RESEARCH REVIEW

A Review on Shariah Stock Portfolio Optimization

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One of the essential concerns of investors of all time is to choose the best investment opportunities to capitalize on the value of their investment in stocks. Its objective is to minimize risk and at the same time also maximize return. This refers to portfolio optimization as the procedure of choosing the weights of a number of stocks to be included in a portfolio so that the optimum objective is achieved. Several studies have been shown by economists, mathematicians, and practitioners that provided sufficient and critical information for conducting stock portfolios. Approaches, methodologies, and techniques in those researches have to be reviewed for purposes of synthesis of published research in this area, insight into how to carry similar studies, and criticize gaps to be filled in the future research. In this report, we adopted a thematic review of stock portfolio optimization theories and applications, including some current issues on Shariah stock portfolio. A comprehensive overview of theories and approaches for stock portfolio selection, both fundamental and technical, is presented. The report will end with an overview of the mathematical model (exact and heuristic) for solving stock portfolio optimization problems.

Keywords: Shariah stock portfolio, fundamental analysis, technical analysis, portfolio optimization, exact and heuristic.

JEL Classification: C44, C61, E61, G11, G32

Stock portfolio management provides important information for government policy, authorities, or investors to make an investment decision. There are different approaches and methodologies for performing such analysis. Recently, the optimization had prompted research interest in developing the optimal financial decision. Therefore, it is necessary to provide an overview of the development in these studies.

This review highlights some contemporary issues on stock investment and its characteristics in connection with market fluctuation. The review also looked into the current trend on Shariah stock investment, which are claimed to experience a rapid evolution and expansion of the Islamic financial services industry. It has also received a wider acceptance and appreciation beyond the conventional one.

We also adopted a thematic review of methodologies and techniques used by several authors in forming a set of stock portfolios based on fundamental and technical analysis. The review considered the pros and cons of two techniques from recent papers published in the subject areas. The review style included analyzing the underlying economic theory, mathematical theory and methods, and its application.

Furthermore, this study attempts to review the methodologies for solving stock portfolio optimization problems. Two approaches that are frequently used are heuristic and exact optimization models. A review of these two approaches provides insight and guide in the direction of future research interest. This review aims at summarizing work on stock portfolio optimization. Application of better techniques on forming a set of stock portfolios and constructing the optimization model are underway; therefore, this review only provides a threshold in the understanding of stock portfolio, stock portfolio selection, and stock portfolio optimization.

Stock Investment

A share of stock, a type of financial investment and literally referred to as "stock," is a share in the ownership of a corporation (Pentheny, 2009). Stocks can be bought and sold at a price determined by the financial success of the securities and the overall demand for the stock securities. It is one of the most versatile sectors in the financial system and plays an important role in economic development (Yadav, 2017). An aggregation place of buyers and sellers where stocks, bonds, or other securities are bought and sold is known as the stock market.

The concept of a share market was first introduced in France in the 13th century. The Dutch East India Company was the earliest company to issue shares on the Amsterdam Stock Exchange in 1602 (Osmani & Abdullah, 2009). According to Siegel and Coxe (2002), a century later, the first actively traded U.S. stocks, floated in 1791, were issued by two banks: the Bank of New York and the Bank of the United States. Both offerings were enormously successful and were quickly bid to a premium. However, they collapsed the following year when William Duer attempted to manipulate the market and precipitated a crash. However, stock prices in the 1990s were dramatically increased and influence stock markets across countries (Duong & Siliverstovs, 2006). These situations indicated that the stock market is commonly fluctuated due to particular economic reasons.

Investment in stocks can be risky, particularly due to stock price fluctuation. Fluctuation is said to occur if there are a lot of shares for sale and no one is interested in buying them, and the price will quickly fall (Vincent & Bamiro, 2013). Fluctuations of stock prices and stock indices result in a problem of uncertainty, which is common to all stock markets. As presented in Table 1, there are several causes influencing the stock price in the world as described by Yadav (2017), Kearney and Daly (1998), Pentheny (2009), Vincent and Bamiro (2013), and Siegel and Coxe (2002). Consequently, many researchers suggested the importance of stock portfolio risk management (Andersen, 2008; Ridha & Alnaji, 2013).

