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Investor's Psychology In Portfolio Optimization: A Goal Programming Approach

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Abstract: This paper attempts to develop the portfolio optimization model using the Goal-Programming technique for investors with multiple goals and constraints. Methodology: In the proposed model, the stock return, systematic risk, covariance, unsystematic risk, and dividend have been used as financial indicators to analyze the stocks of Nifty 50. This study designed the portfolio optimization model using LINGO software from 1st April 2018 to 31st March 2019. Findings: The developed model help in-stock selection for growth and income portfolios in two different forms of market structure, i.e., optimistic and pessimistic. Further, the developed model also supplements fundamental and technical research, strengthening the stock selection criteria.

Keywords: Portfolio optimization, Goal Programming model, Growth Portfolios, Income Portfolios, Indian Stock Market, Stock Selection.

JEL Classification Number: G11, G12

1.1 Introduction

The first analytical framework for determining the optimal portfolio based on the mean-variance approach was developed by Harry Markowitz. Sharpe developed another model to overcome the computational limitations of applying the Markowitz model based on the notion that all stocks are affected by movement in the stock market. The beta coefficient used in the Sharpe model measures the expected change in the individual return of the security given a shift in market return. The existing portfolio optimization models assume that investors only make investment decisions based on risk and return. This approach is just the simplification of reality. However, in the real financial world, along with risk and return, the investor considers several other conflicting factors for portfolio optimization. Further, the nature of factors also depends upon the investor's risk-taking capacity.

Among other portfolio management techniques, Goal programming (GP) is the only technique that gives the investor the leverage to minimize the deviation between their stated goals and the aspiration levels. It is an approach that is used for solving a multiple-objective optimization problem. Using this technique, the investor can balance a trade-off between the conflicting objectives in particular priority order. Further, to develop the specific priority order, an investor can weigh different goals based on their importance. It helps the investor deal with all those objectives that cannot be entirely and simultaneously achieved so that the most important goals are first achieved, at the cost of less important ones. It is an advanced version of linear programming with added dimensions. It is more robust than any other portfolio selection technique because it optimizes portfolios with a single goal with multiple sub-goals or numerous goals and sub-goals. Further, Goal programming is based on the principle of "Satisficing." Herbert Simon (1956) coined the concept of "Satisficing," a decision-making technique in which the decision-maker searches for available alternatives until an acceptable threshold level is met.

The current research aims to create stock market portfolios while taking into account investors' various goals and limits in various market scenarios. The goal programming technique is not commonly used in the Indian stock market for portfolio optimization, which is one of the driving forces behind this study.

1.2 Review of Literature

Charnes & Cooper (1957) suggested the idea of goal programming as an extension of linear programming for the first time, which was further developed by Iijri (1965), Contini (1968), and Lee (1972; 1981; 1983). The goal programming models handle multiple, usually conflicting goals. On the other hand, linear programming models focus on a single linear objective function with linear constraints. Iijri (1965) laid the foundation for pre-emptive goal programming models. In Pre-emptive models, the goals of more importance receive priority; those of secondary importance receive second priority, and so on.

