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Portfolio Optimization of FTSE Bursa Malaysia KLCI Using Genetic Algorithm

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Abstract
The purpose of this study is to investigate the application of genetic algorithm (GA) in Portfolio Optimization. Portfolio optimization is an important problem in financial decision-making since it aims to create an optimal investment portfolio that maximizes returns while minimizing risks. Traditional portfolio optimization methods frequently rely on mathematical models that assume ideal market circumstances and linear correlations, which may not fully reflect the complexities of real-world financial markets. Genetic algorithms (GAs), which are inspired by natural selection and genetic principles, have emerged as a viable technique for portfolio optimization, providing a more flexible and adaptive approach. This paper provides an overview of how genetic algorithms are used in portfolio optimization. The data consists of daily open price, daily highest price, daily lowest price, daily closing price, daily volume that is in the range from 1 January 2021 to 1 Jan 2023. 30 stocks in the FTSE Malaysia KLCI (KLSE) are considered in the portfolio to determine the optimize. The genetic algorithm-based technique makes use of a population of prospective portfolios, represented as chromosomes, that are repeatedly evolved using genetic operators like selection, crossover, and mutation. The fitness evaluation is done using established parameters such as risk, return, and other portfolio-specific constraints. The advantage of genetic algorithms in portfolio optimization lie in their capacity to handle non-linear connections, huge search areas, and a variety of constraints. The algorithm's inherent ability to explore numerous alternatives concurrently and resolve on the optimal portfolio increases its performance even further. The results obtained in this study were investigated and interpreted. Based on the results, it shows the weightage for each stock in order for the portfolio to be optimized. The values of the fitness function are increasing exponentially which indicate that the portfolio is optimized. Even though the returns obtained may not be the highest, but it decreases the risks and uncertainty of the stocks.

Keywords: Portfolio Optimization; Genetic Algorithm; Returns and Risks; Stocks.

1. Introduction

The Malaysian economy is stable, with a favorable business environment, infrastructure, and skilled workforce, making it an attractive investment destination. Foreign Direct Investment (FDI) into Malaysia increased to RM48.1 billion in 2021 from RM13.3 billion the previous year, driven by higher equity and investment fund shares. FDI reached RM788.8 billion by the end of 2021. High FDI has a positive impact on economic growth, leading to increased GDP and access to advanced technologies. A strong economy boosts corporate earnings and stock prices, creating wealth and optimism among investors and consumers.

Malaysia's economy has consistently grown since the 1990s, fueled by global demand for electronics and commodities like oil and gas. Factors such as a robust labor market, favorable investment conditions, and infrastructure spending have contributed to this strong performance. Despite challenges posed by the pandemic and a government crisis in 2021, the Malaysian economy is now on a recovery path. Stable labor market conditions and reduced inflation are expected to support growth in 2023, according to Malaysian Industrial Development Finance (MIDF) Research. The International Monetary Fund (IMF) has raised the GDP forecast for ASEAN-5 countries, including Malaysia, indicating positive prospects for long-term investment in Malaysia.

Investing allows individuals to grow their wealth by putting their money to work. It involves diversifying investments across stocks, bonds, real estate, or mutual funds, which can yield returns that outpace inflation and provide passive income through dividends, interest, or rent. The power of compounding further enhances wealth accumulation over time. Investing also safeguards against uncertainty by spreading risks and reducing exposure to market volatility. It supports personal aspirations such as starting a business, funding education, or planning for retirement. Ultimately, investing offers financial independence, stability, and the fulfillment of long-term goals. In summary, investing is crucial as it enables wealth growth, generates passive income, hedges against inflation, helps achieve financial goals, manages risks, and promotes independence. By recognizing these benefits and making informed choices, individuals can secure their financial future and create opportunities for themselves.

The global economy has experienced significant structural transformations due to factors like technological innovation, urbanization, resource scarcity, and demographic shifts. Recognizing these macro-level themes is essential for investors to capitalize on future trends and identify promising investment opportunities. There are 11 major stock market sectors, including Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Healthcare, Financials, Information Technology, Communication Services, Utilities, and Real Estate. Understanding structural transformations is vital for financing and investment, enabling businesses, policymakers, and individuals to engage in long-term planning. With knowledge of the underlying drivers of change, stakeholders can make strategic decisions that align with the evolving economic landscape. This applies to investment decisions, company strategies, and policy creation, allowing proactive responses to new challenges and opportunities. Structural transformations in the global economy can introduce new risks or alter existing ones, such as changes in demographics or consumer preferences. By staying updated on these changes, investors can adjust their portfolios and risk management approaches to mitigate potential risks and maximize returns.

