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Multi-Choice Goal Programming Approach for Multi-Objective Portfolio Optimization Problem

Aisyah Safiyah Abdul Halim[1], Muhammad Danial Iskandar Nizam[1], Mazura Mokhtar[2,*]
[1]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM) Cawangan Negeri Sembilan, Kampus Seremban, Negeri Sembilan.*
[2]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM) Cawangan Pahang, Kampus Raub, Pahang.*
[*]mazura_mokhtar@uitm.edu.my

Abstract

In real-world investment scenarios, investors tend to make decisions with regard to all the criteria they want including return, risk, and liquidity all together in simple terms to enhance portfolio optimization. In more complex decision-making contexts, they may also have multiple aspirations or preferences associated with these various goals. Thus, the aim of this study is to apply Multi-Choice Goal Programming (MCGP) approach for solving a multi-objective portfolio optimization (MOPO) problem. The model considers three objectives which are maximizing return, minimizing risk and maximizing liquidity. The model also incorporates environmental, social and governance (ESG) constraints alongside other practical constraints, including cardinality, sector, floor and ceiling constraints to reflect real-world investment conditions. Computational experiments were performed to verify and validate the model, using a dataset of 30 companies listed on Bursa Malaysia, which includes monthly return and turnover rates over the period from January 2020 to December 2023. The data was prepared in Excel before being processed in MATLAB2018a. The model was tested across four scenarios to examine the impact of changing priority weight on the solutions. The results show that the MCGP model could generate optimal portfolios that meet the specified target goals. The results also highlight the effectiveness of the MCGP model in providing investors with the flexibility to define their target goals as interval values.

Keywords*:* Goal Programming, Multi-choice Goal Programming, Portfolio Optimization

Introduction

Portfolio optimization is a fundamental concept in finance that involves choosing the best combination of assets to achieve high returns while managing a specific level of risk. Since high returns are typically associated with high risk, investors often diversify their investments across multiple assets to reduce overall portfolio risk. This optimization process uses mathematical models to determine the most optimal or efficient asset allocation. The benefits include improved portfolio performance, enhanced returns through allocation synergies, and reduced risk through diversification.

The foundation of portfolio optimization was laid by Harry Markowitz in 1952 with the introduction of the Mean-Variance model, marking the beginning of Modern Portfolio Theory (MPT) [1]. This model formulates asset allocation as a quadratic programming problem which aims to maximize return and minimize risk. However, solving such problems for large portfolios can be extremely difficult. To address this, several researchers such as Sharpe [2] and Speranza [3] proposed linear programming (LP) approximations of the model. Although the LP approximation simplifies computations, these models are limited to a single objective, which only focuses on optimizing the risk-return trade-off, while real-world investment decisions often involve multiple conflicting objectives.

To accommodate more complex investor preferences, Goal Programming (GP) has emerged as an effective approach for handling multi-objective portfolio optimization problems since it allows for the inclusion of multiple goals, offering flexibility. However, the use of fixed target levels in this model can be restrictive when multiple acceptable outcomes exist. Therefore, to overcome this limitation, this study adopts the Multi-Choice Goal Programming (MCGP) model introduced by Chang [4] to solve the multi-objective portfolio optimization problem. This model enhances traditional GP by allowing multiple aspiration levels for each goal, making it more adaptable to real-world portfolio management scenarios that involve diverse and conflicting objectives.

Literature Review

Multi-Choice Goal Programming (MCGP) is a mathematical optimization approach that improves upon traditional Goal Programming (GP). While traditional GP focuses on achieving a single target for each goal, the primary aim of MCGP is to address complex decision-making scenarios in which decision-makers (DMs) may have multiple aspirations or choices associated with various goals. The concept of MCGP was first introduced by Chang [5] and has since been further developed to facilitate decision-making in uncertain environments.

One significant advantage of MCGP is its ability to allow DMs to express their preferences more accurately by assigning multiple aspiration levels to each goal. This flexibility enables the integration of diverse goals into a single optimization framework [6], making it particularly suitable for multi-objective optimization problems where trade-offs are necessary [7]. Moreover, MCGP effectively addresses uncertainties in decision-making environments by providing a structured approach to incorporating uncertainty through multi-choice parameters. For instance, stochastic elements can be integrated into the programming model, allowing organizations to optimize their decisions under varying conditions. This capability is particularly beneficial in fields such as supply chain management and project portfolio optimization [8-9].