Lee & Lerro, (1973) developed the first Lexicographic goal programming model for mutual funds. In that model, they incorporated multiple goals to maximize expected return, minimize portfolio risk, and maximize dividend yield. Our study used their algorithm for empirical analysis of NIFTY 50 Companies. Kumar et al., (1978) developed the conceptual framework of GP portfolio optimization for dual-purpose funds. In a dual-purpose fund, the stock selection is being made keeping in mind the two different goals of the investors, i.e., dividend maximization and capital gain. In our study, their conceptual framework and an additional constraint of industry specification have been used. Fargher et al., (1996) developed a two-stage GP model for portfolio selection for the first time. First, they analyzed the sensitivity of shares against prevailing interest rates in the UK, US, and Germany, US inflation rate, German inflation rate, Dow Jones index, Nikkie Average, Hang Sang index, Oil price, Gold price, House price, and Sterling index in their model to be included in their portfolios. At the second stage, another GP model was formulated to select an optimal portfolio from the shares obtained from the first stage. Jagannathan & Ma, (2003) studied the role of non-negative constraints in reducing the risk of an optimum portfolio. They found that portfolio constraints minimize the tracking error of the portfolios. In order to take their research work to the next level, we have included the constraint of investment, industry, and individual security diversification in our GP model. Sharma & Sharma, (2006) developed lexicographic goal programming (LGP) model for selecting an optimum mutual fund portfolio. Their study included different conflicting variables: maximization of expected returns, minimization of portfolio beta, standard deviation, and expense ratio. Babaei et al. (2009) developed an optimum portfolio for the investors using five conflicting objectives: risk, return, annual dividends, S&P Star ranking, and returns in later years. The study found that goal programming has successfully solved multi-objective decision-making problems based on pre-emptive priorities and target values. Further, Kansal et al., (2009) applied the fuzzy interactive method to find the solution of multi-objective portfolio problems. This method had incorporated conflicting objectives of short-term return, long-term return, dividend, liquidity, and risk. Ismail et al., (2014) determined the portfolio's composition using the goal programming approach in enhanced index tracking, compared it with the market index and found that optimal portfolio with a goal programming approach outperforms the Malaysia market index. Moghaddam et al., (2017) optimized the Portfolio in the Tehran stock exchange using two-goal programming models, namely meta-goal programming and extended lexicography model. They found that portfolios designed through goal programming give higher returns than any other portfolio optimization model.

Further, Aksarayl & Pala, (2017) stated that Markowitz's portfolio theory helps investors select the optimal Portfolio based on return and risk. However, in real financial work, the stock values get affected by government crises, economic turmoil, and industrial improvement. Therefore, they developed a polynomial goal programming model to consider multiple conflicting goals of mean, variance, skewness, and kurtosis. Gupta et al., (2020) developed a separate fuzzy portfolio optimization model for optimistic and pessimistic investors. Their model considered four objectives: return, variance, skewness, and entropy, along with some realistic constraints such as cardinality constraints, contingent constraints, complete capital utilization, and short selling. Hallman et al., (2021) designed the goal programming model to select the drug projects in the pharmaceutical industry. The developed GP model proved helpful for the pharmaceutical industry, where the decision-maker has to handle the multiple conflicting goals.

1.3 Research Methodology

To formulate the goal programming model for portfolio optimization, the investor must define the goals and constraints. This study's goal programming model has included the following goals and constraints which are as follows

1.3.1 Goals

a. Return (R_i): $\sum_{i=1}^{N} R_i\, X_i + n_1^- =$ To Maximize (Rp) Equ1.

In our study, we used geometric mean return than arithmetic mean return to consider the compounding that occurs from period to period (Marcus et al., 2003; Zhang et al., 2012). As a result, the investors view the geometric mean as a more accurate measure of returns than the arithmetic return.

b. Systematic Risk(β_i): $\sum_{i=1}^{N} B_i\, X_i + n_2^- - p_2^+ =$ Either (Max βp)or (Min βp) Equ2.

In our study, systematic risk is measured by beta. The volatility of a stock in comparison to the market is measured by its beta.

c. Covariance (C_i): $\sum_{i=1}^{N} C_i\, X_i + n_3^- - p_3^+ =$ Either Cp (Max) or Cp (Min) Equ3.

Where $C_i = \frac{2\mathrm{Cov}_{i1}}{R_1} + \frac{2\mathrm{Cov}_{i2}}{R_2} + \cdots + 2\frac{2\mathrm{Cov}_{iN}}{R_N}$ Equ4.

Markowitz defined the portfolio variance as follows:

$$\sigma_p^2 = \sum_{i=1}^{N} \sigma_i^2 X_i^2 + 2\sum_{i=1}^{N}\sum_{j>1}^{N} \mathrm{Cov}_{ij} X_i X_j \qquad \text{Equ5.}$$

Using Chain rule of partial differentiation one can find portfolios at the extreme ends of the efficient frontier.

i.e. $\frac{\partial(\sigma_p^2)}{\partial(E_p)} = \frac{\partial(\sigma_p^2)}{\partial(X_1)}.\frac{dX_1}{dE_p} + \frac{\partial(\sigma_p^2)}{\partial(X_2)}.\frac{dX_2}{dE_p} + \cdots + \frac{\partial(\sigma_p^2)}{\partial(X_N)}.\frac{dX_N}{dE_p}$ Equ6.