Investors need to carefully plan their portfolios to maximize profits while minimizing risks in stocks, bonds, or mutual funds. Portfolio Optimization is a method that helps select the best portfolio based on specific objectives, typically aiming to maximize expected returns while minimizing costs and financial risks. This approach is crucial for investors and banks, allowing them to make informed decisions on allocating their financial resources and assets. Risk management is one of the primary objectives of portfolio optimization. Banks can strategically diversify their assets across different asset classes, geographical locations, and sectors, reducing the risk associated with specific investments by spreading it across a wider variety of assets. This diversification helps mitigate the impact of underperforming or challenging investments on the overall portfolio. Additionally, portfolio optimization enables banks to assess risk-return trade-offs. It allows risk managers to analyze the relationship between potential gains and risk levels, helping them make informed decisions about the trade-offs they are willing to accept and align their investment strategies with their risk tolerance.

2. Literature Review

2.1 Types of Financial Analysis

2.1.1 Fundamental Analysis (FA)

Fundamental analysis involves assessing the intrinsic value of a financial asset by analyzing economic and financial factors. This process entails studying financial statements, earnings reports, industry trends, management quality, competitive advantages, macroeconomic indicators, and market conditions. The focus is on examining factors such as the company's balance sheet, debt, operational performance, and growth prospects. By evaluating this data, one can determine whether the stock market price of a company is undervalued or overvalued [1]. The objective of fundamental analysis is to identify assets that are either undervalued or overvalued, allowing investors to make informed investment decisions based on their underlying value.

2.1.2 Technical Analysis (TA)

Technical analysis involves analyzing the historical price and volume data of a financial asset to predict its future price movements. It revolves around market trends and patterns, examining past pricing behavior to identify patterns that may recur in the future. This analysis helps determine optimal times to buy or sell an asset. It typically employs pictorial patterns, mathematical algorithms, and statistical research [1]. Unlike fundamental analysis, which considers underlying fundamental factors, technical analysis primarily focuses on price movements and market psychology that can provide insights into market trends and potential opportunities.

2.2 Portfolio Optimization

Portfolio optimization has become increasingly important in both practical and academic finance as quantitative asset management has grown in popularity. A portfolio is defined in financial literature as an appropriate collection of investments held by an individual or a financial institution. These investments or financial assets include company stock, government bonds, fixed income securities, commodities, derivatives, mutual funds, and a variety of mathematically complex and business-driven financial instruments. The idea is to allocate a certain amount of capital over different of assets to form a portfolio. Selecting the weights of assets to invest in a portfolio as to meet the expectations about risk and return makes this problem more crucial. To tackle this problem, Harry Markowitz developed a quantitative model called the mean-variance model in 1959 [2]. Markowitz argued that for optimal investment, an efficient portfolio is essential. His portfolio theory aimed to achieve a balance between risk and expected return, seeking to minimize risk while maximizing the potential benefits for each investment. By utilizing Markowitz's mean-variance model, investors can construct portfolios that offer the lowest possible risk for a given expected return or maximize the benefits while minimizing risk for each investment.

2.3 Markowitz Mean-Variance Model

Mean-Variance (MV) portfolio optimization has been a prominent research area in finance since Markowitz introduced the theory in 1952. The theory suggests that portfolio optimizers can address investment uncertainty by selecting portfolios that maximize profits while attaining a predetermined level of calculated risk or, alternatively, minimizing variance while achieving a predetermined level of expected return [2, 3]. By employing MV portfolio optimization, investors can strategically construct portfolios that strike a balance between maximizing returns and managing risk based on their desired risk-return trade-off.

