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A Mean-Variance Approach to Portfolio Optimisation for Effective Stock Selection in the Malaysian Stock Market

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Abstract

Optimization of portfolio selection is very important for overall financial engineering performance. Recent developments in portfolio selection have been developed by many researchers. However, many studies show that prediction with manual models is not enough to achieve highly accurate predictions and prosperous returns. In this paper, a novel portfolio construction approach is developed using the mean-variance (MV) model and maximizing the Sharpe ratio for selecting the best portfolio. The approach model is by choosing the best ratio from the comparison between optimal return and annual standard deviation. Experimental data was taken from the Malaysian Stock Exchange from 2014 to 2020, from several securities the ten most active securities were selected. The purpose of this study is to assist investors in verifying the Malaysian stock market to reduce risk and maximize returns. The results of the study show that the ratio of the optimal return and the annual standard deviation is 0.711. These results are obtained from a comparison between the optimal return of 33.96% and the annual standard deviation of 47.73%. The proposed model by maximizing the comparison between the optimal return and the annual standard deviation can be used to support portfolio selection decisions. The results showed that the efficiency limits of the selected stocks and optimal portfolio weights could be achieved.

1. Introduction

At present, the Malaysian stock market is one of the largest bourse stock exchanges companies in Asia with 925 listed companies. The Malaysian stock market offers two dynamic markets as Main Market and ACE Market to companies that seeking listing in the stock market. The main markets consist of 789 companies which for established companies to raise funds. In contrast, the ACE Market consists of 130 companies that perform as sponsor-driven for those companies with potential growth in all business sectors (Mohd Norsiman, Yakob, and Jr 2019; Pertiwi, Yusuf, and Efrilianda 2022).

This study focuses on the analysis of a portfolio that comprises a variety of investment options. One of the ways that investors make money is through investing. One of the key reasons why people invest is to increase their income or value. The Malaysian stock market's ambiguity presented difficulties for investors. According to investment theory, a stock or financial asset is bought with the hope that it may one day produce income at a better profit margin. In this regard, a variety of mathematical and financial models are available for analysing the finest stocks that offer the best value on the stock market.

The purpose of this research is to find portfolios that best meet less riskiness and more profits (Burbano-Figueroa et al. 2022). Portfolio Optimisation is one of the most effective models that is being used by most investors to select the most effective stocks from the stock market. Portfolio optimisation was introduced by Harry Markowitz is the combination of probability theory and optimisation theory which are to model the behaviour of economic agents (Lejarraga and Pindard-Lejarraga 2020). Besides, Harry Markowitz also been awarded the Nobel Prize for his most influential contributions to creating Modern Portfolio Theory concepts (Kan, 2017).

Portfolio optimisation is one of the techniques used to guide investors in selecting investments from the stock exchange of Malaysia which is from the Malaysian stock market (Jumanto et al. 2022). The Malaysian stock market belongs to an emerging market in which the market will be volatile, and the market environment will be different over time. Through this study, investors can identify the demonstrating and applications of constructing minimum variance or optimal risk or by customised the portfolio based on their target return and risks (Muslim et al. 2023). This research is to minimise the risk and maximise the profits of investors from investing in the stock market so that the expected return must be achieved (Lejarraga and Pindard-Lejarraga 2020).

To conduct this research 10 most active stocks from different sectors have been selected to find out the future performance by using the past 5 years' data from 2014 to 2019. Expected return, variance, standard deviation, covariance and correlation, Sharpe ratio, and efficient frontier analysis have been used to calculate, analyse, and find out the best portfolio to select from the 10 most active stocks from the Malaysian stock market (Fai, Siew, and Hoe 2022; Khan et al. 2020; Tan and Kek 2020). Furthermore, this research will further explain Markowitz mean-variance model, linear programming models, Sharpe ratio analysis, and efficient frontier model.