$$\frac{\partial(\sigma_p^2)}{\partial(E_p)} = \left[\left(\frac{2\sigma_1^2}{E_1} + \frac{2\mathrm{Cov}_{12}}{E_2}\right)X_1 + \left(\frac{2\sigma_2^2}{E_2} + \frac{2\mathrm{Cov}_{21}}{E_1}\right)X_2\right] + \cdots + \left[\left(\frac{2\sigma_1^2}{E_1} + \frac{2\mathrm{Cov}_{12}}{E_2}\right)X_1 + \left(\frac{2\sigma_2^2}{E_2} + \frac{2\mathrm{Cov}_{21}}{E_1}\right)X_2\right] \qquad \text{Equ7.}$$

Using the above Equation 7, equation 4 was derived where coefficients of X_i......X_j were incorporated in the covariance goal.

d.Dividend (D_i): $\sum_{i=1}^{N} D_i\, X_i + n_4^- - p_4^+ =$ Either Dp (Max) or Dp (Min) Equ8.

To incorporate the goal of current income in our model, we computed the geometric mean of the annual dividend yields for each stock.

Hence, $D_i = \frac{\mu_d^{GM}}{\sigma_{d_i}^2}$ Equ9.

e. Unsystematic Risk (ε_i^2) : $\sum_{i=1}^{N} \varepsilon_i^2 X_i + n_5^- - p_5^+ =$ Either Cp (Max) or Cp (Min) Equ10.

In the above equation, unsystematic risk is calculated by subtracting systematic risk from the total variance. Therefore, the investors always try to minimize unsystematic risk through diversification (Horim & Levy, 1980; Scholtz, 2014; Deng & Yuan, 2021). Hence, using our GP model, the portfolio managers can reduce the unsystematic risk, particularly in market downfall.

1.3.2 Constraints

a. Diversification (Industry): $\sum_{i}^{j} \mathrm{X_i} + n_i^- = 0.05$ Equ11.

As per India's securities and exchange board (Mutual Funds) (Amendment) Regulations, 1999 Act, the mutual fund schemes shall not invest more than 5% of its NAV in the equity shares or equity-related investments in case of an open-ended scheme and 10% of its NAV in case of the closed-ended scheme. Hence, the limit of 5% investment in any stock has been imposed in our study.

b. Diversification (Company): $\sum_{i}^{j} \mathrm{X_i} + n_i^- = 0.25$ Equ12.

This study has included the constraint of not investing more than 25% in any industry to diversify the portfolio.

c. No Short Sales: $\sum_{i=1}^{N} \mathrm{X_i} + n_6^- - p_6^+ = 1$ Equ13.

The short sale is generally a transaction in which an investor sells the securities not owned by him. But, instead, they get involved in borrowing and lending. So the model introduced the constraint of no short sales to prevent borrowing and lending.

1.3.3 Formulation of Goal Programming Model

The goal Programming model provides a solution to the investors while choosing stock for their portfolio, particularly in their multiple conflicting objectives. To use the goal programming model for portfolio optimization, they need to specify their goal in the form of an objective function formulated based on three concepts: divergent variables, preemptive priority factors, and assigning weights to divergent variables at the same priority level. Unlike the linear programming model, goal programming minimizes the deviation from established goals based on the priority given to each specific goal. Further, the divergent variables may be represented by the notion n^- for negative deviation and p^+ for positive deviation. Then, ranking of the goals is to be done to optimize the divergent goal in the order of their importance. In some cases, it may be necessary to give weights to the divergent variables with the same priority level. This study has developed the GP model to optimize the portfolios across the above-mentioned multiple goals and constraints. Further, the ordinal weights are assigned to different goals, whereby after attaining the higher-order goals, the model attempts to achieve the lower-ranked goals.

The weighted GP model identified as follows:

Minimize $z = \sum_{i=1}^{N} (\mathrm{w_i}\, n_i^- + \mathrm{w_i}\, p_i^+)$ Equ14.