Table 1. *Summary of Analysis on Stock Price Fluctuation in the World*

Country	Causes	Reference
India	Inflation rate, interest rate, financial leverage, corporate earnings, dividends yield policies, bonds prices, and social and political variables	Yadav, 2017
Australia	Inflation rate, interest rates, and money supply	Kearney & Daly, 1998
United Kingdom	Financial success of the company, the investor's demand, and the confidence of investors	Pentheny, 2009
Nigeria	Monetary policy, a shift in mortgage lending toward the less creditworthy and marginal borrowers, and high operating costs in Nigeria	Vincent & Bamiro, 2013
United States	World conflict, gold price, monetary policies, and business cycle	Siegel & Coxe, 2002

Shariah Stock Investment

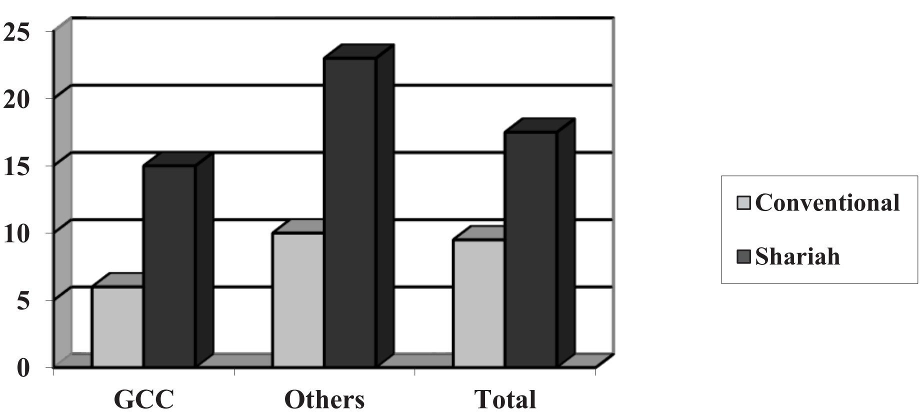
Recently, the trend of investments based on ethical, social, and environmental standards has expanded substantially (Karim et al., 2014). Louche et al. (2012) outlined responsible investment as a process through which investors try to influence companies' behavior on a range of moral issues. Albaity and Rubi (2008) concluded that investment in Shariah stocks is referred to the Islamic principles of transactions (Muamalat), and therefore, in their view, Islamic investments also fall into the type of ethical investment.

Global Shariah stock indices, represented by 12 major active (as seen in Table 2), have gained popularity due to the greater potential of growth and profitability (Ho et al., 2014). Moreover, Hussain et al. (2015) conveyed in their IMF working paper that during 2009-2013 the assets growth of Shariah stock markets—both Gulf Cooperation Council (GCC) countries and others—grew, on average, by 17.5% or almost twice as the attainment of the conventional stock market (see Figure 1). Countries (both GCC and others) measured include Bahrain, Egypt, Indonesia, Kuwait, Malaysia, Pakistan, Qatar, Saudi Arabia, Turkey, and United Arab Emirates.

Table 2. *Global Shariah Stock Market From the U.S., European Countries, and Asian Countries*

Index	Country of origin	Number of constituents	Year of origin
Dow Jones Islamic Market Index (DJIMI)	United States	2,374	1999
Standard & Poor Shari'ah Index (S&PSI)	United States	512	2007
Russell-Jadwa Shari'ah Global Index (RJSGI)	United States	2,700	2007
FTSE Islamic Index (FTSEII)	United Kingdom	2,700	2009
Royal Bank of Scotland Shari'ah Index (RBSII)	United Kingdom	-	2004
DMI 150 Islamic Index (DMII)	Switzerland	150	2008
Societe Generale Wise Shari'ah Index (SGWSI)	France	600	1999
Bombay Stocks Exchange Shari'ah 50 Index (BSESI)	India	50	2008
Jakarta Islamic Index (JII)	Indonesia	30	2003
Kuala Lumpur Shari'ah Index (KLSI)	Malaysia	30	2000
Hong Kong Islamic Index (HKII)	Hong Kong	16	2007

Source: Ho (2014)



Source: *(Hussain et al., 2015)*

Figure 1. Growth of Conventional and Shariah Assets in Percentage (2009-2013)

Some scholars have also shown that the performance of the Shariah stock market tends to be better in terms of return, for example, the Malaysia Dow Jones Islamic Index (DJIM) and FSTE Bursa Malaysia Index (KLCI; Karim et al., 2014; Reddy & Fu, 2014) and stable against crisis (Abu Bakar & Ali, 2014; Reddy & Fu, 2014) compared the conventional one, for example, Australian Stock Exchange (ASX).

Furthermore, many researchers also made a comparison between the Shariah stock market and the conventional stock market (Alam et al., 2017; Geumei, 2018; Hussain et al., 2015; Osmani & Abdullah, 2009). Table 3 exhibits their comparison based on different views. However, in Reddy & Fu (2014), later researchers have reported evidence of a correlation between conventional market indices between North American, European Union, Far East, and Pacific markets compared to the Islamic index returns (Dania & Malhotra, 2013). They argued that the price of Islamic and conventional securities corresponds to macroeconomic elements. Consequently, both are almost the same except for certain terms in trades mechanism and halal products (Alam et al., 2017; Samra & Joseph, 2018).