Portfolio theory is initially formulated by economist Harry Markowitz (Ling and Chia 2016). Portfolio measures the benefits of diversification and analyse how risk-averse investors build portfolios to optimise return against market risk and expected return (Yeter and Garbatov 2021). Portfolio optimisation was one of the most significant research areas in modern finance theory (Leow, Nguyen, and Chua 2021). In the other term, portfolio optimisation is also known as risk management. In recent years, many experts on portfolio decision-making such as (Kalayci, Ertenlice, and Akbay 2019; Li et al. 2022; Tan and Kek 2020) have been attracted by how to obtain the optimal solution for portfolio allocation (Chen et al. 2021; Wang and Zhou 2020). Hence, to obtain the risk or return model, which to maximising the profit or minimising the cost of portfolio optimisation based on the of mean-variance (MV) analysis. Mean-variance (MV) analysis is a mathematical framework that in part of portfolio optimisation (Klman, and Sivalingam, 2010). In the other term, mean-variance (MV) analysis is referred to as Modern Portfolio Theory (MPT). Mean-variance (MV) analysis is one of the most influential portfolio management theories being used in investments and stock markets (Lejarraga and Pindard-Lejarraga 2020). Harry Markowitz has received the most valuable Nobel Prize for his pioneering contributions to Portfolio theory (Kan, 2017). Mean-variance (MV) analysis plays a crucial part in how to contract portfolios based on the expected performance of investments (Kan, 2017).

Portfolio optimisation is one of the major keys for investors to formulate a portfolio profitable and secure investment. The main criterion of having a well-structured portfolio is related to the risk diversification concept which is depicted as “not putting all eggs into a basket”. In the modern days of investing, investors are exposed to an abundance of information. Investors can use secondary data to forecast the stock market by using various models. Besides, investors may face the situation with a lack of information and exposure on selecting the best stocks and rely on information from news, newspapers, and websites as the Malaysian stock market and Yahoo Finance. Sometimes, this information does not help with their stock acquisition because the stock price will always vary in every second. These situations will lead the investors to invest in unworthy investments which are riskier or not profitable investments (Mohd Norsiman, Yakob, and Jr 2019). Furthermore, some investors invest and focus on specified stocks. If they find certain stocks will lead to profit and they just invest all their money, there. Eventually, it might be a bad decision because if the selected stocks run in loss and the investor might lose all his invested money. As a result, investing in one asset is riskier. In this case, investors should diversify their stock selections. Through diversification, investors can reduce the unsystematic risks in their portfolios. By diversifying in selecting stocks, investors can reduce the risk and the chance of maximising their profit is higher. In this study, various stocks are selected, and the stocks have also been selected from different sectors.

Moreover, the main focus of this research is to study the performance of the stocks from the selected market in the Malaysian stock market to help investors overcome their problems in investing in stock markets. It is suggested to use any mathematical or financial model that will provide accurate and statistical information to overcome these situations. One of the well-proven models that can be suggested and widely used by investments across the world is portfolio optimisation. Portfolio optimisation by using Markowitz mean-variance with linear programming model is one of the models that can be used by investors to identify the future performance of any selected stocks.

To examine the performance of the stocks in Malaysia, it is crucial to build an ideal portfolio because stock markets play a significant role in a nation's economic growth and development. This study tries to create the ideal portfolio in the Malaysian stock market using a mean-variance Markowitz with a linear programming model to optimisation technique that may produce the desired return with the least amount of risk and is one of the models that can be used by investors to identify the future performance of each selected stock.

2. Literature Review

This section explains further the history of portfolio theory then followed by, the concept of the mean-variance model, constructing a portfolio model based on mean-variance, linear programming model, Sharpe ratio, and efficient frontier model.

Generally, the mean-variance model formulated as a probability distribution of return on investment is classified as the return by means of the expected value. However, the variance of return is classified as the risk of investments (Lejarraga and Pindard-Lejarraga 2020). The mean-variance model portfolio optimisation is a forecasted model of portfolio analysis. According to Pedersen et al. (2021), portfolio optimisation is derived as a process of constructing a portfolio that should give the maximum possible expected return for a specified level of risk. Sharpe emphasise on basic concept too which a logical investor would prefer to invest in an investment that offers maximum expected return in relation to risk.

The Sharpe ratio was constructed by Sharpe (1964). He has also been awarded the Nobel Prize for his findings. Sharpe ratios help investors to understand well on the investment relative to its risk. The ratio measures the average return gained above the risk-free rate per unit of the overall risk. The Sharpe ratio is one of the most effective performance measures. Sharpe ratio depicts the risk-reward ratio that measures the correlation between standard deviation and mean. More specifically, the risk in the Sharpe ratio will be measured by the standard deviation (Ling and Chia 2016). Most of the investors will prefer to invest in an asset that offers the highest return and low risk. An optimal risky portfolio will maximise the Sharpe ratio.