Subject to

$$\mathrm{aX_i} + n_i^- - p_i^+ = \mathrm{g_i}, \quad \text{Equ15.}$$

$$X_i, n_i^-, p_i^+ \geq 0 \ \forall \ for\ all\ i = 1,2, \ldots.. N. \quad \text{Equ16.}$$

Where;

$\mathrm{p_i^+}$ = divergent variables above the specified goals

$\mathrm{n_i^-}$ = divergent variables above the specified goals

$\mathrm{w_i}$ = priority coefficients assigned to goal i, $\mathrm{w_i} \gg\gg\gg \mathrm{n\ w_{i+1}}$

n = number of goals in the model

X = is constrained to be non − negative

1.4 Results and discussion

The present study analyzed the daily stock data of companies listed on NSE (National Stock Exchange) from 1st April 2018 to 31st March 2019. The information for the same has been collected from the Centre for Monitoring Indian Economy (CMIE) prowess database. The National Stock Exchange (NSE) is one of the leading stock exchanges of India and ranked 4th in the world as per the statistics maintained by the World Federation of Exchange (WFE) for the calendar year 2020[2].

Table 1.Input Data for Goal Programming model

S.No	Stocks	Security Classification	Ei	B_i	C_i	D_i	ε_i^2
1	Asian Paints Ltd.	Consumer Goods	0.001056	0.993541	5.817022	0.006878	0.013162
2	Bajaj Auto Ltd.	Automobile	0.000145	0.874091	3.239639	0.006877	0.236381
3	Bajaj Finance Ltd.	Financial Services	0.002062	1.443100	1.517731	0.006874	-1.081832
4	Bajaj Finserv Ltd.	Financial Services	0.001173	1.451295	4.160504	0.006876	-1.105768
5	Bharat Petroleum Corpn. Ltd.	Energy	-0.00025	1.542372	0.926636	0.006871	-1.377683
6	Bharti Airtel Ltd.	Telecommunication	-0.00069	1.170806	4.964230	0.006874	-0.370005
7	Britannia Industries Ltd.	Consumer Goods	-0.00203	0.487532	7.420694	0.006861	0.765156
8	Cipla Ltd.	Pharmaceuticals	-0.00034	0.760135	-1.752787	0.006878	0.422626
9	Divi'S Laboratories Ltd.	Pharmaceuticals	0.001807	1.031230	4.262923	0.006875	-0.062749
10	Dr. Reddy'S Laboratories Ltd.	Pharmaceuticals	0.001075	0.511583	-1.399834	0.006876	0.738985
11	Grasim Industries Ltd.	Cement	-0.00096	1.211267	6.907846	0.006876	-0.466685
12	H C L Technologies Ltd.	IT	0.000423	0.559338	0.007598	0.006877	0.687728
13	H D F C Bank Ltd.	Banking	0.000741	0.663418	0.315143	0.006880	0.560023
14	H D F C Life Insurance Co. Ltd.	Financial Services	-0.00098	0.614295	0.089313	0.006877	0.623161
15	Hero Motocorp Ltd.	Automobile	-0.00144	0.930917	0.588536	0.006877	0.133892
16	Hindalco Industries Ltd.	Metals	-0.00011	1.427657	-2.663197	0.006873	-1.037354
17	Hindustan Unilever Ltd.	Consumer Goods	0.000946	0.738624	3.951549	0.006878	0.454731