2.4 Sharpe Ratio

The mean-variance framework provides a basis for various optimization approaches aimed at achieving specific investment goals, such as maximizing the Sharpe ratio, achieving optimal diversification, or minimizing variance. The Sharpe ratio, proposed by Sharpe, combines the objectives of maximizing expected return and minimizing risk into a single financial measure. It is calculated as the average return of an investment portfolio minus the risk-free rate, divided by the portfolio's volatility [4]. A higher Sharpe ratio indicates better performance for a stock, implying a higher expected return relative to the additional volatility introduced by holding a risk-free asset. Conversely, a lower Sharpe ratio suggests poorer risk-adjusted performance. By considering the Sharpe ratio, investors can evaluate and compare investment opportunities based on their risk-adjusted returns.

2.5 Sortino Ratio

The Sortino Ratio is a financial metric that measures the risk-adjusted return of an investment or portfolio. It is similar to the more commonly known Sharpe ratio. However, while the Sharpe ratio evaluates the volatility of overall returns (or standard deviation), the Sortino ratio specifically focuses on downside volatility, which refers to the volatility of negative returns or downward deviation. By emphasizing downside volatility, the Sortino ratio provides a more comprehensive assessment of an investment's performance [5]. It calculates the excess return per unit of downside risk and penalizes downside volatility more than upward volatility. This ratio is particularly valuable for risk-averse investors as it quantifies the risk associated with losses by considering downside deviation instead of total volatility.

2.6 Efficient Frontier

The efficient frontier is a fundamental concept in modern portfolio theory (MPT) that aims to optimize the risk-return balance in investment portfolios. It depicts the combinations of assets that offer the best expected return for a given level of risk or the lowest level of risk for a given expected return [6]. To construct the efficient frontier, different assets are combined into portfolios with varying risk-return characteristics. Each portfolio's projected return and risk are calculated, and these data points are plotted on a graph to create the efficient frontier curve. This curve showcases the optimal portfolios that offer the highest expected return for a specific level of risk or the lowest expected risk for a given level of return. The shape and position of the efficient frontier depend on factors such as asset selection, expected returns, and correlations. By analyzing the efficient frontier, investors can gain insights into the risk-return trade-off when designing portfolios.

2.7 Methods for Portfolio Optimization

2.7.1 Genetic Algorithm (GA)

In the 1960s and 1970s, John Holland and his colleagues introduced the genetic algorithm (GA), which is a computational model inspired by Charles Darwin's theory of natural selection. Holland was among the pioneers who applied the principles of crossover and recombination, mutation, and selection to the study of adaptive and artificial systems. These genetic operators form essential components of the genetic algorithm, which serves as a problem-solving approach. Since its inception, numerous variants of the genetic algorithm have been developed and applied to a wide range of optimization problems. These applications span diverse domains, including graph coloring, pattern recognition, discrete systems like the traveling salesman problem, continuous systems like aerospace engineering for efficient airfoil design, financial markets, and multi-objective engineering optimization [7]. Genetic algorithms have proven successful in tackling real-world problems and have demonstrated superior search efficiency compared to traditional optimization methods in many instances. They offer a viable solution for complex financial problems that require efficient and robust optimization techniques. Some practical applications of genetic algorithms in financial markets include return forecasting, portfolio optimization, discovery and optimization of trading rules, and addressing complex challenges [8].

2.7.2 Differential Evolution (DE)

The differential evolution algorithm was introduced by Rainer Storn and Kenneth Price, both American academics, in 1997 [9]. Inspired by Darwin's theory of biological evolution and the concepts of natural selection and survival of the fittest, it is an optimization method that mimics the mechanisms of genetic and evolutionary processes. The differential evolution algorithm operates based on swarm intelligence and is categorized as a population-search-based meta-heuristic technique. It has gained popularity across various industries due to its notable characteristics of robustness, fast convergence, and ease of implementation. The algorithm follows four main steps: population initialization, mutation, crossover, and selection [10]. This approach has proven to be effective in addressing a wide range of optimization problems and has become a preferred choice in the field.

2.7.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a metaheuristic algorithm inspired by natural systems, originally proposed by James Kennedy and Russell Eberhart in 1995 [11]. It operates by simulating a swarm of particles that exchange information among their neighbors to search for the best solution. PSO has found applications in various fields, including structural design, control systems, and power distribution optimization. In computer science, PSO has been utilized for tasks like data mining, machine learning, and optimizing neural networks. Furthermore, PSO has proven useful in operations research for solving combinatorial optimization problems and resource allocation. Its effectiveness has also been demonstrated in economics and finance for portfolio optimization and risk control. Additionally, PSO has been employed in image and signal processing tasks such as picture reconstruction and denoising. Its versatility extends to bioinformatics, renewable energy optimization, healthcare, traffic and transportation, and numerous other sectors, making it a valuable tool for addressing a wide range of optimization challenges.

