs increase. This is due to the observation of more than 200 epochs in which fitness changes within 5% or recognition of repeating patterns above the fitness value of 0.80. Analysis makes the profile of the riskiest clients using the product. The results of identifying successful profiles are expected to be similar.

Results of similarity calculation are shown in Table 2.

Similar values are found on average different from 4-5 variables 19. Similarity analysis shows that insurance risk carriers have similar behavioral characteristics. Approved similar numbers in the groups show similar behavioral characteristics compared to the number of accidents and other features compared to the observed use of the product.

Table 1. Profiling results

Group number	Best fitness (0...1)	Number of epochs in PSO	Successful profiling
A/1	0.27	1131	No
B/2	0.69	1342	No
C/3	0.92	578	Yes
D/4	0.99	591	Yes
E/5	0.96	761	Yes
F/6	0.84	525	Yes
G/7	0.85	386	No
H/8	0.45	2484	No
I/9	0.65	3841	No

Figure 1. Profiling results viz

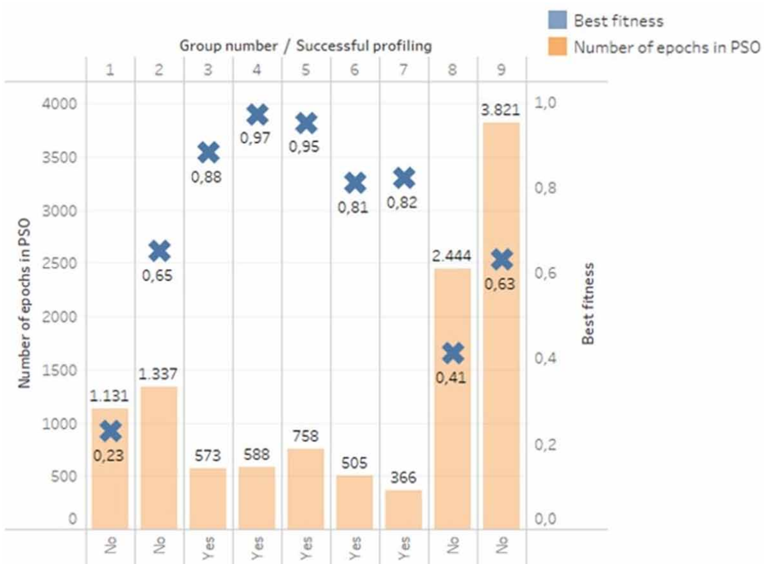

Table 2. Similar profiles

Group number profile	Similar profile
3	6
4	7

DISCUSSION AND FUTURE RESEARCH

Predictive analysis is the practice of extracting information from existing data to identify patterns, and to anticipate future outcomes and trends. Predictive models are typically used to “predict” probable events in the future with a certain level of reliability. There are some links, however, our guitars are software for data mining that, through certain mining algorithms and historical data, “gathers” what will happen in the future. In business terms, predictive analytics serves to predict some of the things that ordinary “business intelligence” tools can not do for us, and this is mostly related to a better understanding of customers, products, partners in order to identify potential risks and opportunities for the company (Malhotra, 2014).

The real challenge is to understand what target is suitable for prediction. A large number of things are easily predictable; however, quality data are needed for this. Today’s market is somewhat different, and today people are mostly replacing computers and software products, but not completely. Let's go back to the predictive analytics and start from predicting the most complex things, which are people and their behaviors. Anthropologists consider that humans are quite predictable and that our every step is easy to predict. Imagine your way from home to work and imagine that each time you unlock the door from home, start the car and go to work, you are actually creating data about your behavior. Now that we have found out that we can easily predict, the question is how can we apply this in business. And every day companies use predictive analytics on us only that we are not aware of. You must know the situation when your aunts in Konzum gave a loyalty card to get points. However, based on your purchases, they know what you can buy with them in the future and give you discounts on these products. A slightly more extreme overview situation is the use of predictive analytics on Big Data data, where the company knows what you will buy, without you being aware of it and all based on data that we share with fist and cap on either social networks or some other services. On the one hand, this is great, because I know that I will get advertisements only for what interests me (I do not want to watch political advertisements Of course, to avoid the corporate spirit of data usage, let's move on to more positive things. What has fascinated me is the application of big data analytics in medicine, ie, with DNA data. In the near future, we will be able to see the likelihood that we are suffering from a disease based on our genetic data, and then our doctors can proactively overwrite the insurance or investment that is "tailored" to us only (Sharkey 2006).

TRANFORMATIVE ROLE OF BIG DATA

Fast growth of structured and unstructured data being available in large volumes becomes very difficult to maintain using common conventional methods and relational database management. Not only the data are being hard to maintain, sometimes choosing right approach, hardware platform and/or tool for specific purpose can be crucial for achieving result. Thus, different industries that are highly data intensive, or simply can benefit from use of data science, require support which can be delivered as high-performance analytical tools and concepts to utilize large volume of data. This kind of instrument is represented by innovative technologies and tools. This mechanism can be applied in various industries and organizations as well, often rarely provided with a tool capable of gathering billions of data records, of their value comparison, of offering different types of simulations after the ingestion of this massive amount of inputs or having massive industry expertise in data driven decision making.

By improving ability to use big data, company can speed up process in creating business value using data science and to lower risk related to level of outcomes that can be unlocked from often lucrative projects (they can unlock great value but at the same time they carry significant risk of not being able to reach to delivery point or to create value that cannot be captured). Additionally, given the fact that the business (industry) target group has certain characteristics which require a business-oriented training methodology, innovative techniques will be action driven so that companies will be immediately able to see the relevance of each action to their workplace and understand benefits from using them.

Business transformation towards data driven business enables significant savings through resource management and business process improvement. It changes the way we use the information we have, the type and amount of data we can collect. To make this data more usable, we use modern analytical and visualization tools whose task is to get useful and timely information from a large amount of different data in a simple and flexible way. The issues that arise in this area of interest range from how to visualize data, which methods to use to find knowledge hidden in data, and how to develop forecasting models using data. Researchers and industry are giving special focus to weather data that may have a significant impact on prediction in times of unpredictable climatic changes and weather influences. In technical matter for companies that want to make the first step in this area, they are encountering questions from how to store data into a “cloud”/”big data” container, is it possible to develop data project which “grows together with a company” and more and more acquired data, whether it can all work in real-time and is this “package” available to them in terms of cost and knowledge needed.

Advnaced analytics changed face of portfolio management through enabling the management of control and data management systems under controlled conditions. These facts essentially change many processes in this industry and a similar trend is expected in the future. Future, data streams, and cognitive computing will be able to manage portfolio and timely inform, but also suggest any transaction-level, regulatory or service-level decision. Such an approach becomes a critical resource for every company in the sector and the ever more disturbing impact of these changes on business in the future. The industry is generally characterized by fragmentation, heterogeneous market structure, large number and usually poor interaction between different players within the environment. Different market layers and their needs can be fully answered through a selective approach where the digital future has a global approach, but focuses on each individual level, to the individual / user if necessary. The obvious trend is that those markets with the best prospects for understanding benefit from these solutions at the same time and the most active. For one launch of the water monitoring and control system, and the analytics of these data, the exploitation is multifaceted, so here we are pointing to how companies that use such solutions are advancing and to what extent they are active in the market. Identifying active partners helps decide how to capitalize on these solutions and initiate these processes. Portfolio management is a historic area rich in data. Measured data is used to make decisions about how to best share and move water between its many applications. With the emergence of new technology, it can now be managed at a higher level and frequency and accuracy, volume, speed, truth, diversity and value. This information gives us an opportunity to improve portfolio management understanding and better management later.

CONCLUSION

Analytical projects that involve data mining as a key factor of the solution are increasingly complex and require different sources of data to effectively disclose the hidden knowledge that can be used to make decisions. Large data analytics integrates different approaches. Scientific research is mainly focused on high performace computing, data sampling, parallel processing in a big data environment where large data technology and strategic business aspects of large data analysis should not be neglected

A methodology is proposed to achieve this goal in a situation when the company develops predictive models. One of the simplest yet effective techniques that will be presented as effective for linking structured and unstructured data to analytical models is to measure the influence of some word or phrase used, for example in the target call center, the variable as a "casting obligation." For the sake of meaningful Word Detection is recommended for long words in the discovery of texts Data mining as a discipline brings a completely new direction to business planning over the last decade Developing a casting model, fraud detection models, and user segmentation have become an important element of successful business in conditions of market competition. Data mining has become a tool to reduce uncertainty and business planning tools, and it also has the role of a decision support tool, even though these techniques relate to huge amounts of data, and at the very beginning, the sources for analysis were mostly local transactional databases and local lna data warehouse.

For the sake of meaningful profiling it is recommended to consider new disciplines, which brings a completely new direction to business planning over the last decade. Developing a casting model, fraud detection models, and user segmentation have become an important element of successful business in conditions of portfolio optimozation. Data mining has become a tool to reduce uncertainty and business planning tools, and it also has the role of a decision support tool, even though these techniques relate to huge amounts of data, and at the very beginning, the sources for analysis were mostly local transactional databases and local lna data warehouse. When a company needs to develop anti-dumping strategy, it mainly relies on existing local transaction data or data warehouse for modeling purposes. These strategies relied on huge amounts of data to find useful forms, mostly on local data sources.

It is important to keep in mind that the presented methodology does not guarantee success in finding the risk profiles for each product / product group defined. As shown in results based on empirical data, it is not surprising that a certain risk profile can not be found for a particular product / group of products. This depends on the data itself, as well as on the type of predictive model used. Acceptable is the situation where appropriate profiles are identified with a certain threshold for most products / product groups.

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Chapter 4
Conditional Value-at-Risk-Based Portfolio Optimization:
An Ant Colony Optimization Approach

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ABSTRACT

Over the past few decades, an extensive research on the multi-objective decision making and combinatorial optimization of real world's financial transactions has taken place. The modern capital market theory problem of portfolio optimization stands to be a multi-objective problem aiming at the maximization of the expected return of the portfolio in turn minimizing portfolio risk. The conditional value-at-risk (CVaR) is a widely used measure for determining the risk measures of a portfolio in volatile market conditions. A heuristic approach to portfolio optimization problem using ant colony optimization (ACO) technique centering on optimizing the conditional value-at-risk (CVaR) measure in different market conditions based on several objectives and constraints has been reported in this paper. The proposed ACO approach is proved to be reliable on a collection of several real-life financial instruments as compared to its value-at-risk (VaR) counterpart. The results obtained show encouraging avenues in determining optimal portfolio returns.

DOI: 10.4018/978-1-5225-8103-1.ch004

INTRODUCTION

In the present volatile market conditions in the field of Finance, Mathematics, Computational Literature and Statistics, the financial portfolio optimization has proved to be a problem to be researched widely enhancing to show an equitable balance between risks and returns which in turn stand vital for any investor to derive at an optimum standpoint (Brown,2004; McNeil,Frey & Embrechts,2005). Regardless the prevailing volatility, the impersonate advantage lies within the correlation about the combination of financial instruments/assets over a financial portfolio within a particular market condition. In recent times, the need for the study of portfolio management has cropped up because for making decision within the different investment opportunities in a high-risk scenario in turn proving the present day's risks and returns to be undoubtedly interlinked emerging the importance in the decision making procedure in the investment opportunities. It provides the whereabouts of the risk-reward tradeoff allowance of investments into numerous assets so that returns can be maximized in order to minimize risk in a given investment period. As stated by Markowitz (1952), valuation of risk as standard deviation of returns is done signifying diversification into different investment factors having limited or negative correlations in terms of their movements reducing overall risk which is measurable by a correlation coefficient varying between + 1 and -1.

Hence for quantifying the value of an asset or else of a portfolio of assets in the market which usually gets decreased by a specific course of time (ordinally considered over 1 day or 10 days) subservient to conventional market circumstances, Value-at-Risk (*VaR*) (Dowd,2005; Holton,2003; Jorion & Philippe,2001) proves to be an effective tool. High value is also given to it for being incorporated within industry regulations (Jorion,2001), nevertheless in case of normal distribution of losses it suffers from the unstableness as well as difficulty to work using numerical values because loss distribution often contribute to present "fat tails" or else empirical differentiation. Presumed by Artzner et al (1999), *VaR* moreover fails to be coherent.

Unlikely Value–at-risk, Conditional value-at-risk (*CVaR*) prevails to be one risk measuring technique subject to risk having significant advantages, for obtaining distribution of losses in finance which involves discreteness (Rockafellar & Uryasev,2002). Different proposed structures derived on varied scenarios and finite sampling, the application of such distributions has become an important property in the financial markets because of its customariness.

CVaR can be ascertained along with the weighted average of *VaR* along with *CVaR*+ (the values themselves be contingent on the decision *x* along with the weights), where not even a single value of *VaR* and *CVaR*+ stands to be coherent. The specific method of assessing *CVaR* in terms of probability of *VaR* value generates the value of weights, when one exists.

Computational advantages of *CVaR* over *VaR* have developed into the crucial stimulus in the *CVaR* methodology development procedure, in spite of considerable efforts for finding out the efficient algorithms for the process of optimization of *VaR* in high-dimensional environs which are still unavailable. *CVaR* stands to be a new coherent risk measuring structure having distinct advantages in comparison to *VaR* (Rockafellar & Uryasev,2000), quantifying risks beyond *VaR*, consistent at different confidence levels a (smooth w.r.t a) and furthermore a static statistical estimate with integral characteristics. *CVaR* is thus been entrenched to be an excellent tool in the risk management procedure and optimization of portfolio accompanied by linear programming having huge dimensions in the company of substantial numerical implementations. With different levels of confidence in various courses of time periods, distributions are also shaped for multiple risk constraints along with the previously mentioned tasks, which in turn stand as fast algorithms for online usage. Rockafellar & Uryasev (2000,2002) have considered *CVaR* methodology to be a consistent one having mean-variance method under minimal portfolio consideration (with return constraint), which can also be considered to be a variance minimal in case of normal loss distribution.

Here in this chapter, an Ant Colony Optimization (ACO) algorithm has been used to evolve optimized portfolio asset allocations in a volatile market condition. The proposed approach is pivoted on optimizing the Conditional Value-at-Risk (*CVaR*) (Rockafellar & Uryasev,2000; Engle & Ng,1982) measure in different market conditions which are based on several grails and restrictions. The authors have concentrated here into dealing with fully discrete distributions enhancing the usefulness and properties of *CVaR* in case furnishing the elementary way of direct calculation of *CVaR*. The results are compared with those obtained with the optimized Value-at-Risk (*VaR*) values in regard to the portfolios within deliberation. A comparative application of the proposed approach along with the *VaR* (Ying,2001) approach is manifested on a set of various financial instruments along with a real life data set of TATA Steel during the month of August and early September'2015, enabling a distributional supposition for employing the particular series of financial assets for developing a much more generalized framework.

The authors have shaped the chapter into the following different sections providing an overview of the conventional concept of Conditional Value-at-Risk in section II just after mentioning the Literature Review. Section III illuminates the Mathematical formulation of the *VaR* and the *CVaR* measure. Discussion of the Ant Colony Optimization procedure briefly, along with the algorithm associated is done in section IV. The findings of the work has been summarized in section V. Conclusions added to future directions of research are drawn out finally in section VI.

LITERATURE REVIEW

"Portfolio Optimization with Factor, Scenarios and Realistic Short Positions", by Bruce I.Jacobs, Kenneth N. Levy & Harry M.Markowitz describes some actual short- sale arrangements which are varying from time to time. The usage of general Mean variance Problem and Solution to General problem is stated along with CLA tracing out a linear set of efficient portfolios subject to any finite system of linear equality or inequality constraints meant for any covariance matrix and expected return vector.

Valdemar Antonio Dallagnol Filho within their work, " Portfolio management Using Value –at- Risk: A comparison Between Genetic Algorithms and Particle Swarm Optimization", provides an investor a portfolio that is optimal for worst case scenario and guarantees performance for the improvement if there is no worst cases. It also protects the investor from errors that arise from uncertainties in the expected return values for assets. There is the usage of Mean variance approach. Value at Risk is been depicted by Parametric Method, Historical Simulation Method and Monte Carlo Method. Coherent Risk Measures along with GA is also applied.

"Conditional value- at- Risk in Portfolio Optimization: Coherent but fragile", by Andrew E.b.Lim, J.George, Shanthi Kumar, Gah-Yi & Vahn uses the Mean variance optimization along with Mean CVaR optimization and the coherent measures of risk is reported within the literature.

Parlo Krokhmal, Jonas Palquist & Stanislav Uryasev in their work, " Portfolio optimization with Conditional Value at risk Objective and Constraints" extends the approach to the optimization problems with CVaR constraints where maximization of the expected returns is done under CVaR. Multiple CVaR constraints with various levels of confidence are utilized for shaping the distribution of profit/loss. Any of the optimization formulations can be used for the purpose. The work is able to handle instruments and scenarios large in number which can be used in applications under various conditions for binding the percentiles of loss distribution.

"Portfolio optimization via pair Copula-GARCH-EVT-CVaR Model", by Ling Deng, Chaoqun Ma, Wenyu yang depicts the problems of VaR taken under consideration while application. Covariance matrix with GARCH model is also calculated. The modified version of Memtic Algorithm is then applied in order to deal with the computational problems. Results in much better approximation of conditional volatility structure are found rather than a simple historical estimate. Mean –CvaR Model, Pair Copuk-GARCH-EVT Model is used along with Pair Copula decomposition of multivariate distribution and parameter estimation. However, adjusting the portfolio to the dynamic approximation of conditional volatility structure also results in some overconfidence with regard to risk constraints.

Table 1.

Sl No.	Works Done	Authors	Source
1.	Portfolio Optimization with Factor, Scenarios and Realistic Short Positions.	Bruce I.Jacobs, Kenneth N. Levy & Harry M.Markowitz	Operations Research, Vol.53.No.4, pp. 586-599, July August 2005
2.	Portfolio optimization with Conditional Value at risk Objective and Constraints.	Parlo Krokhmal, Jonas Palquist & Stanislav Uryasev	Journal of Risk, 2003
3.	Portfolio optimization Via pair Copula-GARCH-EVT-CVaR Model.	Ling Deng, Chaoqun Ma, Wenyu yang	Systems Engineering Procedia, 2011
4.	Conditional value- at- Risk in Portfolio Optimization: Coherent but fragile	Andrew E.b.Lim, J.George, Shanthi Kumar, Gah-Yi & Vahn	Journal Of Operations Research, Vol 39 (3), May, 2011 pp. 163-171 Elsevier Science Publishers
5.	Portfolio management Using Value –at- Risk: A comparison Between Genetic Algorithms and Particle Swarm Optimization.	Valdemar Antonio Dallagnol Filho	Master Thesis Informatics & Ecconomics, July 2006
6.	Portfolio Optimization Under VaR Constraints Based on dynamic Estimates of the Variance-Covariance Matrix.	Katja Specht and Peter Winker	Computational Method in Financial Engineering, 2008
7.	Risk measures and portfolio Optimization.	Priscilla Serwaa, Nkyira Gambrah and Traian Adrian Pirv	Journal of Risk and financial Management, Vol 7(3),pp.113-129,2014
8.	Ant Colony Optimization Approach to Portfolio Optimization- a Lingo Companion.	Kambiz Forqandoost Haqiqi & Tohid Kazemi	International Journal of Trade, Economics and Finance, Vol 3 (2),pp.148-153, April 2012
9.	IS strategic relevance Political environment Past experience	Jiang & Klein	Importance of internal, extern al and project metrics, 1999
10.	Project type Organizational environment	Blomquist & Müller	Program and portfolio mana gement (roles, responsibilities, practices), 2006
11.	Single-project management Project management efficiency	Martinsuo & Lehtonen	Portfolio management efficiency, 2007
12.	Project type Internal dynamics Governance types Geographical location	Müller et al.	Portfolio success, 2008
13.	Organizational culture	Prifling	Project portfolio management and risk management in IT projects, 2010
14.	Strategic orientation	Meskendahl	Business success (influenced by project portfolio success), 2010

"Portfolio Optimization Under VaR Constraints Based on dynamic Estimates of the Variance- Covariance Matrix", where Katja Specht and Peter Winker have shown VaR based estimates of the Conditional Covariance matrix along with the " principal Components GARCH model" . The recent advances in heuristic optimization which in turn is a modified version of Memtic algorithm are also applied. The article also depicts the PC GARCH model.

"Ant Colony Optimization Approach to Portfolio Optimization- a Lingo Companion.", a work by Kambiz Forqandoost Haqiqi & Tohid Kazemi uses the ACO approach to portfolio optimization which we have also used in our study along with the DE and PSO approaches.

Priscilla Serwaa, Nkyira Gambrah and Traian Adrian Pirv in their research work, "Risk measures and portfolio Optimization", have shown portfolio optimization under Value at Risk, Average Value at Risk and Limited Expected Loss Constraints during a continuous time framework, in which stocks follow a Geometric Brownian Motion.The Analytic expressions for VaR along with the derivation of Average VaR and Limited Expected Loss is also done.

Conventional Concept of Conditional Value-at-Risk

Within the process of portfolio optimization, introduction attributed to return risk management framework by Markowitz (1952) has already come a long way. Of late, the usage of the alternative coherent technique is been done reducing the probability, incurring large amount of losses by a portfolio which in turn is possible by assessment of the specific loss that will be exceeding the value at risk. The outcome risk portion is termed as the Conditional Value-at-Risk (*CVaR*) (Uryasev, 2000; Rockafellar, 2002). Appreciation is directed towards the developing territory of intelligent data management and factual techniques for enlightening the fields of industrial portfolio management. Risks, constraints and adequate modeling of utility functions and efficient handling of huge numbers of scenarios and instruments has been developed by simulation of two basic requirements in turn developing in the portfolio optimization procedure. In mathematics, *CVaR* is derived by considering the values of the weighted average at the intervals of the value-at-risks in addition to the losses outstripping the value-at-risks. When *CVaR* is compared to *VaR*, it detects various dissimilar loss classifications which are freely indicated in minimization rule stated by Rockfellar, 2000; Krokhmal, 2000; Andersson, 2001.

Measures of risk plays a vital role especially while coping with losses which might have been incurring in finance under the shed of uncertain conditions. Loss, being derived to be a function $z = f\left(x, y\right)$ of a decision vector $x \in X$ C characterizing different values of numerous variable viz. interest rates or else data in terms of the future values. If y is assumed as a random variable with accepted probability distribution, z then turns out to be a random variable having its dependent distribution on the accepted choice of x.

Percentile measures of loss or reward can be done by $f(x, y)$, which is taken to be the loss function relying on the decision vector $x = (x_1, x_2, x_3, \ldots, x_n)$ and the random vector $y = (y_1, y_2, y_3, \ldots, y_m)$, next *VaR* can be calculated as $\boldsymbol{a}$- percentile of the loss distribution, considered to be the inconsiderable value where the probability which loss exceeds or else is equivalent to the value which is considerable or equivalent to $\boldsymbol{a}$. In such case $CVaR^+$ or specifically "upper *CVaR*" is the expected loss which strictly exceeds *VaR* is known as Mean Excess Loss and Expected Shortfall. $CVaR^-$ known as "lower *CVaR*" is the expected loss weekly exceeding *VaR*, which is the expected loss equal to or exceeding *VaR*. It is also known as Tail *VaR*.

Thus, *CVaR* is considered to be the weighted average of *VaR* and $CVaR^+$ (Uryasev2001) which can be derived from the following formulation:

$$C\ \mathrm{va}\ R = \lambda VaR + (1-\lambda)\ C\ \mathrm{va}\ R^+,\ 0 \le \lambda \le 1 \tag{1}$$

Syllabary: proposed by Stan Uryasev (2001)

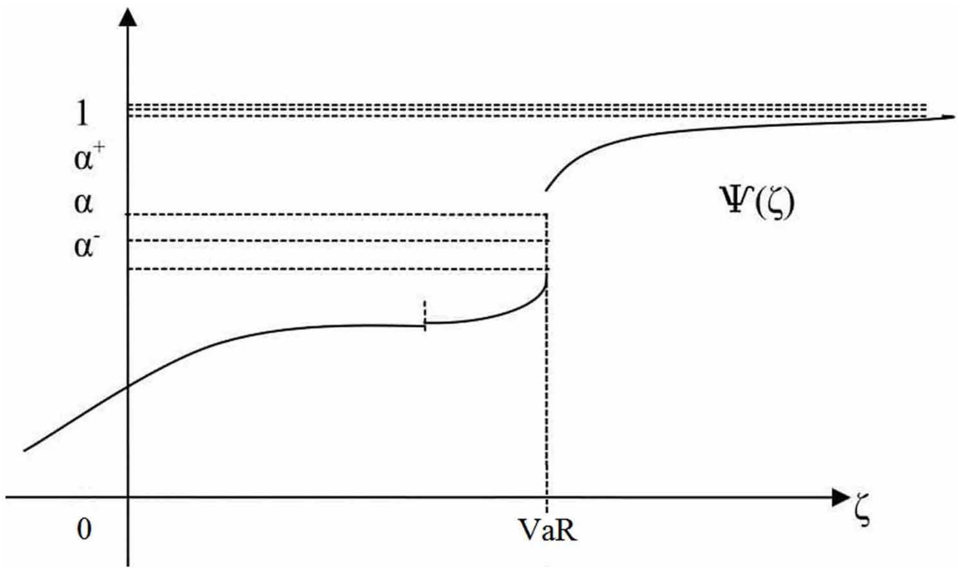
ψ = cumulative distribution of losses,

$\psi_\alpha = \alpha$ -tail distribution, equaling to zero for losses beyond *VaR* level, also equaling to

$(\psi - \alpha)/(1-\alpha)$ accounting to the losses exceeding or equal to *VaR*

In Figure 1 *CVaR* is mean of α -tail distribution ψ_α where Cumulative Distribution of losses is shown as ψ ,while in Fig 2. *CVaR* is mean of α-tail distribution ψ_α , α – Tail Distribution, ψ_α has been suggested by Stan Uryasev (2001), proclaiming that *VaR* = α -, percentile of loss distribution (an inconsiderable value such that probability that losses outstrip or equal to this value is greater or equivalent to *a* $CVaR^+$ ("upper *CVaR*") = expected losses strictly outstripping *VaR* (also known to be Mean Excess Loss and Expected Shortfall) $\psi(VaR)$ = probability that losses not exceeding *VaR* or equivalent to *VaR* and $\lambda = (\psi(VaR) - a)/(1-a), (0 \le \lambda \le 1)$.

Figure 1. CVaR to be mean of a-tail distribution ψ_α
Cumulative Distribution of losses, ψ



In Figure 3 Credit Risk Measures has also been depicted in the literature.

Syllabary: proposed by Stan Uryasev (2001)

VaR = *a*-percentile of loss distribution (an inconsiderable value such that probability that losses exceed or equivalent to this value is greater or equivalent to *a*).

CVaR+ ("upper *CVaR*") = expected losses strictly outstripping *VaR* (also known to be Mean Excess Loss and Expected Shortfall)

$\psi\left(VaR\right)$ = probability that losses do not outstripping *VaR* or equivalent to *VaR*

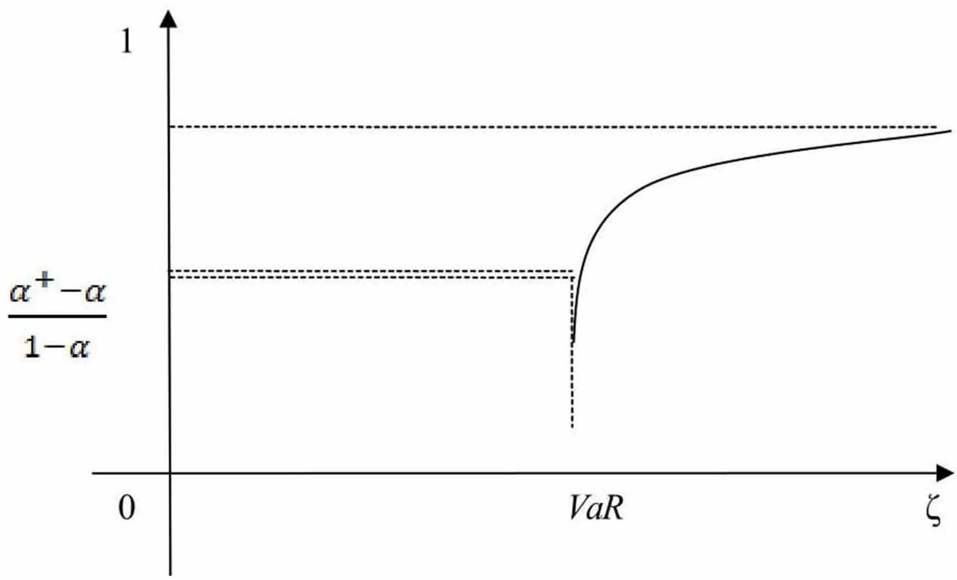
$$\lambda = \left(\psi\left(VaR\right) - a\right) \Big/ \left(1 - a\right), \left(0 \le \lambda \le 1\right).$$

Mathematical Formulation

VaR is considered to be an important measure for the disclosure of a stipulated financial portfolio in terms of varied risk situations, instinctive in financial structures which in turn are also considered to be of paramount importance in the portfolio optimization purpose.