18	Housing Development Finance Corpn. Ltd.	Financial Services	0.000277	1.195465	2.316378	0.006878	-0.428896
19	I C I C I Bank Ltd.	Banking	0.001722	1.296584	7.520891	0.006876	-0.680626
20	I T C Ltd.	Consumer Goods	0.000570	0.875117	1.886267	0.006879	0.234406
21	Indusind Bank Ltd.	Banking	-0.00005	0.996105	-4.740816	0.006877	0.008192
22	Infosys Ltd.	IT	-0.00171	0.810943	4.016724	0.006861	0.345162
23	J S W Steel Ltd.	Metal	-0.00004	1.254363	-9.270608	0.006876	-0.572846
24	Larsen & Toubro Ltd.	Construction	0.000147	0.971047	3.252225	0.006878	0.057321
25	Mahindra & Mahindra Ltd.	Automobile	-0.00042	1.270933	3.480889	0.006877	-0.614865
26	Maruti Suzuki India Ltd.	Automobile	-0.00121	1.131535	3.722230	0.006877	-0.280005
27	N T P C Ltd.	Energy	-0.00095	0.576316	2.576813	0.006877	0.668413
28	Nestle India Ltd.	Consumer Goods	0.001122	0.737414	4.684179	0.006877	0.456680
29	Power Grid Corpn. Of India Ltd.	Energy	0.000062	0.601397	5.941244	0.006878	0.638647
30	Reliance Industries Ltd.	Energy	0.001714	1.436131	4.015447	0.006877	-1.062135
31	S B I Life Insurance Co. Ltd.	Financial Services	-0.00064	0.380576	-0.149126	0.006877	0.855747
32	Shree Cement Ltd.	Cement	0.000522	1.197259	8.926341	0.006877	-0.433006
33	Sun Pharmaceutical Inds. Ltd.	Pharmaceuticals	-0.00023	0.852824	-4.059587	0.006874	0.273643
34	Tata Consultancy Services Ltd.	IT	-0.00151	0.082899	-0.128842	0.006860	0.996233
35	Tata Consumer Products Ltd.	Consumer Goods	-0.00123	0.974406	1.013972	0.006875	0.051279
36	Tata Steel Ltd.	Metals	-0.00042	1.297916	-1.463358	0.006876	-0.684015
37	Tech Mahindra Ltd.	IT	0.000778	0.703168	2.422805	0.006876	0.506199
38	Titan Company Ltd.	Consumer Durables	0.000770	0.890671	-0.204179	0.006877	0.207194

39	U P L Ltd.	Chemicals	0.000982	1.279864	6.059763	0.006875	-0.637356
40	Ultratech Cement Ltd.	Cement	0.000020	1.145126	19.388433	0.006877	-0.310914
41	Wipro Ltd.	IT	-0.00051	0.395466	-1.188485	0.006874	0.844528

Source: Research Compilation

The securities used in this study are shown in Table 1. Only 41 companies out of 50 on the NIFTY index had complete data. The NIFTY 50 index includes equities from 13 different sectors of the Indian economy, giving investment managers enough exposure to manage all of the stocks in a single portfolio. In addition, Ei denotes the geometric mean return over a year, Bi the beta value, Ci the covariance target, Di the dividend goal, and ε_i^2 the unsystematic risk. For the computation, the aforementioned information was taken from the CMIE Prowess database.

Table 2. Structures of goal programming models

Goal Programming Model Structure								
Goal or Constraint equation	**Optimistic Market Outlook**				**Pessimistic Market Outlook**			
	Growth Portfolio (GP1)		**Income Portfolio (GP2)**		**Growth Portfolio (GP3)**		**Income Portfolio (GP4)**	
	Value	**Priority**	**Value**	**Priority**	**Value**	**Priority**	**Value**	**Priority**
$\sum E_i x_i + n_1^-$	**E_i Max. (0.0020)**	**P_4**	**E_i Max. (0.0020)**	**P_2**	**E_i Max. (0.0020)**	**P_3**	**E_i Max. (0.0020)**	**P_1**
$\sum \beta_i x_i + n_2^- - p_2^+$	**β_i Max. (1.5423)**	**P_2**	**β_i Max. (1.5423)**	**P_1**	**β_i Min. (0.0828)**	**P_4**	**β_i Min. (0.0828)**	**P_3**
$\sum C_i x_i + n_3^- - p_3^+$	**C_i Max. (19.3884)**	**P_3**	**C_i Min. (-9.270)**	**P_3**	**C_i Max. (19.3884)**	**P_2**	**C_i Min. (-9.270)**	**P_4**
$\sum D_i x_i + n_4^- - p_4^+$	**D_i Min. (0.00685)**	**P_1**	**D_i Max. (0.00687)**	**P_4**	**D_i Min. (0.00685)**	**P_1**	**D_i Max. (0.00687)**	**P_2**
$\sum \varepsilon_i^2 x_i + n_5^- - p_5^+$	**ε_i^2 Max. (0.9962)**	**P_1**	**ε_i^2 Min. (-1.3776)**	**P_3**	**ε_i^2 Max. (0.9962)**	**P_3**	**ε_i^2 Min. (-1.3776)**	**P_3**