The efficient frontier is a graph that helps the investor to find out the optimal portfolios that can offer better value according to investors' preferences. It can offer the highest expected return that can reach the maximum given level of risk or offer the lowest risk for the given level. Furthermore, portfolios that lie away from the efficient frontier line will be considered as not providing enough return for the optimal risk (Ta, Liu, and Tadesse 2020).

In brief, the literature review is based on the research done by previous researchers and will be used as a reference to enhance the process in this study. It is important to go through other researcher works to get a better understanding and to identify the proper research methods that can be used to collect relevant data and appropriately conduct the research.

Kurtosis has gained importance over the past few decades when choosing a portfolio (Naqvi et al. 2017) and its inclusion is emphasised when choosing and improving a portfolio. A portfolio selection becomes non-convex when kurtosis and skewness are present (Kellner, Lienland, and Utz 2019). After higher-order moments are taken into account, the non-convex feature allows for the achievement of a number of goals, such as maximising returns and positive skewness while simultaneously decreasing variance and skewness. Studies in the past have employed the mean-variance approach to reduce the complexity of the quadratic function (Fai, Siew, and Hoe 2022; Khan et al. 2020; Tan and Kek 2020). Finance literature has evolved several strategies throughout the years to address difficult problems (Juszczuk et al. 2020). These techniques include evolutionary experimental setting algorithm approaches or non-parametric efficiency measures (Sajith et al. 2019).

3. Method

This chapter discussed the research methodology that is being used in this study. Research methodology is an essential method that should be used in conducting research. A fundamental part that focuses on this section is based on how to construct a portfolio based on the expected performance of each stock. In this chapter, the appropriate methods or models that need to be used to construct an optimal portfolio are discussed.

3.1 Data Description

This research focuses on the Malaysian stock market which is Malaysian stock market. For the evaluation purpose, the 10 most active diversified stocks from different sectors have been selected from energy, plantation, technology, financial services, consumer products & services, telecommunications & media.

The weighted of the securities can be obtained by solving optimisation problems that based on targeted preference (Marakbi 2016). Moreover, the model and data analysis can be calculated using Microsoft Excel. The selected data can be shown in Table 1.

Table 1 *Selected data of most active assets in Bursa Saham, Malaysia*

	Malaysian stock market code	Name of the company	Sector
1	AIRASIA (5099)	Airasia Group Bhd	Consumer Products & Services
2	SAPNRG (5218)	Sapura Energy Berhad	Energy
3	DSONIC (5216)	Datasonic Group Bhd	Technology
4	MYEG (0138)	My E.G. Services Bhd	Technology
5	AEONCR (5139)	Aeon Credit Service (M) Berhad	Financial Services
6	VELESTO (5243)	Velesto Energy Berhad	Energy
7	GPACKET (0082)	Green Packet Bhd	Telecommunications & Media
8	ARMADA (5210)	Bumi Armada Bhd	Energy
9	RSAWIT (5113)	Rimbunan Sawit Berhad	Plantation
10	HIBISCS (5199)	Hibiscus Petroleum Berhad	Energy

3.2 X

To conduct the portfolio optimisation several computations will be conducted. At first stage mean-variance analysis will be conducted which depicts expected return (mean) and risk (variance) as given below. Expected Return (ER) define by

$$ER = \sum_{i=1}^{n} (R_i \ , P_i) \tag{1}$$

Variance ( ) and standard deviation ( ) be calculated as follows.

$$\sigma^2 \ = \sum_{i=1}^{n} \frac{\big(R_i - E(R_i)\big)^2}{n-1} \tag{2}$$

Where Ri is the return on the i[th] security, Pi is the probability of return on the i[th] security, $E(R_i)$ represents the mean of stock, n is the number of stocks. and σ2. If larger the variance for the expected return is, then the larger the dispersion for the expected return, and as a correlation the risk of the investment also will be greater. The same concept applies to smaller variances in the other way around. The standard deviation (σ) is as standard deviation which is depicted as the square root of variance. The standard deviation is used to measure the overall riskiness of stocks. If the fluctuation of an asset return is higher than the mean or the average return over a certain period, the standard deviation will be higher. Consequently, the investments will be riskier (Yusof, 1997).