MCGP has been widely applied across various sectors to solve complex and multi-objective decision-making problems. In the project portfolio management, Zhai et al. [10] demonstrated the use of MCGP in improving decision-making by analyzing project interactions. In the supply chain and logistic sector, Rosyidi et al. [11] applied MCGP for supplier and carrier selection, incorporating corporate social responsibility (CSR) considerations. Similarly, Jadhav et al. [12] used it to develop a decision support system aimed at reducing risks and improving customer satisfaction.

In agriculture, MCGP has supported crop and resources optimization such as crop planning, livestock management, and environment adaptation. A study by Mohd Nawawi et al. [13] focused on maximizing crop yield under resource constraints, while Silva [9] applied a revised MCGP model for planning sugarcane harvests. In healthcare, Attari et al. [14] used MCGP to reduce costs and meet patient demands by minimizing blood product waste. Hezam et al. [15] explored sustainable resource allocation in hospitals through a neutrophilic goal programming model.

The education and finance sectors have also benefited from MCGP. For example, Zuhanda et al. [16] optimized educational program costs and profit targets. In finance, Das et al. [17] used MCGP to manage limited investment resources across goals such as retirement and education. Kamil et al. [18] applied MCGP for Islamic banking resource allocation in line with Shariah principles. Alam [19] built a financial planning model for the case of Saudi Basic Industries Corporation (SABIC) to minimize expenses and maximize profit, while Sharma et al. [20] developed a loan allocation model with sensitivity analysis.

In summary, MCGP has proven to be a flexible and effective approach in addressing multi-objective problems across sectors such as healthcare, agriculture, supply chain, education and finance. Its ability to accommodate multiple aspiration levels makes it a valuable tool for realistic and practical decision-making in both public and private sectors.

Methodology

The methodology of this study consisted of three stages. Stage 1 focused on formulating the Multi-Objective Portfolio Optimization (MOPO) model through four steps. First, data collection was carried out using a dataset of 30 stocks traded in Bursa Malaysia. It included the average monthly return and turnover rates from January 2020 to December 2023, as well as Environmental, Social, and Governance (ESG) scores for each stock in 2023, all obtained from the *Eikon Refinitiv* platform. Secondly, the identification of parameters and decision variables was conducted, forming the basis for MOPO model formulation. Third, the model's constraints were established. This study considered five constraints such as ESG, floor and ceiling, class, cardinality, and budget constraints. Lastly, the objective functions of the portfolio were defined, which include maximizing return, minimizing risk, and maximizing liquidity.

Stage 2 involved formulating the MCGP model to solve the MOPO problem. In this stage, the MOPO model obtained from stage 1 was transformed into a single objective problem using the MCGP approach proposed by Chang [4]. This stage consisted of two steps. The first step is to convert the objective function of the model into goal constraints by assigning positive and negative deviation variables to each objective function. Second, the achievement function of the model was constructed by minimizing the unwanted deviation variable for each goal, ensuring the model prioritizes the closest possible attainment of each target goal. According to Chang [4], for '*the more, the better*' target goal, the MCGP-achievement can be formulated as follows:

$$\text{Minimize} \quad \sum_{i=1}^{m}\left[w_i\left(d_i^+ + d_i^-\right) + \alpha_i\left(e_i^+ + e_i^-\right)\right] \tag{1}$$

subject to,

$$f_i(X) - d_i^+ + d_i^- = y_i \qquad i = 1, 2, \ldots, n \tag{2}$$

$$y_i - e_i^+ + e_i^- = g_{i,\max} \qquad i = 1, 2, \ldots, n \tag{3}$$

$$g_{i,\min} \leq y_i \leq g_{i,\max} \tag{4}$$

$$d_i^+, d_i^-, e_i^+, e_i^- \geq 0 \qquad i = 1, 2, \ldots, n \tag{5}$$

$$X \in F$$

For the case of '*the less, the better',* the MCGP-achievement is formulated as

$$\text{Minimize} \qquad \sum_{i=1}^{m} \left[w_i \left(d_i^+ + d_i^- \right) + \alpha_i \left(e_i^+ + e_i^- \right) \right] \tag{6}$$