2.7.4 Simulated Annealing (SA)

Simulated Annealing (SA) is a metaheuristic optimization technique that was developed by Scott Kirkpatrick, Daniel Gelatt, and Mario Vecchi in 1983. It draws inspiration from the process of metallurgical annealing and aims to find optimal solutions by iteratively exploring the solution space. The SA algorithm follows a series of steps, including initialization, perturbation, evaluation, acceptance, and iteration, until a termination criterion is met [12]. One of the key features of simulated annealing is its ability to overcome local optima. Unlike other optimization methods that strictly pursue improving solutions, SA occasionally accepts inferior solutions, allowing for exploration of a broader range of the solution space. As the algorithm progresses, the acceptance of suboptimal alternatives decreases, leading to convergence towards a near-optimal solution. This approach provides a balance between exploration and exploitation, making simulated annealing an effective tool for solving optimization problems.

2.7.5 Modern Portfolio Theory (MPT)

Modern Portfolio Theory (MPT), developed by Harry Markowitz, is widely employed in the investment industry as a valuable tool. MPT, along with risk-reward analysis, aids investors in assessing assets consistently and identifying portfolios that minimize risk while maximizing expected returns [2]. In essence, Modern Portfolio Theory provides a structured framework for optimizing portfolios by considering historical performance, risk measures, and the benefits of diversification across different assets. By constructing efficient frontiers and optimizing portfolio allocations, investors can aim to achieve the most favorable balance between risk and return according to their individual preferences. MPT offers a systematic approach to portfolio optimization, facilitating informed decision-making and potentially enhancing investment outcomes.

2.7.6 Harmony Search Algorithm (HSA)

The Harmony Search Algorithm (HSA) is a metaheuristic algorithm introduced by Geem et al. that aims to optimize mathematical functions and engineering problems [13]. This algorithm has demonstrated successful applications in various engineering disciplines, including civil, mechanical, electrical, and chemical engineering, for tasks such as optimal design and scheduling. In the realm of computer science, HSA has been utilized for data mining, machine learning, and image processing tasks such as feature selection and classification. Operations research benefits from HSA in the areas of combinatorial optimization and supply chain management. In economics and finance, HSA is valuable for portfolio optimization and risk management. Additionally, HSA finds application in renewable energy, bioinformatics, telecommunications, healthcare, and other fields. Its versatility makes it a powerful tool for addressing optimization challenges across diverse sectors. The algorithm mimics the process of musical improvisation as it searches for optimal solutions to optimization problems.

2.7.7 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) was first proposed in the early 1990s by Marco Dorigo, an Italian computer scientist. Inspired by the foraging behavior of ants, Dorigo and his colleagues developed the algorithm, and its first publication appeared in 1991 [14]. Initially introduced as a solution to the traveling salesman problem, a classic optimization problem in computer science, ACO has gained significant attention and has been widely studied and applied. Over the years, researchers in the field have developed various extensions and modifications to enhance the algorithm's performance. Marco Dorigo's contributions to ACO have greatly influenced the field of swarm intelligence and optimization algorithms as a whole.

3. Research Methodology

3.1 Data and Sources

The data of FTSE Bursa Malaysia KLCI (KLSE) are collected by using finance.yahoo.com. It consists of 30 major stocks in the KLSE. The historical prices are ranged from 1 Jan 2021 to 1 Jan 2023. The collected data is based on daily Open price, Highest price, Lowest price, Closing price, Adjusted Closing price, Volume of trades.