Coefficient of Covariance (CoV), the portfolio risk is determined through covariance and correlation of the stocks within the portfolio. Each stock has a certain yield over a specified period and a tendency to vary over the year. Moreover, this type of risk is not just the average of individual security risk. To determine the portfolio risk, it is important to take note of the interrelationships between returns which is known as covariances (Norsiman et al., 2019). The covariance is the degree of calculation at which two variables move in contrast to their relative individual mean value. A negative covariance indicates that the rate of return for two investments tend to move in opposite direction while positive covariance indicates that the rates of return continue to move in the linear direction. However, if the value is zero, it indicates that there is no linear relation between the rates of return for two assets. The covariance is defined as follows.

$$COV_{ij} = \sum \frac{(R_i - E(R)_j)(R_j - E(R)_j)}{N-1} \tag{3}$$

Correlation is a measure which specifies to what degree the movements of two variables are correlated with. The correlation coefficient varies from -1 to +1. A perfect negative correlation indicates as -1 while a perfect positive correlation indicates as +1 (Mohd Norsiman, Yakob, and Jr 2019). The correlation coefficient is determined by.

$$P_{ij} = \frac{Cov(R_i, R_j)}{\sigma_i \sigma_j} \tag{4}$$

Therefore, in general term Markowitz derived the standard deviation of a portfolio as below:

$$\sigma_{port} = \sqrt{\sum_{i=1}^{n} Wi^2\, \sigma_i^2 + \sum_{i=1}^{n} . \sum_{j=1}^{n} W_i W_j COV_{ij}} \tag{5}$$

where σ_{port} is the portfolio standard deviation, W_i is the weight of the individual asset in the portfolio, σ_i^2 is the variance of the rates of return of asset i and COV_{ij} is the covariance matrix between the rates of return of assets (security) i and j. $COV_{ij} = \rho_{ij}\sigma_i\sigma_j$

The equation (5) indicates that the standard deviation depends on the variances in the portfolio of the individual assets and covariances between all the assets in the portfolio. The larger the portfolio, then the more impact to the covariance on the portfolio risk whereas the lower the effect on the individual variance.

Suppose that the return of asset i which is ri at the time t. The return on a portfolio Xi (i = 1, 2,...,N) at the time t is defined by

$$R_t = \sum_{i=1}^{N} r_{it}\, X_i \tag{6}$$

3.3 Linear Proframming Portofolio

Some portfolio analysis problems can be reduced to linear or parametric Linear Programming problems. Maximising the expected return is subject to linear constraints, such as the initially expected return and the variance of the return on calculating the efficient set of the portfolio.

Formulation of the Linear Programming (LP) Model (Oladejo, Abolarinwa, and Salawu 2020), can be shown in equation (7):

$$\begin{aligned} &Optimize:\quad f(x) \\ &Subject\ to:\ \left.\begin{array}{ll} g_i(x) \le b_i, & 1 \le i \le p \\ g_i(x) = b_i, & p+1 \le i \le k \\ g_i(x) \ge b_i, & k+1 \le i \le n \end{array}\right\} \end{aligned} \tag{7}$$

Where $f(x)$ is the objective function of vector variable $x = (x_1, x_2, \dots, x_n)^T$ represents the measure of the effectiveness of a decision. Then, $g_i(x)\ (1 \le i \le m)$ is the constraint function of x. The variable $x_j\ (j = 1, 2, \dots, n)$ is the activity level associated with the decision-making problem. The term $b_i(1 \le i \le m)$ represents the upper or lower limit of the i^{th} constraint functions. Constraints $x \ge 0$ restrict the decision variables $x_j\ (j = 1, 2, \dots, n)$ to non-negative real numbers.