subject to,

$$f_i(X) - d_i^+ + d_i^- = y_i \qquad i = 1, 2, \ldots, n \tag{7}$$

$$y_i - e_i^+ + e_i^- = g_{i,\min} \qquad i = 1, 2, \ldots, n \tag{8}$$

$$g_{i,\min} \leq y_i \leq g_{i,\max} \tag{9}$$

$$d_i^+, d_i^-, e_i^+, e_i^- \geq 0 \qquad i = 1, 2, \ldots, n \tag{10}$$

$$X \in F$$

where $g_{i,\min}$ and $g_{i,\max}$ are the upper and lower bounds, respectively for the i-th aspiration level y_i, while $f_i(X)$ is the linear function of $x_1, x_2, \ldots, x_n$ for i-th goal. d_i^+ and d_i^- are the positive and negative deviations attached to the i-th goal, $\left| f_i(X) - y_i \right|$ in Eq. 2 and Eq. 7, respectively. e_i^+ and e_i^- are the positive and negative deviations attached to $\left| y_i - g_{i,\max} \right|$ and $\left| y_i - g_{i,\min} \right|$. w_i and α_i are the weights attached to the sum of the deviations, while F is a feasible set.

The last stage, Stage 3, focused on the validation of the MCGP model, which involved conducting computational experiments and sensitivity analysis. Computational experiments were carried out for imaginary investors using a real dataset and implemented in MATLAB 2018a software. A sensitivity analysis was performed to identify the changes in parameters that affect the results of the model. The model was tested by changing the cardinality parameters or number of selected stocks in the portfolio to observe how the changes influence the model's outcomes and overall portfolio performance.

The Multi-Objective Portfolio Optimization (MOPO) Model

To describe the multi-objective portfolio optimization model conveniently, all the index, parameters, and decision variables used in this study are listed as follows:

Index

i : Index for each stock $(i = 1, 2, \ldots, n)$

Parameters

e_i	:	The ESG score of the i-th stock
ε_i	:	The minimum proportion of budget that can be invested in stock i
δ_i	:	The maximum proportion of budget that can be invested in stock i
L_m	:	The lower proportion limit for class m
U_m	:	The upper proportion limit for class m
C_m	:	Mutually exclusive sets of stocks $(m = 1, 2, \ldots, M)$
r_i	:	The expected rate of return of stock i
r_{it}	:	The actual rate of return determined from the historical data $(t = 1, 2, \ldots, T)$
l_i	:	The liquidity or the turnover rate of stock i
P_t	:	The unbounded variables to represent the realizations of the portfolio return under the scenario t
E	:	The required total ESG score
k	:	The number of stocks held in the portfolio

Decision variables

x_i	The proportion of stock i in the portfolio
z_i	The binary variable which takes value 1 if stock i is selected in the portfolio, 0 otherwise

Thus, the multi-objective portfolio optimization model is formulated as follows:

$$\text{Maximize} \quad R(x) = \sum_{i=1}^{n} r_i x_i \tag{11}$$

$$\text{Minimize} \quad S(x) = \frac{1}{T}\sum_{t=1}^{T} P_t \tag{12}$$

$$\text{Maximize} \quad L(x) = \sum_{i=1}^{n} l_i x_i \tag{13}$$

subject to,

$$\sum_{i=1}^{n} e_i x_i \geq E \tag{14}$$

$$\varepsilon_i z_i \leq x_i \leq \delta_i z_i \qquad i = 1, 2, \ldots, n \tag{15}$$

$$L_m \leq \sum_{i \in C_m} x_i \leq U_m \qquad m = 1, 2, \ldots, M \tag{16}$$

$$\sum_{i=1}^{n} z_i = k \tag{17}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{18}$$

$$P_t \geq -\sum_{i=1}^{n} (r_{it} - r_i) x_i \qquad t = 1, 2, \ldots, T \tag{19}$$

$$P_t \geq 0 \qquad t = 1, 2, \ldots, T \tag{20}$$

$$z_i \in \{0, 1\} \qquad i = 1, 2, \ldots, n \tag{21}$$

$$x_i \geq 0 \qquad i = 1, 2, \ldots, n \tag{22}$$

In the above model, Eq. 11 denotes the objective function that intends to maximize the portfolio return. Eq. 12 minimizes the portfolio risk while Eq. 13 maximizes the portfolio liquidity. Constraint (14) requires limiting investment in companies with poor environmental, social and governance practices. Constraint (15) determines the minimum and maximum bounds of any stock that can be included in a portfolio. Constraint (16) keeps the portfolio well diversified by limiting total number of stocks in a particular class or sector. Constraint (17) is the cardinality constraints which limit the number of stocks in a portfolio. Constraint (18) ensures the total weight of the portfolio remains equal to 1 as limiting the invested money among all stocks. Constraints (19) and (20) are the mean semi-absolute deviation to measure how much the portfolio performs either overperforms or underperforms. Constraint (21) is the binary variable, while constraint (22) is the non-negative constraint.