Investment (Budget)								
$\sum x_i+n_6^- - p_6^+$	**1**	**P_1**	**1**	**P_1**	**1**	**P_1**	**1**	**P_1**
For Industries								
$\sum x_i+n^- - p^+$	**0.250**	**P_1**	**0.250**	**P_1**	**0.250**	**P_1**	**0.250**	**P_1**
Individual Equity								
$x_i+n^- - p^+$	**0.05**	**P_1**	**0.05**	**P_1**	**0.05**	**P_1**	**0.05**	**P_1**

Source: Research Compilation

Table 2 depicts the structure of the goal programming model developed in this study. There are two sets of portfolios, i.e., growth and income, designed in this study. The growth portfolios are for investors who seek to increase their capital through high growth and capital reinvestment levels. On the other hand, income portfolios are for those who seek to earn a constant and consistent income by investing in financial instruments. The developed models are as follows:

Growth portfolio model for optimistic market outlook (GP1): In this model, the positive deviation for dividend goal, negative deviation from unsystematic risk, positive and negative deviation for investment goal, and positive deviation for industry and individual equity diversification goal have all been given top priority. The second priority is to keep the negative deviation from the beta value to a minimum. The third priority is to keep the negative divergence from the covariance goal to a minimum. The goal of minimising the negative deviation from expected return has been given last priority.

$$Min.\ \omega_1\left(n_4^- + p_4^+ + n_5^- + p_5^+ + n_6^- + p_6^+ + \sum_{i=7}^{18} p_i^+ + \sum_{i=19}^{59} p_i^+\right) + \omega_2(n_2^- + p_2^+) + \omega_3(n_3^- + p_3^+) + \omega_4\,(n_1^- + p_1^+) \qquad \text{Equ. 17}$$

Income portfolio model for optimistic market outlook (GP2): In this formulation, maximum priority has been provided to reduce the negative deviation for beta goal, positive and negative deviation for investment goal and positive deviation for industry and individual equity diversification goal. The second aim is to keep the negative deviation from the target expected return value as low as possible. The third priority is to reduce unsystematic risk and positive divergence from the intended covariance goal. The last task is to keep the negative deviation from the dividend goal to a minimum.

$$Min.\ \omega_1\left(n_2^- + p_2^+ + n_6^- + p_6^+ + \sum_{i=7}^{18} p_i^+ + \sum_{i=19}^{59} p_i^+\right) + \omega_2(n_1^- + p_1^+) + \omega_3(n_3^- + p_3^+ + n_5^- + p_5^+) + \omega_4\,(n_4^- + p_4^+) \qquad \text{Equ. 18}$$

Growth portfolio model for pessimistic market outlook (GP3): The goal of minimising positive deviation for dividend goal, positive and negative deviation for investment goal, and positive deviation for industry and individual equity diversification has been given top importance in this formulation. The second aim is to keep the negative deviation from the intended covariance value as low as possible. The third priority is to reduce unsystematic risk and negative departure from the target return goal. The goal of minimising the positive deviation from the beta goal is given last priority.

$$Min.\,\omega_1\left(n_4^- + p_4^+ + n_6^- + p_6^+ + \sum_{i=7}^{18} p_i^+ + \sum_{i=19}^{59} p_i^+\right) + \omega_2(n_3^- + p_3^+) + \omega_3(n_1^- + p_1^+ + n_5^- + p_5^+) + \omega_4\,(n_2^- + p_2^+)$$ **Equ. 19**

Income portfolio model for pessimistic market outlook (GP4): The goal of minimising negative deviation for the return goal, positive and negative deviation for the investment goal, and positive deviation for industry and individual equity diversification has been given top emphasis in this formulation. The second aim is to keep the negative deviation from the desired dividend value as low as possible. The third aim is to reduce unsystematic risk and positive departure from the intended beta value. The goal of minimising the positive deviation from the covariance goal is given last priority.