3.2 Mathematical Formulation for Portfolio Optimization

3.2.1 The Daily Return for each stock is computed as below [15]:

$$R = \frac{P_{t+1}}{P_t} - 1$$

where,
R denotes the daily return on a stock
P_{t+1} denotes the closing price for the day
P_t denotes the closing price for the previous day

3.2.2 The covariance between stocks is calculated as below:

$$cov_{x.y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{N - 1}$$

where,
x_i denotes the data value of x
$\bar{x}$ denotes the mean of x
y_i denotes the data value of y
$\bar{y}$ denotes the mean of y
N denotes the number of data values

3.2.3 The Mathematical Model are proposed as below [16]:

The expected return, $(E(w_i))$ of the individual assets i is presented as a polynomial of first degree:

$$E(w_i) = w_i \, . r_i$$

where,
w_i denotes the weight of the individual asset i
r_i denotes the expected return of asset i

The total expected return, r_w of the portfolio can be written as:

$$r_w = \sum_{i=1}^{n} w_i r_i$$

where n denotes the number of assets.
The downside values of the variance, σ_w of an asset's returns over time are used to define its risk:

$$\sigma_w = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}$$

where,
$\sigma_{ii} = \sigma_i^2$ denotes the variance of r_i
σ_{ij} denotes the covariance between r_i and r_j

3.2.4 Fitness Function Development

The fitness function which is also the objective function of the Portfolio is presented below: [17]

$$fitness = \frac{r_w}{\sigma_w}$$

$$= \frac{\sum_{i=1}^{n} w_i r_i}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}}$$

Given the constraint in the model:

$$\sum_{i=1}^{n} w_i = 1$$

$$0 \leq w_i \leq 1$$

The weights of the assets must be positive and must be less than 1. Also, the sum of the weight is exactly equal to 1.

3.3 Formulation in Genetic Algorithm

3.3.1 Initialization

The process of producing an initial population of individuals or solutions for the algorithm to operate with is referred to as initialization. The technique we using for this paper is Random Initialization where individuals are generated randomly without specifying any criteria. Each chromosome is produced by randomly assigning values to its genes within a predetermined range of possible values. The values we assigning here is the weightage of each stocks.

It's also vital that we have to identify our parameters used in this problem such as the population size, the number of generations, crossover and mutation rates.

Population size = 50
Number of generations = 100
Crossover probability = 0.5
Mutation rate = 0.01

3.3.2 Population Initialization

After computing all the mean returns and covariance of each stocks, we will assign the weights randomly for each chromosome (stocks) where the minimum weight is 0 and the maximum weight is 1. To ensure a completely invested portfolio, the sum of all weights should be equal to 1. Therefore, we will normalize the weights by using the formula below:

$$w_i = \frac{w_r}{\sum_{i=0}^{n} w_r}$$

where,
w_i denotes the weight of the individual asset i
w_r denotes the weight assigned randomly
$\sum_{i=0}^{n} w_r$ denotes the summation of weights assigned randomly

3.3.3 Fitness Evaluation

The fitness values are utilized to govern individual selection, reproduction, and evolution in succeeding generations. We have our fitness function here as defined previously:

$$fitness = \frac{r_w}{\sigma_w}$$

$$= \frac{\sum_{i=1}^{n} w_i r_i}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}}$$

The fitness function here considers 2 objectives which is maximizing the return and minimizing the risk. The fitness function receives as input the individual's features or properties, which is its chromosome(stock) with the gene values(weights) computed.

3.3.4 Selection, Reproduction, Mutation

In this paper, the selection method chosen is by Tournament Selection. It is similar to a tournament-style competition in which members of the population compete against one another and the winners are chosen as parents for the following generation. The number of individuals (tournament size) that will be participate in each tournament is determined which is 2.

After that, we will go through reproduction method which is Crossover. Here, we use a binary crossover, which is also known as a one-point crossover. A random crossover point is chosen in binary crossover, and the genetic material (genes) from the parents are exchanged at that time to form an offspring. The crossover probability we have mentioned is 0.5.

Next, the portfolio will undergo Mutation. Mutation generates random changes in an individual's genetic material. As we have set the mutation rate as 0.01. By iterating through each asset in the portfolio, we apply a function that generates a random number between 0 and 1.

3.3.5 Termination

From our parameters, the stopping criterion for this problem is based on the maximum number of generations set which is 100. The algorithm will keep evolving the population and producing new generations until the maximum number of generations has been reached.