The Multi-Choice Goal Programming (MCGP) Model

The MOPO model was solved by transforming the model into a single objective problem using the MCGP approach proposed by Chang [4]. The model is as follows:

$$\text{Minimize} \quad w_1 d_1^- + w_2 d_2^+ + w_3 d_3^- + e_1^+ + e_1^- + e_2^+ + e_2^- + e_3^+ - e_3^- \tag{23}$$

subject to,

$$\sum_{i=1}^{n} r_i x_i - d_1^+ + d_1^- = y_1 \tag{24}$$

$$y_1 - e_1^+ + e_1^- = g_{1,\max} \text{ for } |y_1 - g_{1,\max}| \tag{25}$$

$$g_{1,\min} \leq y_1 \leq g_{1,\max} \text{ for bound of } y_1 \tag{26}$$

$$\frac{1}{T}\sum_{t=1}^{T} P_t - d_2^+ + d_2^- = y_2 \tag{27}$$

$$y_2 - e_2^+ + e_2^- = g_{2,\min} \text{ for } |y_2 - g_{2,\min}| \tag{28}$$

$$g_{2,\min} \le y_2 \le g_{2,\max} \text{ for bound of } y_2 \tag{29}$$

$$\sum_{i=1}^{n} l_i x_i - d_3^+ + d_3^- = y_3 \tag{30}$$

$$y_3 - e_3^+ + e_3^- = g_{3,\max} \text{ for } \left| y_3 - g_{3,\max} \right| \tag{31}$$

$$g_{3,\min} \le y_3 \le g_{3,\max} \text{ for bound of } y_3 \tag{32}$$

$$d_1^+, d_1^-, d_2^+, d_2^-, d_3^+, d_3^-, e_1^+, e_1^-, e_2^+, e_2^-, e_3^+, e_3^- \ge 0 \tag{33}$$

Constraints (14) – (22)

In the above model, Eq. 23 denotes the formulation model of the MCGP achievement function. Constraints (24) until (26) are the conversion of portfolio return into goal constraints by adding positive and negative deviations, aspiration level of the goal, and lower and upper bounds. Constraints (27) to (29) formalize the transformation of portfolio risk into goal constraints by incorporating upper and lower bounds relative to the aspiration level, along with corresponding positive and negative deviation variables. Constraints (30) to (32) represent the transformation of the objective function aimed at maximizing portfolio liquidity into a set of goal constraints, while constraint (33) is the non-negative constraint.

Results and Discussion

In the computational experiments, the number of selected stocks was fixed at eight as selecting too few or an excessively large number of stocks is generally not recommended due to its adverse impact on portfolio diversification. The maximum and minimum proportion of budget that can be invested in each selected stock are 30% and 5% respectively. The upper bound and lower bound for consumer sector were set at 40% and 20%, respectively. Meanwhile, the upper bound for energy sector, industrial sector and property products were at 30%, 40% and 30% each. As for the healthcare sector, the minimum proportion of budget that could be invested was 10%. The value for the ESG score parameter is 60% and lastly, the number of periods is 48. The upper bound and lower bound values for each goal are presented in Table 1 below.

Table 1. The value of lower bound and upper bound for each goal

Goal	Parameter	Symbol	Value
Return	Upper bound	$g_{1,max}$	0.05
	Lower bound	$g_{1,min}$	0.01
Risk	Upper bound	$g_{2,max}$	0.03
	Lower bound	$g_{2,min}$	0.003
Liquidity	Upper bound	$g_{3,max}$	0.5
	Lower bound	$g_{3,,min}$	0.1

To explore the impact of changing the weight of the goals on the solution, four runs of the MCGP were performed, each time with different weight as shown in Table 2. Each run produced an optimal portfolio.

Table 2. The weight assigned to return, risk and liquidity goals

Run	Return	Risk	Liquidity
Run 1 (Portfolio 1)	0.5	0.3	0.2
Run 2 (Portfolio 2)	0.7	0.2	0.1
Run 3 (Portfolio 3)	0.3	0.5	0.2
Run 4 (Portfolio 4)	0.3	0.2	0.5

Table 3 presents a comparison of the optimal values obtained for each run. Portfolio 1 produced the best optimal values of 0.0218 for return, 0.0292 for risk, and 0.1238 for liquidity. For Portfolio 2, the best optimal values were 0.0239 for return, 0.0279 for risk, and 0.1125 for liquidity. Portfolio 3 yielded the best optimal values of 0.0209 for return, 0.0274 for risk, and 0.1213 for liquidity. Portfolio 4 resulted in optimal values of 0.0200 for return, 0.0316 for risk, and 0.1285 for liquidity. Portfolio 2 achieved the highest optimal value for return, attributable to the greater weight assigned to this goal. The lowest value for risk goal was obtained in Portfolio 3, as this portfolio assigned a higher weight for risk goal. As for the liquidity, the highest value was achieved in Portfolio 4 since this portfolio assigned the highest weight for liquidity. Thus, it can be concluded that changing priority weight of the goals gives effect on the optimal solutions of the MCGP model.