$$Min.\,\omega_1\left(n_1^- + p_1^+ + n_6^- + p_6^+ + \sum_{i=7}^{18} p_i^+ + \sum_{i=19}^{59} p_i^+\right) + \omega_2(n_4^- + p_4^+) + \omega_3(n_2^- + p_2^+ + n_5^- + p_5^+) + \omega_4\,(n_3^- + p_3^+)$$ **Equ.20**

Table 3: Output Table for 4 Multi-objective Portfolio Selection Algorithms

GOS	GP1		GP2		GP3		GP4	
OV	12.01		9.79		13.52		9.77	
TSI	71		66		76		64	
V	W_i	RC	W_i	RC	W_i	RC	W_i	RC
X1	0.05	-	0.05	-	-	1.04	0.05	-
X2	0.05	-	0.05	-	0.05	-	-	0.06
X3	-	4.18	-	1.99	-	8.08	-	2.48
X4	-	2.81	-	0.66	-	6.47	-	1.10
X5	-	5.46	-	2.65	-	10.46	-	3.20
X6	-	0.079	0.05	-	-	1.82	0.05	-
X7	0.100	-	0.05	-	0.15	-	0.05	-
X8	0.05	-	-	0.47	0.05	-	-	0.72
X9	0.05	-	0.05	-	-	0.57	0.05	-
X10	-	0.65	-	2.03	0.02	-	-	2.26
X11	-	3.30	-	2.55	-	5.08	-	2.84
X12	0.029	-	-	1.33	0.05	-	-	1.53
X13	-	0.089	-	1.17	0.05	-	-	1.41
X14	-	0.075	-	1.28	0.05	-	-	1.51

X15	-	1.01	-	1.25	-	1.91	-	1.58
X16	-	6.35	-	4.10	-	10.59	-	4.67
X17	0.05	-	0.05	-	0.05		0.05	-
X18	-	1.72	-	0.87	-	3.89	-	1.26
X19	0.05	-	0.05	-	-	1.87	0.05	-
X20	-	0.25	-	0.52	-	2.43	-	0.80
X21	-	4.30	-	4.09	-	6.11	-	4.55
X22	0.05	-	0.05	-	0.05	-	0.05	-
X23	-	8.51	-	6.96	-	12.32	-	7.62
X24	0.05	-	0.05	-	-	0.57	-	0.22
X25	-	1.63	-	0.46	-	4.16	-	0.85
X26	-	0.49	0.037	-	-	2.13	-	0.33
X27	0.05	-	-	0.01	0.05	-	-	0.17
X28	0.05	-	0.05	-	0.05	-	0.05	-
X29	0.05	-	0.05	-	0.20	-	0.05	-
X30	-	2.76	-	0.69	-	6.64	-	1.13
X31	0.05	-	-	1.47	0.05	-	-	1.63
X32	-	2.11	-	1.49	-	3.56	-	1.73
X33	-	3.18	-	3.53	-	4.20	-	3.93
X34	0.05	-	-	1.89	0.05	-	-	1.94
X35	-	1.23	-	1.10	-	4.01	-	1.44
X36	-	4.58	-	3.08	-	7.81	-	3.59
X37	0.05	-	-	0.10	0.05	-	-	0.31
X38	-	1.25	-	1.59	-	2.03	-	1.93
X39	-	0.31	0.05	-	-	2.60	0.05	-
X40	0.835	-	0.835	-	0.82	-	0.85	-
X41	-	0.39	-	2.01	0.05	-	-	2.18

Source: Research Compilation

The outcomes of the four multi-objective portfolio selection algorithms given by equations 17 to 20 are shown in Table 3. GOS stands for Global Optimal Solution, OV stands for Objective Value for 4 multi-objective portfolio optimizing algorithms, with lower values indicating higher goal achievement and vice versa. TSI stands for Total Solver Iterations, and V represents, the variables of 41 Nifty securities in the above table. The symbols for stocks range from X1 to X41. Wi represents the weight of each security in the portfolio. Finally, the letter RC stands for "reduced cost." It's only present for stocks that aren't in the portfolio. It also specifies how the portfolio's objective value will rise if that particular security is added.