Figure 2. CVaR to be mean of α-tail distribution ψ_α

a – Tail Distribution, ψ_α



Considering a portfolio *P,* level headed by *k* assets, $S = \{S_1, S_2, \ldots, S_k\}$, $W = \{W_1, W_2, \ldots, W_k\}$, and considered as the respective weights or else portions of the assets within the stipulated portfolio, the price is then computed as:

$$P(t) = \sum_{i=1}^{k} S_i(t) W_i \tag{2}$$

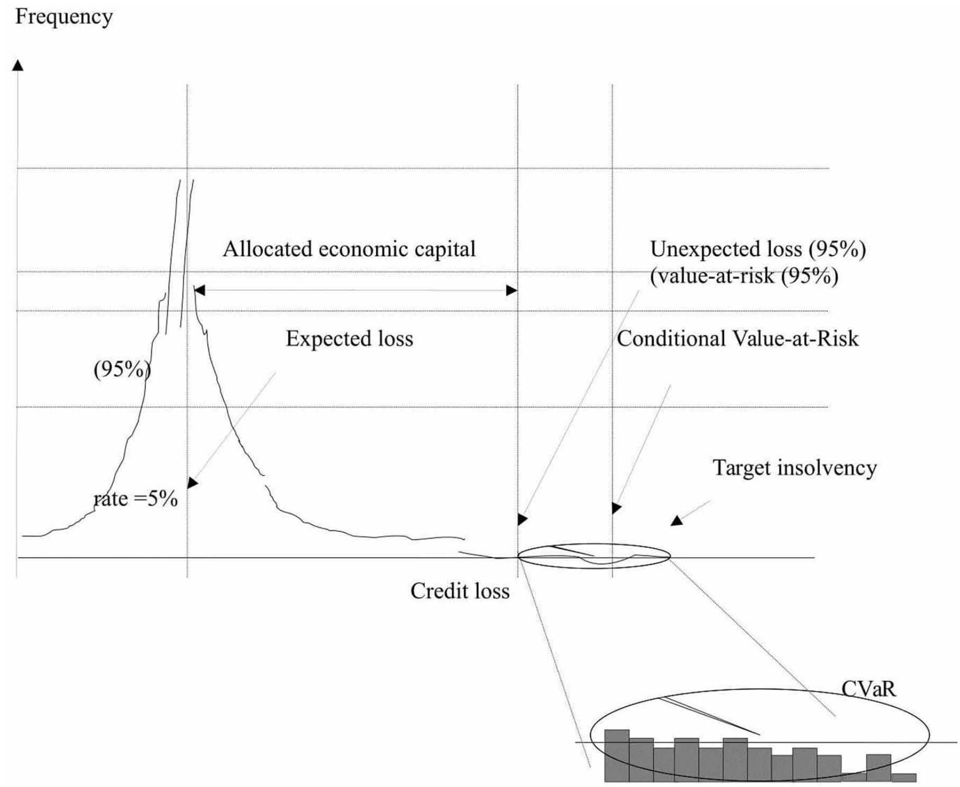
wherein $S_i(t)$ and W_i are considered as the values and the level of importance of a portfolio at a stated time period *t*, accordingly.

The *VaR* of any portfolio *P*, that denotes the maximum expected loss within a stated holding period at a stated level of confidence (***a***), again considered to be the minimal number l such that the probability that the loss *L* exceeds *l* is not bigger than (1 - ***a***), i.e.

$$VaR_a = \inf\left\{l \in R : P\left(L > l\right) \leq 1 - a\right\} = \inf\left\{l \in R : F_l\left(l\right) \geq a\right\} \tag{3}$$

A supersite of techniques and models for estimating *VaR* from the time horizon, level of confidence and the unit of *VaR* is accessible within the literature

Figure 3. Credit risk measures



(Holton,2003;Jorion and Philippe, 2001; Prearson,2002;Glasserman,2004;Rouvinez,1997;Wilson,1999).

Almost all the techniques and models depends on a set of assumptions of its own. However, the most common assumption that stands to be the outstanding estimator for future changes in market conditions is the historical trace of available market data. Some of the well-known models for estimating *VaR* include:

1. 1. **Variance-Covariance (VCV) Model:** It is conducive for the assumption of the risk factor returns which is to be normally (jointly) distributed in every cases, and in the interim the portfolio return is also to be normally distributed. It is also advantageous in hypothesis of the revision within portfolio value which is counting on all risk factor returns. In the beginning of 1990s, J.P. Morgan familiarized the variance-covariance or the delta-normal model. The supposition of the portfolio return to be normally distributed gives an implication of composition of assets in the portfolio, whose deltas being linear states the

modification in the portfolio value which in turn is counting on all the changes in the values of the assets hence implying that the return on portfolio is again counting on on all the asset returns and that the assets' return further jointly be enormously distributed. With further assumption of the exclusive risk factor correlated along with a stated financial portfolio is known to be the value of the portfolio itself, the 95% level of confidence, *VaR* for *N* assets within a stated period, is given by

$$VaR = -V_p\left(\mu_p - 1.645\sigma_p\right) \tag{4}$$

In which, the mean μ_p is delineated as

$$\mu_p = \sum_{i=1}^{N} \varpi_i \mu_i \tag{5}$$

The standard deviation σ_p is given as

$$\sigma_p = \sqrt{\Omega^T \sum \Omega} \tag{6a}$$

$$\Omega = \begin{bmatrix} \varpi_1 \\ \varpi_2 \\ \varpi_3 \\ . \\ . \\ \varpi_N \end{bmatrix} \tag{6b}$$

$$\Omega^T = \left[\varpi_1 \quad \varpi_2 \quad \varpi_3 \quad . \quad . \quad \varpi_N\right] \tag{6c}$$

where, *I* noting to the assets' return *i* and *p* attributing to the portfolios'return for standard deviation $\left(\sigma_p\right)$ along with mean $\left(\mu_p\right)$. V_p appropriated as the portfolios'value at the beginning (in currency units). $\boldsymbol{\varpi}_i$ hence considered to be the ratio of V_i and V_p. $\sum$ further taken as the covariance matrix within every the N assets' return.

VCV model is advantageous in terms of management of further compressed along with a conceivable data set which is repeatedly bought from third parties. The expectation that as the portfolio customarily comprised of assets whose delta being linear and the accepted market price returns/asset returns are expected to be normally distributed stands to be its drawbacks.

2. **Historical Simulation (*HistSim*) Model:** It appears as the industry approval for computing *VaR;* it is established on the thinking that the forthcoming asset returns will always bear an equal amount of distribution as they had in the former period (historical vestige). *HistSim* is considered as the most understandable and most clear technique for calculation of VaR. It is the model for evaluating a percentile (*VaR*), which associates running the present portfolio within a set of historical price changes for yielding a distribution of fluctuations in portfolio value. Its simplicity of implementation stands to be its most important benefit along with not assuming a normal distribution of asset returns like VCV model. Its intensive calculation along with the necessity for a huge market database fall under its main drawbacks.

In *HistSim*, *VaR* is calculated as:

$$VaR = 2.33M\sigma_p\sqrt{10} \tag{7}$$

In which, *M* being the market value of any portfolio, σ_p considered as historical volatility of the stated portfolio. The constant 2.33 denotes for the number of σ_p which is necessary for a level of certainty of 99% and the constant $\sqrt{10}$ attributing to the number of days within the holding period.

Basically, computation of VaR in two simple steps is done in the *HistSim* method. Firstly, construction of a series of pseudohistorical portfolio returns is calculated, accepting present portfolio weights along with historical asset returns. Secondly, computation of yield *VaR* and the current asset returns quantile of the pseudohistorical portfolio returns is found out.

3. **Monte Carlo Simulation:** This model basically undergoes the random simulation of future asset returns. Usage of this simulation is done generally in consideration of computation of *VaR* for any portfolios holding securities with non-linear returns wherein the computational effort necessitated is non-trivial.

Conceptually simplicity of this method stands to be its added advantage, but moderately it is computationally more demanding than both VCV and *HistSim* models. Generic Monte Carlo *VaR* evaluation incorporates the following steps.

1. Predefining *N*, denoting the number of iterations which is to be performed.
2. For every iteration in *N*,
   a. Generating a random market scenario which is affected by the usage of some existing model present in the market.
   b. Revaluing the portfolio under the simulated market volatility scenario.
   c. Computing the portfolio profit or loss (*PnL*) in case of the simulated scenario and for doing so, subtracting the current market value of the portfolio from the market value of the portfolio which is already been computed in the previous steps.
   d. Sorting the result *PnLs* required for obtaining the simulated Profit and loss (*PnL*) distribution for the portfolio.
   e. Finally, for calculation of*VaR* at a particular level of confidence with the usage of the function of percentile.

Features of *CVaR* represent the risks which are simple and convenient in nature hence measuring the downside risks, and are applicable to non symmetric distribution of losses. Stable statistical estimate is another feature (*CVaR* to be the integral characteristic in comparison to *VaR* which can get influenced by any scenario). Being *CVaR* to be in a continuous process in terms of confidence level α, steady at different levels of confidence in comparison with *VaR* (*VaR*, $CVaR^-$, $CVaR^+$ may not be continuous to α). *CVaR* portfolios coincide in case of normal distribution of loss in optimal variance to the level of consistency in mean variance approach. *CVaR* is variedly acceptable due to its easy control and optimization process for non normal distributions, even shaping of loss distribution is being done using *CVaR* constraints for the first online procedures.

Almost accurate market performance function is recommended by Uryasev (2000; 2002) given in the following equations which can be tested to acquire the optimal portfolio against several collection of portfolios of financial instruments.

Minimization of $CVaR : \min_{\{x \in X\}} CVaR$

CVaR can be minimized with the help of a linear programming problem:

$$\min_{\{x \in X, \zeta \in R, z \in R^J\}} \zeta + \vee \sum_{\{j=1,2,\ldots,J\}} Z_j$$

Specifying,

$$Z_j \geq f\left(x, y^j\right) - \zeta, Z_j \geq 0, j = 1,2,\ldots,J\left(v = \left(\left(1-\alpha\right)J\right)^{-1} = const\right)$$

1. We can evaluate the optimal portfolio x^* by solving linear programming, *VaR* = the lowest optimal ζ*, *CVaR* = optimal value of the linear performance function.
2. $x \in X$, being constraints which in turn may be considered for diversified trading constraints which includes mean return constraints (e.g. assumed return not less than 10%)
3. Variance analysis having similar characteristic to return, can be used for constructing an effective perimeter for finding a tangent portfolio.

$$F\left(x,\zeta\right) = \zeta + v\sum_{j=1,J}\left(f\left(x,y^j\right)-\zeta\right)^+, v = \left(\left(1-\alpha\right)J\right)^{-1} = const \qquad (8)$$

$$CVaR_\alpha\left(x\right) = \min_{\zeta \in R} F\left(x,\zeta\right) \qquad (9)$$

with $\zeta_\alpha(x)$ as an essential

Remark: This equality utilized for defining *CVaR* (Pflug).

$$\min_{\{x \in X\}} CVaR_\alpha\left(x\right) = \min_{\{x\in X, \zeta \in R\}} F\left(x,\zeta\right) \qquad (10)$$

By minimization of $F\left(x,\zeta\right), VaR = \zeta_\alpha\left(x\right)$ can be calculated along with x = optimal decision and optimal *CVaR*.

Rockafellar(2000;2002) has proposed approximated market performance function which can be applied in the given equations for obtaining an optimal portfolio from any set of portfolios of financial instruments outlined by position vector $x = \left(x_1, x_2, x_3, \ldots, x_n\right)$ with the constraint.

For a stated loss function, $g\left(x,y\right)$ from a decision vector $x\left(\varepsilon R^n\right) = \left(x_1, x_2, x_3, \ldots, x_n\right)$ which represents a portfolio having a random vector $y\left(\varepsilon R^m\right) = \left(y_1, y_2, y_3, \ldots, y_m\right)$ which in turn is considered to be the market parameters affecting market deficits, where the Value-at-Risk can be stated to be α- percentile for the loss dispersion considered to be the nominal value, where the probability of the losses occurred exceeding or equivalent to this amount should be greater than or equivalent to α. This probability that $g(x, y)$ never exceeds a threshold α is stated by Rockafellar (2000;2002).

$$X(x,a) = \int_{g(x,y)\in a} p(y)\,dy \tag{11}$$

In which, $p(y)$ considered to be the probability of y function, $\zeta(x,\alpha)$ representing the cumulative loss distribution in association to x. According to Rockafellar (2000; 2002) the $\beta \in (0,1)$ is considered for the loss variable.

$$A_b(x) = \min\left\{a \in R : x(x,a) \geq b\right\} \tag{12}$$

β -*CVaR* considered for the loss variable is said to be the conditional expectation with the associated loss in respect of x where loss being greater than or equivalent to $\alpha_\beta(x)$. β -*CVaR* thus can also be referred to the weighted average of β -*VaR* and β -*CVaR*$^+$ referring to the expected loss outstripping strictly β -*VaR*, β -*CVaR* (Rockafeller 2000; Rockafeller 2002)

$$Z_b(x) = \frac{\int_{g(x,y)\geq a_b(x)} g(x,y)\,p(y)\,dy}{(1-b)} \tag{13}$$

where the market function is delineated in terms of $\zeta(x)$ as Rockafellar (2000;2002)

$$G_b(x,a) = \frac{\int_{y\in R^m} \left(g(x,y)-a\right)^+ p(y)\,dy}{(1-b)} \tag{14}$$

The above equation provides a general description of the market deficits in terms of β -*CVaR* which can be nearly into a discrete form in terms of examining the probability distribution of y along with its probability density function(Rockafeller 2000: Rockafeller 2002)

$$x_j \geq 0 \text{ for } j = 1,2,3,\ldots,n \text{ and } \sum_{j=1}^{n} x_j = 1 \tag{15}$$

If y_j considered to be a return on j instrument, the portfolio return for financial instruments n can be calculated by

$$g\left(x, y\right) = \mathring{a}_{j=1}^{n} x_j y_j \tag{16}$$

The portfolio loss thus can be stated as $-g(x, y) = -x^T y; y = \left(y_1, y_2, y_3, \ldots, y_m\right)$. If $m = \left(m_1, m_2, m_3, \ldots, m_n\right)$ represents the mean of the associated deficit correlated with x, where the mean portfolio deficit is delineated according to Rockafeller 2000: Rockafeller 2002

$$X\left(x\right) = -x^T m \tag{17}$$

Along with

$$X\left(x\right) \leq -R \tag{18}$$

in which r being the tolerable portfolio deficit. Thus the portfolio selection difficulty by the usage of *CVaR* Risks in terms of stated portfolio return *R* minimizes to optimization of

$$\frac{1}{q\left(-b\right)} \mathring{a}_{k=1}^{q} u_k \tag{19}$$

In which, u_k is taken to be the term of portfolio loss, in case of having the restrictions stated by equations (8) & (10) with $u_k \geq 0$ and $x^T y_k + u_k$ for $k = 1, 2, 3, \ldots, q$.

Ant Colony Optimization Toward Future Selection

Over the past decades due to speedy growth of computer and database technologies there is an eruption of data composed by immense information. Due to which, we are now drowning in information rather than starving for knowledge.

ACO is predominantly a useful tool in case if the features turns worthless individually and yet immensely predictive. ACO is at the same time considered to be a modern algorithm that has been casted in numerous researches for adopting the salient features. During its operation, numerous artificial ants traverse the feature space to build feature subsets iteratively. When the subset is constructed, the approaches already in use define the size of the constructed subsets with a fixed number for every iteration. Almost all algorithms design the pheromone updated rules depending on the outcomes of subset evaluations. Ascertaining the constructed subsets again is a vital part in the study of ACO. In a suitable fashion within these algorithms, the selected subsets bigger in size may include numerous least significant features. Moreover, almost all the ACO-based algorithms do not include the random and probabilistic behavior of ants within subset constructions (SC). The solutions assertained in these algorithms might be incomplete.

Snags originates while choosing the assets due to their doubtful return providing behavior. The sole purpose is focused in portfolio selection verdict, the excellent proportions of the stock obligatory for architecture of a portfolio in turn complementing the preference of the investor assuming that the investor wishes to strike a balance between maximization of the return on his investment with the minimization of the risk factors (Gupta,Mehlawat & Saxena,2008)

The destination of the Multi-Objective Portfolio Optimization lies in finding the Pareto optimal which is able to find the point of balance between the minimum risk involved along with the maximum return obtained (Radziukyniene & Zilinskas,2008).

Multi-Objective Portfolio Optimization

It is approved that $R_1, R_2, \ldots, R_n$ be stochastic return rates of assets $1, 2, \ldots, n$, where we presume that $E\left[\left|R_i\right| < \infty\right]$ for all $i = 1, 2, \ldots, n$. For investing the capital in these assets in order to earn some charming attribute of the total return rate on the investment. Denoting bt $x_1, x_2, \ldots, x_n$ the fraction of the original capital invested in assets $1, 2, \ldots, n$ the formula for the whole return rate:

$$R_1 x_1 + R_2 x_2 + R_3 x_3 + \cdots + R_n x_n$$

Apparently, the set of feasible asset allocations can be determined as follows (Dentcheva & Ruszezynski, 2006; Elahi & Mohd-Ismail, 2011)

$$X = \left\{ x \in R^n : x_1 + x_2 + \cdots + x_n = 1, x_i \geq 0, i = 1, 2, \ldots, n \right\} \tag{20}$$

The important two criteria for portfolio optimization are expected return and risk at the time of setting target by an investor for maximizing the first one and minimizing the second one.

ACO algorithm starts by initialization of pheromone values followed by solution of problem of probabilistic method and finally continues with updating of pheromone.

ACO procedure has four steps:

Step 1: Initialized by Ant

Within this step the Ant colony generates. Equation (21) is used for selecting the fragment I between the *K* possible choices. τ_k being the amount of pheromone related to fragment k (Haqiqi. & Kazemi,2012).

$$\text{Prob}_i = \frac{\tau_i}{\sum_1^k \tau_k} \tag{21}$$

Step 2: Evaluate

This is considered to be an evaporation phase (where the evaporation rate is denoted by γ), and a pheromone deposit phase

$$(t+1) = \tau_i(t) + (1-\gamma) + \delta_i \tag{22}$$

While in process of updating the quantities of pheromone gets deposited on each solution which in turn has direct relation to the operation of the algorithm (Haqiqi. & Kazemi,2012).

Step 3: Ant distribution

During this step ants get distributed in respect to their distance.

Step 4: Stopping the iteration

Finally repeating the last process comes to an end till the maximum number of ants or lack of optimal solutions is obtained.

Methodology Used and Findings

The prospective approach intensifies around the optimization of the Conditional Value-at-Risk (*CVaR*) measures of a portfolio constituting of disparate financial instruments at divergent market conditions positioned on distinct objectives and constraints. Appliance of Ant Colony optimization positioned on *CVaR* optimization procedure is exhibited with allusion to the curtailing of the risks muddled in the portfolio within certain constraints, thereby curtailing the portfolio losses aroused.

Value-at-Risk (*VaR*) (Jorion,2001) at a confidence level hence is premeditated to be the loss outstripping not exceeding with a stated probability, over a stipulated time period. *VaR* always been driven by three parameters, viz. the time horizon (typically 1 day, 10 days, or 1 year) which is to be scrutinized as the time period within which any financial institution should be devoted for holding its portfolio, or to the time period required for liquidating its assets, the confidence level (common values are 99% and 95%), which is the interval appropriation where the *VaR* would not be expected to exceed the unit of *VaR* in currency and the maximum probable loss structure.

The Historical Simulation (HistSim) model (an industry standard) for computing *VaR*, presumes equal future distribution in the asset returns structure as they had in the past records. In this model, *VaR* is evaluated as shown already implicated in Equation (7) stated by Jorion, 2001

$$\left(VaR = 2.33M\sigma_p\sqrt{10}\right)$$

where, M indicates to be the portfolio market value and σ_p indicates as the historical volatility. The constant 2.33 assigns for the number of σ_p required within a level of certainty of 99% and the constant 10 specifies to the number of days in the stipulated holding period.

As already been stated that the *HistSim* model has been used for the estimation of *VaR*. Hence, equation (7) has been employed for doing so. None the less this function has been employed as the fitness function in the Ant Colony optimization procedure. The parameters taken under consideration for the Ant Colony optimization procedure are given in Table 2.

The procedure of portfolio asset allocation optimization has been revealed on a collection of 30 portfolios and real life data set of Tata Steel with disparate asset variations. Here in this process of optimization, usage of an Ant Colony optimization technique/algorithm has been run along with two different numbers of generations viz., 500 and 1000 with the constants already been specified in Table 2. The average

Table 2. Ant colony optimization parameters employed

Sl. No.	ACO Parameter	Values used
1.	Number of Generations	(500, 1000)
2.	Inertia weight	0.8
3.	Acceleration Coeffient (φ_1)	1.5
4.	Acceleration Coeffient (φ_2)	1.5

of the best fitness results are reposited and delineated following in Table 3 and Table 4 which lists the different archived average optimized portfolios over two different number of generations, along with their costs and with *VaR* techniques for a confidence level of 95%.

The conditional value-at-risk (*CVaR*) is competent in ascertaining market risks for loss distributions, which display distinct behavior. Hence, it is capable to appraise risks outstripping the ambit of the value-at-risk technique. Furthermore, this is comprehensible in furnishing ways for extracting optimal values in diversified conditions of market volatilities. It is given by (Rockafellar&Uryasev, 2000; Rockafellar&Uryasev, 2002)

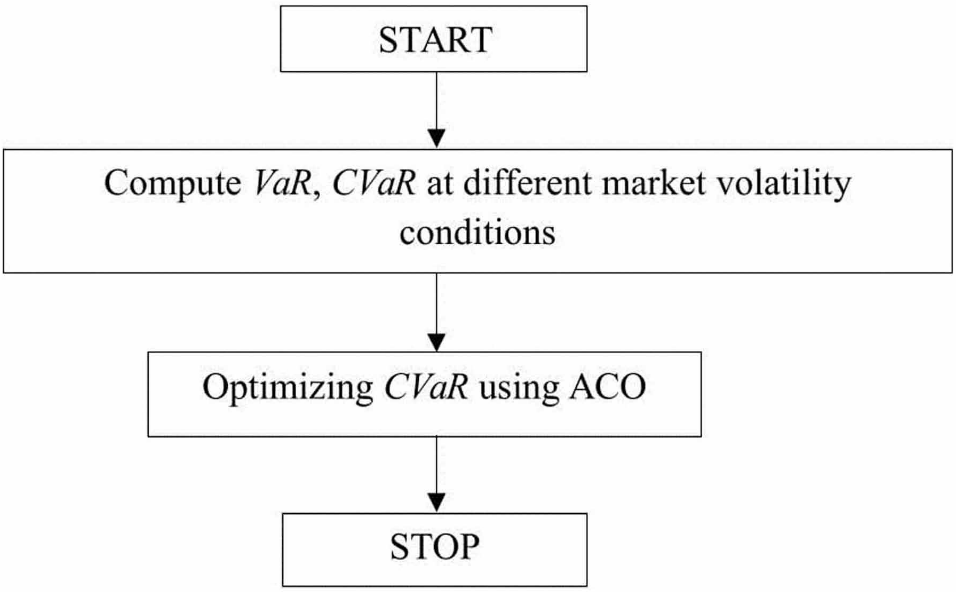
The flow chart in Figure 4 explains the procedure of the work starting with computation of *VaR* and *CVaR* at different market volatility conditions and finally optimizing *CVaR* using ACO.

The optimization of the portfolio asset allocation is accomplished with Ant Colony optimization (Ying,Yi-ming&Shang,2006; Christopher,2000). In contemplation of allocating assets faithfully in a given level of confidence, it minimizes the Conditional Value-at-Risk (*CVaR*) of the portfolio. It has been exposed on a collection of 30 portfolios and a real life data set of Tata Steel with several asset combinations. Table 3 and Table 4 lists the best fitness based average optimized portfolios, their costs, *CVaR* and *VaR* measures for a confidence level of 99%.

$$CVaR = \frac{e^{-\left(\frac{VaR^2}{2}\right)}}{\sigma\sqrt{2\pi}} \tag{23}$$

In which, $a = 0.01$considering a confidence level of 99%.

Figure 4. Flow diagram depicting the proposed methodology



In Table 3, a data set as assumed cost price has been randomly generated for experimental purpose stating the comparative results of portfolios showing *CVaR* along with *VaR* values at a confidence level of 99%.

Table 4, shows a portfolio structure for TATA Steel for 23 days' time from 11.08.2015 to 01.09.2015 stating the opening prices, highest prices, lowest prices and closing prices of assets within the portfolio. Difference in values of the closing prices of the assets for the consecutive days have been calculated and are considered for calculating the values of *CVaR* and *VaR*. It is indisputable that the *CVaR* measures provides a more realistic impact in relation to the allocation of financial instruments since for all the portfolios, the *CVaR* measures emulate minimized market risks as correlated to their *VaR* measures.

In the fields of economics and finance, portfolio management has been assumed to be of supreme importance as a systematic discipline given the strategies for diversification in investment. This article endeavors to emerge a selection and allocation strategy of portfolios in a volatile market condition by the mechanism of the optimization of the Conditional Value-at-Risk (*CVaR*) measures of the portfolios under consideration. An Ant Colony optimization procedure is accepted on historical portfolio data with this intention. Faithful selection of results is presented on a collection of 30 different portfolios and a real life data set of Tata Steel with several asset combinations.

Table 3. Comparative results of optimized portfolios with their costs, CVaRs and VaRs at a confidence level of 99%

Sl.No	Cost Price	*CVaR*	*VaR*
1	2083.189129	0.044107	0.299297
2	2428.230147	0.044107	0.301404
3	3227.947623	0.044107	0.302147
4	4780.752879	0.100588	0.290006
5	8403.925822	0.125462	0.252583
6	9067.774895	0.202365	0.256022
7	9314.056761	0.123779	0.242035
8	11606.92303	0.240051	0.261827
9	11798.68306	0.05857	0.257168
10	11838.02404	0.055557	0.261991
11	11992.44548	0.099808	0.240495
12	12774.75076	0.112072	0.286053
13	12789.05315	0.224539	0.267183
14	16421.12085	0.061501	0.240659
15	16710.43471	0.188438	0.284628
16	16839.09215	0.080628	0.30625
17	18420.88081	0.152462	0.269497
18	18873.66182	0.052131	0.305894
19	18889.77476	0.050735	0.236834
20	19122.82793	0.15523	0.290246
21	19478.95607	0.457527	0.264473
22	20938.78044	0.067316	0.303391
23	20966.67278	0.075125	0.241561
24	21038.90152	0.074258	0.320105
25	21143.15076	0.044107	0.232379
26	23095.86382	0.213705	0.264474
27	23118.41805	0.121051	0.300329
28	24896.33912	0.076323	0.300337
29	24980.74704	0.075472	0.291904
30	25167.69985	0.070362	0.308259

The authors observed that ACO is able to provide a conscientious selection/ allocation approach of assets in the financial portfolio which can be derived by

Table 4. Comparative results of optimized portfolios of tata steel ltd. with their costs, CVaRs and VaRs at a confidence level of 99%

Date	Symbol	Open Price	High Price	Low Price	Last Traded Price	Closing Price	Total Traded Quantity	Turnover (in Lakhs)	Difference Of Closing Prices of Consecutive Days	*CVaR*	*VaR*
01/9/15	TATA STEEL	218.9	225.9	210.3	220.9	219.5	8909770	19476.16	3.200000	0.063405	0.200530
31/9/15	TATA STEEL	222	226.25	213.05	216.4	216.3	6475249	14253.2	-9.100000	0.055507	0.202098
30/8/15	TATA STEEL	225.3	228.7	223.65	225.3	225.4	5782337	13047.13	-3.550000	0.063312	0.200600
29/8/15	TATA STEEL	232.6	234.6	223.2	229.5	228.95	9387248	21607.97	2.550000	0.057788	0.201397
28/8/15	TATA STEEL	220	229.8	215.1	227.2	226.4	14227129	31569.67	10.750000	0.059370	0.201831
27/8/15	TATA STEEL	213	219.7	208.95	214.8	215.65	8336683	17819.13	2.200000	0.051036	0.201310
26/8/15	TATA STEEL	210	217.9	200.1	215	213.45	14206932	29799.94	7.350000	0.056202	0.207461
25/8/15	TATA STEEL	229.3	229.3	202.65	204.45	206.1	11711489	25572.86	-31.150000	0.061982	0.199182
24/8/15	TATA STEEL	238.5	238.5	231.5	236.3	237.25	5247042	12325.35	-4.300000	0.053047	0.207824
23/8/15	TATA STEEL	247.7	248.4	240.5	242	241.55	4626334	11255.37	-8.250000	0.068857	0.200007
22/8/15	TATA STEEL	250.1	253.35	246.75	249.55	249.8	4304085	10772.08	-2.550000	0.056428	0.201295
21/8/15	TATA STEEL	248.1	254.9	246.6	252.4	252.35	9805064	24641.63	5.600000	0.053580	0.205028
20/8/15	TATA STEEL	238.5	248.5	234.2	247.5	246.75	8524452	20665.62	9.150000	0.064736	0.202478
19/8/15	TATA STEEL	234.25	239.2	229	237.5	237.6	9065329	21282.27	4.000000	0.061239	0.202971
18/8/15	TATA STEEL	253.35	253.9	232.3	234	233.6	13764560	32979.36	-15.450000	0.052852	0.206802
17/8/15	TATA STEEL	254.4	257.9	246.1	249.45	249.05	15172684	38227.01	2.250000	0.054439	0.204902
16/8/15	TATA STEEL	259.95	260	245.7	247.3	246.8	8827248	22200.72	-14.350000	0.048024	0.204045
15/8/15	TATA STEEL	262.9	265	260	260.25	261.15	3401136	8929.59	-0.900000	0.059495	0.200862
14/8/15	TATA STEEL	261	264.55	260.15	262.05	262.05	3791638	9948.04	1.050000	0.074268	0.201326
13/8/15	TATA STEEL	262.35	265.4	256.25	260.25	261	6376740	16691.22	-1.300000	0.054476	0.205098
12/8/15	TATA STEEL	260	268.5	259.95	262.3	262.3	7979075	21145.9	6.000000	0.057288	0.202807
11/8/15	TATA STEEL	249.7	259.75	246.05	258.8	256.3	9723318	24527.2	-	-	-

the acceptance of an optimization procedure in particular iteration and generated a solution which is local optimum. Moreover, ACO further explores to find much optimized solution using *CVaR* techniques than the one generated by ACO by usage of *VaR* techniques. The proposed approach aims at minimizing the *CVaR* measures of the portfolios under consideration using Ant Colony optimization. The optimized portfolios are seen to outperform the corresponding *VaR* based optimized portfolios as regards to minimization of market risks. To the best of our knowledge, no such attempts have been reported in the literature so far. Hence, this initiative has broached proposition in this direction.