As one of the rich countries in both renewable (agricultural products) and non-renewable sources (mining and minerals), Indonesia, even though still behind Malaysia when based on Islamic finance fundamentals (Yusof & Majid, 2009), has the opportunity to develop the Shariah investment. This prediction is based on the country's narrow fiscal deficits, low public indebtedness, healthy economic growth prospects, the large scope of the Indonesian economy, and the potential of the largest Muslim population in the world. Lusyana and Sherif (2017) added that the performance of the Indonesia Shariah-compliant Stock Index (ISSI) and Jakarta Islamic Index (JII) was promising by reason of the increasing number of investors whose concern in the ethical investment. Hence the Shariah investment atmosphere in Indonesia might be interesting to observe further.

Table 3. *Comparison of Shariah and Conventional Stock Market based on Some Views*

Basis of comparison	Shariah	Conventional
Existences	It exists for Islamic corporations to raise capital in a Halal way following the laws of the Shariah	It exists mainly to channel the wealth of savers to those who can put it to long-term productive use (to raise capital)
Products	Sukuk, stocks, sharia-compliant equities, Islamic funds, equity funds Islamic exchange-traded funds (IETFs), Islamic real estate investment trusts (IREITs)	Equities, derivatives (swaps, options, futures, forward), and bonds
Places	Traded in the same places as the conventional ones since no Islamic only exchanges exist	Available in approximately all the countries
Activities	Only allowed to offer investment instruments for projects that are useful and add value to the society	Offer investment instruments for any profitable project whether it is beneficent to the society or not; the only important factor is how profitable and how risky is it
Rules	Shariah principles: (1) free from all forms of Riba, Al-Maysir, Al-Gharar, price controlling, Al-Ihtikar, misinformation, and coercion, (2) halal product (3) no pornography	It is not bound by any restrictions
Contract	Mudharabah	Interest
Risk and Return	Market risk sharing is essential. So the return should be associated with the risk	Risk is better to be avoided. Most derivatives are speculative and developed to hedge against the risk

Stock Portfolio Selection

A portfolio as a set of stocks needs to be selected appropriately to obtain the expected result. As the stock markets fluctuate dramatically, shares analysis is one of the leading issues for investors to consider the market trend and reduce gambling facets of stocks investment (Hooke, 2010). Basically, there are two known leading investment decisions tools that are usually employed by investors in portfolio selection, that is, fundamental analysis and technical analysis. Both of them can be used to determine the value of a stock and forecast its future performance (Cohen et al., 2011; Wafi et al., 2015).

Many researchers compared the credibility between technical and fundamental analysis. According to Moosa and Li (2011), Neely et al. (2010), and Wafi et al. (2015), technical analysis outperforms fundamental analysis. However, it contrasts with the study of Jakpar et al. (2019) that fundamental analysis is able to forecast and generate a positive return better than technical analysis in the food manufacturing in Bursa Malaysia. In addition, Silva et al. (2014) included a fundamental analysis using financial ratios instead of technical before dealing with the optimization algorithms. They claimed that financial ratios, which are quantitative measures, can intensely analyze the performance of a company in terms of profitability, liquidity, debt, and growth. Return on equity (ROE), one of the financial ratios, has shown to be firm in discriminating the performance of institutional investors (Mustilli et al., 2018). Overall, there is no such judgment of the two investment tools (fundamental or technical) that better select stock portfolios.

Fundamental Analysis

Fundamental analysis is defined as a method of evaluating a security by attempting to measure its intrinsic value. It deals with real data reports issued by corporate financial as evaluation by examining related economic, financial, and other qualitative and quantitative factors (Drakopoulou, 2016; Suresh, 2013; Thomsett, 2005). More precisely, it attempts to study everything that can affect the security's value, including macroeconomic factors (like the overall economy and industry conditions) and specific factors (such as the financial condition and management of companies). Campanella et al. (2015) added that fundamental analysis could predict the abnormal returns to be triggered by dividend announcements in the European securities market. Fundamental analysts also proclaim that financial results are the only dependable means for establishing the value of a company. Nevertheless, Suresh (2013) argued that one should capture not only the financial performance of the company but also the economic situation and industrial environment. He labeled such examination steps as EIC (economy, industry, company) framework.