Table 3: The comparison of optimal value for all portfolios.

Goal	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Return	0.0218	0.0239	0.0209	0.0200
Risk	0.0292	0.0279	0.0274	0.0316
Liquidity	0.1238	0.1125	0.1213	0.1285

Table 4 presents the results of sensitivity analysis. Reducing the number of selected stocks, k from 8 to 6 causes a slight decrease in the portfolio return but resulting in a greater portfolio risk and liquidity. This may be due to the limited number of stocks with high returns that can be selected in the portfolio. However, when k increased from 8 to 10, the portfolio returns slightly increased while risk and liquidity are decreased. This indicates that the portfolio with 10 stocks performed better than with 6 and 8 stocks, since it gave the highest return and the lowest risk.

Table 5 shows the optimal value for Portfolio 2 when the number of selected stocks is changing. A similar result as Portfolio 1 was obtained for Portfolio 2. When k decreased from 8 to 6, portfolio return slightly decreased, while risk and liquidity increased. Next, when k increased from 8 to 10, the return increased, and both risk and liquidity decreased. It was also found that, a portfolio with 10 stocks performed better compared to 6 and 8 stocks because it gives high return and the lowest risk.

Table 4: The comparison of optimal value for portfolio 1 in different selected number of stocks

Number of selected stocks (k)	Portfolio 1		
	Return	Risk	Liquidity
6	0.0211	0.0311	0.1352
8	0.0218	0.0292	0.1238
10	0.0222	0.0270	0.1103

Table 5: The comparison of optimal value for portfolio 2 in different selected number of stocks.

Number of Selected stocks (k)	Portfolio 2		
	Return	Risk	Liquidity
6	0.0233	0.0286	0.1237
8	0.0239	0.0279	0.1125
10	0.0235	0.0257	0.1016

Meanwhile, in Table 6, the results pattern for Portfolio 3 is different from Portfolios 1 and 2. When k decreased from 8 to 6, the optimal values for return, risk and liquidity all increased. In contrast, when k increased from 8 to 10, the value for return, risk and liquidity all decreased. Thus, a portfolio with 10 stocks performed better than 6 and 8 because it gives the lowest risk value.

Table 6: The comparison of optimal value for portfolio 3 in different selected number of stocks.

Number of selected stocks (k)	Portfolio 3		
	Return	Risk	Liquidity
6	0.0212	0.0283	0.1285
8	0.0209	0.0274	0.1213
10	0.0208	0.0256	0.1103

Based on Table 7, when k decreased from 8 to 6, the optimal values for all goals increased. However, when k increased from 8 to 10, the portfolio return is increased while risk and liquidity are decreased. Thus, a portfolio which consists of 6 stocks performed better compared to 8 and 10 because the optimal solution gives the highest value of liquidity and return.

Table 7: The comparison of optimal value for portfolio 4 in different selected number of stocks.

Number of selected stocks (k)	Portfolio 4		
	Return	Risk	Liquidity
6	0.0210	0.0323	0.1364
8	0.0120	0.0316	0.1285
10	0.0176	0.0313	0.1202

Conclusion and Recommendation

This study has formulated a model for multi-objective portfolio optimization problem by considering three objectives which are maximizing portfolio's return, minimizing portfolio's risk and maximizing portfolio's liquidity. Several real-life constraints such as cardinality constraint, sector constraint as well as floor and ceiling constraints were also considered, thus adding to the realism of the model. The model was verified and validated using real data. The results from computational experiments have verified that the MCGP models could be used for generating a set of more realistic and flexible optimal solution in solving multi-objective portfolio optimization problem. However, a few recommendations need to be highlighted for future research to get a better result. The first recommendation is to consider a larger number of stocks, which is hundreds or thousands of stocks, instead of 30 stocks. Having a broader number of stocks will improve diversification and provide a more comprehensive representation of real market situations. In addition, including other real-life constraints such as minimum transaction lot instead of proportion reflects the real-life trading situation.

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