Mechanism after all continues to be researched to incorporate the facet of return maximization in the portfolio allocation rundown with the usage of multi-objective optimization techniques. Presently the authors are betrothed towards this direction.

CONCLUSION

In this article, a profitable hybrid ACO-based algorithm is being proclaimed. As ants are treated to be the foremost power of an ACO algorithm, it is a must for guiding the ants in the correct directions which in turn is an urgent requirement for high-quality solutions. Subsequently, ACO mentors ants during SC by determining the subset size additionally along with new sets of pheromone update and heuristic information measurement rules for individual features which enhances the potential of the global search capability of ACO.

Comprehensive experiments have been carried out in this article to evaluate how well ACO has behaved in discovering the salient features on different data sets (Table II & Table III). Correspondingly, more suitable heuristic schemes are necessary in order to guide the ants appropriately.

Though numerous computing approaches are reported addressing the issues of portfolio management, here usage of ACO algorithm having computing techniques for different risk structures is taken under considerations which indicates the modeling flexibility, consistency/reliability, proving the effectiveness of ACO for being a component toward finding risk minimization solution of different financial portfolio.

CVaR being into a new risk measuring procedure provides significant advantages when compared to *VaR* which in turn is able to quantify risks beyond the level of *VaR* and so known to be a coherent risk measurement procedure which is consistent in different confidence levels.

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Chapter 5
Metaheuristic-Based Feature Optimization for Portfolio Management

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ABSTRACT

In the last two to three decades, use of credit cards is increasing rapidly due to fast economic growth in developing countries and worldwide globalization issues. Financial institutions like banks are facing a very tough time due to fast-rising cases of credit card loan payment defaulters. The banking institution is constantly searching for the perfect mechanisms or methods to identify possible defaulters among the whole set of credit card users. In this chapter, the most important features of a credit card holder are identified from a considerably large set of features using metaheuristic algorithms. In this work, a standard data set archived in UCI repository of credit card payments of Taiwan is used. Metaheuristic algorithms like particle swarm optimization, ant colony optimization, and simulated annealing are used to identify the significant sets of features from the given data set. Support vector machine classifier is used to identify the class in this two-class (loan defaulter or not) problem.

DOI: 10.4018/978-1-5225-8103-1.ch005

INTRODUCTION

Credit card refers to a card with a magnetic strip and/or a microchip ensuring its uniqueness. Credit cards are issued by banks, credit providers and other financial institutions that allow the card holder to have a loan of funds. These funds can be used to pay for products/services as per necessity of the card holder. The credit cards are issued based on the state that the card holder will pay the loan amount and any extra charges that have been mutually decided. The loan provider institution also grants a line of credit (LOC) to the cardholder. This facility allows the consumer to borrow loan in the form of cash. The issuer can set maximum limit of loan depending upon the credit rating. Generally credit card transactions are categorized under two heads:

- Point of Sale (POS) Transaction,
- ATM Transaction.

In case of POS Transaction, the card holder may purchase items as per his/her necessity and the bill is settled through credit card. The settlement involves the transfer of fund from bank to the merchant's account and consequently the card holder completes his purchase. But the amount that the bank pays to the merchant on behalf of the hard holder is amount that the bank / credit provider company charges the card holder with in the credit card bill at the end of the month. As the cardholder pays back the billed amount he / she become eligible for the credit amount for the next month.

Obvious from the prior section, that huge number of transactions is being made through credit cards. Card holders generally have a specific pattern of transactions. Based on these patterns or deviation from these patterns lots of works have been proposed regarding fraud-detection in credit card transactions. For instance (Ingole, & Thool, 2013), (Jiang, et al. 2018), (Dhankhad, et al. 2018), (Raj, & Portia, 2011) (Kazemi, & Zarabi,) and (Pozzolo, et. al 2018) have mentioned contribution on fraud identification in credit card transaction.

Metaheuristic optimization technique is a state of the art searching method which can be used to optimize a function with different parameters (Wahono, et al. 2014). There are two type of searching method local and global search. A wide range of metaheuristic technique has emerged over the last few decades (Zhao, et al. 2016). Metaheuristic technique like Simulated Annealing (SA), Tabu Search (TS) and Iterated Local Search (ILS) fall under local search technique and Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Differential Evolution (DE) and Genetic Algorithms (GA) fall under global search technique.

In today's world any financial and banking transaction is very sensitive in terms of risks involved due to uncertainty and volatility in the market. In this scenario identifying loan defaulter or credit card defaulter is very essential by the financial institution.

In this present work different features or parameters of portfolio dataset collected from UCI repository are optimized with metaheuristic method like SA, PSO and ACO and then the optimized feature set is used to classify the data with different supervised and unsupervised machine learning technique.

Most of the portfolio management datasets have multiple features which may lead to data over fitting and may result in inaccuracy in classification (Busetti, 2000). This is due to the concept of "curse of dimensionality". This feature set can be optimized with metaheuristic algorithm which produces good result (Derigs, & Nickel, 2003; Jarraya, 2013). In this chapter the next two sections deal with literature survey and scope of the work. The third section is related to overview of different Meta-heuristic algorithms. Then a brief description is given on feature selection and optimization in the next section. Then dataset used and result and discussions are given. Finally in the conclusion the importance of the work is given.

The objective of the work is to apply different metaheuristic algorithms to determine accurately credit card defaulter of some financial institute. In this work authors have also tried to find whether an increase in selection of number of features also has some influence on the accuracy of determining defaulters.

LITERATURE SURVEY

In the recent past the credit cards usage has noticeably increased. It has been seen that as the credit card becomes the main admired means of payment for regular and on-line purchase, cases of defaulter using it are increasing. So it is very important to identify the case for defaulter customer.

A credit card default happens when an individual fails to make any payments towards their credit card outstanding bill for a long period of time. If a customer fails to make even the minimum payment amount to the credit card company for six months in a row, he/she will be put in the defaulter list and their credit card account will be immediately deactivated.

Many research works have been found on credit card defaulter dataset. Desai et al. (Desai, et al. 1996) and Jagielska et al. (Jagielska, et al. 1996) have presented experimental result which shows neural network is an effective tool for credit card risk estimation for a banking sector. They mainly focus on the ANN model for credit card loan performance forecast. Thomas et al. (Thomas, 2000) presented an article on credit card scoring techniques. This scoring techniques help an organization decide whether to allow credit to consumers. They surveyed statistical as well as operational based techniques.

In 2003, Baesens et al. (Baesens, et al. 2003a) presented a result by analyzing few credit card data sets using ANN rule extraction methods. They finally concluded that ANN rule extraction is an important tool that allows building advanced decision support systems for credit evaluation. In another paper Baesens et al. (Baesens, et al. 2003b) study the performance of various classification algorithms on 8 credit scoring data sets. They have used some well-known algorithms like logistic regression, K-nearest neighbors (kNN), Artificial neural networks (ANN), Support Vector Machine (SVM)and decision trees. Their result shows that both the SVM and ANN classifiers give way a better performance result.

The authors, Yeh et al. (Yeh, et al. 2009) presented a paper that reported the case of default payments by customers' in Taiwan and judge against the accuracy of probability of defaulter using 6 different data mining methods i.e. discriminant analysis, logistic regression, Bayes classifier, nearest neighbor, ANN, and classification trees. They finally conclude that artificial neural network is the preferred tools.

Abbas Keramati et.al (Kerama, et al. 2011) have done a review on credit card defaulter dataset. Their work does not investigate influence of feature selection and role of classification algorithms. The authors Patidar et al. (Patidar, et al. 2011) presented a paper that used ANN along with the genetic algorithm to detect deceptive transaction. They also used genetic algorithm, combined Genetic Algorithm and Neural Network (GANN) to detect the credit card fraud successfully

In 2011, Wang et al. (Wang, et al. 2011) conducted different machine learning technique for credit scoring system. They show a comparative evaluation of the performance of 3 well accepted ensemble methods, i.e., Bagging, Boosting, and Stacking. All these methods based on four base learners, i.e., Logistic Regression Analysis, Decision Tree, ANN and SVM. Finally they found that Bagging performs better than Boosting for all credit datasets.

Abellan & Mantas (Abellán, et al. 2014) applied dissimilar ensemble methods for complex classifiers for credit card scoring system. Their result shows that the Random Subspace method constitutes the best solution. Marques et al. (Marqués, et al. 2015) presented a paper on credit card scoring system which used seven different techniques as members of 5 different ensemble methods. Finally their results and statistical tests revels that the best solution of most ensemble methods is the C4.5 decision tree. The MLP and logistic regression are closely followed the best solution.

SCOPE OF THE WORK

Fraud Detection in Credit Card Transactions is an established area of work for a long time and quite a few number of papers have been proposed in the domain as shown listed in Introduction and Related work section. For the said work numerous parameters have been proposed, some of which happen to be mutually exclusive, while others happen to be overlapped. Taking the cue from the above, the current chapter proposes to identify the parameters that dominatingly determine credit card payment defaulter detection methodology. In order to determine the said parameters, the authors have resorted to metaheuristic optimization techniques for feature selection. The consolidated list of parameters are examined for their effectiveness in determining the credit card payment defaulter and thereafter attempt has been made to shorten the list using the aforementioned optimization techniques for identification of the minimal set of parameters for encompassing the maximal set of instances of credit card payment defaulters. The forthcoming sections shall throw more light on the methodology, problem formulation and proposed solution.

METAHEURISTIC ALGORITHMS

In this section different meta-heuristic algorithms are discussed.

GENETIC ALGORITHM

One of the well-liked evolutionary algorithms is Genetic Algorithm (GA), which also has other forms, namely, genetic programming, and evolutionary programming (EP). GA converts a population of candidate solutions as optimization problem. Stochastic operations are applied repeatedly on the population, which keeps on changing after every iteration. GA follows the principle of solutions to the problem which adjusts most with the surrounding. Iteratively new population is generated by useful features, which are new and better than previous population and they are generated by fitness function. GA starts a loop with a random initial population produced from an arbitrary set of individuals. In every iteration (known as 'generation'), a new population is formed applying a number of operations to the earlier population known as crossover and mutation.

GA was proposed by John Holland (Holland, 1975) to find worthy solutions to problems that were otherwise difficult to compute.GA was found to be of highly efficient approach and as a result, the use of GA grew quickly and the technique was successfully used to a large range of problems in domain of science and engineering.

PARTICLE SWARM OPTIMIZATION

It is a population based global search technique introduced by Ebehart and Kennedy, (Kennedy & Eberhart 1995; Eberhart, 1998) motivated by behavior of animals. When a group of fish is randomly moving in the water for food, then only one area of water is being searched for food. If they individually have no idea where the food is, but they have a better idea of what the position of the food is, in iteration by iteration. The best process is to track the fish, which is nearest to the food source. PSO learns and solves this type of optimization. Here, each single solution of the problem is a “fish”. It is known as “particle”. Each particle has a velocity, which directs the “fish” or particle.

PSO starts using a random solution and then update it in each iteration. In each generation, each solution or particle is updated by local best i.e. Pbest (P_b) and global best known as Gbest (G_b). After getting the 2 best value positions, every particle revises its velocity and position using equation (1) and (2) in $(t+1)^{th}$ time.

$$\text{Velocity}_i^{t+1} = iw \times \text{Velocity}_i^t + c_a \times rad_1 \times \left(Pb_i - X_i^t\right) + c_b \times rad_2 \times \left(G_b - X_i^t\right) \tag{1}$$

$$\text{Position}_i^{t+1} = \text{Position}_i^{(t)} + \text{Velocity}_i^{(t+1)} \tag{2}$$

here, i is index of each solution, t is the present iteration count, rad_1 and rad_2 are random numbers. Pb_i is the best experience of the i^{th} solution noted. Gb_i is the best position of the particle of among all, c_a and c_b are the factors which drag each solution/particle to the path of Pb_i and Gb_i, iw is known as inertia weight.

The factor c_a and c_b is used to check the effect of the personal (Pb_i) and global (Gb_i) best. When c_b is greater than c_a, the solution has an affinity to meet the best position originated by Gb_i rather than the best position originated by Pb_i, and vice versa.

PSO shares many similarities with GA though unlike GA, PSO has no genetic operators such as crossover and mutation. PSO comes with some advantages over GA that its implementation is easy and involves adjustment of few parameters. The drawback of PSO is its tendency to a fast and early convergence in mid optimal points and has a low convergence rate in the iterative process.

ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) happens to be yet another efficient as well as effective tool for achieving swarm-based optimization. The approach is often utilized for solving the ELD problems. The said approach derives the idea from the movement of ant for the search for food. It is based on the fact that as an ant reaches the food through a path that is shorter than other available paths, it returns to its nest earlier than the others. Now, the other ants following deposited pheromone shall follow the route that has more pheromone deposited on it and hence it represents the optimized route. It is so because more pheromone is deposited on the shorter route than the longer routes.

The approach that ACO follows is that multiple search threads perform parallelly following the behavior of the 'ants'. In other words, one thread, after obtaining a solution, shares its information with the other search threads as in the case of ants (Nada, et al. 2009). Although each search thread can discover a solution, better solutions are obtained utilizing the information sharing within a search community (Dorigo, et al. 1997). The development of a solution is achieved by each search thread utilizing two information sources.

- Nodes that are previously visited by the search thread
- Heuristics guiding the decisions taken at branch points

The set of decisions that the heuristic based search thread executes throughout the path right from the beginning happens to be publicly available. In order to prevent sluggishness in the search approach, owing to excessive pheromone deposits may be prevented by implementing the concept of pheromone evaporation as mentioned in (Dorigo, 1992).

The advantages of ACO over other evolutionary approaches are offering positive feedback resulting in rapid solution finding. Although the convergence in ACO is assured, but the time taken for convergence is unsure, thus ACO comes with the drawback that its convergence time required is much higher than other heuristic-based methods.

SIMULATED ANNEALING

Simulated Annealing (SA) as mentioned in (Kirkpatrick, et al. 1983) happens to be another efficient approach for achieving solutions to a big set of optimization problems. The same has been executed on ELD problems with satisfactory results. In this case, the approach is based on the annealing process of metallurgical operations.

Here, the temperature of metal is raised to a high value and thereafter cooled in steps until the metal reaches its state of lowest energy. Simulated Annealing search approach, starts at a random state (analogous to starting temperature) and iterates through intermediary temperature levels and in subsequent stages converge to a global optima.

In SA, the objective function evaluates the optimality of every new stage achieved and computes the variation in energy from the previous values to the value that is newly achieved. If the new value achieved happens to be lesser than the previously achieved value the new point is taken up as the current optimal point. Else, the newly generated point is preserved with probability based on "Boltzmann probability distribution". The effectiveness of SA in providing solution to ELD problems is based on the crucial factor of selection of the starting point. Reduction of temperature in linear or exponential pattern aids at escaping the stuck up of solutions at local minima and reaching at global minima point.

SA is a robust and general technique. The advantages of SA are its flexibility; comparatively easy to implement and its ability to provide reasonably good solutions for many problems.

FEATURE SELECTION AND OPTIMIZATION

Machine learning algorithms are usually applied on datasets with huge number of features. But working with large number of features in a scenario where all of them do not contribute to the algorithm is a challenging job. To overcome this problem feature selection is a way out. Feature selection also known as attribute selection is a mechanism to select attributes that are most relevant for model construction. Feature selection can be represented by Figure 1.

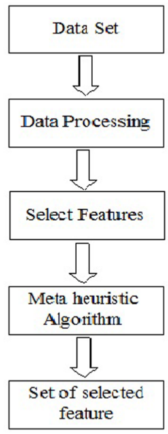
Model with selected feature has various advantages:

1. Model constructed has improved accuracy
2. Model gets trained faster
3. Model overcomes the problem of overfitting

Thus, selecting features among large number of features is a popular research domain in data mining and pattern recognition. In this chapter authors have tried for feature selection using Metaheuristic approach.

Feature selection technique has the following basic steps:

Figure 1. Steps of feature selection

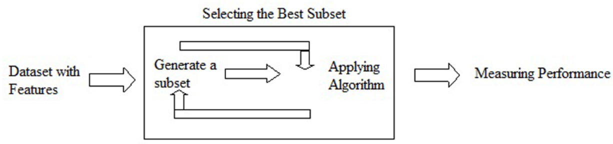


a. **Filter Method:** It is a preprocessing technique which suppresses the least interesting variables Figure 2 shows that features are selected on the basis of various statistical tests.
Different correlation co-efficient measures used for filtering are:
1. Linear discriminant analysis (LDA)
2. Pearson's Correlation
3. Analysis of variance (Anova)
4. Chi-square

b. **Wrapper Method:** A model is constructed based on a sunset of features and performance of the model decides whether to remove or add features from the set considered and again the performance is measured for the new model as shown in Figure 3.
Well known wrapper methods are
1. Forward Selection
2. Backward Elimination
3. Recursive Feature Elimination

Figure 2. Mechanism for filtering in feature selection

Figure 3. Mechanism of wrapper technique in feature selection



c. **Embedded Methods:** It is a combination of filter and wrapper methods. Well known embedded methods are
   1. Lasso regression
   2. Ridge regression

For feature selection many local, greedy search techniques are proposed over time, but Genetic Algorithm (GA) is found to be better since it performs global search. GA is a random selection method, which explores large global search spaces with high degree of accuracy. Genetic algorithms have proved significant improvement over various random and local search methods. A large number of Metaheuristics techniques of feature selection have been proposed in the literature (Yesodha, & Amudha, 2015; Raymer, et al. 2000). In addition to GA, other metaheuristic algorithms are also used for feature selection, namely, ACO (Aghdam, et al. 2008) and PSO (Chantar, & Corne, 2011; Zahran, & Kanaan, 2009). Other popular approach used for feature selection are Rough Set Theory, Information Gain etc. (Agarwal, & Mittal, 2013). Even hybrid approaches are also proposed combining different metaheuristics approaches. Methodology used here are based on metaheuristic approaches, which try to find results which are close to optimal results on these large data sets but within some limited time frame.

DATASET

The dataset used in the work is taken from standard UCI repository. The multivariate dataset has 30000 samples and 24 features, with all integer and real number including class level (Loan defaulter or not) of credit card defaulter customers in the country of Taiwan (Yeh, & Lien, 2009). The first 23 features are used as predictor and the 24th feature is used as class level or predictor. The dataset consists of features like credit amount, gender, education, marital status, age, six past payment history, bill statement amount and previous payment amount. The details of the 24 features are given in the Table 1. In the first, second and third column of the Table 1 feature number, feature type and feature description is given. These feature numbers are

Table 1. Details of the 24 features present in the dataset and used in the work

Feature Number	Feature Type	Feature Description
F1	Credit amount	Individual customer credit including family credit in dollars
F2	Gender	Male/Female
F3	Educational qualification	Graduate/ Post graduate/ High school/ Others
F4	Marital status	Unmarried/ Married/ Others
F5	Age	In years
F6-F11	Payment history	September, 2005 to April, 2005 (e.g. Feature F6 is payment status history for the month of September 2005 like duly paid, not used, payment delayed for 1,2,3 etc. months)
F12-F17	Bill amount	September, 2005 to April, 2005 (e.g. Feature F12 is the bill amount for the month of September 2005)
F18-F23	Previous amount paid	September, 2005 to April, 2005 (e.g. Feature F18 is the previous bill amount paid for the month of September 2005)
F24	Class level	Credit card defaulter or not

also used in the table in result and discussion section to identify the feature selected by metaheuristic technique.

RESULT AND DISCUSSION

In this work the credit card defaulter dataset of Taiwan is used for metaheuristic feature selection and classification work. All the codes are written in MATLAB 16a software platform.

The authors have applied three different aforementioned metaheuristic approaches with an objective to execute the work for feature selection. The list of approaches as mentioned above is presented as follows:

- Particle Swarm Optimization
- Ant Colony Optimization
- Simulated Annealing

With all the 23 features as mentioned in Table 1, the accuracy achieved is 80.9% (Table 3). Linear Kernel SVM has been used for classification, when class level two (credit card defaulter or not) is used. There are several reasons for using SVM classifier e.g., it has different kernel which can be used in different applications. SVM uses convex optimization which is an efficient method. SVM has several regularization parameters. Three metaheuristic algorithms SA, PSO and ACO are used to select optimized features from the whole dataset. For these metaheuristic algorithms neural network is used as the fitness function. In Table 2 the feature numbers selected by SA, PSO and ACO are given. The number of features are selected in an incremental way (e.g. 2, 4, 6, 8, etc.). In each row of the Table 2 the

Table 2. Feature number selected when fixed number of feature selected by SA, PSO and ACO

Feature	2	4	6	8	10	12	14	16	18	20	22
SA	10 , 6	7, 15,8,6	16,19,1, 6, 9, 10	23, 10, 16, 6, 1, 7, 19, 11	3, 18, 7, 8, 9, 10, 14, 6, 22, 17	13, 19, 17, 9, 16, 3, 10, 4, 1, 7, 15, 6	20, 17, 8, 21, 6, 7, 22, 3, 12, 4, 15, 16, 9, 1	7, 22, 2, 9, 16, 10, 23, 1, 13, 18, 8, 17, 5, 11, 6, 12	15, 11, 1, 12, 18, 3, 23, 17, 6, 14, 7, 21, 13, 8, 9, 4, 2, 10	2, 4, 16, 15, 19, 21, 3, 8, 14, 17, 20, 10, 9, 2, 5, 23, 1, 6, 11, 7	23, 19, 10, 18, 9, 13, 21, 14, 11, 22, 2, 1, 4, 8, 16, 3, 6, 17, 7, 20, 5, 12
PSO	6, 10	16, 11, 8, 6	8, 1, 6, 7, 4, 11	18, 3, 6, 7, 19, 10, 9, 13	9, 22, 12, 21, 14, 11, 5, 8, 1, 6	10, 12, 8, 19, 23, 15, 22, 1, 9, 2, 6, 7	1, 10, 11, 14, 19, 18, 13, 9, 17, 5, 6, 3, 23, 8	16, 11, 14, 23, 21, 17, 13, 7, 9, 15, 8, 5, 12, 1, 6, 10	4, 22, 17, 11, 7, 23, 3, 15, 8, 6, 20, 1, 10, 14, 12, 2, 9, 21	15, 10, 22, 21, 2, 14, 17, 1, 12, 9, 7, 5, 8, 6, 23, 16, 4, 11, 3, 20	1, 21, 9, 6, 2, 5, 15, 10, 16, 18, 3, 8, 17, 23, 4, 22, 7, 11, 19, 14, 13, 20
ACO	6,10	6,1,21,8	1, 9, 14, 19, 8, 6	20, 8, 14, 3, 21, 1, 10, 6	11, 10, 7, 16, 18, 19, 5, 6, 9, 1	5, 6, 1, 11, 17, 15, 22, 20, 9, 7, 3, 23	11, 8, 15, 6, 5, 4, 18, 14, 10, 19, 1, 3, 20, 9	10, 18, 21, 22, 6, 2, 20, 1, 9, 13, 14, 3, 23, 5, 8, 7	13, 15, 12, 17, 22, 6, 14, 21, 2, 7, 8, 11, 1, 5, 9, 23, 4, 20	10, 15, 14, 11, 8, 13, 7, 20, 19, 23, 3, 16, 17, 9, 1, 18, 12, 5, 2, 6	5, 1, 19, 6, 8, 7, 18, 20, 4, 3, 13, 14, 16, 22, 10, 11, 21, 17, 15, 9, 12, 23

Table 3. Accuracy (%) with different feature number using SA, PSO and ACO feature selection

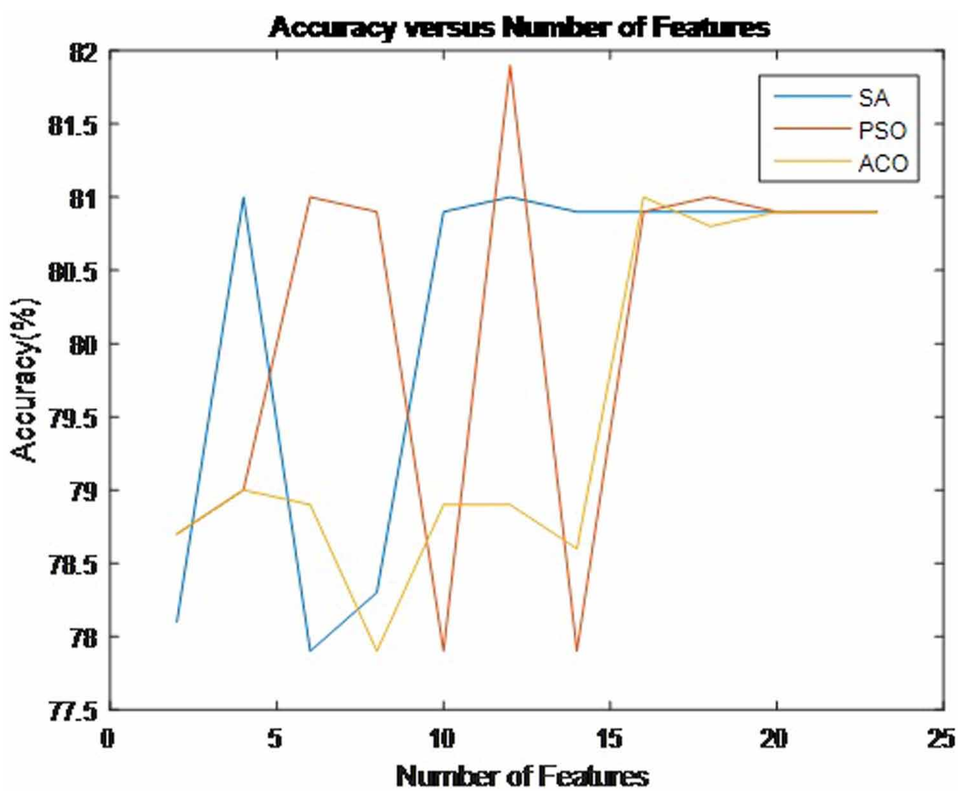
Feature No	2	4	6	8	10	12	14	16	18	20	22	23
SA Accuracy (%)	78.1	81	77.9	78.3	80.9	81	80.9	80.9	80.9	80.9	80.9	80.9
PSO Accuracy (%)	78.7	79	81	80.9	77.9	81.9	77.9	80.9	81	80.9	80.9	80.9
ACO Accuracy (%)	78.7	79	78.9	77.9	78.9	78.9	78.6	81	80.8	80.9	80.9	80.9

feature number given can be matched with the feature number given in the dataset section. As in this work linear SVM is used, so to reduce the error, minimization of sum of slack variable is required. In linear separable problem like this the sum of the slack variable is to be made nearly zero.