Table 4. *Sequence of Fundamental Analysis*

Steps	Activities	Formula/Indicators	Reference
1st: Economic analysis	Understanding macroeconomic environment and development (situation of a nation)	Inflation rate, interest rate, monetary policy, etc.	Sathyanarayana & Gargesa, 2018; Suresh, 2013
2nd: Industry analysis	Analyzing the prospects of the industry to which the company belong (industry grouping)	Industry life cycle, competitive analysis of the industry, etc.	Sabol et al., 2013; Suresh, 2013
3rd: Company analysis	Assessing the financial performance of a company	Debt, earning sale, earning per share, equity, etc.	Jakpar et al., 2019; Silva et al., 2014
4th: Ratio analysis	Predicting the future projections of earning	$\text{ROE} = \frac{\text{net income}}{\text{total equity}}$ $\text{P/E} = \frac{\text{share price of stock}}{\text{earning per share}}$	Mohammed et al., 2020; Ghaeli, 2017; Silva et al., 2014

Notes: *ROE = Return on equity and P/E = Price earnings ratio*

Moreover, Mohammed et al. (2020) enriched an extra step so-called ratio analysis. There are many ratios that can be used, but they are all categorized into one of three groups: liquidity ratios (determine how quickly the company will fulfill its obligations at maturity without incurring a loss), profitability ratios (measure and evaluate the ability of a company to generate income (profit) relative to revenue), and leverage ratios (indicate the utilization of borrowed money or level of debt). Table 4 illustrates the sequence of fundamental analysis along with supporting information desired.

Although there are different and varying concepts related to the fundamental analysis, the economists agree on the same objective, that is, to forecast future earnings and the true value of the assets so that investors can make investment decisions at the right time to gain profit. In addition, from all formulas of ratio analysis displayed in Table 4, the price/earnings ratio (P/E) is perhaps the most primary measurement of a stock's value. As a fundamental indicator, according to Ghaeli (2017), it is normally implemented as a metric to compare individual stocks and the market as a whole relative to historical valuations. Accordingly, the portfolio selection might be executed by considering the properties on fundamental analysis as base choices, but it seems that it needs to be verified by other analyses.

Technical Analysis

Unlike fundamental analysis that focuses on intrinsic value, technical analysis deals with the behavior of the market, which only focuses on the price action, such as the historical price of a certain period. The aim of technical analysis is to help investors select the proper portfolio and the best time to buy and sell the stock by spotting demand and supply levels plotted on a chart (see Eiamkanitchat et al., 2017; Jakpar et al., 2019). The term "best" refers to the most appropriate period to either perform (buy or sell) or not perform (hold) the trading by employing one of some common useful methods in technical analysis such as exponential moving average (EMA), simple moving average (SMA), relative strength index (RSI), the stochastic oscillator (STO), the moving average convergence divergence (MACD), and the average directional index (ADX). Eiamkanitchat et al. (2017) recommended EMA; the trend of the prices indicates by the exponent values those plotted on the price chart, as a suitable method in resulting the best average earning compared to MACD, STO, and RSI. In addition, de Souza et al. (2018) revealed that stock markets in BRICS member nations that are technically analyzed based on SMA, EMA, and its combination are profitable in terms of return, whereas Jakpar et al. (2019) preferred to employ MACD to test its correlation with stock returns.

The portfolio selection, firstly introduced by Markowitz (1952), is well-known as the main problem in the finance literature and investment practice; because the future returns of shares are not known at the day of the investment decision, the problem is one of decision-making under risk measure (Geambasu et al., 2013; Kulali, 2016). The most important aspect of Markowitz's model was his description of the impact on portfolio diversification by the number of securities within a portfolio and their covariance relationships (Mangram, 2013). Substantially, it was argued that an infinite number of "efficient" portfolios exist along a curve defined by three variables: standard deviation, correlation coefficient, and return. The efficient-frontier curve consists of portfolios with the maximum return for a given level of risk or the minimum risk for a given level of return (Todoni, 2015).

Such remarkable invention is based on modern portfolio theory (MPT), which focuses on risk measures by employing variance or standard deviation. Unfortunately, a considered risk has been a debatable topic. Many scholars such as Rockafellar and Uryasev (2016), Rom and Ferguson (2009), Roman and Mitra (2009), and Mangram (2013) suggested new risk measures even though nowadays MPT remains the most commonly used measure in portfolio selection practices. Furthermore, with the intention of risk-adjusted return on MPT, Sharpe (1994) then proposed the Sharpe ratio (Kolbadi & Ahmadinia, 2011; Pilotte & Sterbenz, 2006). It is the ratio of the excess return to the standard deviation of that return. Additionally, Jack Treynor (1965) provided an alternative reward-to-risk ratio, that is, the Treynor ratio. It is the ratio of the excess return to the systematic risk of that return and reliant upon a portfolio's beta (market who decides risk; Pilotte & Sterbenz, 2006).