Since the objective and constraint functions are linear, they are precisely defined in the equations (8) and (9).

$$f(x) = c_1x_1 + c_2x_2 + \cdots c_nx_n = \sum_{j=1}^{n} c_jx_j, \tag{8}$$

$$g_i(x) = a_{i1}x_1 + a_{i2}x_2 + \cdots a_{in}x_n = \sum_{j=1}^{n} a_{ij}x_j. \tag{9}$$

From equations (8) and (9), we then write the linear programming in equations (10) and (11):

$$Optimize:\quad Z = \sum_{j=1}^{n} c_jx_j, \tag{10}$$

$$Subject\ to: \left.\begin{array}{l} \sum_{j=1}^{n} a_{ij}x_j, \quad 1 \le i \le p \\ \sum_{j=1}^{n} a_{ij}x_j, \; p+1 \le i \le k \\ \sum_{j=1}^{n} a_{ij}x_j, \quad k+1 \le i \le n \\ x_j \le 0, \quad 1 \le j \le n \end{array}\right\} \tag{11}$$

Where a_{ij} and c_j are called technological and cost coefficients, respectively. b_i is the main parameter of the models. Equation (12) and (13) can be shown in the forms of the matrix:

$$Optimize: \quad Z = C^T x, \qquad Subject\ to: \left.\begin{array}{l} Ax \le b \\ x \ge 0 \\ C = (c_1 c_2, \ldots, c_n)\ T \end{array}\right\}, \tag{12}$$

Defined K as a feasible set where $K = \{x \in R^n : Ax = b, \quad x \ge 0\}$. If $x \in K$ or if x satisfies $Ax = b$ and $x \ge 0$, then x is a feasible solution. Let $C^T x$ be the objective function of a LP to be maximized. $x \in K$ is an optimal solution (maxima) if for all $y \in K$, then $C^T x > C^T y$. Let x be a basic solution of $Ax = b$. If $x \ge 0$, then it is called a basic feasible solution (BFS).

4. Result and Discussion

This paper presents data analysis and the portfolio optimisation process using mean-variance approach with linear programming in the Malaysian stock market. The mean-variance, standard deviation, sharpe ratio and data analysis conducted using Microsoft Excel. Next, 6 portfolios will be constructed based on target return.

The historic price from selected stocks from Malaysian stock market used to compute the future performance in term of risk and return (Marakbi 2016). Average monthly market close price (1st January 2014 to 30th September 2020) collected for the selected 10 stocks (Airasia, Datasonic, MyEG, Green Packet, Bumi Armada, Rimbunan Sawit, Aeon Credit, Sapura Energy, Velesto Energy Berhad and Hibiscus Petroleum Berhad).

The computation conducted to find out the most optimum portfolio to be invested. For the first step, a target set as maximum return at 10% for Portfolio A. Then the cycle continues with maximum return at 20% (Portfolio B), 30% (Portfolio C), 40% (Portfolio E) and the peak possible maximum at 46.26% (Portfolio F). Moreover, the computation repeated to get an optimum portfolio by set target by optimising the Sharpe ratio (Portfolio D). The results are shown in the following Table 2.

Table 2 *Results of portfolio optimisation*

Portfolio	Portfolio A Max R, 10%	Portfolio B Max R, 20%	Portfolio C Max R, 30%	Portfolio D Max Sharpe Ratio	Portfolio E Max R, 40%	Portfolio F Peak Max R, 46.26%
AIRASIA	0.59%	0.00%	0.74%	0.00%	0.00%	0.00%
DSONIC	0.00%	0.00%	11.71%	18.28%	56.19%	100.00%
MYEG	66.77%	75.39%	78.07%	77.87%	43.81%	0.00%
GPACKET	0.00%	3.61%	4.29%	3.85%	0.00%	0.00%
ARMADA	3.49%	2.50%	0.80%	0.00%	0.00%	0.00%
RSAWIT	1.33%	2.84%	0.71%	0.00%	0.00%	0.00%
AEONCR	0.00%	1.95%	0.59%	0.00%	0.00%	0.00%
SAPNRG	14.68%	5.92%	1.25%	0.00%	0.00%	0.00%
VELESTO	13.14%	5.45%	1.19%	0.00%	0.00%	0.00%
HIBISCS	0.00%	2.34%	0.64%	0.00%	0.00%	0.00%
Σw	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Monthly Return	0.8333%	1.6667%	2.5000%	2.8303%	3.3333%	3.8550%
Annual Return	10.0000%	19.9999%	29.9999%	33.9637%	40.0000%	46.2602%

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Variance	0.01271	0.01384	0.01661	0.01899	0.04292	0.11138
Monthly Std Dev	11.2747%	11.7624%	12.8864%	13.7790%	20.7174%	33.3735%
Annual Std Dev	39.0567%	40.7462%	44.6397%	47.7317%	71.7670%	115.6092%
Risk-free Rate	5%	5%	5%	5%	5%	5%
Sharpe Ratio	0.12802	0.36813	0.56004	0.60680	0.48769	0.35689

Based on Table 2 above, at the first stage of optimisation, the risk-free rate was set to 5% which is an average risk-free rate for the Malaysian market. Consequently, all the portfolios have been computed with their weight, mean, standard deviation, variance, and Sharpe ratio.