In Table 3 the accuracy of classification in percentage (%) with linear SVM is given.

It can be seen from the result that the accuracy is relatively constant throughout the dataset irrespective of the number of features. It can be understood from the result that the best accuracy 81.9% is found from 12 features with linear SVM when the features are selected by PSO. It is also seen that feature number 6 (Payment history) is present in all feature set selected by SA, PSO and ACO. In Figure 4 Accuracy versus Number of Features for SA, ACO and PSO algorithm are given. It is found from the result that generally with increase in number features accuracy of these approaches increases. Hence number of features plays a vital role in determining the accuracy of class determination.

Figure 4. Accuracy versus Number of Features for SA, ACO and PSO algorithm



CONCLUSION

Feature selection can be done in many ways as discussed in this chapter. Literature survey suggests that Metaheuristic feature selection is the most effective way to do so. The result suggests that fewer features are useful enough to predict the credit card defaulter class than the whole feature set. With all 23 features the system achieves an accuracy of 80.9% but if only 2 features are selected then an accuracy of 78.7% is achieved which is less than 2% of the overall best accuracy. With only 12 features selected by PSO the system achieved 81.9% accuracy which is 1% greater than overall accuracy but requires less than half features to predict the result. It can also be found from the result that Particle Swarm Optimization (PSO) works better with respect to its counterpart Simulated Annealing (SA). Other metaheuristic algorithms like Genetic Algorithm, Differential Evolution, Tabu Search etc. can also be used for feature selection.

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Chapter 6
Optimizing Social Media Data Using Genetic Algorithm

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ABSTRACT

Twitter-based research for sentiment analysis is popular for quite some time now. This is used to represent documents in a corpus usually. This increases the time of classification and also increases space complexity. It is hence very natural to say that non-redundant feature reduction of the input space for a classifier will improve the generalization property of a classifier. In this approach, the researchers have tried to do feature selection using Genetic Algorithm (GA) which will reduce the set of features into a smaller subset. The researchers have also tried to put forward an approach using Genetic Algorithm to reduce the modelling complexity and training time of classification algorithm for 10k Twitter data based on GST. They aim to improve the accuracy of the classification that the researchers have obtained in a preface work to this work and achieved an accuracy of 87% through this work. Hence the Genetic Algorithm will do the feature selection to reduce the complexity of the classifier and give us a better accuracy of the classification of the tweet.

DOI: 10.4018/978-1-5225-8103-1.ch006

INTRODUCTION

In today's world, people communicate with each other mostly through social media. Social media sites like Twitter, etc. are hence gaining large popularity. Social media has become main stream for data source. This is clearly seen by the ever-growing number of users. As mentioned above, Twitter has gained popularity among people due to it being a platform which allows access to real time updates on breaking news and other ongoing events. People express their views and opinions on social media. Hence, the study of the sentiments and their analysis of the people posting their views and opinions on social media has become a hot topic. Sentiment analysis and opinion mining on social media not only helps to identify the mass opinion on certain topics, it also indicates the ongoing as well as future trends of the social pathway, political future, even economy of a country. Finding out what is leading to such social trends thus helps the third parties, as said. For example, the government of a country might want to track down the concerned issues and if any security issues are present or not, twitter-based research for sentiment analysis is popular for quite some time now. Twitter is a micro blogging platform, where people express dynamic and short textual tweets. Twitter has a million numbers of users which keeps on increasing day by day. Occasionally the tweets can contain multimedia resources like links from external websites, images or videos and so on. The social trends reveal what is going around the world at the current moment discovering the breaking news. Twitter witnessed a large number of expressions of opinions regarding a few recently happened cases like USA's presidential election or anti-harassment movement like Me Too or demonetization as well as the implementation of Goods & Services Tax (GST) in India.

The main objective of this chapter is to study impact of execution of GST event on stock market which is useful to the portfolio manager, regulatory bodies and investors. Reflection of stock indices is based on value of stock prices of the manufacturing, automobile, agriculture, healthcare, banking, FMCG and textile industries which are pertaining to Bombay Stock Exchange (BSE). We have analyzed sentiment of people on GST dataset to predict impact of GST on stock market. We have used optimized algorithm on the twitter data to identify positive or negative sentiment with better accuracy. Finally it is showing that stock markets are expressing positive sentiment more rather negative sentiment. The paper is organized as follows: Section 2 is discussed about related works, Section 3 is mentioned about Impact of stock market on GST tax rate, where section 4 and section 5 are GST data corpus on stock market and proposed approach respectively, section 6 is about Feature set development sentiment rating, section 7 and section 8 are result and comparative analysis respectively, section 9 is discussed about Conclusion and future work.

RELATED WORKS

We have divided entire related research work into two sections: i) social network related research (ii) optimization related research.

Social Network Related Research

Sentiments can also be context or topic based, besides being tweet based (Vanzo et al, 2014). In this work, the researchers approached for a dual model of tweet classification; first to extract the conversation information from the tweet itself, and secondly to utilize that information over all the tweets of the same sequence. In a previous work from 2013, the named entity classifier problem has already been demonstrated for both single objective and multi-objective ensemble approach (Saha et al, 2013). The strength of predictions and outputs of each classifier tends to differ from class to class, hence it is necessary to find out the better class within an ensemble system to find out the better outcomes and predictions. The researchers here used a number of distinct classifiers to build several heterogenous models like a black box tool, without using any supervised or prior language specific library knowledge. They primarily implied the model for less resourced regional Indian languages such as Bengali, Hindi and Telegu, while the multi-objective optimization-based approach proposed by the authors claimed to be the most successful among the model.

As tweets can be expressed as instant dynamic textual segments, hence one main problem with tweets is that generally they are unstructured and noisy. Tweets can contain a lot of misspelled words, unnecessary punctuation marks, and several other impurities. In a shared task work from 2013, authors have addressed this issue regarding noisy Twitter data, where natural English parsers or POS tagging does not perform as per expectations (Chawla et al, 2013). Authors here proposed a model to detect polarity from discourse relations. Alongside they also proposed how the inherent conjunctions, connectives, modals and conditionals affect the polarity construction within tweets. Also, tweets can commonly contain abbreviations, popular SMS terminologies, slangs etc., which the authors have also considered.

A popular domain of work in NLP is to develop a machine translation bridge to perform sentiment analysis of a less discourse language from an annotated more resourceful language (Balamurali et al, 2013). It can be done if the latter's developed corpora, POS tagged, stemming or lemmatized is readily available and already well-rehearsed. However, success of this concept also depends on the availability of machine translation system between the two languages.

Another research work shows a system for real time twitter data (or tweets) analysis of US presidential election (Wang et al, 2012). This was an event-based sentiment analysis work, which relies heavily on time and content. With that, the researchers wanted to portray the aggregation and visualization of the key results they found. Authors of AVAYA (Becker et al, 2013) proposed a system capable of classifying the polarity of tweets based on both lexical and syntactic level. The trained data by the researchers helped them to find out the previous polarity of words, and it also became an advantage for the model to gather more features for the purpose of more self-training. For improving the performance, they also combined document classifications with polarity features. It can be often witnessed that people who share the same thoughts and perspectives on a particular given topic, also express the same on social platforms. These people can be grouped into individual and distinct communities based on their beliefs, statements, opinion polarity and so on. A previous work has already demonstrated the dynamic community detection on large scale social networks (Stopczynski et al, 2014). While most of the community detection algorithms are static and are unable to capture the shift of user opinions with the change of time, the researchers proposed a dynamic community optimizer framework to eradicate this problem and to identify and group the communities more efficiently.

Since tweets are dynamic and expressed with a short span, hence users also tend to tweet sarcastically, crack short jokes, in humorous or satirical ways. A work from 2015 shows any of the past sarcastic tweet about any topic of the authors matches with their present-day ideology or not (Khattri et al, 2015). For this, the authors have stated to use a bi-predictor approach to determine the sentiment contrast for sensing the sarcasm within a large tweet, along with another predictor to find out the historical sarcastic tweet of the same user on any given topic, if any. Also, their approach is said to gather the texts generated by the author while tweeting, to detect the sarcasm within them.

One of the primary problems of working on tweets is that when the tweets are newly collected from Twitter, they often consist of misspelled words, wrong and exaggerating use of punctuation marks, unnecessary emojis or emoticons and so on. These impure tweets can be said as noisy tweets, or noisy data in a broader perspective. Noisy data is not appropriate for labeling or processing, hence tweet filtration is a must need just after collecting a tweet corpus. In 2015, a group of researchers have addressed this issue in their work (Akhtar et al, 2015). They have worked for the normalization of the noisy tweets based on their lexical and syntactic properties using a hybrid approach. This approach consists a combination of machine learning algorithm and rule-based classifier. The machine learning algorithm used is a supervised “conditional random field”, which is first developed. Henceforth in the second step, a set of heuristics rules has been applied to the wordforms gained from the first step, for normalizing them. The researchers also trained the classifier with a set of features which were derived without using any domain-specific feature or resources. The experiment is stated to achieve a precision value of 90.26%.

Nowadays twitter has become an open public platform to express opinions about political matters, government policies, economy and so on. On 2016, a group of researchers presented a work to harness the political issue extractions and issue dependent standings and positions (Joshi et al, 2016). The authors developed the model to discover political issues and positions from unlabeled tweets. Their model is capable of discovering political issues and positions from an unlabeled dataset of tweets. The model estimates word-specific distributions (that denote political issues and positions) and hierarchical author/group-specific distributions (that show how these issues divide people). Their experiments using a dataset of 2.4 million tweets from the US show that this model effectively captures the desired properties (with respect to words and groups) of political discussions. We also evaluate the two components of the model by experimenting with: (a) Use to alternate strategies to classify words, and (b) Value addition due to incorporation of group membership information. Estimated distributions are then used to predict political affiliation with 68% accuracy.

In another previous work, authors selected corpora for weekly supervised training based on previous sentiment association score (Wang et al, 2016). They also demonstrated that their weekly supervised corpora was able to extract rich lexical features, and it outperformed the previous state-of-the-art result. Another work from 2016 shows the multidimensional polarity weightage for corpora based on the regional distributions (Teng et al, 2016). Instead of taking the approach for conventional bipolarity analysis, i.e. positive and negative, the researchers took the step for multidimensional sentiment analysis on "valence arousal (VA) space", where a regional CNN-LSTM model can be deployed for inputting a text into several distinct regions, and from that, it can further be processed for extracting the information out of every regional CNN model. In such scenario, the models of different regions can be able to produce heterogeneous information or feature for different regions. Based on that, it can also be categorized if the regional information has any long-distance dependency among them or not.

A research work from 2016 for a shared task demonstrates the experiment of classifying a large number of Twitter named entity system recognition, i.e. classifying a large number of Twitter user's names, employing a supervised machine learning algorithm (Sikdar ete al, 2016). The researchers classified the task into two distinguished parts such as, extracting the named entity from tweets in first phase, and classifying the names into ten different categorizations. The "Conditional Random Classifier" algorithm was trained on a feature rich Twitter dataset, and the obtained F1 score was 63.22%, while the F1 measure score based on the unseen test data was lower (40.06%).

While social media boasts of a large number of users, which is also growing constantly, many bots are being used on social media for spreading malicious news, rumors, hate statements and so on. A work has been done on detecting such types of bots on social media and removing them on the basis of recall balance (Morstatter et al, 2016). The researchers aimed to keep the precision rate high and obtain a balance between precision and recall to achieve the optimization results of removing the bots from social media.

A recent and one of the first research works on GST from 2017 demonstrates an approach for text mining and henceforth sentiment analysis of GST tweets (Das et al, 2017). The authors collected GST tweets during its implementation phase in India, developed a twitter data corpus. They implied Naïve Bayes algorithm as the baseline algorithm of their work to gain polarity ratings of labelled tweets. After processing, with the help of tokens and cumulative tokens from GST specific tweets, the authors depicted the vicissitude of GST related buzzwords within the implementation phase, as well as the range, frequency, cumulative frequency and zip f score of such most popular words. With that the authors made a step to do a unified sentiment polarity percentage of the whole data corpus from the previously gained data insights.

Since, twitter is a dynamic social platform to express their views and perspectives on the go, hence tweets often come out to be short, witty or satirical, rather than being utterly serious and long. Keeping this prospect in mind, the scope of satire detection in twitter and in any other social network platforms are on the rise. Besides the traditional satire detection from mixed 'bag-of-words', the human hand-eye movement while reading such texts can also be considered for capturing the natural text processing flavor of human behaviors while reading something satirical or funny. Researchers have demonstrated their framework for managing this concept (Mishra et al, 2017). Apart from extracting the textual features, the researchers also emphasized the eye movement or gazing on texts while reading. They developed a CNN model, which can learn both from text features and gaze. For testing their model, they used an annotation of diverse people's reaction to reading the same text. With this bi-modal approach, the authors have established to show a better outcome for sarcastic texts. A large number of research work has been carried out to detect and analyze public sentiment on social network platforms through text, and for any specific emergency event. To measure the scope of visual content such as images posted on social media, a group of researchers performed an analysis to study and compare sentiments reflecting through the images and texts posted on Facebook during the terror attacks that took place in Paris in 2015 (Dewan et al, 2017). These researchers approached for a generalized 3-tier pipeline which utilizes state-of-the-art computer vision techniques to extract high-level human understandable image descriptors. With that, they also state their analytical findings which came out be negative for textual contents on Facebook after the attack in Paris, while images depicted positive sentiment. In a most recent work, the authors have proposed an "ontology" tool for sentiment analysis based on a large semantic network (Dragoni et al, 2018). This tool not only helps to identify word sentiments, it also produces the contexts, associated meaning with those words, and even their annotations linked with external resources. Instead of only following the keyword counts from social media texts, this work also utilizes the natural meaning of associated words that are being processed. Their proposed tool "OntoSenticNet" can detect expressed sentiments by analyzing the multiword expressions which are also related to other concepts.

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Optimization Related Research

We intend to reduce the complexity of the model that classifies the sentiments of tweet. We all know that text classification is one of the special cases of classification in machine learning and has been famous as a work domain for quite some time. Their research intends to optimize the accuracy of the tweet classification of the GST dataset using Genetic Algorithm (GA). We all know that Sentiment Analysis has been described as a Natural Language Processing work at different levels. It has been applied to different levels like a document level classification task to sentence level classification to phrase level classification (Bo Pang et al, 2004; Tuney et al, 2002; Soo-Min et al, 2004; Minqing et al, 2004; Wilson et al, 2005). Most of the text classification including Twitter sentiment classification uses bag of words model. This bag of words contains unique word or phrases to convert those occurring in a corpus to vector space-based model of language. But the major disadvantage is that, the Bag-of-words generates a lot number of features in input space. Hence this is not an efficient way of vectorizing features in input space. The language model does contain high feature space and most of the generated features that this technique generates are usually redundant, irrelevant or noisy (Buck et al, 2014). Hence filtering these redundant features is a very hectic job. It is one of the major primary problems while doing text classification. Thus, having feature selection applied before putting the huge dataset for training using the training algorithms reduces the computational complexity of these training algorithms. Classification models built using features with high discriminative power reduces the complexity (Guo eta l, 2012). Feature selection provides with the advantage of model accuracy and stability. Feature selection helps in predictive results using high dimensional input space. The most important advantage of using feature selection is that it reduces the complexity of classification hypothesis (Chu et al, 2012). Feature selection also provides with other benefits like avoiding over fitting of classifier function

(Maladeni'c et al, 2004), reducing the consumption of the memory for learning algorithms and also by removing the unwanted irrelevant features from text data set (Yu eet al, 2004; Rodriquez-Lujan et al, 2010).

Feature selection methods can be classified in two ways: filter and wrapper methods (Chandrashekar et al, 2014) In filter methods, feature selection is done using an evaluation function where each feature is ranked according to a metric such as fisher score, t-test or information gain (Song ete al, 2013). Though filter methods are very fast and efficient to compute, this method is independent on the classifier algorithms. Drawback of this approach is that it selects subset of feature which has redundant features. The second way is wrapper method where the feature selection algorithms use feature set's subset as well as the accuracy of the classifier function which is trained using the feature set's subset. This method unlike the filter method is dependent with the classifier algorithm. Heuristic algorithms also have been used for feature selection for large scale huge amount of data sets. Kabir et.al (2012) combined both the advantages of filter and wrapper-based methods to develop ant colony optimization-based feature selection methods for algorithm of neural network. They compared the results of the existing feature selection algorithms with the one they developed. Unler et.al. (2010) developed a feature selection method which uses relevance and dependence of the features which are included in the feature subset. This approach was based on particle swarm optimization algorithm for feature selection. Ant colony optimization using rough set theory-based feature selection was also developed by Chen et.al. (2010), which was based on mutual information-based significance of the feature. Bae et.al (2010) developed a new approach based on particle swarm or intelligent swarms for heuristic search. This helped them to overcome the premature convergence of the objective function. A new algorithm considered both the F1 score of the classifier function as well as the number of features present in the feature subset for text classification. F1 score is generated using the classifier function and is mostly used for information retrieval domain in the model selection method. Their overall contribution is that they found a method to find a very small feature subset that is possible along with a high F1 score. Their main contribution was made to make this approach suitable for information retrieval and in the area of classification of text so that unwanted, noisy and irrelevant features from the input space of dataset can be removed, at the same time improve the performance of the classification of the texts. In short, they used a F1 based selection method and made their approach use an algorithm with a very low iteration size. They used feature selection to reduce the very high usage of memory that is used for the input matrix. Hence, in this approach the complexity of the input matrix is reduced by using such feature selection.

EFFECT OF GST ON STOCK MARKET

The prediction of Stock Market change based on reaction of stock price on different event is the subject of study over the years. In this regard, GST is the most sensitive and much awaited tax reform event in India. Now India's tax system is free from multiple levies and all kind of cascading effect after implementation of GST. The implementation of GST removes all the ill effects of earlier system. A lot of positive and negative discussions were going on regarding its implication on the economy. This was the first reaction of stock market return. So the movement of stock prices indices would assist us to realize the investor's view on the GST rates. Eventually indices of stock prices would reflect the implementation of GST as "good" or "bad" that is sentiment of people.

To determine public reaction on GST, various surveys have been conducted such as stock split, union budget, monetary policies, mergers and short term efficiency of the Indian stock market. Our main objective of this work is to observe the reaction of stock market after launching of GST on 1st July 2017 based on Collected GST tweet corpus.

ST – Analysis and Opinions for the Portfolio Management

GST has introduced an 'one nation one tax' system, but its impact on different industries is a little different. The initial differentiation will come up based on industry deals with retailing, distributing and manufacturing. However, due to GST in business several indirect taxes have been included which were not under the tax category previously and will now need to register to GST. Sector-wise Impact Analysis are presented below.

Logistic sector in India is the backbone of the economy that has been helped by GST under the "Make in India" scheme of the Government of India.

The growth of e-commerce sector is very fast in India. In this regard, GST will help e-com sector's growth in many ways. In case of long-term effects, GST law introduces a 1% Tax Collection at Source (TCS) mechanism, which e-commerce sector is not too happy with.

GST is helping pharma sector by introducing a level playing field for generic drug makers and simplify the tax structure that relates to the pricing structure. The pharma and healthcare industries are expecting a tax relief since it will make healthcare medicine affordable to all sections of people.

GST reduces the telecom sector prices and manufacturers will bring down prices through efficient management of inventory. GST has eliminated the requirement to establish state-specific entities and relocation stocks. Overall all management will save up on logistics costs.

Both pharma and telecom sectors have positive impact on stock market value.

The Indian textile industry is an important sector as per job related issues. In this sector large numbers of skilled and unskilled workers are involved. It is expected that tax revenue is going to increase more after launching GST, which earlier was 10% of the total annual export. GST would create a bit of negative impact on most small and medium industries due to imposing of tax on cotton value chain of the textile industries as it was earlier set zero central excise duty.

Textile sector has a bit of negative impact on stock market.

The Real Estate sector is one of the most employment generating sectors playing an important role in Indian economy. Accountability and transparency of industrial taxation system in GST has a huge positive impact in stock market rather than earlier VAT based complicated taxation slabs.

Agriculture sector has large impact in Indian GDP that covers almost 16% ofcountry's GDP. Transportation of agri-product across India face huge difficulties, this major problem is resolved by GST. So, agri-sector has enormous positive reflection in stock market.

FMCG sector is getting profitable benefit in logistics and distribution costs as GST has removed the requirement of several sales depots.

With the effect of GST, freelancers pay easily their taxes online as service providers. Present GST oriented tax structure has reformed more consistency and accountability in this sector. So both FMCG and Freelancers have positive mood in stock market.

Automobile sector is one of the most influential sectors that has been benefited under one GST tax by removing several taxes such as motor vehicle tax, road tax, excise, sales tax, VAT and registration duty.

Indian startup companies have been boosted by GST after eliminating several Indian states several VAT laws which made things complicated and confusing for companies that have a pan-India presence, especially e-com sector. Automobiles and startups have tremendous impact on GST.

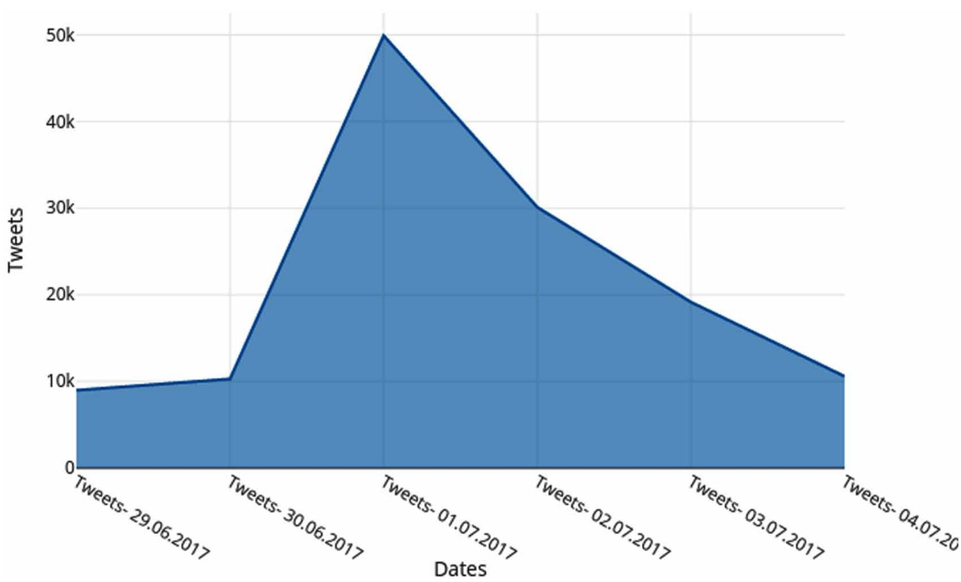
The main advantage of GST is the reduction in tax fees which amounted to 25% to 30% before announcement of GST and minimum time and charges on tax payment. From this scenario of Manufacturers, the advantage is free of cost movement of Goods and Services all over the state borders without going through extra taxes and paper work.

Collection of GST Data Corpus on Stock Market

India has a number of 26.7 million active twitter users in 2017[1], i.e. currently the second highest in the world. Since GST was the clearly one of the largest taxation reforms in the history of independent India, twitter witnessed a social opinion outburst on this topic during Jun-July 2017.

In this context, the researchers gathered tweets by employing live twitter streaming API[2] in two major sections as follows. At the early stage, they collected tweets in synchronization with the implementation phase of GST in India during June-July 2017. GST was one of the top trending topics back then, and people were tweeting about it frequently rather than any other topics. Since the evening time slot (between 6 p.m-10 p.m.) is considered to be the "prime-time" in terms of entertainment and online social activities, the researchers aimed primarily to gather tweets between the aforesaid time window. While twitter API mostly allows its users to live-stream only 1-2% of the total tweets on any keywords, the researchers observed that they were able to collect tweets at a rate of 24 thousand per hour. In this context, one thing is worth mentioning that up to October 2017, twitter used to support a highest of 140 characters per tweet including emojis, whereas, from 7th November 2017, twitter expanded its character limits to 280 characters per tweet. However, since they have started collecting the GST tweets from June 2017, for most of the time (5 months out of 7 months), the researchers were able to collect tweets with 140 characters only. One thing worth mentioning is that they are stating the total number of their collected tweets while taking all the impurities within tweets in the account. In Figure 1, the authors represent the ascension and declination of GST tweets during its implementation week in India.

Figure 1. Rise of GST tweets during Jun-July 2017



It was observed that after the appliance of GST all over India, the dust was settled after a few months and it seemed that finally, people are not tweeting about it like before. Meanwhile, India's GST council held a meeting on 10th November 2017[3], which eventually led the way for a rate shift of 177 products. This decision again boosted up the topic and also the tweets about these reforming rates, which motivated us again to collect the tweets as the second phase of data collection. During the tweet collection phase, the researchers streamed live tweets randomly both from normal population as well as the Twitter handles of @*narendramodi*, @ *arunjaitley*, @*FinMinIndia*, @*RBI*, @*GST_Council* and so on. After combining two phases, they gathered a number of 1,99,864 tweets, or almost 200k unprocessed and raw tweets containing the hash-tagged keywords such as *#gst*, *#gsttax*, *#gstlaunch*, *#gstrollout*, *#gsteffect*, *#onenationonetax* etc. along with the main tweet bodies.

PROPOSED APPROACH

The researchers have approached for an algorithm that proposes to select the features from the data set of 10,000 tweets of GST using Genetic Algorithm. As the preface of this work, they have worked on a deep learning inspired lexical-level sentiment analysis of GST tweets. The researchers approached for a topic-sentiment based tweet crawling and thereafter word polarity vs. popularity generation for discovering and clustering the GST exclusive topic words from GST tweets in India. The researchers collected a number of almost 200k tweets solely on GST, pre-processed and filtered the tweets, extracted unigrams, bigrams and trigrams from the tweets, compared these grams with previous state-of-the art lexical and twitter datasets. They separated the words that we found are matching, and did the stemming and POS tagging. This helped us to create a Bag-of-Words from the GST tweets which they retained separately. Simultaneously, the researchers developed an NLTK based Naïve Bayes sentiment analyser; the researchers gave their twitter dataset sentiment ratings on a scale of 1.0 to 5.0. Now using the bag-of-words that they obtained, and the sentiment rated tweets, they developed a sentiment-trend model, by which they were able to generate the scores for word popularity and polarity for most occurred words in the GST related tweets during the course of GST implementation phase in India. The researchers identified a number of 9871 words within a miniature sample of 10,000 tweets from their entire data corpus and visualized their sentiment polarity using a 3D data cluster and polarity vs. polarity mapping as a whole. Now using this newly developed rated dataset, they implied their bi-directional LSTM model for training and testing of their data. The researchers kept a split of 80:20, i.e. 80% data for training, and 20% data for testing. After 10,000 epochs as of now they achieved an accuracy of 84.51%.

Since the researchers already obtained a textual (tweets) data corpus and have achieved an accuracy of 84.51% on sentiment prediction of that corpus, now they are employing a GA baseline algorithm for competitive learning to ensure the optimization which can be achieved by deploying these algorithms. Their model which has been proposed here selects features from this dataset using Tournament Selection where the tournament size is 3. The model then performs crossover, that is, one-point crossover followed by mutation where the mutation rate is 0.05. They expect it to be more enhanced and accurate with the ongoing research flow. The feature selection using GA, for random and unbiased choice of the best properties for textual tasks, is also being implemented to choose the best fit tweet topics and sentiment themes to assure the absolute relevance of the tweets with the topic being discussed, to achieve a more optimized result. The number of population and the number of generations that they have taken is 100 and 10 respectively. The 10K tweets have been divided in 80:20 ratios, that is the training size is 80% of the data set and the rest 20% is kept for the testing of the data. The researchers read the data from a CSV format file which has the following attributes for each tweet – the 'index' of the tweet, the tweet itself, the 'class' of the tweet that is, positive or negative and the 'prob' of the tweet. In this approach, they have taken the 'prob' attribute which has different values and from there they have tried to do feature selection of the tweets. Their main aim is to optimize the accuracy level of the classification of the tweets that is gaining more accuracy than they have achieved in the deep learning method.

FEATURE SET DEVELOPMENT: SENTIMENT RATING OF TWEETS

The authors retained the GST exclusive words from Feature I as a separate file. For assigning the sentiment rating, they developed an NLTK based Naïve Bayes sentiment analyzer to assign sentiment scores to the tweets which were previously labeled using the topic and sentiment to ensure their relevance with the subject matter. Nave Bayes Classifier algorithm was chosen as it is one of the widely popular Supervised Machine Learning algorithms used for text classification and clearly provides less computational time compared to other Supervised Machine Learning Techniques. Naive Bayes Classifier primarily works on the conditional probability theory. It offers the assumption of a particular feature from a class of features. But not necessarily, it will come out as the accurate one. The word naive indicates the novice assumption of each condition. For any given case, where something else has already occurred, in that scenario, by using the conditional probability, which is the base of Nave Bayes algorithm, we can calculate the probability of occurrence of a future event using the prior knowledge gained from the previous sample case. Based on this principle, the Naive Bayes Classifier works. It is the type of classifier, which predicts all possible membership probabilities for each class, i.e. the probability that is already recorded for a particular class. Naive Bayes is one of the most popular methods because, despite its relatively easier approach to implementation, it is fairly complicated, and often outperforms most other more complicated algorithms in performance. Naïve Bayes algorithm provides promising results for textual tasks, often in the experiments related with the Natural Language Processing. Another thing which gives Naïve Bayes an advantage over other Machine Learning algorithms is that it has a smaller and robust model than the random forests, so we can keep all the training sets in memory. It allows the system to perform better, easy to train and understand the results and provides different extensions for different needs of the experiment.