Another theory to fill the gap of MPT, particularly on the market reality, is termed post modern portfolio theory (PMPT). Geambasu et al. (2013) claimed that it includes the behavior of the investor in the computation of risk measure, considering the risk

Table 5. *Differences Between MPT and PMPT Based on Some Perspectives*

Perspectives	MPT	PMPT	Reference
Risk measure	Standard deviation	Downside risk	Roman & Mitra, 2009; Todoni, 2015
Risk-adjusted return	Sharpe ratio (SR) $\text{SR} = \frac{r_p - r_f}{\sigma_p}$ Treynor ratio (TR) $\text{TR} = \frac{r_p - r_f}{\beta_p}$	Sortino ratio (SoR) $\text{SoR} = \frac{r_p - r_f}{\sigma_d}$	Geambasu et al., 2013; Kolbadi & Ahmadinia, 2011; Pilotte & Sterbenz, 2006; Todoni, 2015
Return distribution	Symmetrical (penalizing upside and downside part)	Asymmetrical (penalizing downside part only)	Mangram, 2013; Rom & Ferguson, 2009; Roman & Mitra, 2009
Benchmark rate	Risk-free rate, driven by government	Minimum acceptance rate (MAR), driven by market	Rasiah, 2012; Todoni, 2015
Assumption used	Not considering investor expectation	Considering investor expectation	Geambasu et al., 2013; Mangram, 2013
Tested by bootstrapping simulation	Resulting in a lower return	Resulting in a higher return	Cheng, 2001

Notes: r_p = portfolio return, r_f = risk free rate, σ_p = standard deviation, β_p = portfolio beta, σ_d = downside risk

Table 6. *Resume Between VaR and cVaR Stand on Some Views*

Views	VaR	cVaR	Reference
Formula	$\text{VaR}_\alpha(X) = \min\{z \mid F_X(z) \geq \alpha\}^*$	$\text{cVaR}_\alpha(X) = \int_{-\infty}^{\infty} z \, dF_X^\alpha(z)^*$, where , $F_X^\alpha(z) = \begin{cases} 0, & \text{when } z < \text{VaR}_\alpha(X) \\ \frac{F_X(z) - \alpha}{1 - \alpha}, & \text{otherwise.} \end{cases}$	Rockafellar & Uryasev, 2016; Roman & Mitra, 2009; Sarykalin et al., 2008
Function profile	Non-convex and discontinuous	Convex and continuous	AlHalaseh et al., 2016; Rockafellar & Uryasev, 2016)
Average of losses	Lower	Higher	Rockafellar & Uryasev, 2016; Sarykalin et al., 2008
Losses scenario	VaR does not control scenarios exceeding VaR	cVaR accounts for losses exceeding VaR	Sarykalin et al., 2008
Deviation measure	VaR is not a deviation measure	cVaR is strong competitor to standard deviation	Roman & Mitra, 2009; Sarykalin et al., 2008

Notes: $^*X$ = random variable with the cumulative distribution function, $F_X(z) = P\{X \leq z\}$, and confident level $\alpha \in [0,1]$

as to the chance that the investment return is less than the minimum return expected by the investor from his portfolio. Compared with MPT, Lee and Eid (2018), Rom and Ferguson (2009), and Roman and Mitra (2009) argued downside risk metrics of PMPT as the essential difference in favor of more appropriate risk measures for asymmetric distributions of returns. Moreover, to calculate risk-adjusted return based on downside risk, Sortino proposed a modified version of Sharpe ratio, named Sortino ratio (Rasiah, 2012). It includes minimum acceptance rate (MAR) and downside risk as variables to be considered (Rom & Ferguson, 2009). Table 5 reviews in more detail the differences of methods between MPT and PMPT.

The next popular risk measure of portfolio performance is value at risk (VaR). It considers the confidence level of maximum losses. Although VaR is one of the most accepted measures of risk, according to AlHalaseh et al. (2016), it has undesirable mathematical characteristics such as a lack of sub additively, convexity, and coherent only when it is based on the standard deviation of normal distributions. To overcome this lack, the other risk measure introduced by Rockafellar and Uryasev (2016), i.e., Conditional Value at Risk (cVaR) was performed. It is the average of some percentage of the worst-case loss scenarios and approximately equal, at the same confidence level, to the average of losses greater than or equal to VaR (Roman & Mitra, 2009; Sarykalin et al., 2008). Furthermore, Rockafellar and Uryasev (2016), Sarykalin et al. (2008), and AlHalaseh et al. (2016) showed that CVaR is superior to VaR in optimization applications. Table 6 summarized the method's characteristics between VaR and cVaR.