Portfolio A has been set targeted maximum return of 10%. After computation, it has a low annual standard deviation of 39.06% which is the lowest standard deviation obtained compared with other portfolios. The variance obtained from portfolio A is at 0.01271 and the Sharpe ratio is 0.12802. Portfolio B resulted in a maximum target return of 20% with 40.7462% of annual standard deviation and the variance and Sharpe ratio are at 0.01384 and 0.3681 respectively. Portfolio C with a targeted maximum return of 30% contributed annual standard deviation of 44.64%, variance at 0.0166 and Sharpe ratio of 0.56004 attained. Furthermore, for Portfolio E has set a target maximum return of 40%. Portfolio E had a high annual standard deviation of 71.77%. The variance is at 0.04292 and the Sharpe ratio of 0.4877. Next, Portfolio F is the peak possible maximum target return which is at 46.26%. this is the riskiest return which solely investing in Datasonic. The standard deviation for Portfolio F is 115.61% which is the largest annual standard deviation compared with other portfolios. The variance is 0.11138 and the Sharpe ratio is 0.3569. Nevertheless, to get the most effective and optimum result maximising the Sharpe ratio will be the efficient option. By maximising the Sharpe ratio in portfolio D, the return is at 33.96% and the standard deviation is 47.73%. The variance for portfolio D is 0.1899 and the Sharpe ratio achieved at 0.6068.

Lastly, after computing 6 sets of portfolios, the result can be used to determine the most effective portfolio that investors can invest in the future. The portfolio frontier will give a clearer picture of the difference between computing portfolios based on specific target return with optimising with the Sharpe ratio.