Table 4: Portfolio optimization under different market Situations

S.No	Optimistic Market Outlook				Pessimistic Market Outlook			
	Growth Portfolio (GP1)		Income Portfolio (GP2)		Growth Portfolio (GP3)		Income Portfolio (GP4)	
	Stock	Weights	Stock	Weights	Stock	Weights	Stock	Weights
1.	Asian Paints Ltd.	**0.05**	Asian Paints Ltd.	**0.05**	Bajaj Auto Ltd.	**0.05**	Asian Paints Ltd.	**0.05**
2	Bajaj Auto Ltd.	**0.05**	Bajaj Auto Ltd.	**0.05**	Britannia Industries Ltd	**0.15**	Bharti Airtel Ltd.	**0.05**
3.	Britannia Industries Ltd.	**0.1**	Bharti Airtel Ltd.	**0.05**	Cipla Ltd.	**0.05**	Britannia Industries Ltd.	**0.05**
4.	Cipla Ltd.	**0.05**	Britannia Industries Ltd.	**0.05**	Dr. Reddy'S Laboratories Ltd.	**0.02**	Divi'S Laboratories Ltd.	**0.05**
5.	Divi'S Laboratories Ltd.	**0.05**	Divi'S Laboratories Ltd.	**0.05**	H C L Technologies Ltd.	**0.05**	Hindustan Unilever Ltd.	**0.05**
6.	H C L Technologies Ltd.	**0.029**	Hindustan Unilever Ltd.	**0.05**	H D F C Bank Ltd.	**0.05**	I C I C I Bank Ltd.	**0.05**

7.	Hindustan Unilever Ltd	**0.05**	I C I C I Bank Ltd.	**0.05**	H D F C Life Insurance Co. Ltd.	**0.05**	Infosys Ltd.	**0.05**
8.	I C I C I Bank Ltd.	**0.05**	Infosys Ltd.	**0.05**	Hindustan Unilever Ltd	**0.05**	Nestle India Ltd.	**0.05**
9.	Infosys Ltd.	**0.05**	Larsen & Toubro Ltd.	**0.05**	Infosys Ltd	**0.05**	Power Grid Corpn. Of India Ltd.	**0.05**
10.	Larsen & Toubro Ltd.	**0.05**	Maruti Suzuki India Ltd.	**0.037**	N T P C Ltd.	**0.05**	U P L Ltd.	**0.05**
11.	N T P C Ltd.	**0.05**	Nestle India Ltd	**0.05**	Nestle India Ltd.	**0.05**	Ultratech Cement Ltd.	**0.05**
12.	Nestle India Ltd.	**0.05**	Power Grid Corpn. Of India Ltd.	**0.05**	Power Grid Corpn. Of India Ltd.	**0.2**		
13.	Power Grid Corpn. Of India Ltd.	**0.05**	U P L Ltd.	**0.05**	S B I Life Insurance Co. Ltd.	**0.05**		
14.	S B I Life Insurance Co. Ltd.	**0.05**	Ultratech Cement Ltd.	**0.835**	Tata Consultancy Services Ltd.	**0.05**		

15.	Tata Consultancy Services Ltd.	**0.05**			Tech Mahindra Ltd.	**0.05**		
16.	Tech Mahindra Ltd.	**0.05**			Ultratech Cement Ltd.	**0.82**		
17.	Ultratech Cement Ltd.	**0.835**			Wipro Ltd.	**0.05**		

Source: Research Compilation

Table 4 represents the proportion of different stocks for portfolio optimization, keeping investors' multiple objectives and constraints in different market outlooks.

1.5 Conclusion

Portfolio managers are increasingly focusing on quantitative investing in order to take advantage of the benefits of diversity while avoiding emotional buy and sell decisions. The purpose of this work is to construct alternate quant portfolios utilising statistical pattern recognition and quantitative value investing with goal programming. Fundamental and technical researches are supplemented by quantitative investment, which strengthens analyst recommendations.

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