Portfolio Optimization

There are always two sides to an investment, namely risk and return. As a general rule in the economy, one who seeks more return must expect more risk, and conversely, one who hunts for less risk will gain less return. The objective of such a problem is to minimize risk and, at the same time to maximize return. This refers to portfolio optimization as the procedure of choosing the weights of a number of stocks to be included in a portfolio so that the optimum objective for certain condition is obtained. The condition would be combined directly or indirectly in considerations of the expected value of the portfolio's rate of return as well as the return's dispersion and possibly other measures of financial risk.

Portfolio optimization is the technique of finding the best portfolio for the investors, given the available set of portfolios and the investor's tolerance for risk. It is often called mean-variance optimization (MVO). The term refers to the expected return of the investment, and variance is the measure of the risk associated with the portfolio. The mean-variance concept is constructed initially by Markowitz (1952). It deals with a point of view of portfolio investment decision that allows investors to plan, predict, monitor, and decide on the desired risk and return. The fundamental goal of MVO is to optimally allocate investments between different assets. Kulali (2016) asserted that investors who are risk-averse and efficient portfolios must meet two conditions, namely minimizing the variance of portfolio for a given expected return or maximizing the expected return for a given variance. The first condition results in the problem of finding a minimum variance portfolio of the stocks that yields at least a target value of the expected return. Mathematically, the model of MVO is derived from the convex quadratic programming (Fu, 2019; Mussafi, 2012). The basic idea here is to consider an investor with a fund to invest in n different stocks. Let r_i be the random variable associated with the rate of return for stocks i for $i = 1,\ldots,n$, and define the random vector $z = (r_1, r_2, \ldots, r_n)^T$. Set $\mu_i = E(r_i)$, $m = (\mu_1, \mu_2, \ldots, \mu_n)^T$, and $\mathrm{cov}(z) = \Sigma$. If $w = (w_1, w_2, \ldots, w_n)^T$ is a set of weights in a portfolio. The rate of return of this portfolio $r = \sum_{i=1}^{n} r_i w_i$ is also a random variable with mean $m^T w$ and variance $w^T \Sigma w$. If μ_b is the targeted value of expected return, then an optimal portfolio is a portfolio that solves the following quadratic programming (QP).

$$\begin{aligned} &\min_x \frac{1}{2} w^T \Sigma w \\ &s.t.\ \ m^T w \geq \mu_b,\ e^T w = 1, \text{ and } w \geq 0, \end{aligned} \tag{1}$$

where e denotes the vector of ones.

Having a portfolio constructed properly either by fundamental or technical analysis, one can see the emphasis on how to solve portfolio optimization, that is, how to allocate the assets optimally. In recent years, mathematical programming techniques have become vital tools to support assets allocation, making process and being gradually applied in financial decision. It is one of the Operations Research techniques which seek to maximize or minimize a function of many variables subject to a set of constraints enforced by the nature of the problem being studied and integrally restrictions on some or all of the variables. In contrast to other mathematical tools such as statistical models, forecasting, and simulation, mathematical programming models allow the decision maker to find the optimal solution (Mokhtar et al., 2014).

Furthermore, the research community has focuses on the identification of efficient and effective solution approaches for solving the mathematical programming model of portfolio optimization problems. Ordinarily, the methods can be categorized into two main types: exact approach and heuristics approach.

Exact Approaches

Numerous exact approaches have been suggested to solve portfolio optimization either for single objective or multi-objective. Mixed integer quadratic programming (MIQP) and QP are most widely used to represent real-world problems in a deterministic manner. Nevertheless, another deterministic method of linear programming (LP) is employed but still goes through the transformation process from QP based on mean absolute deviation (MAD). Papahristodoulou and Dotzauer (2004) formulated two different LP models by transformation procedure, based on minimization of MAD and maximizes the minimum return (Maximin) formulation. These models were then compared to the classical quadratic programming formulation to test to what extent all these formulations provide similar portfolios. The results from this study showed that the Maximin formulation yields the highest return and risk while the quadratic formulation provides the lowest risk. In addition, all the three formulations were found to outperform the top equity fund portfolios in Sweden and performed much better than the market portfolio (Mokhtar et al., 2014).

Another linear programming model for the portfolio optimization is offered by Ibrahim, Kamil, and Mustafa (2008). In this study, the problem was modelled as a mean-risk bi-criteria portfolio optimization problem with the mean absolute negative deviation of annual return from the average annual return is used as the downside risk. In order to evaluate the performance of the proposed model, the authors compared the results from the proposed model with the results from mean-variance model and MAD model. According to their results, the proposed model provides better returns than the mean-variance and MAD models.

Yousfat (2015) stated that by having a set of portfolio, one could minimize risk and obtain the fund allocation by employing the quadratic programming (QP) proposed by Markowitz. The main objective of QP is to reduce the variance, which considers the upside and downside parts. The QP model is defined as follows.