4. Results and Discussion

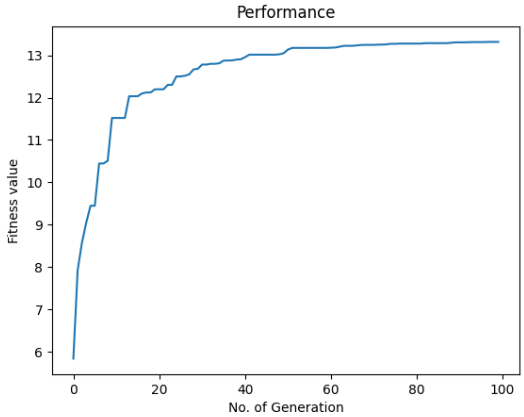
4.1 Descriptive Analysis

Table 4.1 Average Returns of each stock

AMMB Holdings Bhd	0.000544
Axiata Group Bhd	-0.000049
CIMB Group Holdings Bhd	0.000885
Dialog Group Bhd	-0.000442
Digi.com Bhd	0.000243
Genting Bhd	0.000384
Genting Malaysia Bhd	0.000292
Hong Leong Bank Bhd	0.000377
Hong Leong Financial Group Bhd	0.000224
IHH Healthcare Bhd	0.000370
Inari Amertron Bhd	0.000290
IOI Corp Bhd	0.000072
Kuala Lumpur Kepong Bhd	0.000142
Malayan Banking Bhd	0.000418
Maxis Bhd	-0.000278
MISC Bhd	0.000500
Mr D.I.Y. Group (M) Bhd	0.000122
Nestle Malaysia Bhd	0.000135
Petronas Chemicals Group Bhd	0.000667
Petronas Dagangan Bhd	0.000451
Petronas Gas Bhd	0.000185
PPB Group Bhd	0.000030
Press Metal Aluminium Holdings Bhd	0.000575
Public Bank Bhd	0.000348
QL Resources Bhd	-0.000028
RHB Bank Bhd	0.000426
Sime Darby Bhd	0.000250
Sime Darby Plantation Bhd	0.000304
Telekom Malaysia Bhd	0.000217
Tenaga Nasional Bhd	0.000104

This is the results of mean return of every stock obtained from 1 Jan 2021 to 1 Jan 2023. In financial analysis, the average rate of return is used to measure for assessing the stock's historical performance and to estimate its potential future returns.

4.2 Genetic Algorithm Analysis



From the figure above, we can observe that the values are increasing exponentially towards an optimal. In the initial stages, the fitness value increases relative quickly as the algorithm iterates and searches the solution space and identifies better locations.

Table 4.2 Weightage Allocations to each stock

AMMB Holdings Bhd	0.002114
Axiata Group Bhd	0.000781
CIMB Group Holdings Bhd	0.074032
Dialog Group Bhd	0.000666
Digi.com Bhd	0.000504
Genting Bhd	0.121020
Genting Malaysia Bhd	0.002558
Hong Leong Bank Bhd	0.111807
Hong Leong Financial Group Bhd	0.002681
IHH Healthcare Bhd	0.038556
Inari Amertron Bhd	0.000568
IOI Corp Bhd	0.003352
Kuala Lumpur Kepong Bhd	0.003429
Malayan Banking Bhd	0.267201
Maxis Bhd	0.000168
MISC Bhd	0.091564
Mr D.I.Y. Group (M) Bhd	0.003846
Nestle Malaysia Bhd	0.159534
Petronas Chemicals Group Bhd	0.064806
Petronas Dagangan Bhd	0.003064
Petronas Gas Bhd	0.025950
PPB Group Bhd	0.001218
Press Metal Aluminium Holdings Bhd	0.003330
Public Bank Bhd	0.001750
QL Resources Bhd	0.002299
RHB Bank Bhd	0.007213

Sime Darby Bhd	0.002760
Sime Darby Plantation Bhd	0.001524
Telekom Malaysia Bhd	0.000066
Tenaga Nasional Bhd	0.001637

The above table illustrates the weightages allocations to each stock in the FTSE Malaysia KLCI Index Stock Prices. These weightage allocations represent the optimal distribution of investing among the 30 stocks in KLCI to maximize the portfolio's expected return while considering the risk tolerance and investment goals.

Conclusion

In conclusion, in the world of investment research, genetic algorithms have emerged as a potential tool for portfolio optimization. To handle difficult allocation problems, this optimization technique draws inspiration from natural selection and evolution principles. Genetic algorithms provide a strong optimization framework for portfolio allocation, allowing researchers and practitioners to build diverse and efficient investment portfolios. Their ability to manage complicated associations and react to changing market situations makes them useful tools in portfolio optimization.

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