For a given variable class a and a feature vector series of b, Bayes theorem can be expressed as:

$$P\left(a|b\right) = \frac{P\left(a\right)\ P\left(a|b\right)}{P\left(b\right)}$$

where,

- P(a|b) is the posterior probability of class (i.e. the target) given predictor,
- P(a) is the prior probability of the target class,
- P(b|a) is the chance, which is the probability of given class,
- P(b) is the prior probability of predictor.

Let us have an example of the working principle of Naïve Bayes classifier or algorithm in text categorization implying the above-mentioned theorem on a following real-time tweet on GST.

"MG_Indian b'@askGSTech: What is a percentage of GST for govt. contracts give some letter on notice board or bring some GR as some dept. claim 18 percent?'.."

Now, let us assume that the prior probability of the target class is GST, while the percentage for govt contracts give some letter on notice board or bring some GR would be 50%. Hence,

P(GST|xi), xi = [50%, 50%]

Let,

- xix be the feature vector of sample i, i∈{1,2,...,n}i,i∈{1,2,...,n},
- ωjωj be the notation of class j, j ∈{1,2,...,m}j,j∈{1,2,...,m},and
- P(xi|ωj)P(xi|ωj) be the probability of observing sample xixi given that belongs to class ωjωj.

The general notation of the posterior probability can be written as:

- P(ωj|xi) = P(xi|ωj)·P(ωj)P(xi)
- P(ωj|xi) = P(xi|ωj)·P(ωj)P(xi)

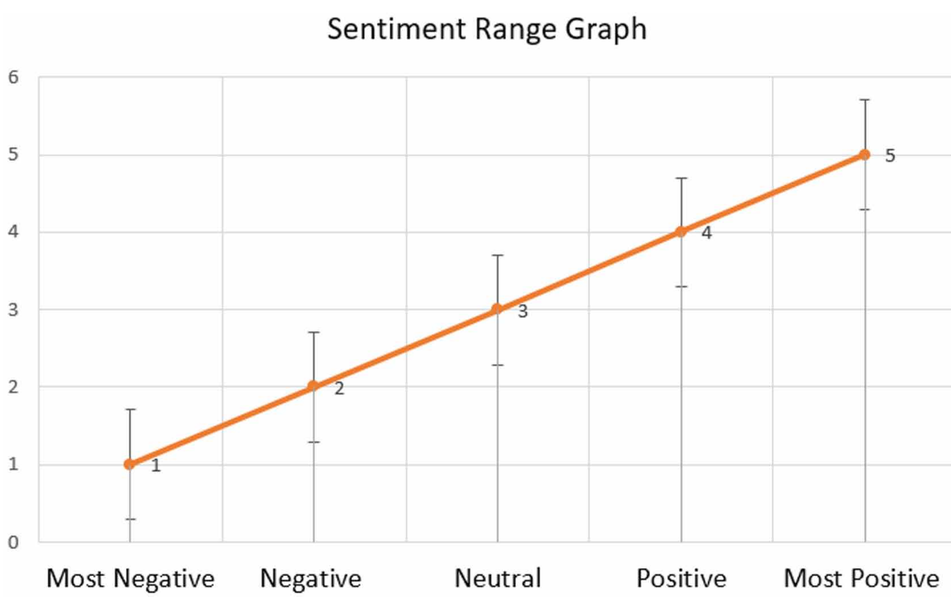
The objective function in the naive Bayes probability is to maximize the posterior probability given the training data in order to formulate the decision rule.

To conclude from the above example, we can formulate the decision rule based on the posterior probabilities as follows:

Govt. will bring GST rates on contract letters as,P(GST|xi) ≥ P(18%|xi), Otherwise not, for 82% cases.

This entire analysis through coding was done in python importing NLTK and Naïve Bayes Classifier package, thereafter implying the Naive Bayes Classifier for classifying the text from our Twitter dataset for assigning the further sentiment rating.

Figure 2. Sentiment range of their GST tweet dataset with each corresponding sentiment class



Since tweets are short in nature, for such short texts or textual fragments, Naïve Bayes tends to perform better than other baseline algorithms (Wang and Manning, 2012). The scale of the sentiment scores provided by us was in the range from 1 to 5, such as *very negative (1.0)*, *negative (2.0)*, *neutral (3.0)*, *positive (4.0)*, and *very positive (5.0)*. Based on this scale and their classification, they successfully assigned sentiment ratings, where each tweet belongs to exactly each sentiment label and sentiment rating.Following further, the researchers generated a sentiment range graph from this table. The sentiment ratings are unified as a total range of most negative to most positive. The authors show this graph in Figure2.

RESULTS

For two distinctive approaches of creating a pool of best features as unique chromosomes, they opted for the Feature Selection. Now Feature Selection from Machine Learning perspective can be done in a number of ways. But since their approach resembles the perception of Genetic Algorithmic optimization, hence selecting the best features for latter descendants was their primary objective, so that when the chromosomes get overlapped for final feature selection, only the best tweet properties should come out on the top for the development of the classification matrix. Therefor they choose Embedded Methods for feature selection, which learn which features best contribute to the accuracy of the model while the model is being created. The researchers implemented the regularization method, which is one of the most common type of embedded feature selection methods. Regularization methods are also called penalization methods that introduce additional constraints into the optimization (like the sentiment labelling of the tweets along with the polarity ratings) of a predictive algorithm that bias the model toward lower complexity (fewer coefficients) but for enhanced results.

For step-by-step feature selection, the authors used the scikit-learn library along with python on their previously discussed labelled datset.

Univariate Selection

Univariate feature selection examines each feature individually to determine the strength of the relationship of the feature with the response variable. This method is simple to examine and execute, to understand and are in general good for gaining a better understanding of data. For their approach, they experimented with the tweets to be expressed as the features of *indexing*, the *sentiment rating* and *label* as [[1, 1.0, 0],[2, 2.0, 0]…..]] etc. They show the results of their univariate selection through a sample number of tweets in Table 1.

Table 1. Example of tweets belonging to each sentiment class and category

Index	Tweet	Class	Polarity Rating
1	"@CNBCTVLive These anchocrs dont know actual rules of GST how talk about that I dont know !!"	Very Negative	1.0
2	"I think #GST will force us to go back to the ages where bear trade was practiced."	Negative	2.0
3	"@INCIndia Watch Press briefing by State Ministers Manpreet Badal, Kamala Kaan @krishnabgowda on #GST"	Neutral	3.0
4	"@timesofindia #GST gets simpler for small businesses and exporters."	Positive	4.0
5	"@jitu_vaghani Congratulate PM narendramodi ji and FM arunjaitley ji on taking landmark decisions and making #GST even simpler."	Very Positive	5.0

Recursive Feature Elimination

Next, the authors approached for recursive feature elimination that works by recursively removing attributes and building a model on those attributes that remain. It uses the model accuracy to identify which attributes (and combination of attributes) contribute the most in predicting the target attribute. RFE filters the already selected features and brings up only the top features to present the best possible results among the set or pool of features. They selected only the *tweet ratings* and *predictions* (or labels) through this feature.

Tuning the Parameters

In Genetic Algorithm, we have certain parameters as following:

- Number of Generations,
- Number of populations,
- Mutation Rate,
- Mutation percentage on population,
- Crossover percentage on population.

Among these parameters mutation rate must be very low, as low as two tweets (one consisting positive polarity, another negative polarity) or even smaller, which is the mixing of tweets from various unauthenticated sources. Because the higher value could destroy the solution. Mutation percentage and crossover percentage (i.e.

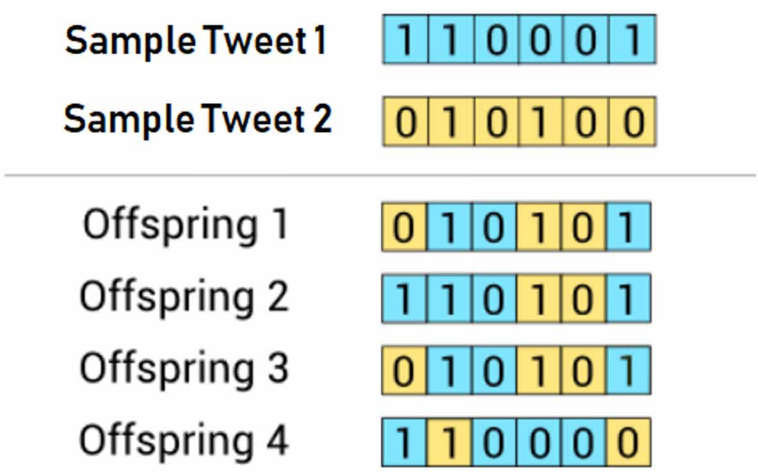
the polarity combination of tweets) depends on the problem and their own efficiency that they could find an optimal value for them by different runs. They settle for a hypothetical optimal value for these three parameters, the first two parameters would be settled simply. To get faster convergence, researchers vary the values of GA operators (crossover and mutation) along with generations. Studying the problem philosophy is very essential also.

Crossover

Once the selection operation is done, and exactly the half of the best selected features from the total population remains, the crossover operator recombines the selected individuals to generate a new population. This operator picks two individuals at random and combines their features to get four offsprings for the new population, until the new population has the same size than the old one.

The uniform crossover method decides whether each of the offspring's features comes from one parent or another. Based on the features that the researchers converted to respective binary values, they perform the crossover operations similarly as depicted in Figure 3, where four offsprings can occur combining all the featured value of their parents. The polarities from sample tweets can further be crossover and preserved for sample cases, which helps to reproduce the offsprings' polarity combinations in future.

Figure 3. Offspring crossover possibilities from parent tweet's features



Mutation of Features

The crossover operation generated offsprings that resembles quite similar features to that of their parents. This certainly causes a new generation with low diversity but assured enhanced output. The mutation operator solves this problem by changing the value of some features in the offsprings at random.

In order to decide if a feature will be mutated, the researchers generate a random number between 0 and 1. If this number is not equal to the binary cumulation of other feature values called the mutation rate, that variable is flipped. The mutation rate is usually chosen to be 1/m, where m is the number of features.

Confusion Matrix and Classification Report

The authors compared their previously gained features for their respective tweets with their already standardized sentiment rated corpus to validate the prediction-based analysis. They compared the predicted tweets with the actual tweets to find out the *confusion matrix* consisting of *true positive*, *true negative*, *false positive* and *false negative*. Using these features, they further calculated *precision*, *recall*, *accuracy*, and finally *f1 score*. For the analysis, they used a shrink down fractional sample of the whole data corpus, i.e. for a number of 10,000 tweets from their entire dataset. The main reason behind this is to reduce the time complexity as much as possible, by making the overall analysis much faster. Another reason is that a fractional overview of the results can be the showcase of the entire data corpus's characteristics. This analytical observation of their data corpus also represents the error rate in both respect to positive predicted and negative predicted tweets. With 10,000 tweets, their training (standard) set has total 9908 entries (tweets) with 3211actual positive, 2841 actual negative and 3856 actual neutral tweets. The researchers' validation set has 3211 positive predicted tweets (32.4%), 2841 negative predicted tweets (28.67%) and 3856 neutral predicted tweets (38.91%). The authors represent the predicted results in Table 2. Next, they present the classification report in Table 3, in which they show the statistical measures calculated from Table 6. Validation result for

Table 2. Confusion Matrix & Classification Report shows the differences between the predicted and actual tweets along with the prediction parameters

	Predicted		
Actual		*Positive*	*Negative*
	Positive	3211 (TP)	478 (FP)
	Negative	512 (FN)	2841 (TN)

Table 3. Confusion Matrix & Classification Report shows the differences between the predicted and actual tweets along with the prediction parameters

Precision	Recall	Accuracy	F1 Score
0.8704	0.8624	0.8594	0.9953

10,000 tweets reveals that the null accuracy is 48.61% whereas the overall accuracy score is 85.94%, which is 37.33% more accurate than null accuracy.

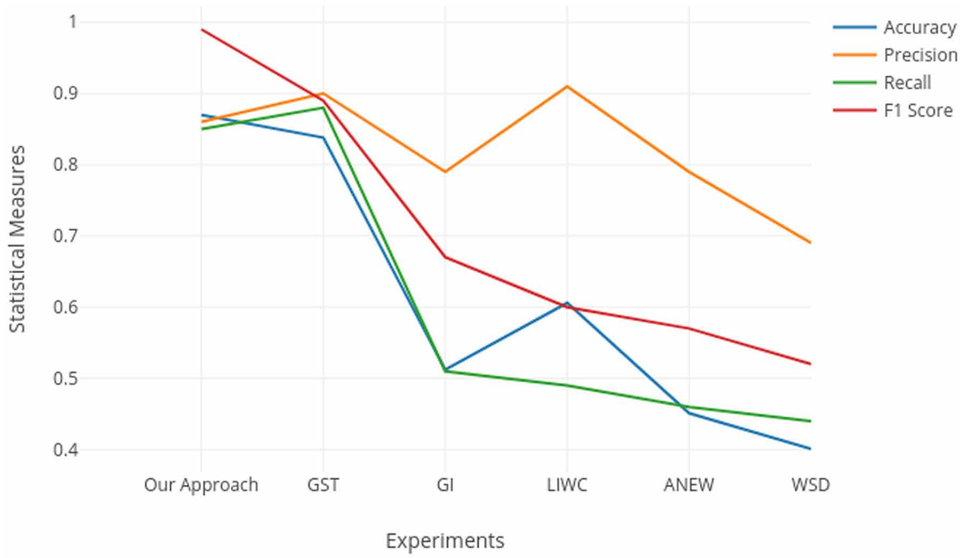
COMPARATIVE ANALYSIS

Next, the researchers did a comparison of their results in Table 7 with four already established sentiment analysis lexicons: *GST: Analysis by Popularity-Polarity Model* (Pennebaker et al, 2015) *Linguistic Inquiry Word Count (LIWC)* (Wilson et al, 2005), *General Inquirer (GI)* (Bradley et al, 1999), *Affective Norms for English Words (ANEW)* (Gao et al, 2014), *Word-Sense Disambiguation (WSD)* using *WordNet* (Gao et al, 2014), for analyzing the performance of their sentiment-based accuracy along with the classification parameters. The previous works are mainly based on a cumulation of manual human ratings on some particular textual topics from time to time. As seen in Table 4, in most scenarios, their approach outperforms the other previously well-established lexicons for sentiment analysis. In case of social media texts (here tweets), their approach provides better overall classification parameters than the manually given human ratings in the previous experimental works.

Table 4. Comparison of classification performance on social media posts

	Overall Accuracy Ground Truth (of the Respective Corpora)	Classification Accuracy Metrics		
		Overall Precision	**Overall Recall**	**Overall F1 Score**
Social Media Texts (Range: 10,000 Tweets)				
Optimization of Social Media Data using GA	0.870	0.86	0.85	**0.99**
GST	**0.838**	**0.90**	**0.88**	0.89
GI	0.512	0.79	0.51	0.67
LIWC	0.606	0.91	0.49	0.60
ANEW	0.451	0.79	0.46	0.57
WSD	0.401	0.69	0.44	0.52

Figure 4. Visual comparative analysis between the new work and some previous established experimental works



Further, the researchers visually compared their achieved results with that of the previous experiments in Figure 4. From the figure, it can be visualized that though their approach does not always come to the top, or as the best result, but it maintains a significantly consistent position with the highest overall *F1 score*.

This accuracy proved that reaction of Indian Stock Market is overall positive with respect to declaration of GST rates. Initially, it was believed that short term impact of GST could be negative or neutral but in long term effect huge tax burden is expected to be reduced and gradually market will get further direction towards economy. This result is helpful to the portfolio manager, regulatory bodies and investors.

CONCLUSION AND FUTURE SCOPE

In this work, a feature selection task has been performed on 10k GST Twitter datasets in machine learning area using Python. Aim of this research work is to determine the reflection of implementation of GST on stock market that is influenced by different industries such as IT, manufacturing, automobile etc. To execute this work, researchers have analyzed sentiment of people on GST dataset to predict impact of GST on stock market. They have used optimized algorithm on the twitter data to identify positive or negative sentiment with better accuracy. The previous work done had an accuracy of 84.51%. Their method intends to find a feature subset as small as possible and increase the classifying accuracy level.

As future scope, they will define fitness functions based on F1 score. F1 score is defined using two terms– 'accuracy' and 'recall'. In that perspective the optimization level of the classification of the above tweets might be more accurate and the accuracy achieved can be higher. The researchers can also apply their approach on more datasets. They can do comparative study by changing population sizes, iteration sizes, number of generations, changing mutation rate, applying other crossover models or applying other selection approaches. Also, they can mathematically define customized fitness function to enhance the feature extraction quality of their data. And finally, since their work is one of the first optimization works on such a large-scale economic reform, the authors are keen to publish their GST data with all the components on an open-source data repository platform like Github, so that other researchers and students feel free to experiment with the researchers' findings from this event, and they com-pare their achieved results with that of theirs.

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Chapter 7
The Genetic Algorithm:
An Application on Portfolio Optimization

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ABSTRACT

The portfolio optimization is an important research field of the financial sciences. In portfolio optimization problems, it is aimed to create portfolios by giving the best return at a certain risk level from the asset pool or by selecting assets that give the lowest risk at a certain level of return. The diversity of the portfolio gives opportunity to increase the return by minimizing the risk. As a powerful alternative to the mathematical models, heuristics is used widely to solve the portfolio optimization problems. The genetic algorithm (GA) is a technique that is inspired by the biological evolution. While this book considers the heuristics methods for the portfolio optimization problems, this chapter will give the implementing steps of the GA clearly and apply this method to a portfolio optimization problem in a basic example.

INTRODUCTION

Portfolio optimization has been one of the most studied subjects by practitioners and researchers in the last decades. Portfolio optimization is intended to ensure to gain maximum return with minimum risk. There are various methods used to establish the optimum portfolio. In some cases, it is difficult to use the mathematical models, because of the long calculation time and its constraints in the parameters. Therefore,

DOI: 10.4018/978-1-5225-8103-1.ch007

researchers and practitioners have used heuristic techniques that do not involve the problems of these methods. With the implementation of heuristic methods in the field of finance, the solution of complex models has been facilitated as time and cost. It also expedites the understanding of these processes through the use of heuristic methods in the modeling and control of dynamic financial systems.

Optimization is defined as maximizing the desired factors, minimizing the undesirable factors, under the given restrictions to find the solution that is most cost-effective or exhibits the highest performance. In a sense, optimization is the process of doing something better. The complexity of the optimization problems causes some diffuculties in solving by deterministic methods. Therefore, heuristics algorithms, which are the optimization algorithms based on natural events, were developed to solve them. The simplicity of these algorithms, give opportunity to researchers for implementing easily this algorithm in all area of science. Portfolio optimization problem, under certain expectations and constraints, is the search for a solution for selecting the most suitable alternative among all financial stocks. The aim of the portfolio optimization problems is to comprise portfolios by giving the best return at a certain risk level from the stock pool or by selecting stocks that give the lowest risk at a certain level of return Yeo et al. (2002). Solving portfolio optimization problems in modern finance is one of the important areas of study. This chapter focuses on one of the heuristic optimization techniques that proceeds from the genetic evaluation: The Genetic Algorithm (GA). The GA is an algorithm that is inspired by the biological evoluation. It is developed by simulating the natural generation stages such as selection and mutation in biological evoluation. It has come into prominence within heuristics with the simplicity in adapting to various kinds of problems. It is considered as one of the most important heuristic algorithms. The aim of this chapter is to explain the application of GA for generating the optimum portfolio for the selected stocks. For this purpose, basic components and the application steps of the Genetic Algorithm are explained and related literature is searched. For GA's portfolio optimization application, the 6 shares traded in Borsa Istanbul are discussed. The daily price movements for the years between 2015 and 2018 are considered for the dataset. Their returns were calculated by the logarithmic function. These returns are used in order to achieve the optimum risk by using GA and Nonlinear Programming. The results showed that the GA method generally yielded near-optimum results.

EVOLUTIONARY ALGORITHMS

Evolutionary Algorithms (EAs) are the metaheuristics algorithms that are based on population (Vejandla, 2009). The algorithms use processes from the biological evolution such as selection, mutation and recombination (Slim et al. 2011). These algorithms commonly use the natural evolution concept. There are several heuristics classified as Evolutionary Algorithms (Streichert, 2002). The common characteristics of EA can be listed as;

1. Easy to implement,
2. Flexible,
3. Quantitative,
4. Allows wide variety of extensions and constraints different from traditional methods,
5. Easily combined with other optimization techniques,
6. Can be extended to Multi-objective optimization.

The most important Evolutionary Algorithms can be listed as Genetic Algorithms, Genetic Programming, Evolutionary Strategies, Evolutionary Programming and Learning Classifier Systems (Streichert, 2002).

EVOLUTIONARY ALGORITHMS AND THE GENETIC ALGORITHM

"Survival of the Fittest" is a principle in Darwinian Metaphysics. Based on this principle, Holland (1975) initiated the Genetic Algorithm (GA) in 1975. As the common characteristics of EA are given in the previous section, GA is classified as an evolutionary algorithm. In common with EAs, the Genetic Algorithm uses the steps of genetic evolution process (McCall 2005). GA is a stochastic optimization algorithm that is proposed by John Holland in 1975 (Holland, 1975). It is listed as Evolutionary Algorithms (Baeck et al. 2000: p. 64) and inspired by the natural selection and mimics the biological evolution. Genetic Algorithms are defined as an intuitive research and optimization technique that aims to find optimal results in a wide range of solution space for a given problem. It is applied by utilizing the science of biology in order to direct the results of the research to optimal or near-optimal solutions (Wong & Tan, 1994). The general idea of the algorithm is to create an artificial biological system consisting of chromosomes.

BACKGROUND

The emergence of GA approach was early in the 1970s. In 1975, John Holland applied the genetic evaluation process to the machine learning (Holland, 1975). The

GA is used widely in all areas of science from biology (Jones et al. 1997) to design industry (Bentley & Reilly, 1999; Togan & Daloglu, 2006; Hacioglu & Ozkol, 2003), fashion design (Kim & Cho, 2000), machine learning (Nguyen et al., 2018) to a selection problem (Yang et al. 1998; Alt et al. 2018). Horn et al. (1994) and Alijo, et al. (2018) used Genetic Algorithm together with Multicriteria Analysis Methods. It is also used together with other methods like clustering analysis (Maulik et al. 2000), Muhlenbein et al. (1991) used genetic algorithm to optimize the continuous funtions for very large problems. Reeves, C.R., (1995) used GA for flowshop sequencing and compared the performance of the algorithm with Neighbourhood Search technique.

As the focus of this chapter is on portfolio optimization, the literature search is focused on the studies that applied the GA on portfolio optimization problems. The selected studies are summarized briefly.

One of the first studies related to portfolio diversification using Genetic Algorithm in Turkey belongs to Gokce and Cura (2003). From the beginning of 1999 to the June 2000 period, the weekly data were analyzed and it was stated that the number of shares in the portfolio should be between 6 and 14. In a similar study in which ISE-30 was examined, Demirtas and Gungor (2004) determined that 19 of the shares were suitable.

Lai et al. (2006) proposed a Genetic Algorithm method that consists of two stages. In the first stage, the quality stocks are choosen from the data of 100 companies randomly selected. Next stage, weights of the stocks in optimal portfolio are determined. As their results of the study incidates that GA has ability to create the most appropriate and useful pool.

Lin & Liu (2006) used Genetic Algorithms as an appropriate solution for their study on Taiwan investment funds through monthly data between 1997 and 2000. The contributed portfolio is very close to the effective limit of the portfolio with the lowest risk at a certain yield level or the highest yield at a certain risk level.

Another study that recommends the use of genetic algorithms for index fund management is Oh et al. (2006). Yang (2006) also analyzed portfolio optimization with GA. Chang et al. (2000) used GA and Tabu Search in their study to find the optimal portfolio.

Wang et al. (2006) used quarterly data from the Taiwan Stock Exchange between 1995 and 2003 to establish the appropriate portfolio using genetic algorithms. As a result of the study, Stochastic Portfolio Genetic Algortime (SPGA) method was found to be effective.

Shaikh and Abbas (2009) constitude a Genetic Algorithm (GA) approach for the constrained portfolio optimization problem. They aimed to optimize the portfolio that is consisting of selected stocks from Karachi Stock Exchange (KSE) in their study. The classical Markowitz mean-variance theory is considered in their study. The problem is solved with MS Excel to compare the results of the proposed model.

The proposed model was found to work well because of the high probability of local minima.

Chang et al. (2009) introduce genetic algorithm (GA) to solve the portfolio optimization problems and compare the performance of the algorithm with mean–variance model.

Soileimani et al. (2009) solve problem of the portfolio optimization by taking into account the minimum transaction lots, cardinality constraints and market capitalization by using GA.

Mishra et al. (2010) applied Micro Genetic algorithm and Multiobjective particle swarm optimization to the bi-objective portfolio optimization problem.

Ozdemir (2011) investigated the effective investment portfolio selection of genetic algorithms by using the daily data of 100 stocks of ISE-100 index and 100 stocks between 15.05.2008 and 26.06.2009 and decided that the optimal portfolio selection should be composed of 8 shares.

Yu et al. (2012) used GA on multicriteria portfolio selection problem. The resuls showed that the GA can be used as a suitable and efficient solution to solve the multi-criteria portfolio selection problems.

Yakut and Cankal (2016) applied Markovitz Variance Model, Goal Programming and Multi Objective Genetic Algorithm to a portfolio optimization problem and compared the results. Different from other studies investigated in this section, in terms of optimization techniques, it is determined that quadratic goal programming gives better results than genetic algorithm in their study.

Kalayci, et al. (2019) searched the literature in the perspective of the portfolio optimization problems that are solved by using GA. They listed the main characteristics of the portfolio optimization problems and classified the variances of suggested genetic algorithms for these problems.

The method is used with fuzzy and gray number theory. Yi et al. (2013) and Jalota & Thakur (2018) used fuzzy GA in Portfolio optimization problem. Indeed, Bermudez et al. (2012), Li & Xu (2013), Qin et al. (2009), Abiyev and Menekay (2007), Huang (2007) and Skolpadungen et al. (2007) combined GA with fuzzy numbers to cope the uncertainity on return.

As can be gleaned from the results of the most studies using the GA in portfolio optimization problems, the GA gives good results as a heuristic method.

THE PARAMETERS AND IMPLEMENTING STEPS OF THE GENETIC ALGORITHM

The first step of the Genetic Algorithm is to set a population. It is generated by random numbers. The population is the set of all candidate solutions. These candidate solutions are illustated by a row in the population array. Each row in the population is called a chromosome. Chromosomes represent a candidate solution to the problem. This means, each chromosome in the population refers a candidate solution. Generation is the process of evolving the chromosomes to the next generations. This is made for going to a better solution. All generations, the chromosomes are appraised by fitness function. The fitness function is the objective function of the model. All candidate solutions (chromosomes) are evaluated by using this function. After determinig the fitness value of each chromosome, the next generation is needed to be created. Creating the next generation with new chromosomes is called offspring. The offspring are reproduced by using the crossover operator and/or mutation operator. The croosover operator is to merge two chromosomes. Also the offsprings can be reproduced by using the mutation operator that is used to avoid the solution from stucking to an area. This section briefly explains the basic terms and implementing steps of Genetic Algorithm.

The Parameters of the Genetic Algorithm

The parameters of the Genetic Algorithm are summarized in Table 1.

Table 1. Parameters of the genetic algorithm

Terms	Definitions
Gene	Any cell in the chromosome.
Chromosome	Every row in the population matrix represents a chromosome. It represents the candidate solution of the considered problem.
Population	The set of solutions.
Generation	Evolving chromosomes to the next generation.
Fitness Function	The objective function of the model.
Offspring	Creating the next generation with new chromosomes.
Population Size	It is the size of each generation. It shows the number of chromosomoes in population.
Crossover Probability (Chance)	The ratio of performing crossover. If there is a crossover, the child will be generated from some parts of the chromosomes of the parents. %0 Means that there is no crossover and the parent will be copied as a child.
Mutation Probability (Chance)	The ratio of mutating the part of chromosomes. %0 Percent means that, there will be any change after the crossover step. %100 mean that all the chromosomes will be changed. It prevents solution to stick in to a local extreme.
Iteration Number	Number of runs for the algorithm.