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m}\sigma_{ij}x_i x_j \tag{2}$$

$$\text{s.t.} \quad \sum_{i=1}^{n}E_i x_i \geq L, \quad \sum_{i=1}^{n}x_i = 1, \quad 0 \leq x_i \leq p_i, \; i = 1,....,n$$

where x_i is the amount of invested funds in the financial assets of the firm i, L is the rate of revenue or the growth factor, p_i is the highest level of the relative investment allocated to the shares or the bonds of the firm i, E_i is the revenue of the financial asset of the period studied, and σ_{ij} is the common covariance of the revenue of the financial asset i with financial asset j. Note that for $i = j$, $\sigma_{ii} = \sigma_i^2$ refers to the variance or the diagonal elements of covariance. He used QP for selecting the optimum portfolio of the Malaysian Stock Exchange by dealing the 10 biggest firms in 2014. The results showed that the optimum portfolio includes 22% of Axiata Group shares, 11% of Genting shares, 30% of Petronas Chemicals shares, 1% of Sime Darbi shares, and 36% of Tenaga Nasional shares.

Another quadratic programming model for the portfolio optimization is done by Kulali (2016). He tested Markowitz's mean-variance approach to 252 days of data belonging a year of 2015 on Istanbul Stock Exchange (BIST). The author compared two hypothetical portfolios by considering diversification strategy: (a) 10 stocks with equal weights chosen from three different industries and (b) eight stocks with different weights. By employing Excel data solver, the empirical results exhibited that the second hypothetical provides more return than a portfolio with equal shares of 10 stocks.

Best and Kale (2000) also employed QP to solve large-scale portfolio optimization. They proposed the specialization of the QP algorithm for large-scale portfolio optimization consists of three innovations:

(a) determination of good starting point for the QP algorithm, (b) efficient solution of the Karush-Kuhn-Tucker system for the active constraints using a small kernel matrix, and (c) handling of all upper and lower bounds as well as breakpoints for variable transactions costs implicitly rather than explicitly. The results produce improvements of over 1000 times in execution times for the optimization of large portfolios.

In Zhang and Zhang (2011), the authors built a series of pivoting algorithm for solving convex QP and then shows how to use it together with a parameter technique to solve the system of linear inequalities, convex quadratic programming, and mean-variance portfolio selection problems proposed by Markowitz. These algorithms are brief for understanding and efficient for computing, as shown by the numerical examples and computer experiments for 1072 stocks. They also proved the convergence of the smallest index rule for convex QP.

Cesarone et al. (2009) observed QP solve the Limited Asset Markowitz (LAM). Unlike the classical Markowitz model that can be solved using QP, the LAM model is modeled by adding binary variables, thus becoming a mixed-integer quadratic programming (MIQP) problem that is considerably more difficult to solve. The LAM is obtained as follow:

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m} \sigma_{ij} x_i x_j \tag{3}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} \mu_i x_i = \rho \text{ and } \sum_{i=1}^{n} x_i = 1$$

$$x_i = 0 \text{ or } l_i \le x_i \le u_i, \quad i = 1,....,n, \quad |\operatorname{supp}(x)| \le K$$

where n is the number of assets, μ_i is the expected return of asset i, σ_{ij} is the covariance of return of asset i and asset j for $i, j=1,...,n$, ρ is the required level of return for the portfolio, the realistic constraint $|\operatorname{supp}(x)|$ is no more than K assets for $\operatorname{supp}(x) = \{i : x_i > 0\}$, and the quantity x_i of each asset should be limited within a given interval $[l_i, u_i]$. He established the new method so-called reduction to standard QP. It tested on five new data sets involving real-world capital market indices from major stock markets that have been used in Chang et al. (2000). The performance of the portfolios obtained from the LAM model is more efficient compare to the classical Markowitz portfolio.

Table 7. *Solution of Exact Approaches for Portfolio Optimization*

Authors	Data analyzed	Exact approaches				
		LP	MAD	QP	PA	MIQP
Papahristodoulou & Dotzauer, 2004	Monthly returns from 67 shares traded in the Stockholm Stock Exchange (SSE), between January 1997 and December 2000	✓	✓			
Ibrahim et al., 2008	60 random stocks registered on the main board of Bursa Malaysia and listed on May 2004	✓	✓			
Yousfat, 2015	10 biggest firms posted on Bursa Malaysia during 2014			✓		
Kulali, 2016	252 days of data belonging a year of 2015 on Istanbul Stock Exchange (BIST)			✓		
Best & Kale, 2000	Large-scale portfolio optimization			✓		
Zhang & Zhang, 2011	Arbitrary weekend closed prices of 1072 stocks.				✓	
Cesarone et al., 2009	Weakly price data from March 1992 to September 1997 for the Hang Seng, DAX, FTSE 100, S&P 100, and Nikkei 225 capital market indices. In addition, also around 2000 assets taken from the OR-Library.					✓