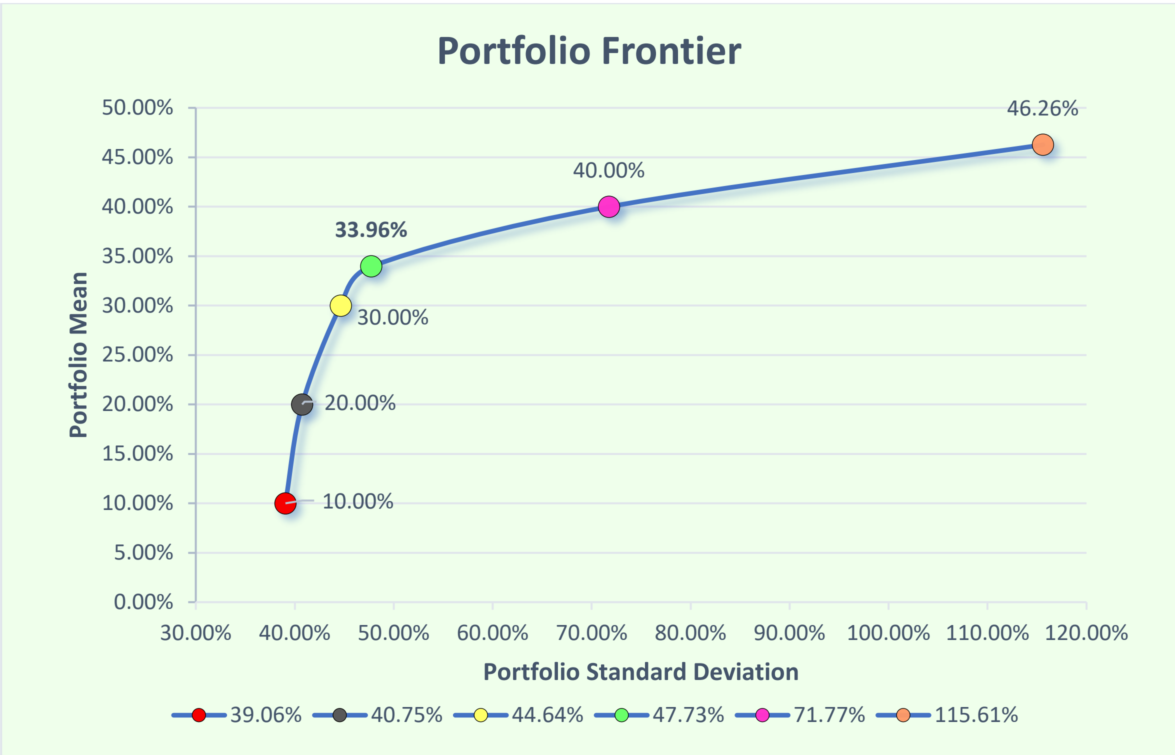

Fig. 1 *Efficient frontier graph*

An efficient frontier will be constructed to outline all the risk and return combinations available for the investors (Kan 2018). The portfolios that lie on the efficient frontier line will be considered efficient and will generate maximum expected return and the same risk. The portfolio away from the line will be considered less efficient.

Moreover, based on the analysis conducted, the portfolio frontier will give a clearer picture of the difference between computing portfolios based on specific target returns and optimising with the Sharpe ratio. Therefore, referring to the efficient frontier graph in Fig. 1, it is shown that Portfolio A, Portfolio B, Portfolio C, Portfolio E, and Portfolio F are not an effective portfolio to invest. At first, Portfolio A is an inefficient portfolio as it gives lower risk and returns at 39.06% of risk at a given 10% of return. Even though it is a less risky portfolio, most of investors are not interested in selecting this portfolio as the return is too low. Moreover, Portfolio B is also an inefficient portfolio as its risk level is at 40.75% for a targeted return of 20%. Meanwhile, Portfolio C is equally inefficient to Portfolio A and B as it also resulted in higher risk at 44.64% for a given 30% of return. Portfolios A, B, and C are inefficient for investors for a target return and the risk-taking level is quite underwhelming. However, Portfolios A, B, and C can be well suited for risk-averse investors who wish for a lower level of risk for their investments. This type of portfolio mostly will attract new or non-experienced and less expert investors. This is because, Portfolio A, Portfolio B, and Portfolio C are well-diversified portfolios. By choosing this, the investors can invest in many stocks. A well-diversified stock doesn't correlate with each other as it is selected from different sectors. A more diversified portfolio will lead to less risky investments. However, a well-diversified portfolio doesn't lead to a huge return on investment. Hence, risk-averse investors will select portfolios from the low left end in the efficient frontier graph.

On the contrary, Portfolio E and Portfolio F are an efficient portfolio to be recommended for risk tolerance investors. Based on the graph above, Portfolio E resulted in high risk at 71.77% for a target maximum return of 40%. Meanwhile, Portfolio F gives the highest risk at 115.61% for a maximum return tolerance of 46.26%. Notably, with the diversification of all the 10 selected stocks, the maximum return tolerance for investors is at 46.26%. Therefore, Portfolio E and Portfolio F are well recommended for risk-tolerance investors that willing to take a high risk to attain the highest return possible. This type of portfolio will attract investors who well experience and expertise in investing in the stock market. However, high-risk and return portfolios don't focus on the diversification of stocks. These portfolios will suggest investing in the most-performing stocks. Thus, risk-tolerance investors will choose portfolios that lie on the top right end of the efficient frontier line.

Moreover, in investment theory, most investors won't go with too little return or too high degree of risk portfolios. Most of the investors will go after an optimal portfolio that leads to the efficient amount of return with the amount of the risk taken. Therefore, in this case where Markowitz optimal portfolio theory will be well executed accordingly. Based on the graph, computing using the Sharpe ratio will lead to an optimal portfolio with well optimised between risk and return. Sharpe ratio computed with Portfolio D which with an optimal return of 33.96% and with a standard deviation of 47.73% only. The value of Sharpe's obtain here is the highest at 0.5798. Compared with other portfolios such as Portfolio A, Portfolio B, Portfolio C, Portfolio E, and Portfolio F it is visible that the other portfolio is not optimised well with its given risk and return. Hence, both the Sharpe ratio and efficient frontier depict that Portfolio D is superior compared with others as it gives the maximum rate of return for the level of given risk or a minimum risk for the level of given return.