Figure 1. Illustration of gene, chromosome and the population in a matrix

1	0	0	1	1	1	0	1
0	1	1	0	0	1	0	1
0	1	0	1	1	1	0	1
0	1	0	1	1	1	1	0
1	1	1	1	0	0	0	1
1	0	1	0	1	1	1	0

Every row represents a chromosome. Any cell in the chromosome is defined as gene. The population showed in the Figure 1 is consisting of 6 chromosomes.

Implementing Steps of the Genetic Algorithm

The Genetic Algorithm starts with encoding the problem. Encoding is the way of illustrating the problem solution as a Genetic Algorithm.

Encoding of Genetic Algorithm

The encoding is the way of expressing the possible solutions as a chromosome. Binary strings are widely used for representing. Also integer, real-value or symbols can be used for encoding. A typical binary coded chromosome is illustrated in Figure 2. x_1, x_2, x_3, x_4, x_5 and x_6 represents the variables of the problem and the values "0" and "1" shows the presence or absence of these variables in the solution.

Figure 2. Encoding with binary numbers

x_1	x_2	x_3	x_4	x_5	x_6
1	0	0	1	0	1

After encoding, the process of Genetic Algorithm is continuing in 7 steps (Zhang, 2015);

Step 1: Generation of Initial Population
Step 2: Evaluation of Each chromosome according to the fitness function
Step 3: Selection Process
Step 4: Crossover Process
Step 5: Mutation Process
Step 6: Obtain the best solution (If the solution is not met the criteria, return to the Step 2 and select the best individual as a solution.)
Step 7: Back to Step 2 until a criterion is met. (The algorithm stops when the maximum number of iteration is reached or a sufficiently good fitness value is achieved.)

Generation of Initial Population

Basic working principle of Genetic Algorithm is to start with a population of randomly generated chromosomes and evolve to better solutions. Genetic Algorithms begin by creating an initial population of chromosomes that are coded as in the solution steps according to the specified pattern of illustration. Chromosomes that make up the initial population can be coded randomly or by using specific information about the problem. Each chromosome represents an alternative solution.

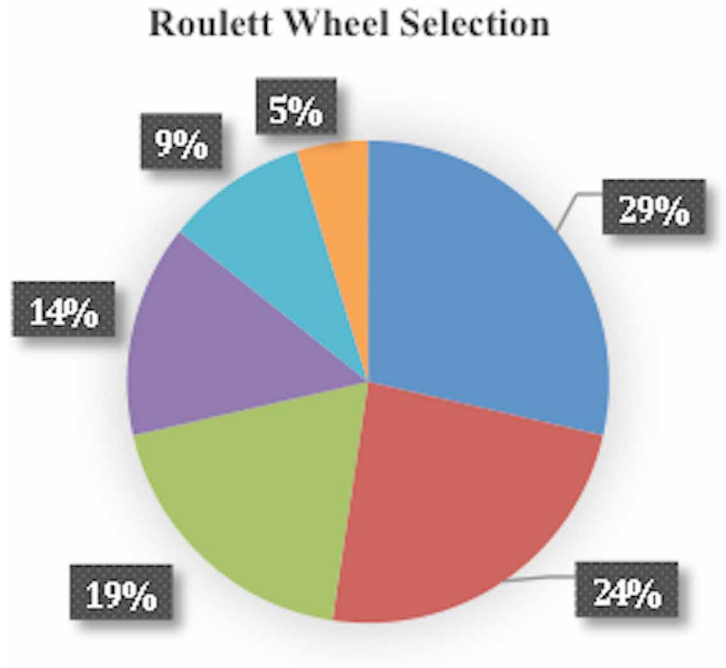
The size of the population is generally set between 100 and up. It depends on the nature of the problem, the size of the solution space, encoding and so on... It is generally needed to be set greater than the number of the variables in the problem.

Fitness Function

The ultimate goal of using Genetic Algorithms is to find a best or close to a best solution for a complex optimization problem in the shortest time and easiest way (Pereira, 2000). For this purpose, Genetic Algorithms measure the performance of existing solution alternatives using a fitness function and try to achieve better solution alternatives. The fitness function matches the solution candidate to a numerical value that shows the suitability value of the chromosomes (coded sequences) of individuals. The calculated fitness value shows the value of the chromosomes according to the fitness function. Hence it also shows its proximity to the best solution.

The aim in financial problems can be formulated as maximizing the profit and expected return or minimizing the loss or risk. For example, considering the optimal portfolio selection problem, the aim would be to determine the weights of the stocks in the portfolio to minimize the risk at a certain expected level of return.

Figure 3. Roulette wheel selection



Selection Process

The purpose of the selection process is to allow individuals with high fitness values to be produced more through generations. This process ensures the availability to find the highly qualified individuals within the new population.

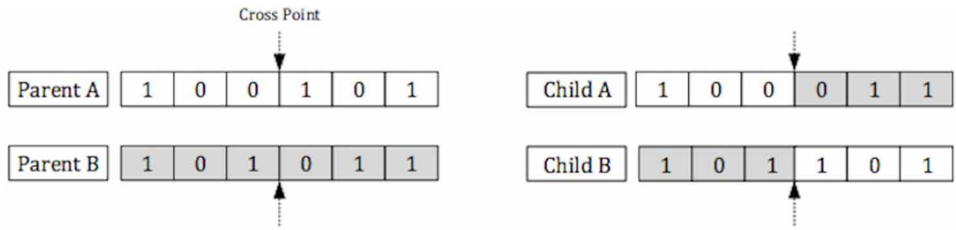
Many selection processors have been reported in the literature. Examples of general stochastic sampling and sequential selection are roulette wheel selection and tournament selection processors.

In this study Roulette Wheel Selection is used. Its name is coming from the roulette game. The operator acts like a roulette. Parts of the roulette wheel are assigned to population in proportion to the relative fitness score of the individual (see figure 3). A larger part implicates larger fitness.

Crossover Process

The crossing process allows producing individuals that have the ability to exchange the information between individuals. When crossing, certain genes of the two individuals are mutually displaced. Thus, two new individuals, in other words,

Figure 4. Crossover process



two new possible solutions are produced (Soke, 2004). The crossover process is illustarated in Figure 4.

Mutation Process

In some cases the chromosomes can form a population of the same type. If there is only one type of chromosome within the population, the new chromosomes obtained from the result of the crossing process will be the same type. Therefore, there would be no diversity among the chromosomes that make up the population. The mutation processor is used to prevent this problem. Figure 5 illusrates the mutation process.

The Advantages of The Genetic Algorithm

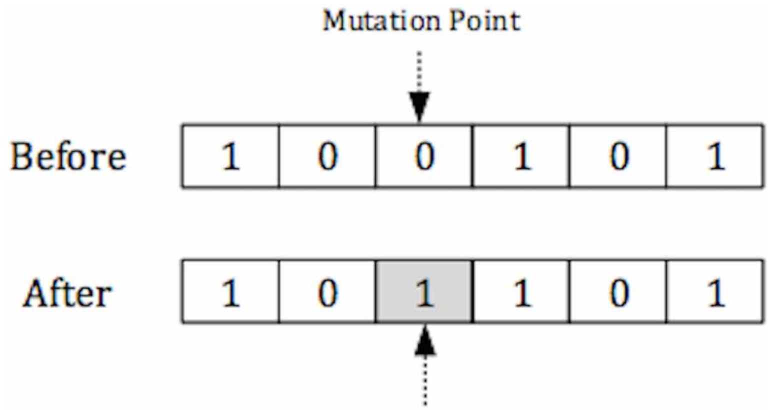
Unlike deterministic algorithms, Genetic Algorithms use probabilistic selection rules instead of using deterministic selection rules. Genetic Algorithms are very suitable for NP Hard and large-scale problems. The main advantage of the algorithm is to find near optimal solutions for these problems in a very less time. In addition to this advantage, others can be listed as;

1. The extent values can be trapped by mutation process.
2. It is easy to code the problems with GA compared to other heuristics.
3. It can be used in Multi-objective optimization problems,
4. Researches gain a great flexibility to hybridize to a partiular problem with domain-dependent heuristics bu using GA.

The Disadvantages of The Genetic Algorithm

Despite the Genetic Algorithm being a useful tool to solve various kinds of problems, it has some difficulties. The main disadvantages of the Genetic Algorithm can be listed as;

Figure 5. Mutation process



1. The algorithm can not guarantee an optimal solution in some cases,
2. It can be difficult to determine suitable value of the parameters such as the number of generations or the population size,
3. They are not suitable for real time applications and take long to converge to the optimal solution.
4. The most difficult and time consuming issue in the successful application of GA is to determine the approximate settings of GA parameters.

THE MARKOWITZ MEAN-VARIANCE MODEL AND THE SHARPE RATIO

The investor desires to maximize the return and minimize the risk. It is not always possible to achieve this goal with only one stock. A single stock with a high return will also contain high risk. The inverstor needs to make investment on more than one stock (Chou et al. 2017). Portfolio optimization is a problem that arises from the desire to minimize risk while maximizing the investor's returns.

Modern Portfolio Theory

There are two main approaches that have been developed to help investors in the creation of optimal portfolio: Traditional Portfolio Theory (TPT) and Modern Portfolio Theory (MPT). Until 1950, TPT says the portfolio risk would decrease as the securities varieties increased and suggested to invest in securities with high yields. In the early 1950s, the Traditional Portfolio Theory has lost its importance

Table 2. The parameters of the mean variance model

Parameters	Definitions
N	The number of variables in the problem.
σ_{ij}	The covariance between stocks i and j.
w_i	The weight of the stock i in the portfolio.
μ_i	The expected return of stock i.

with the development of the modern portfolio theory and the mean variance model by Harry Markowitz. Markowitz has suggested that investors should select the optimum portfolios that are appropriate for them, at a certain expected level of return, from the portfolios with the minimum and maximum returns at a certain risk level. By portfolio diversification, the risks of the investors can be minimized, and the return of the portfolio can be maximized.

The parameters of the Mean Variance model are defined in Table 2. Where, N is the number of variables in the problem, σ_{ij} is the covariance between the stock i and stock j, w_i is the weight of the stock I in the optimal portfolio and μ_i is the expected return of stock i.

The Mean-Variance model is shown in the equations 1, 2, 3, and 4 respectively.

$$\min \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} \tag{1}$$

Subject to;

$$\sum_{i=1}^{n} w_i r_i = R^* \tag{2}$$

$$\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{w}_{\mathrm{i}} = 1 \tag{3}$$

$$0 \le \mathrm{w}_{\mathrm{i}} \le 1,\ \mathrm{i} = 1, \ldots.., \mathrm{N} \tag{4}$$

The aim of the model is to minimize the total variance (risk) of the portfolio. Equation 1 illustrates the objective function. The constraints are illustrated in equation

Table 3. Parameters of the sharpe ratio model

Parameters	Definitions
$E\left(r_p\right)$	The expected return of the portfolio.
R_f	The risk-free rate of stock.
$\tilde{A}_p$	The standart deviation of the portfolio.

2 and equation 3 respectively. Equation 2 ensures the return of the portfolio to an expected return of R*. Equation 3 ensures the sum of the weights equal to one. Equation 4 is the constraint that ensures all the ratios held in each stock is between zero and one. This means the weight of the stock within the portfolio can be at least 0 and maximum 1. When the mean variance model is used in portfolio optimization, a solution is obtained by quadratic programming. It can be solved optimally using available software tool.

Sharpe Ratio

Sharpe ratio is used to measure the return of the portfolio according to risk. It was developed by William F. Sharpe (Chou et al. 2017). The Sharpe ratio is calculated by dividing the average return of the portfolio to the total risk calculated. The high Sharpe Ratio of a portfolio indicates that the return of the portfolio is good compared to its risk.

The parameters of the Sharpe Ratio Model are defined in Table 3. Where $E\left(r_p\right)$ is the expected return of the portfolio, R_f is the risk free rate of stock and σ_p is the standart deviation of the portfolio.

The Sharpe ratio is calculated by the formula given in Equation 5.

$$\text{Sharpe Ratio} = \frac{E\left(r_p\right) - R_f}{\sigma_p} \qquad (5)$$

AN EXAMPLE: PORTFOLIO OPTIMIZATION PROBLEM

In order to illustrate how GA is used to solve the portfolio optimization problem, a basic example has been made with 6 stocks that are trading on the Istanbul Stock Exchange. The optimum portfolio, which has the minimum risk, is aimed to investigate with Genetic Algorithm for the selected stocks. MS Excel Solver tool is used to calculate the optimum portfolio of Markowitz Mean-Variance model by using nonlinear GRG Model. MATLAB is used for coding and running GA. The results obtained by using Nonlinear GRG and GA are compared.

PROBLEM DEFINITION AND THE DATA

The aim of the problem is to minimize the poftfolio risk while maximizing the portfolio return. 6 stocks are considered to make up the portfolio. The three-year daily data between 31.08.2015 and 31.08.2018 is used for these stocks. Logarithmic returns are widely used rather than the arithmetic returns thus, the data set has been obtained by using the logarithmic differences of last price series by using equation 6.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{6}$$

The average log return, variance and standard deviation of the stocks are calculated and shown in Table 4.

It can be seen from Table 4 that all the stocks have a positive average return that are calculated from the daily data between 31.08.2015 and 31.08.2018. Variance-Covariance Matrix is calculated and can be seen in Table 5.

Table 4. Return, Variance and Standart Deviation of Three Transportation Stocks

	Stock 1	Stock 2	Stock 3	Stock 4	Stock 5	Stock 6
Average Log Return	0,0025293	0,0003205	0,000773	0,000798	0,0003	0,000933
Variance	0,0578355	0,0229800	0,022967	0,021685	0,0239	0,023398
Standart Deviation	0,0033449	0,0005281	0,000527	0,000470	0,0006	0,000547

Table 5. Variance-Covariance matrix of the transportation stocks

	Stock 1	Stock 2	Stock 3	Stock 4	Stock 5	Stock6
Stock 1	**0,00946707**	0,000100924	-0,000167711	-4,45111E-05	3,71862E-05	-5,1972E-05
Stock 2	0,00010092	**0,001494609**	0,000527476	4,65912E-05	0,000641862	0,00063884
Stock 3	-0,00016771	0,000527476	**0,001492924**	0,000220289	0,000688413	0,000682876
Stock 4	-4,4511E-05	4,65912E-05	0,000220289	**0,001330851**	7,70173E-05	0,00011968
Stock 5	3,7186E-05	0,000641862	0,000688413	7,70173E-05	**0,001616854**	0,001139224
Stock 6	-5,1972E-05	0,00063884	0,000682876	0,00011968	0,001139224	**0,001549417**

Portfolio Optimization by Using Markovitz Mean Variance Model and the Results

In order to make a comparision of the Genetic Algorithm with a mathematical method, the problem is solved with a non-linear Markowitz Mean-Variance model. It is solved as a nonlinear programming and the results are shown in Table 6. The results shows that the Stock 4 has the biggest weight within the portfolio with the ratio of 34,6%. Stock 5 has the smallest weight within the portfolio with the ratio of 0,07%.

According to the calculated weights the return, variance, and the standard deviation of the portfolio is calculated and the results are given in Table 7. The return of the optimal portfolio is calculated as 0,12%.

Table 6. Weights of the stocks in optimal portfolio calculated by non-linear GRG

Stocks	Weights
Stock 1	0,0588
Stock 2	0,1718
Stock 3	0,1350
Stock 4	0,3467
Stock 5	0,0708
Stock 6	0,0858
TOTAL	1,00000

Table 7. Return, sharpe ratio, variance and standart deviation of optimal portfolio calculated by non-linear GRG

	Optimal Portfolio
Portfolio Return	0,005533
Sharpe Ratio	0,066475
Portfolio Variance	0,005625
Portfolio Standart Deviation	0,0005479

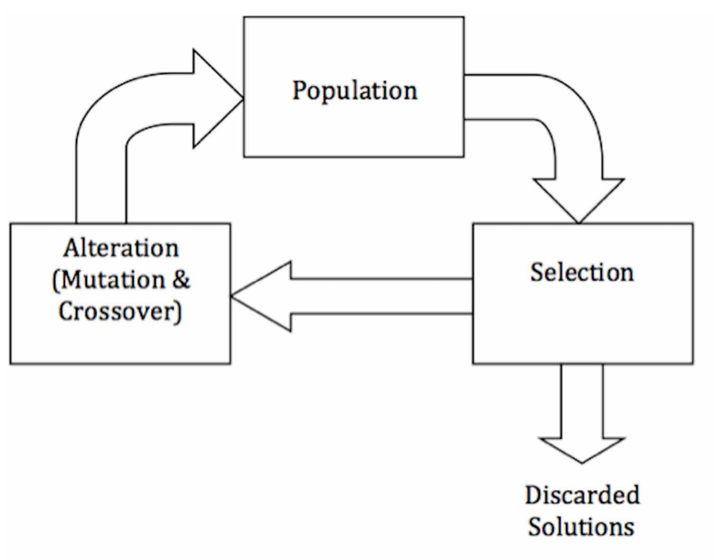
Portfolio Optimization by Using GA Algorithm and Results

The same problem is solved by using the Genetic Algorithm. In this section it is decribed how the genetic operators are modified and performed in the algorithm.

The evolutionary cycle of Genetic Algorithm is illustrated in Figure 6. The first step is problem definition and defining the fitness function (Objective Function). The fitness function in the application is the objective function used in Markowitz Model.

In case of having specific informations or situations related to the problem being sought, the solution space set of the starting population can be limitated by using these criteria. In the case of portfolio optimization problems, the chromosomes represent the weights of stocks. Therefore, in the portfolio optimization problem, an initial population containing a fixed number of chromosomes is generated randomly. The

Figure 6. Genetic algorithm evolutionary cycle



chromosomes with the best fitness value are selected to be parents (Kamali, 2014). The fitness function depends on the specification of the problem and objective of the optimization (Petridis et al, 1998). In portfolio optimization problem, the aim can be to maximize the portfolio return and minimize the portfolio risk. The weights of the asssets are determining in this respect.

Population and Generation Size

The population size of this study is determined as 20 chromosomes and the number of the generations is determined as 100.

İnitial Population

The initial population for the genetic algorithm is randomly selected and becomes an individual, and several individuals combine to become the population by using 1 and 0.

In this application, numbers between 0 and 100 uniformly distributed are used for the second part of the chromosomes.

Figure 7. Illustration of initial population and normalization

Initial Population:

Chromosome 1	1	0	1	0	0	1	81	0	23	0	0	45
Chromosome 2	0	1	1	0	1	0	0	42	63	0	29	0

Sum of the Random Numbers:

													Total
Chromosome 1	1	0	1	0	0	1	81	0	23	0	0	45	149
Chromosome 2	0	1	1	0	1	0	0	42	63	0	29	0	134

After Normalization:

							Total
Weights 1	0,544	0,000	0,154	0,000	0,000	0,302	1,000
Weights 2	0,000	0,313	0,470	0,000	0,000	0,217	1,000

Figure 7 represents the forming steps of the initial population of the algorithm. The genes are normalized to ensure the constraint of the sum of the weights of the invested stocks being equal to one.

Selection Process

The purpose of the selection process is to allow individuals with high fitness values to be produced more through generations. This process ensures the availability to find the highly qualified individuals within the new population.

Many selection processors have been developed and reported in the literature. Examples of general stochastic sampling and sequential selection are roulette wheel selection and tournament selection processors.

Crossover Process

There are various ways to make the crossover process in Genetic Algorithm. Single, two-point and arithmetic crossover methods are the ones usually used in literature. The crossover process used in this application is made by dividing the chromosomes into two parts. Figure 9 illustrates the crossover process used in the application.

Figure 8. Roulette wheel selection

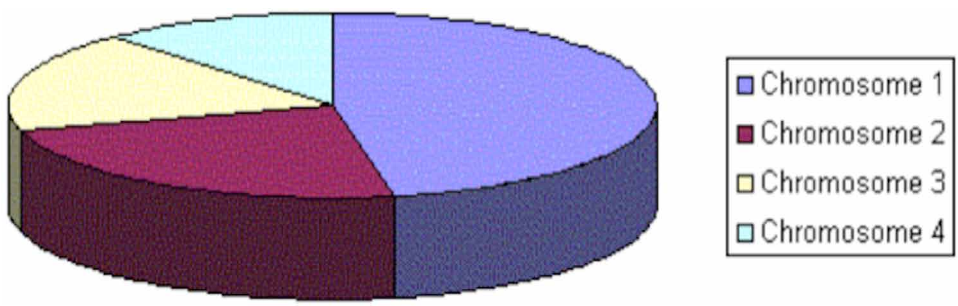


Figure 9. Crossover process

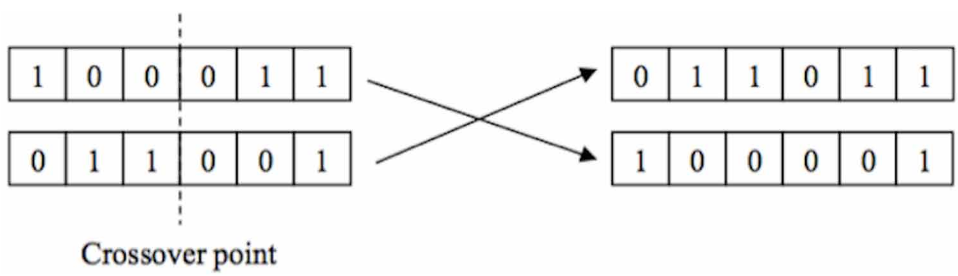


Figure 10. Crossover and mutation process of the genetic algorithm

Mutation Process

The chromosomes in the population can also be mutated after the crossover process. Mutation is necessary for avoiding the solution to stick in a local area. To apply mutation to a chromosome, some genes are randomly selected and changed with a mutation rate identified in the algorithm. The crossover and the mutation processes are illustrated in Figure 10.

Results

The main objective of this section is to illustrate the application of genetic algorithm on a portfolio optimization problem. Thus, a six-stock portfolio example is considered. The MATLAB software is used to design the algorithm. Weights of stocks in optimal portfolio calculated by genetic algorithm are shown in Table 8. Population size and number of runs are selected as 20 and 1000 respectively.

The results of optimal weights calculated by using the GA can be seen in Table 8. Elapsed time is 164.108 seconds. The number of iteration is 50050. Portfolio return has been calculated according to the weights that minimize the risk level. Optimal portfolio return, Sharpe Ratio, variance and standard deviation are calculated and shown in Table 9.

Table 8. Weights of stocks in optimal portfolio calculated by GA

	Weights	Percentage
Stock 1	0,0000	% 0,00
Stock 2	0,1884	% 18,84
Stock 3	0,6957	% 69,57
Stock 4	0,0000	% 0,00
Stock 5	0,1159	% 11,59
Stock 6	0,0000	% 0,00
Total Weights	1,0000	% 100

Table 9. Return, sharpe ratio, and variance of optimal portfolio calculated by genetic algorithm

	Optimal Portfolio
Portfolio Return	0,01600
Sharpe Ratio	14,4079
Portfolio Var	0,00110

The Sharpe Ratio of the optimal portfolio is calculated as 14,4079. The results show that GA method gives similar results with the traditional Markowitz Mean-Variance mathematical model.

FUTURE RESEARCH DIRECTIONS

The emerging trade in the field of optimization is to use of heuristices with fuzzy and gray numbers theory. For the future researches the Genetic Algorithm can be used together with fuzzy or grey number theory. The portfolio can be optimized by Genetic Algorithm with fuzzy or grey numbers in order to cope the uncertainity on portfolio variables.

CONCLUSION

Various markets around the world offer many options for people who are going to invest. As a result of the studies conducted using various methods, optimum portfolios that can be presented to the investor have been formed. These portfolio types vary according to the variety of stocks and their weight in the portfolio. By portfolio diversification, the risks of the investors can be minimized, and the return of the portfolio can be maximized. In these portfolios, the portfolio with the best performance measure is taken as the optimum portfolio. The performance measures can be Sharpe Ratio, return and/or variance of the portfolio. This chapter considered a portfolio optimization problem with 6 stocks. The Sharpe ratio is calculated from the portfolios made up by using the Markowitz Mean Variance model and the Genetic Algorithm. The results show that GA method gives similar results with the traditional Markowitz Mean-Variance mathematical model. As a suggestion, anyone can use Genetic Algorithms to reduce the unsystematic risk of a portfolio in a portfolio selection problem.

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KEY TERMS AND DEFINITIONS

Chromosome: Every row in the population matrix that represent the candidate solution of the problem.

Evolutionary Algorithms: Evolutionary algorithms are the population-based metaheuristic optimization algorithms that are inspired by biological evolution.

Gene: Any cell in the chromosome.

Genetic Algorithm: A heuristics algorithm that is based on the mechanism of natural selection and natural genetics.

Markovitz Mean Variance Theory: The Financial theory that is suggested by Markowitz. According to the theory, the investors should select the optimum portfolios that are appropriate for them, at a certain expected level of return, from the portfolios with the minimum and maximum returns at a certain risk level.

Offspring: Creating the next generation with new chromosomes.

Population: The set of solutions.

Sharpe Ratio: Sharpe ratio is used to measure the return of the portfolio according to risk.

Chapter 8
Heuristic Optimization of Portfolio Considering Sharpe's Single Index Model:
An Analytical Approach

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ABSTRACT

Selection of weights of the selected securities in the portfolio is a cumbersome job for any investor. The famous nonlinear Sharpe's single index model has been simplified with a linear solution and the risk-taking propensity of the investors have been taken into consideration in the simplified formulation. The coefficient of optimism is included to observe the effect of risk-taking propensity in the portfolio selection. After the empirical analysis it is found that heuristically an investor can reach near to the optimum solution. For empirical analysis 126 months data have been considered of NSE Bank Index. To reduce the volatility of the data the whole period again has been divided into two parts each of 63 months duration, and separately the data pertaining to the three periods have been considered for calculation. The city block distance is used to calculate the nearness between the optimum solutions and the heuristic solutions.

DOI: 10.4018/978-1-5225-8103-1.ch008

INTRODUCTION

Investment in securities confronts with the problems of selection of assets in the portfolio. Inclusion of more than one asset in the portfolio increases the chances of risk reduction. Therefore, for diversification inclusion of more than one asset is desirable in the portfolio. Portfolio management faces another problem related to the selection of weight or the proportion of investment of the selected assets in the portfolio. Extant literature proposes noble approaches to solve the problems in portfolio optimization. The pioneering work was proposed by Noble Laureate Markowitz (1956) proposing the optimization of portfolio by Mean-Variance (M-V) model. The Markowitz mean-variance model has assumed that the investors are risk averse in nature. The investors are always looking for the high risk premium without taking much risk. Therefore, they penalize the return for involvement of certain amount of risk. According to the model, a rational investor either maximizes his return subject to a certain level of risk or minimizes his risk subject to a certain level of return. Starting from the seminal work of mean-variance model of Markowitz, portfolio optimization has assumed many variations and interventions mostly to address the evolving financial landscape and the new issues of financial modeling. After his pioneering work, W. Sharpe (1962) introduced another optimization model to address the data requirement of the previous model. He simplified the mean-variance model. Researchers are focusing in the field of portfolio optimization to make it simpler or statistically more appealing. As the classical models of portfolio optimisation are difficult to understand and require expert knowledge. Heuristic optimisation can give an easy, near accurate and faster solution which can be comprehensible without having to be expert in the subject. Therefore, the dynamism of heuristic portfolio optimisation has an appeal to the researchers.

The purpose of the work is to construct an optimum portfolio based on the Sharpe's Single Index Model and to offer a heuristic portfolio which can help the general investors having less technical knowledge about complex mathematics or statistics.

LITERATURE REVIEW

Asset allocation in the portfolio in order to achieve the targeted risk return paradigm influences investors to proportionately distribute their investment in the different asset class. The dynamic portfolio allocation model and subsequent optimization were attempted in the seminal work of Markowitz (1952) thereby paving the way for the investors. Based on the seminal work of Markowitz many effective algorithms subsequently developed to solve and provide a solution code for the optimization problem. The seminal work was not very supportive in the portfolio optimization as the assumptions of the model rest on the oversimplification of the model and on the normality assumption of the return. The criticism of Mean-Variance Model is based on the fact that the assumptions and the constants in the model are not subsequently met in real life. As a fall out of the process, the researchers tried to relax the assumptions thereby including additional constraints in the model leading to complex optimization problem exhibiting multiple local extrema and discontinuities. In some of the earlier attempts the holding size of the assets in the portfolio were considered along with the consideration of the constraints thereby restricting the string variable, the number of assets to be included in the portfolio was also considered and attempted in the earlier studies (Jobst et al., 2001; Gilli and Ke¨llezi, 2002; Chang et al., 2000; Crama and Schyns, 2003;).In case of large instances the classical optimization method fails to work efficiently and thus realistic optimization techniques emerged as an alternative solution to reach near optimal solutions thereby reasonably reducing time and effort in the part of the practitioner. Few authors have tried to understand and use local search metaheuristic thereby making attempts to search for the optimum solution to the selection problem of the portfolios (Crama and Schyns, 2003). The first attempt of use of metaheuristic optimization technique in the popular selection model was proposed by Mansini and Speranza (1999). The securities in the model when associated have multiples of transaction around lot size. Some of the attempts have visualized the portfolio optimization problem in the light of mixed integer programming problem. The philosophy of constructing the mixed integer programming problem is based on designing the problem as mixed integer subproblem and solving the proposed heuristic solution to reach near optimum solution. Chang et al. (2000) extended the standard model of metaheuristic in order to include the cardinality constraints limiting the portfolio capacity to hold a number of assets. The idea of incorporating the Lagrangian term in the objective function (Crama and Schyns, 2003) was designed in a way to include the return constraints. The shape of the efficient frontier in the mean-variance model including thresholds constraints and by incorporating branch and bound algorithm combined with heuristic were investigated by (Jobst et al., 2001). In the heuristic optimization technique using threshold accepting in the portfolio choice problem where the risk was measured by value at risk or expected shortfall was attempted by Gilli and Ke¨llezi (2002).