Table 3 *Weight to be invested in Portfolio D*

Portfolio D	
Stocks	**Weights**
AIRASIA	0.00%
DSONIC	18.28%
MYEG	77.87%
GPACKET	3.85%
ARMADA	0.00%
RSAWIT	0.00%
AEONCR	0.00%
SAPNRG	0.00%
VELESTO	0.00%
HIBISCS	0.00%
∑w	100.00%

After optimising with the Sharpe ratio, the composition for Portfolio D can be obtained. It is shown that some of the stocks (Airasia, Armada, Rimbunan Sawit. Aeon Credits, Sapura Energy, Velesto, and Hibiscus) have 0% weight. This means that these stocks are excluded from the portfolio. Hence, the total number of stocks that can be invested is reduced to 3 stocks which are Datasonic, MyEG and Green Packet. Therefore, investors who want to invest in an optimised portfolio can invest in Portfolio D. Investors can invest 18.28% in Datasonic, 77.87% in MyEG, and 3.85% in Green Packet. In addition, the result in Sharpe ratio is presented in the following table.

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Table 4 *Sharpe ratio*

Portfolio	Sharpe Ratio
Portfolio A	0.128019
Portfolio B	0.368130
Portfolio C	0.560037
Portfolio D	0.606802
Portfolio E	0.487689
Portfolio F	0.356894

According to Markowitz portfolio theory, portfolio optimisation by using mean-variance and linear program with Sharpe ratio model will be the effective way to compute and optimise a portfolio (Kan, 2017). Besides that, Sharpe ratio is an evaluation techniques to identify the fund allocation according to its performance level (Pedersen, Babu, and Levine 2021). Based on the evaluation process, it can be concluded that Portfolio D is the most superior portfolio compare with Portfolio A, Portfolio B, Portfolio C, Portfolio E and Portfolio F. To show that, portfolio constructed based Sharpe's shows the highest Sharpe ratio value at 0.5798. In contrast, Portfolio A with Sharpe ratio of just over 0.1280, Portfolio B (0.3681), Portfolio C (0.56), Portfolio E (0.4877) and Portfolio F (0.3569).

5. Conclusion

Optimization of portfolio selection is very important for overall financial engineering performance. Recent developments in portfolio selection have been developed by many researchers. However, many studies show that prediction with manual models is not enough to achieve highly accurate predictions and prosperous returns. In this paper, a novel portfolio construction approach is developed using the mean-variance (MV) model and maximizing the Sharpe ratio for selecting the best portfolio. The approach model is by choosing the best ratio from the comparison between optimal return and annual standard deviation. Experimental data was taken from the Malaysian Stock Exchange from 2020 to 2020, from several securities the ten most active securities were selected. The purpose of this study is to assist investors in verifying the Malaysian stock market to reduce risk and maximize returns. The results of the study show that the ratio of the optimal return and the annual standard deviation is 0.711. These results are obtained from a comparison between the optimal return: of 33.96% and the annual standard deviation: of 47.73%. The proposed model by maximizing the comparison between the optimal return and the annual standard deviation can be used to support portfolio selection decisions. The results showed that the efficiency limits of the selected stocks and optimal portfolio weights could be achieved.

This paper reported the computation of portfolio optimization based on the data taken from the Malaysian Stock Exchange through Yahoo Finance in the period from 2014-2020. The data analysed by using the sharpe ratio led to an optimal portfolio with well optimised between risk and return. The Sharpe ratio is used to compare between annual standard deviation and maximum return obtained Portfolio D is the best choice. The Portfolio D has an optimal return of 33.96%, an annual standard deviation of 47.73%, and contributed to a higher Sharpe ratio of 0.711. Hence, both the Sharpe ratio and efficient frontier depict that Portfolio D is superior compared with other as it gives the maximum rate of return for the level of given risk or a minimum risk for the level of given return. In addition, the mean-variance and Sharpe ratio can be used to support the decision of choices of the portfolio. This study can be extended to employ a machine learning approach to select the best portfolio.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper

Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Yosza Dasril;* ***data collection:*** *Harveend Mahendran;* ***analysis and interpretation of results:*** *Yosza Dasril, Much Aziz Muslim;* ***draft manuscript preparation:*** *Harveend Mahendran, Much Aziz Muslim. All authors reviewed the results and approved the final version of the manuscript.*

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