The perception of the investors regarding the market efficiency and about the risk and return expectations are found to play very prominent role in deciding about the trading dynamics, stock investing, technical analysis as well as risk taking behavior (Hoffmann et al., 2015; Aspara, 2013; Doran et al., 2010; Menkhoff, 2010). It is pertinent in this regard to understand that the past perception plays a significant role which influences the investor's behavioral characteristics (e.g. Merkle, 2013; Weber et al., 2013). Like various other available portfolio optimization solutions, the mean absolute risk function is the easy method to eliminate the problems of the classical mean-variance model. This model is an alternative use of the mean-variance model propounded by Yamazaki and Kono (1991). The investment dynamics in portfolios by using a constant correlation model is discussed by Elton, Gruber, Padberg (1977B) in a very simplified way. It is pertinent from the other models available in the theory that many ways are available to reduce the difficulties and make the methods easy to solve (Ledoit and Wolf 2003, Edward et al.2005). The Single Index Model is better than the previous works from the point of using data and approachable to the investors under the condition of uncertainty for a short period of time (Terol et al. 2006, Briec & Kerstens 2009, Frankfurter et al. 1976). Many authors have argued and empirically prove that the Single Index Model is better and easy to use with short term data set. The model gives significantly good result in Indian context (Nanda, Mahanty, and Tiwari 2012, Meenakshi and Sarita 2012, Saravanan and Natarajan 2012).

Portfolio optimization is associated with the so called butterfly effect (Hensel and Turner, 1992) and the associated problems as identified revolves around four basic dimensions of inappropriate asset allocation (Michaud, 1989), optimal solutions not being stable (Kallberg and Zeimba, 1984 and Adler, 1987), allocations mismanagement (Hensel and Turner, 1992)and optimizer solution not being unique (Michaud, 1998). The problems of higher weights being assigned to higher values of returns and higher values to lower variance yields biased results, whereas contradictory results come with the higher variance being assigned lower weights along with lower returns. In some of the cases, minor changes in inputs lead to larger variations in the assignment of weights for the optimal setting. New estimates of risk and returns highly destabilize the optimal weights in the portfolio revision process. Sometimes inclusion of non traded securities on the portfolio inappropriately distorts the portfolio optimization process, the inclusion of real estate in the portfolio is the classic case in point. One set of estimation of risk and return is often not feasible thus the inclusion of estimation error results in multiple sets of estimation of risk and return thereby leading to a large set of choices rather than unique set.

In order to provide stable portfolio providing for allocations which have a slower rate of change leading to a more diversified portfolio with the reduction in the impact of estimation error (Hensel and Turner, 1992) proposed techniques to fulfill the following discussed criteria in the methodological approach having to contain and constrain optimal weights in the portfolio. In case of a single return towards the mean in the overall asset class Jobson and Korkie (1981) and Michaud (1989) proposed Stein estimation procedures concentrating upon the mean return as the most sensitive input in the optimization process. Elton, Gruber, and Padberg (1976) and Elton, Gruber, and Urich (1978) have successfully design portfolio heuristic with the help of a single correlation coefficient which has an average effect on the portfolio Optimization model. Some of the approaches also focused on the addition of maximum constraint allocation for each of the asset class in the portfolio and the process was tested by Frost and Savarino (1988) in case of individual assets and for general asset class by Chopra (1991). Sharpe (1967) firstly focused on nonuse of optimizer for portfolio estimation and applied heuristic for maximum allocation constraints. The future correlation matrix forecasting with the help of the full correlation matrix was found to be more accurate with the help of beta (Elton, Gruber and Urich, 1978). Risk reward heuristic was designed and proposed by Nawrocki (1983) as derived from (Elton, Gruber and Padberg, 1976).

The functional dynamics of portfolio optimization aims for risk-reward balancing act to churn out optimal portfolio weights. The Mean Variance model of Markowitz rests on the assumption of risk averse investors signifying requirement of higher levels of return for undertaking higher level of risk. However, the possibility of identification of optimal portfolio having risky assets was demonstrated by Markowitz (1952) and Tobin (1958). The data requirement in the portfolio optimization model was monumental including the management of huge of covariance matrices for higher numbers of the asset included in the portfolio; Sharpe minimized the requirement of the data in the portfolio optimization model with the introduction of the Single Index Model. The application of single Index models in handling large numbers of asset giving alternatives to the covariance approach in the portfolio optimization process was supported by Haugen (1990). Frankfurter at al. (1976) advocated the equivalency of the Mean-Variance and the Single Index Model in churning the same set of optimal results with the same number of assets in the portfolio optimization problem under consideration. However, the superiority of the Single index model over the Markowitz Mean-Variance model in reaching optimal portfolio is documented in the literature Omet (1995).

METHODOLOGY

To reach the objective of the paper, 126 monthly data has been considered of Nifty Bank Index. To reduce the volatility of the data the whole period has been divided by 2 parts (January 2005 to March 2010- First part and April 2010 to June 2015- Second part) in each part 63 months data has been considered. Bank Nifty is the index of banking industry of India. Very less work has been done by considering the data of Bank Nifty in heuristic optimisation. Therefore, for empirical analysis the paper has chosen Bank nifty.

Sharpe's Single Index Model and Cut-off principle are used to calculate the optimum portfolios. Hurwicz's coefficient of optimism is included in optimum portfolio and heuristic portfolio to incorporate the risk taking propensity of the investors in the model and to get the maximum return constraints beyond which the investors will not invest. The Sharpe's Single Index Model is simplified to generate a heuristic portfolio model which is named as Near Optimum Portfolio (NOP). To simplify the quantifying process, a linear model has been developed by dropping the nonlinear part of the Sharpe's Single Index Model as it does not have much influence in the portfolio optimization. With the help of the City Block Distance, the closeness or the nearness of the optimum portfolios and the Near Optimum Portfolios (NOP) has been judged.

The return of the Sharpe's Single Index Model is based on market return. The return of the selected securities has been calculated by the following Sharpe's Single Index Model's return:

$$R_i = \alpha_i + \lambda_i R_m + e_i \tag{1}$$

where, λ_i is the systematic risk.

The portfolio's return and risk are calculated by using the following formulas given by Sharpe.

$$R_p = \sum_{i=1}^{n} w_i \bar{R}_i \tag{2}$$

$$\sigma_p = \sqrt{\left(\sum_{i=1}^{n} w_i \lambda_i\right)^2 \sigma_m^2 + \sum_{i=1}^{n} w_i^2 \sigma_{ei}^2} \tag{3}$$

A mathematical programming framework is designed considering a given coefficient of optimism under Sharpe's Single Index Model in order to calculate the minimum return constraint. The design is given below:

$$\text{Min } \sigma_p^2 = (\sum_{i=1}^{n} w_i \lambda_i)^2 \sigma_m^2 + \sum_{i=1}^{n} w_i^2 \sigma_{ei}^2$$

$$\text{Subject to } \sum_{i=1}^{n} w_i (\alpha_i + \lambda_i R_m) \geq \alpha \varepsilon_{\max} + (1-\alpha)\varepsilon_{\min} \tag{4}$$

In the next phase, the cut-off principle has been used to calculate the optimum portfolio and the formula is given below:

$$C_i = \frac{\sigma_m^2 \sum_{j=1}^{n} \frac{(\overline{R}_i - R_f)\lambda_i}{\sigma_{ej}^2}}{1 + \sigma_m^2 \sum_{j=1}^{n} \frac{\lambda_i^2}{\sigma_{ei}^2}} \tag{5}$$

C^* is a value of C_i. The value of C^* is the threshold point before which all the values of C_i are increasing and beyond which all the values of C_i are decreasing.

For Near Optimum Portfolio the following formula has been designed to reduce the original Sharpe's non-linear programming problem to a linear programming problem.

$$\text{Min} \sum w_i \lambda_i$$

$$\text{Subject to } \sum_{i=1}^{n} w_i(\alpha_i + \lambda_i R_m) \geq \alpha\varepsilon_{\max} + \left(1-\alpha\right)\varepsilon_{\min} \tag{6}$$

To check the nearness between the optimum portfolio and the heuristic portfolio, City Block Distance has been considered. City block distance is the distance between two points or two coordinates. It is also famous in the name of Manhattan Distance. It measures the exact farness between two points in a city. The same can be used to validate the empirical testing of the paper. The distance is measured as follows:

$$D_{ij} = \sum_{m=1}^{k} \left| p_{im} - p_{jm} \right| \tag{7}$$

Analysis and Interpretation

The daily return of the securities has been calculated by using Sharpe's Single Index Model equation (1). To get the City Block Distance values, the expected return and risk of the Sharpe's Single Index Model, Cut-off model and Near Optimum Portfolio are required. One by one all the expected values of return and risk have been calculated by ascertaining the optimum weights of the securities under consideration with the help of equation (2) and (3). 126 months data also have been used for calculation

Table 1. Expected return and risk of Sharpe's Single index model for the whole period

Coefficient of Optimism	Expected Return	Expected Risk
0	8.65712243	0.011631191
0.125	8.65711834	0.011631187
0.25	8.65711399	0.0116312
0.375	9.03371593	0.01102172
0.5	9.45484206	0.010846087
0.625	9.8759687	0.011191086
0.75	10.2970949	0.012124363
0.875	10.7182215	0.013972157
1	11.1393474	0.019217758

purpose. Firstly the expected return and risk of the two optimum portfolios and one heuristic portfolio are calculated for the whole 126 months data with the help of equation (2) and (3). Then, 126 months data period has been separated into two parts and the expected risk and return have been calculated for empirical testing under different values of coefficient of optimism for both the parts separately by using equation (2) and (3). At last, the CBD values [equation (7)] for the whole period and the separated period also have been calculated to check the nearness among the optimum portfolio and the heuristic portfolio. Table 1 depicts the calculated values of expected risk and returns of Sharpe's Single Index Model for 126 months.

From Table 1 it can be stated that as the value of coefficient of optimism is increasing the expected return is also increasing with the expected risk. This means that the classical understanding of risk return relationship is establishing. By following the Cut-off principle formula [equation (5)] four banks have been selected in the optimum portfolio. The banks are Bank of Baroda, Bank of India, SBI and ICICI Bank. The expected return and risk of the Cut-off principle for the whole period is given below in Table 2:

Now the expected return and risk of the heuristic Near Optimum Portfolio is calculated and showing in Table 3 for the whole period taken into consideration

Table 2. Expected return and risk of the cut-off principle for the whole period

Expected Return	10.78761
Expected Risk	0.013464

Table 3. Expected return and risk of near optimum portfolio for the whole period

Coefficient of Optimism	Expected Return	Expected Risk
0	7.770336689	0.018632587
0.125	8.191463276	0.020564982
0.25	8.612589349	0.016357223
0.375	9.033715713	0.015394933
0.5	9.454842076	0.017678113
0.625	9.875968367	0.017554587
0.75	10.29709472	0.01484661
0.875	10.71822108	0.015401
1	11.13934744	0.019217758

The near optimum portfolio is giving less return as compared to the Sharpe's Single Index Model which is clear from the above table 1 and table 3. In Near optimum portfolio also the expected return is increasing with the increasing value of coefficient of optimism, but showing a fluctuation in expected risk. Now, the whole 126 months has been separated into two parts each having 63 months' data. For the Cut-off principle two optimum portfolios have been found out. For the First half the portfolio is consisting of Kotak M Bank, Indusin Bank and ICICI Bank. For the Second half the portfolio is consisting of Axis bank, Canara Bank and Indusin Bank. In the above way, the expected return and risk of all the three measures have been calculated one by one and showing in the following Table 4, 5, 6, 7, 8 and 9.

When the data period has been taken in two parts, the first part is showing the same result as table 1 is showing. It means with the increase in the value of

Table 4. Expected return and risk of Sharpe's Single index model for first half

Coefficient of Optimism	Expected Return	Expected Risk
0	7.718335681	0.008289378
0.125	7.718335026	0.008289378
0.25	8.257462547	0.008610908
0.375	8.906479727	0.009678087
0.5	9.521422479	0.011259531
0.625	10.15340141	0.013662251
0.75	10.78538111	0.017009683
0.875	11.99334612	0.033218708
1	12.04933911	0.033924265

Table 5. Expected return and risk of Sharpe's Single index model for second half

Coefficient of Optimism	Expected Return	Expected Risk
0	5.994180436	0.003350629
0.125	5.994218452	0.003350629
0.25	6.811286156	0.00343516
0.375	7.986964993	0.00385269
0.5	9.162644824	0.004623148
0.625	10.33832355	0.005776107
0.75	11.5140045	0.007674023
0.875	12.68968388	0.013171289
1	13.86536346	0.022857681

coefficient of optimism the expected return of the portfolio is increasing with the increase in expected risk.

From Table 5 it has been stated that the expected return of the optimum portfolio is increasing with the increase in expected risk. But the expected return for the values of coefficient of optimism from 0 to 0.375 is lower than that of the first half.

The expected return and risk of the portfolio under Cut-off principle showing a different result. In the first part the expected return is less than that of second part and risk showing the opposite result means first part is having more expected risk than that of second part.

Table 8 is also showing a gradual increase of expected return over the different values of coefficient of optimism but from 0 to 0.625 values of coefficient of

Table 6. Expected return and risk of the cut-off principle for the first half

Expected Return	11.09233
Expected Risk	0.018198

Table 7. Expected return and risk of the cut-off principle for the second half

Expected Return	12.01243
Expected Risk	0.008824

Table 8, Expected return and risk of near optimum portfolio for the first half

Coefficient of Optimism	Expected Return	Expected Risk
0	6.993504525	0.014782
0.125	7.625483741	0.012506
0.25	8.257463199	0.012549
0.375	8.889442414	0.014911
0.5	9.52142154	0.018299
0.625	10.15340114	0.017428
0.75	10.78538011	0.019741
0.875	10.78538038	0.019741
1	12.04933911	0.033924

optimism, the expected risk is volatile after that it is showing an increasing trend that may be due to the presence of volatility in market.

In the second part the expected return and risk both are showing increasing trend with the increase value of the coefficient of optimism.

With the expected risk and return values, the City Block Distance between Sharp's Single Index Model, Cut-off principle and Near Optimum Model have been calculated and shown in the following Table 10, 11, 12 and 13. Table 10 is showing the CBD between Sharpe's Single Index Model and Cut off model and Sharpe's Single Asset Model and Near Optimum Model for the whole period. The values have been plotted in portfolio risk and return space and the Figure 1 has been drawn.

From the above table and figure, it is clear that CBD between Sharp's Single Index Model and NOP is nearer than the CBD between Sharpe's Single Asset Model

Table 9. Expected return and risk of near optimum portfolio for the second half

Coefficient of Optimism	Expected Return	Expected Risk
0	4.459927	0.006462247
0.125	5.635606	0.004921448
0.25	6.811286	0.006599724
0.375	7.986965	0.009790022
0.5	9.162645	0.009789389
0.625	10.33832	0.011095839
0.75	11.514	0.01370937
0.875	12.68968	0.017629984
1	13.86536	0.022857681

Table 10. CBD between Sharpe's Single asset model and cut off model and Sharpe's single index model and near optimum model for the whole period

Coefficient of Optimism	CBD Between Sharpe's Single Asset Model and Cut Off Model	Sharpe's Single Asset Model and Near Optimum Model
0	3.022444706	0.89389801
0.125	2.603250514	0.474588857
0.25	2.177916681	0.049250662
0.375	1.755828028	0.004373434
0.5	1.336984845	0.006832042
0.625	0.915735028	0.006363834
0.75	0.491900694	0.002722429
0.875	0.071328729	0.001429233
1	0.357488783	0

and Cut off model. CBD between Sharpe's Single Index Model and Cut off model is far from the optimum solution. Thus, it can be stated that heuristically one investor can reach the optimum portfolio.

When the CBD between Sharpe's Single Index Model and Near Optimum Model in both the period has been plotted in the risk-return space it is found that the CBD in Second half is far from the First half from 0 to 0.2 values of coefficient of optimism.

Figure 1. CBD between Sharpe's Single Asset Model and Cut off model and Sharpe's Single Asset Model and Near Optimum Model for the whole period

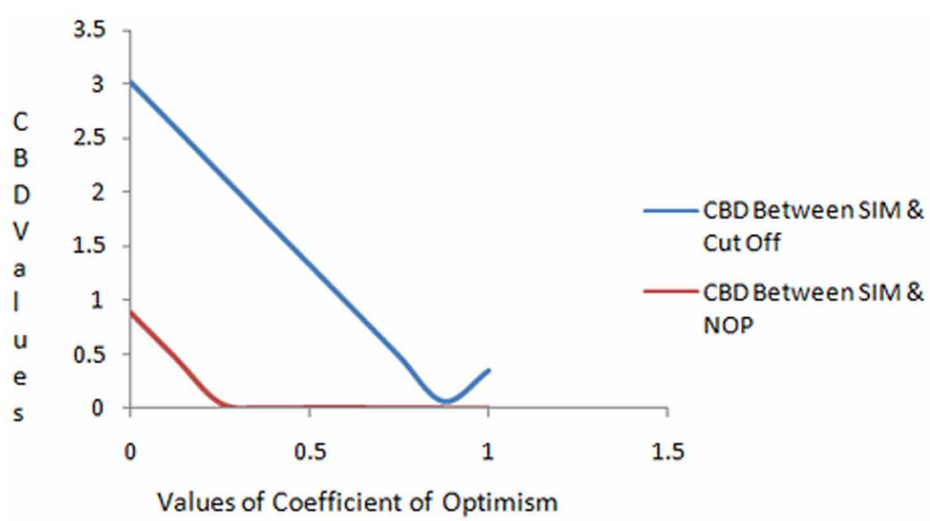


Table 11. CBD between Sharpe's single index model and near optimum model in both the period

Coefficient of Optimism	CBD First Half	CBD Second Half
0	0.731324052	1.537365285
0.125	0.097068044	0.360183019
0.25	0.003938696	0.003164874
0.375	0.022269949	0.005937798
0.5	0.007040316	0.005166712
0.625	0.003765644	0.005321169
0.75	0.00273273	0.006035773
0.875	1.221443041	0.004458812
1	0	0

From 0.2 to 0.8 both CBDs are almost showing the same result while from 0.8 to 1 the Second half CBD is nearer than the First half. So it can be said that during the Second half the risk taker investors are closer to the optimum portfolio while during the First half the pessimistic is closer to the optimum solution considering the Sharp's Single Index Model.

When we are comparing the CBD between the three measures it is shown that CBD between Sharpe's Single Index Model and Cut off model is far from the optimum solution up to the value of 0.8 coefficient of optimism. At value 1, the

Figure 2. CBD between Sharpe's single index model and near optimum model in both the period

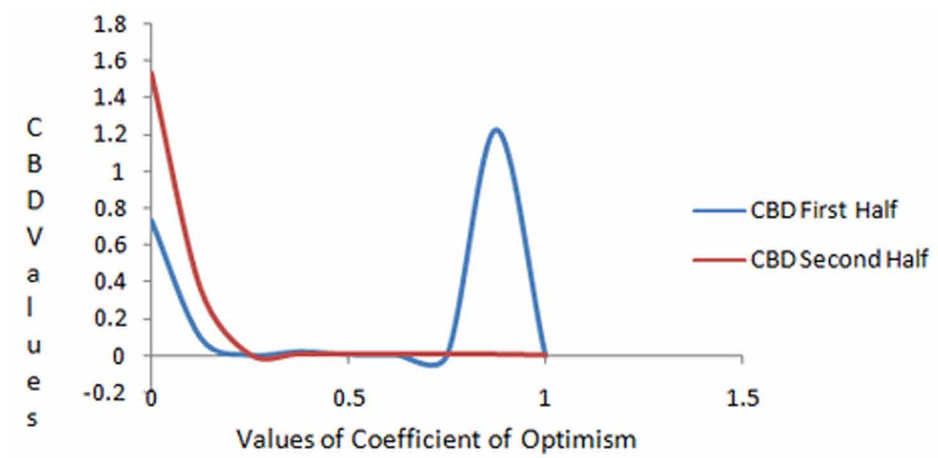


Table 12. CBD between Sharpe's single index model and cut off model and sharpe's single index model and near optimum model for the first period

Coefficient of Optimism	CBD Between Sharpe's Single Index Model and Cut Off Model	Sharpe's Single Index Model and Near Optimum Model
0	3.500603185	0.731324052
0.125	3.50060384	0.097068044
0.25	2.96115479	0.003938696
0.375	2.311070431	0.022269949
0.5	1.694546234	0.007040316
0.625	1.060164581	0.003765644
0.75	0.42483745	0.00273273
0.875	1.002699851	1.221443041
1	1.057987282	0

CBD between Sharpe's Single Index Model and Near Optimum Model for the First Period is again come near to the optimum solution. Therefore, it can be stated that during the first half the NOP gives a better result than the classical models.

Figure 3. CBD between Sharpe's single index model and cut off model and sharpe's single index model and near optimum model for the first period

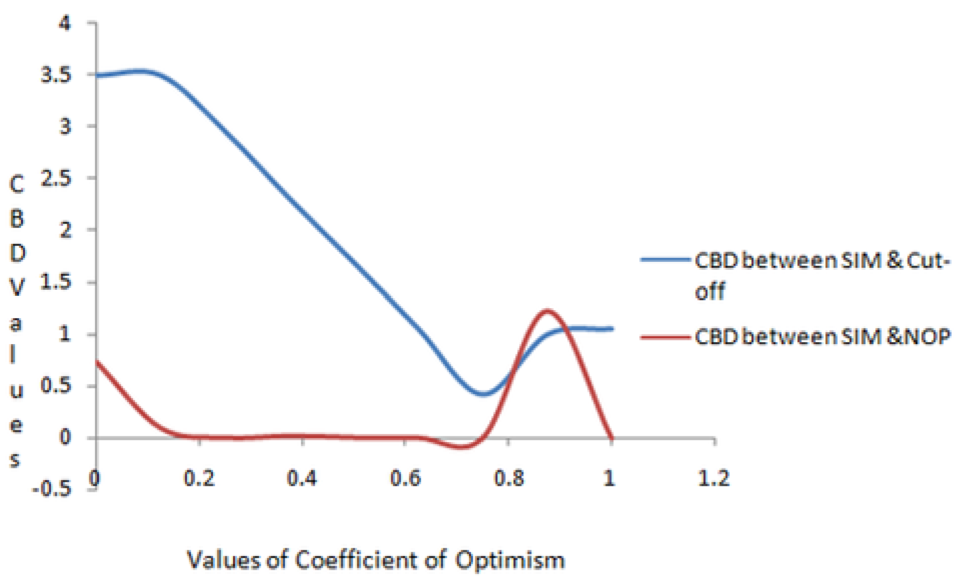
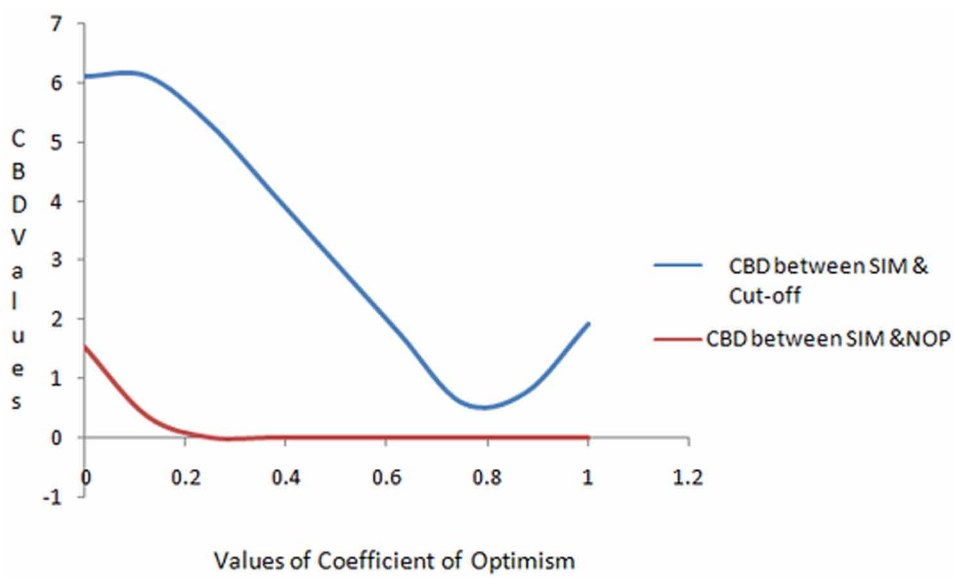


Table 13, CBD between Sharpe's single index model and cut off model and sharpe's single index model and near optimum model for the second period

Coefficient of Optimism	CBD Between Sharpe's Single Index Model and Cut Off Model	Sharpe's Single Index Model and Near Optimum Model
0	6.108835428	1.537365285
0.125	6.108797413	0.360183019
0.25	5.291645178	0.003164874
0.375	4.11554881	0.005937798
0.5	2.939098522	0.005166712
0.625	1.762266834	0.005321169
0.75	0.584687972	0.006035773
0.875	0.758022986	0.004458812
1	1.924016173	0

The Second half results are showing that the CBD between Sharpe's Single Index Model and Cut off model is very far than the CBD between Sharpe's Single Index Model and Near Optimum Model at all the values of coefficient of optimism. From

Figure 4. CBD between Sharpe's Single Index Model and Cut off model and Sharpe's Single Index Model and Near Optimum Model for the Second Period



0.2 to1 values of coefficient of optimism, the decision of the heuristic investors is almost same to the decision of the optimum investors.

Therefore, it can be stated that the investors who are having heuristically inclined are performing well during the whole period taken into consideration as well as both the parts of the periods considered separately. During 126 months period the heuristic investors if want to invest can reach near to the optimum solutions in a better way than the investors who follow the classical methods of optimization. When the whole period has divided into two parts then also the same result is coming. Therefore, it can be argued that the heuristic model generated in this paper is a better fit model as the volatility of the stock market also can not have any effect on the solution of the problem.

CONCLUSION

The most important problem of portfolio management is the proportional allocation of the securities in the portfolio. The classical theories tried to develop insight into the problem but with many limitations. The weight generation problem can be solved by considering heuristic methods. Many authors have provided their own opinion about the heuristic optimization of the portfolio. This present work has proposed a solution to get a portfolio which will be near to optimum solution. By detailed empirical analysis, it is found that the heuristic solution can help an investor to select a portfolio which can give near optimum solution. In this present work, the complicated classical model is simplified into an easy method to observe whether the investors get any benefit out of the simplification process. By simplifying the Sharpe's Single Index Model it is observed that the Near Optimum Portfolios generates a better result than the other two established portfolio theories. Therefore, it can be stated that, heuristically, an investor can also reach the optimum portfolio.

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Chapter 9
Role of Metaheuristic Optimization in Portfolio Management for the Banking Sector:
A Case Study

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ABSTRACT

In this chapter, the importance of optimization technique, more specifically metaheuristic optimization in banking portfolio management, is reviewed. Present work deals with interactive bank marketing campaign of a specific Portugal bank, taken from UCI dataset archive. This dataset consists of 45,211 samples with 17 features including one response/output variable. The classification work is carried out with all data using decision tree (DT), support vector machine (SVM), and k-nearest neighbour (k-NN), without any feature optimization. Metaheuristic genetic

DOI: 10.4018/978-1-5225-8103-1.ch009

algorithm (GA) is used as a feature optimizer to find only 5 features out of the 16 features. Finally, the classification work with the optimized feature shows relatively good accuracy in comparison to classification with all feature set. This result shows that with a smaller number of optimized features better classification can be achieved with less computational overhead.

INTRODUCTION

Complexity in real-life problems demands optimized solution. The solution should be such that it will consider all the constraints while doing the mathematics and probably the trade-off between hostile objectives; where slight tailoring in the requirements or constraints will be reflected in the output. If the solution consists of dominated and non-dominated depending on a continuously updated algorithm, then it can be termed as Pareto optimization (Ngatchou *et. al.*, 2005; Khoroshiltseva *et. al.*, 2016), whereas in scalarization method, multi-objective functions can be made into one solution using the weight factors (Jahn 1985; Eichfelder 2009; Braun *et. al.*, 2017). The weights in the later case may either be equal or rank-sum or rank order centroid (Braun *et. al.*, 2017), determined by the dominance. The same problem can be solved for single objective or multi-objective depending on the demand or angle of inspection, a classic example is the route hazardous materials in transportation network (Erkut & Alp, 2007). The problem can be solved as single-objective solution by separating the boundary constraints like risk of transportation, road condition, distance between two end points, cost of transport, and risk for the population. Looking from a different angle, either from economical aspect, or from societal perspective, the problem may be converted into a multi-objective optimization (MOO) algorithm. In the latter case, Pareto-optimal set is calculated. Comparative analysis is therefore required as the need of the hour between multiple solution mechanisms for the multi-objective solutions of a single problem (Dey & Choudhury, 2016) considering the diversity, degree of convergence and objective space (Liang *et. al.*, 2016). A few specific real-life problems are recently addressed and optimized in diverse fields like politics (Gunasekara *et. al.*, 2014); energy-harvesting (Sessarego *et. al.*, 2015) etc. Complexity of the problems in most of the cases demands adoption of scalarization methods.

Scalarization method is probably the most popular method among multi-objective optimization methods because of the advantages it offer in case-to-case basis where complexity and the input parameters play the crucial role. For convex problems, this method offers solution by linear scalarization method which is easier from computation point of view. As it is able to convert any multi-objective problem in a series of single objective problems, so the solutions are considered in the form of weighted sum. If weight is imported on a particular parameter/unit for all the objectives, then the linearization method becomes very useful. Under this condition, the solution leads to Pareto optimal point. Nonlinear scalarization methods are also incorporated when priori preference is assigned for some specific input parameters, and weights are redistributed according to that information. It is always good to form Pareto frontier at first by using posteriori, and in this context, evolutionary algorithm has been preferred by researchers (Khan *et. al.*, 2019) in recent past, more precisely when information is not shared about the objective functions. Works are also available where gradient properties of multi-objective landscape are used (Kerschke & Grimme 2017) and claim is made for visualization of local optima superposition. This method is also applied in blast furnace iron making process (Mahanta & Chakraborti 2018) and Pareto trade-off is calculated. However, this method faces some criticism due to lack of convergence theory, or availability of a single Pareto optimal point. Henceforth, various approaches are reported on different problems with multiple objectives, and comparative analysis is also presented with that obtained by evolutionary algorithm.

Constraint-based DAC technique is adopted a few years back for online test paper generation (Nguyen *et. al.*, 2011) which provides superior performance in terms of shorter runtime, and thus becomes cost-effective. Optimal Latin Hypercube Sampling (OLHS) method is utilized to design the front-end shape of cycle (Lv *et. al.*, 2018) in order to minimize the probability and also the risk factor involves in the injury between pedestrian and cyclist. Very recently, Brain Storm Optimization (BSO) algorithm is proposed along with decomposition technology (Dai & Lei, 2019) as an alternative and improved version of evolutionary algorithm to enhance the efficiency of searching. Collective Decision Optimization Algorithm (CDOA) is another technique proposed by workers (Xu *et. al.*, 2018) as a modified version of the evolutionary algorithm in order to simulate the human behaviour on decision making. For economic emission dispatch problem, this method exhibits Pareto optimal solutions of higher quality (Xu *et. al.*, 2018). Multi-objective Genetic Algorithm (SPEA2) with fuzzy logic is applied to solve the problem of radial feeder distributions (volt/var problem), and provides very good result when functioned at 69-bus feeder (de Souza & de Almeida, 2010). Genetic Algorithm is used to optimize the performance of photovoltaic system (Zhou & Sun, 2012) where maximum weights are simultaneously given on reduction of installation cost and enhanced power reliability. Concept of Evolutionary Multi-objective Optimization (EMO) is now also practised on engineering problems of search-based mechanism (Deb 2012) including in economic load and emission dispatch problems. Importance of preference-based multi-objective optimization methods in the framework of current academia and industry is discussed precisely when number of objectives becomes very large (Wang *et. al.*, 2017) along with the challenges faced now-a-days. Henceforth, comparative study becomes essential not only between single and multi-objective problems, but also between different algorithms used so far for MOO problems.

For a single problem, both single and multi-objective optimization is applied to make comparison in the outcome where weight is assigned on constraints of highest priority for SOO, and weights are distributed for MOO. For Echo state network, the problem of reservoir architecture design is addressed with multi or mono constraint optimization (Chouikhi *et. al.*, 2016). For multi-objective optimization problems, comparison is carried out for constrained multi-objective evolutionary algorithms (CMOEAs) for generalized optimization problems, or for some specific cases (Zhang *et. al.*, 2017). In the later example, performance evaluation is compared for GA, PSO and DE. In this context, one noteworthy problem area deals with banking sector. Work is already published for asset optimization interlinked with risk management (Bao *et. al.*, 2014) which are very helpful for commercial banks considering their preliminary objectives of lower cost and higher profit subject to minimum risk. Different algorithms are proposed to help the bankers for location selection for opening new branches (Görener *et. al.*, 2013) where evaluation criteria is prioritized based on the identification of several input constraint along with the need of maximizing profit. Approach is functional to the resource procurement by the bank (Mohammad-Zade *et. al.*, 2010), and different expensive deposit methods are identified considering both operational as well as non-operational costs as determining inputs. Among the other issues that arise in the banking sector, the major threat comes in the form of fraud or bad debt problems. In the following section, we have identified a few problems related with banking fraud and have shown how multi-objective optimization algorithms are used to solve the problem.

Researches have been carried out not so long ago to enhance the trust of customers (Liébana-Cabanillas *et. al.*, 2012) to the financial institutions for e-banking, where probability of fraudulent activities is very high. Result not only affects the customers, but also shows how the profitability of the banks increases. Works are also directed for risk management in the financial sectors, where multiple Pareto-optimal sets are generated for optimization of different business objectives. Novel metaheuristic migrating bird optimization technique is evolved to solve the credit card related fraud problems (Duman & Elikucuk, 2013). Adaptive data mining techniques along with intelligent agents is proposed a few years back (Amanze *et. al.*, 2013) to provide secure communication channels for credit card transaction. In another mode, Genetic Algorithm and Scatter Search technique are applied with improved accuracy of detecting fraudulent transactions (Duman & Özçelik, 2011), where authors also pointed out the mis-conceptualization of present fraud detection technique, where only wring transactions are taken into account for fraud detection. In this context, portfolio management plays a vital role where several risk factors on behalf of the financial institutions can be minimized without affecting the customers, and thus profit margin can be enhanced by minimizing the loss. Bad debt or loan to a vulnerable customer is another risk factor for banks and hence calls for predictive portfolio management where probability of taking personal loan of a customer form a bank can be near-accurately and reasonably easily computed form the initial database of the customer and his/her behavioural pattern (considering only selective classified features). Role of multi-objective optimization algorithms lies in risk management through customer efficient services, and accomplishing commercial and regulatory acquiescence.

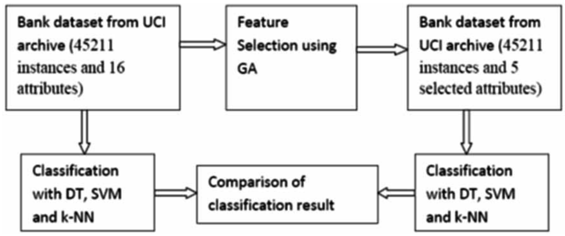
Portfolio Management

Optimization algorithms for portfolio selection are considered a decade ago (Pardalos 1997) using Markowitz mean-variance model for crucial decision making in investments. Different portfolio optimization models are proposed in recent past (Chiranjeevi & Sastry, 2007; Skolpadungket *et. al.*, 2007) using single and multi-objective algorithms where different pragmatic constrictions are considered e.g., cardinality, round-lot, floor etc. Various MOO algorithms are utilized for best performance, and Strength Pareto Evolutionary Algorithm 2nd version (SPEA2) is found as the best without considering the number of generations. Later Non-dominated Sorting Genetic Algorithm II (NSGA II) is found as better algorithm (Mishra *et. al.*, 2011) for risk minimization and profit maximization. For pricing in different options, heuristic algorithms like PSO is used with small variations so that time taken to solve the problem can be drastically minimized (Sharma *et. al.*, 2012), and later can be used in multi-core GPU to validate the reduction of computational time. Scalarization method is exercised in form of parallel splitting algorithms where data are taken from real world. Risk-adjusted expected return is considered for present day financial sectors (Reid & Malan, 2015), and the problem is solved using modified PSO algorithms. Novel technique is recently developed for assessing downside-risk (Janabi 2015) where operational constraints are also considered along with financial limitations. Substitution and standardization methods are invoked (Myrodia *et. al.*, 2017) to support strategic decisions taken at crucial juncture to increase both productivity and profitability of manufacturer as well as contentment of customers. Very recently, research works are reported on forecasting risk so as to curb or optimize the risk at organizational level, which in turn helps the managers to assess risk-return characteristics at the beginning of a project.

Metaheuristic Optimization

In last few years there has been huge development in the field of soft computing and portfolio management may now be more confidently performed using metaheuristic techniques that have become quite popular optimization procedure in recent times. The advantage of this procedure is to obtain a reasonably consistent near-optimum solution for a complex problem where add-on facility of various pragmatic portfolios is allowed, and therefore the problem becomes very hard, precisely in connection with computation time. Very good solutions are already obtained for single-objective optimization cases with adequate computation time, though convergence analysis for most of the meta-heuristic problems are yet to be provided (Yang 2011; Dehghani *et. al.*, 2017) coupled with efficiency analysis, where real-life problems are dealt with. Spring Search algorithm is used to solve the problems with the objective of achieving optimal performance and efficiency. Different quantum versions of meta-heuristic algorithms are reported recently for multi-level thresholding (Dey *et. al.*, 2013), and supremacy of the obtained result is established by t-test method. They have also established the time-efficiency of their novel method (Dey *et. al.*, 2014) w.r.t both classical technique as good as quantum evolutionary algorithm (QEA) proposed by Hans. This optimization technique is also used to solve one-dimensional differential equations in order to minimize weighted residual functions (Sadollah *et. al.*, 2015); later extended in different engineering fields (Rodríguez *et. al.*, 2018). Concept based on prey-predator interaction of animals is utilized to develop a novel metaheuristic optimization algorithm (Tilahun & Ong 2015) which outperforms other well-known algorithms on selected problems. A survey is very recently published (Shishira *et. al.*, 2016) where sub-optimal solutions are considered provided by different algorithms in shorter time span. For multi-level colour image thresholding, novel quantum-inspired Ant Colony Optimization, Particle Swarm Optimization and Differential Evolution are proposed Dey *et. al.*, 2016) where quality of thresholding is judged by computing PSNR at various levels. This optimization technique is also recently utilized in microarray systems (Dankolo *et. al.*, 2017) where it is claimed that application of metaheuristic algorithm for feature selection in data pre-processing stage saves computational time. NP-hard facility location problem is solved (Skakov & Malysh 2018) through parametric meta-optimization technique of the control variables using evolutionary optimization method. Motivated by the effect of Sun Beam on Leaf Optimization (Hosseini & Kaedi 2018), only high-quality solutions are considered for optimum performance where more candidate solutions are generated near the area of previous solutions; thus saving computational time. Spiral-shaped path for Grey Wolf Optimization is recently considered in order to achieve convergence at minimum time (Gai *et. al.*, 2018). Interactive Search Algorithm is proposed and tested with well-established solutions (Mortazavi *et. al.*, 2018), and competitive edge is found for some specific cases. This optimization technique is also applicable for single objective cases where less computational time with greater accuracy is always expected, and that is the prime requirement for real-world highly sensitive problems dealt in financial

Figure 1. Schematic process diagram of the proposed work



sectors. So we have chosen metaheuristic optimization procedure for our present problem of banking portfolio management with the optimization of single objective.

Present Work

The present work is a typical example of portfolio management where a binary outcome is considered and inter-relation with the user database is considered as the attributes responsible for the outcome. The objective for choosing the problem is to establish the complexity of optimization technique for making a financial decision, and yet, making the computation easier by considering only the important relevant attributes for the decision-making process. For any financial decision from user's perspective, it is customary to analyze the optimization procedure, which will help the banker to approach the future customers following the track; and henceforth, accuracy estimation of the optimization procedure should be one of the important aspects of performance analysis. This is also covered and briefly described in the subsequent sections of the chapter where it is shown that only important attributes are sufficient for predictive analysis; and accuracy for determining end result is quite heavily dependent on those important attributes. Rest of this chapter is divided as follows: brief description of the dataset, choice of algorithms for solution, mapping different attribute values with different domain values, and accuracy analysis after end of simulation. Different algorithms are used to check the accuracy, and later the same is computed considering only the important attributes. Results are extremely critical for taking any clone-related financial decision. Figure 1 shows the schematic process diagram of the entire proposed work.

Dataset

The dataset used in this work is downloaded from UCI dataset archive. This dataset is for the interactive bank marketing campaign of Portugal bank, done by phone call. This dataset consists of multivariate, real data with 45211 instances and 16 attributes and 1 response attribute. This dataset is created on the year 2012. This dataset consists of attributes like age, job, marital-status, educational qualification, credit, home/personal loan, how and when contacted, time of contact etc. The output variable is a binary, whether the client has done a term deposit or not. In this work, we have tried to establish the relation of a financial decision on taking a loan to the input variables of any arbitrary customer (Moro *et. al.*, 2014). We have extensively searched and found out the most critical variables (Moro *et. al.*, 2011) which are sufficient for taking conclusive decision.

Metaheuristic Algorithm - GA

In the present work Genetic Algorithm (GA) is used as a metaheuristic optimization algorithm. It is deployed to optimize the number of select features necessary to take a financial decision. The basic principle of GA and its advantage and limitations are briefly outlined here.

Genetic Algorithm (GA)

Genetic Algorithm (GA) is an advanced heuristic search algorithm that is frequently used to solve single and multi-objective optimization problems. This algorithm is based on the mechanics of natural genetics and biological evolution; it is considered to simulate the natural systems for evolution, based on the principle "survival of the fittest" proposed by Charles Darwin. In nature, the competition among organisms evolves over successive generations to better adapt to the environment.

GA considers many points in the search space like many conventional search algorithms. By considering multiple search space points simultaneously GA reduce the probability of converging to local minima. The following characteristic pattern is observed in the processing of GA:

- Initially a population of solution is created.
- Each population is assigned a fitness value based on its evaluation against the current problem.
- Solutions with high fitness value are most likely to parent new solutions during reproduction.
- The old solution set is replaced with the new one.
- A generation is completed and the process again continues from step 2.

The members of the population are improving with the use of genetic operators like crossover, reproduction and mutation. The simple computational methods and powerful search ability of GAs have rendered this algorithm a popular one in various research fields like function optimization, game playing, pattern recognition etc. Figure 2 shows the flowchart of feature optimization using GA.

Advantages of GA

GAs has many advantages. These include –

1. The algorithm does not require any derivative information.
2. The method is faster and efficient as compared to the other meta-heuristics methods
3. It can optimize different types of objective functions - continuous and discrete and also deals with multiple objectives
4. The solution gives an array of good solutions and not a single solution
5. The algorithm is useful when large number of parameters are involved and also the search space is large
6. The algorithm is extremely robust

Limitations of GA

1. GAs is not the right choice for simple problems and for which derivative information is available
2. Repeated calculation of the fitness value might be computationally expensive
3. Being stochastic, there are no guarantees on the optimality or the quality of the solution

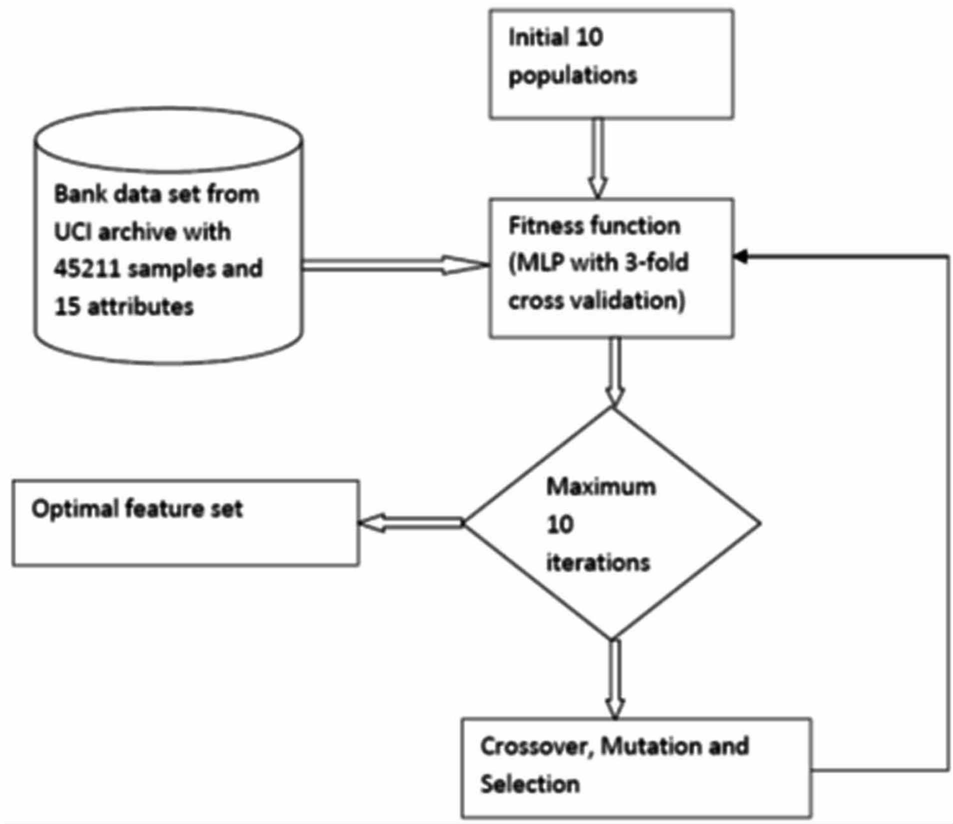
Classification Algorithm

In the present work three classification algorithms are used which are briefly discussed below.

Support Vector Machine (SVM)

SVM is the most popular supervised machine learning algorithm extensively used for soft computing operations specially for classification and regression techniques. SVM was first introduced by Boser, Guyon, and Vapnik in COLT-92 in 1992. SVM can be classified as a discriminative classifier, that is, they used to draw a boundary between clusters of data. In other words this machine learning tool used to increase predictive accuracy while preventing over-fitting of the data. Initially SVM was popular with the Neural Information Processing community but now it is popular in

Figure 2. Flowchart of feature optimization using GA

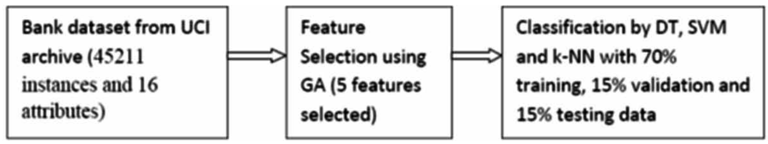


the domain of machine learning research around the world. SVM is used for feature selection in handwriting recognition task, face analysis etc. which are mostly based on regression and pattern recognition. The basics of SVM had been developed by Vapnik and within few years it has become popular among researchers because of its highlighted features like improved empirical results. The conceptualization of the SVM uses the Structural Risk Minimization (SRM) principle rather than traditional Empirical Risk Minimization (ERM) principle.

K-Nearest-Neighbors (KNN)

KNN method of classification is one of the most essential classification algorithms in Machine Learning. Like SVM, KNN classification can also be extensively used for both classification and regression related problems. KNN can be designated under lazy learning, which does not involve any explicit training phase before

Figure 3. Flowchart of classification process



classification. It is very simple to understand and implement based on the principle to find the related data element in the training data, and make a prediction based on the classification results. This mechanism is extensively used in many applications like credit ratings, bank loan, handwriting detection (like OCR), image recognition and even video recognition. The most important aspects of KNN are: easy to interpret output, less calculation time and good predictive power. Although KNN is easy to implement but there are some problems with this algorithm. The training set needs to be kept in primary storage unless the data-set can be reduced for implementing classification. KNN works better for smaller data sets which have less number of features.

Decision Tree (DT)

Decision tree is one of the most popular machine learning algorithms and it is mostly used in supervised learning methods. They are adaptable to solve both regression and classification problems. In this algorithm the data is continuously split according to a certain parameter. The tree can be explained by two entities, namely decision nodes and leaves. The leaves are the decisions or the final outcomes. And the decision nodes are where the data is split. Any Boolean function on discrete attributes can be represented using the decision tree. Figure 3 shows the flowchart of classification process.

Data Preparation

Bank client data set contains 16 input variables and 1 output variable. Among these input variables, 9 are categorical data and remaining 7 are numeric data. Domain of the categorical/ Non-numeric input variables and their mapping with numeric value is shown in Table 1 to Table 9. Input variables with numeric values are shown in Table 10 and the domain of the output variable and its mapping with numeric value is shown in Table 11.

Input Variables

16 different variables are taken as input to determine whether a bank client can receive a term deposit or not. Among 16 input variables 9 attributes are non numerical value, their domain is shown in 2nd column of Table 1, Table 2, Table 3, Table 4, Table 5, Table 6, Table 7, Table 8 and Table 9 and Table 10 contains list of numeric attributes.

Categorical / Non Numeric Data

See Table 1-9.

Table 1. Mapping domain value of the attribute job with numeric value

Attribute Name - Job: Type of Job		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	unknown	1
2	admin.	2
3	unemployed	3
4	management	4
5	housemaid	5
6	entrepreneur	6
7	student	7
8	blue-collar	8
9	self-employed	9
10	retired	10
11	technician	11
12	services	12

Table 2. Mapping domain value of the attribute marital with numeric value

Attribute Name - Marital: Client's Marital Status		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	married	1
2	divorced	2
3	single	3

Table 3. Mapping domain value of the attribute education with numeric value

Attribute Name – Education: Client's Highest Education		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	unknown	1
2	secondary	2
3	primary	3
4	tertiary	4

Table 4. Mapping domain value of the attribute (credit) default with numeric value

Attribute Name - Default: Has Credit in Default?		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	yes	1
2	no	2

Table 5. Mapping domain value of the attribute housing (loan) with numeric value

Attribute Name - Housing: Has Housing Loan		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	yes	1
2	no	2

Table 6. Mapping domain value of the attribute personal loan with numeric value

Attribute Name - Loan: Has Personal Loan		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	yes	1
2	no	2

Table 7. Mapping domain value of the attribute contact with numeric value

Attribute Name - Contact: Contact Communication Type with Clients		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	unknown	1
2	telephone	2
3	cellular	3

Table 8. Mapping domain value of the attribute month with numeric value

Attribute Name - Month: Last Contact Month of Year with Clients		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	jan	1
2	feb	2
3	mar	3
4	apr	4
5	may	5
6	jun	6
7	jul	7
8	aug	8
9	sep	9
10	oct	10
11	nov	11
12	dec	12

Table 9. Mapping domain value of the attribute poutcome with numeric value

Attribute Name - Outcome: Outcome of the Previous Marketing Campaign		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	unknown	1
2	other	2
3	failure	3
4	success	4

Numeric Data

See Table 10.

Table 10. Numeric attributes in the Bank client data set

Sl. No.	Attribute	Description
1	age	Client age
2	balance	Average yearly balance, in euros
3	day	Last contact day of the month
4	duration	Last contact duration
5	campaign	Number of contacts performed during this campaign
6	pdays	Number of days that passed by after the client was last contacted from a previous campaign
7	previous	Number of contacts performed before this campaign

Output Variable

See Table 11.

Table 11. Mapping domain (Boolean type) value of the output variable with numeric value

Output Variable - Has the Client Subscribed a Term Deposit?		
Sl. No.	**Attribute Value**	**Equivalent Numeric Value**
1	yes	1
2	no	2

Result

In the present work total 45211 samples with 16 features in each sample are taken for the classification work. Three supervised algorithm namely, Decision Tree, Support Vector Machine and k-nearest neighbour are used. For the classification work 31647 samples are used for training, 6782 samples for validation and 6782 samples for testing. In this work the output/response variable is taken as "has the client subscribed a term deposit?" or not. The details of features are given in data preparation section. It is found from the work that with all 16 features 90.1%, 88.3% and 90.2% accuracy are achieved using DT, SVM and k-NN. When Genetic Algorithm (GA) is used for the features selection only 5 features are selected. With only optimized 5 features 91.1%, 88.5% and 91.5% accuracy are achieved using DT, SVM and k-NN respectively. Results are mentioned in Table 12. Though there is

Table 12. Classification result with all 16 features and 45211 samples

Classifier	Accuracy (%)
Tree (Complex Tree)	90.1
SVM (Linear SVM)	88.3
k-NN	90.2

very negligible increase in classification accuracy but due to reduction in dimension in feature set the system achieves less computational overhead.

The feature selection algorithm employs Genetic Algorithm (GA), where classification accuracy of Multi-layer Perception (MLP) is used as an objective function. The MLP uses 3-fold cross validation, Levenberg Marquardt training function and Mean squared error performance function. Genetic Algorithm (GA) is used with crossover and mutation percentage of 70% and 30% respectively, mutation rate of 10% with 10 iterations and 10 initial populations. The GA algorithm starts with initial population (candidate solution). The population are used to compute the classification accuracy (fitness function). Then iteratively individual new population are generated using crossover and mutation. Each new individual fitness function is used to replace old individual by new individual. In this present work population are set of features. The GA features selection algorithm selects only 5 features like contact type (like mobile or land line telephone), last contact month (like January, February, March,…., December), contact duration (in seconds), gap after the client was last communicated, result of earlier campaign. This new result is put in Table 13.

Table 13. Classification result with 5 features selected by GA feature selection algorithm and 45211 samples

Classifier	Accuracy (%)
Tree (Complex Tree)	91.1
SVM (Linear SVM)	88.5
k-NN	91.5

Result Analysis

A comparative study between Table 12 and Table 13 reveals that reduction of features for this particular problem increases accuracy to a little extent for all the three classifiers, but saves computational time a lot. Thus this solution can be considered as a near-optimal solution obtained using metaheuristic optimization technique, and serves the purpose. Though the problem is for single-objective optimization, but it can be re-applied to any multi-objective optimization problem as suggested by the test result. In view of portfolio management, bankers can safely take decisions based on the crucial features which does not hamper the accuracy but saves time and decision making becomes faster. k-NN is proved to be the most efficient classifier for the present problem, and 5 features are enough to predict the outcome as revealed from the estimation. This result therefore justifies the title of the proposed work. In Table 14 result comparison is given with a related work with the same data set used in the present work.

Table 14. Result comparison with the related work

Related Work	Classifier Used	Number of Features	Accuracy (%)
Elsalamony and Elsayad (2013)	MLP	17	90.32
Present Work	k-NN	5	91.5

CONCLUSION

The present work deals with the application of metaheuristic objective optimization technique on financial sector where probability of taking term deposit by a customer from a bank can be near-accurately computed from the initial database of the client and his/her behavioural pattern with the bank. Results are obtained with the features selected by GA, and results showed 91.5% accuracy for predicting the outcome. Results are computed in two different methods, in the first case, all attributes are considered, whereas in the second case, only 5 significant attributes are taken into consideration. Though in terms of improvement of accuracy, the difference is considerably minor; but in terms of complexity issue, it is found that that the selective choice of attributes greatly reduces the complexity of the problem. This highlights the importance of the metaheuristic optimization obtained using GA, and the end result will certainly help the bankers for financial gain by selectively removing the probability of bad debt. Since in the present age, loan recovery becomes one of the biggest issues, and is closely related with the potential future growth of any bank; henceforth, findings mentioned in this chapter are greatly beneficial and will certainly help the banking system. Result can also be improved by incorporating further meaningful attributes, and that will help to get secured results from the banker's point-of-view. However, the work is carried out for optimization of a single objective where only the possibility of considering term deposit by a potential customer is judged. This concept can further be extended to multi-objective optimization where possibility of loan repayment with the specified time-period should be considered. This is significant as bad debt now-a-days costs more to the bank and this can't be easily erased. Instead of growth of the bank, this thing will be turned as a non-removable liability of the bank which will increase with passage of time. Once the problem domain will be shifted to MOO, more features should be considered for accurate result, and then the question of time complexity will come into effect. This limitation may be overcome in near future provided the availability of sufficient database which will greatly benefit financial sector. In some cases, loan repayment period may be considered in order to predict the future of loan recovery, and this will greatly be coupled with the business/investment of the amount taken by the customer as loan. This type of multi-objective optimization problem can be considered as a future scope for real-life implementation.

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