Notes: *LP = Linear Programming, MAD = Mean Absolute Deviation, QP = Quadratic Programming, MIQP = Mixed Integer Quadratic Programming, PA = Pivoting. Algorithm and missing of Shariah stock cases for the rare be obtained.*

Heuristic Approaches

Heuristic is a popular non-deterministic approach for solving hard constrained problems. It attempts to yield a good and fast approximation to an optimal solution, that is, seeking approximate answers to the solution obtained from the exact approach. Requirements for mathematical sophistication or programming skills make this approach flexible because adding, removing, or changing objective functions or constraints can effortlessly be achieved (Gilli & Schumann, 2012). There are many studies applying heuristic approaches to solve the problem of portfolio optimization. Crama and Schyns (2003) applied heuristic technique based on Simulated Annealing (SA) to an extended version of the mean-variance model with trading and turnover constraints. Such model is contained within Mixed Integer Quadratic Programming which is then applied to solve a complex portfolio selection model. Computational results for problems with up to 151 stocks seem to show that the approach is promising for medium size problems. Computational results for problems with up to 151 stocks seem to show that the approach is promising for medium size problems (Mokhtar et al., 2014).

John (2014) established five hill-climbing algorithms, namely HC-S, HC-S-R, HC-C, HC-C-R, and guided local search (GLS). Hill climbing, as one heuristic method, is applied to approximate the solution of a problem. It is first tested to standard portfolio optimization problem by retaining Markowitz's constraints that the investor has a fixed budget and no short-selling. The algorithms are next applied to the extended portfolio optimization problem by considering cardinality constraints. Results are benchmarked with the threshold accepting (TA) algorithm and QP. The finding suggests that such five algorithms developed have a similar solution to the exact solution of QP and surprisingly outperformed TA in the extended portfolio optimization.

Chang et al. (2009) introduced a heuristic approach based on genetic algorithm (GA) for solving portfolio optimization problems in different risk measures and compared its performance to mean-variance model in cardinality constrained efficient frontier. The authors collected three different risk measures based upon mean-variance by Markowitz, semi-variance, mean absolute deviation, and variance with skewness. They showed that the problems could be solved effectively by GA if mean-variance, semi-variance, mean absolute deviation, and variance with skewness were used as the measures of risk. They conducted empirical tests to prove the robustness of their heuristic method by verifying the three data sets collected from main financial markets.

Kapiamba et al. (2015) compared a bi-criteria problem having two conflicting criteria to optimize portfolio selection simultaneously. It is well known that such a combinatorial problem is intractable with exact methods for large dimension problems. Then meta-heuristics are useful to find a good approximation of the efficient set. He evaluated the efficiency of two heuristic methods, namely the simulated annealing and the genetic algorithm, to solve the portfolio selection problem. Results of the study indicated that, in terms of calculation time, simulated annealing appears more efficient than the genetic algorithm.

Busetti (2006) developed a realistic portfolio optimization model. He then investigates the efficiency of its solution by two heuristic methods, that is, GA and tabu search (TS). The model is based on the classical mean-variance approach, enhanced with floor and ceiling constraints, cardinality constraints, and nonlinear transaction costs that include a substantial illiquidity premium, and is applied to a large stock portfolio. The solution is benchmarked with the insights provided by the optimization of real portfolios. The study showed that for large portfolios, the performance of genetic algorithms is three orders of magnitude better than that of TS.

Another interesting solution approach was presented by Fernández and Gómez (2007), who employed Hopfield neural networks to solve the mean-variance model with cardinality and bounding constraints. The authors also compared the approach with GA, TS as well as SA and performed the computational experiments using five sets of

Table 8. *Solution of Heuristic Approaches for Portfolio Optimization*

Authors	Data analyzed	Heuristic approaches			
		SA	HC	GA	TS
Crama & Schyns, 2003	Weekly prices of 151 U.S. stocks covering different traditional sectors for 484 weeks, from 6 January 1988 to 9 April 1997, extracted from the DataStream database.	✓			
John, 2014	230 assets are from DAX stock exchange. The data used were daily returns over 1001 days.		✓		
Chang et al., 2009	Historical daily data collected in the HANG SENG, FTSE and S&P 100 with price data of 33, 93, and 99 assets respectively from January 2004 to December 2006.			✓	
Kapiamba et al., 2015	Artificial data	✓		✓	
Busetti, 2006	Arbitrary 100 largest stocks by market capitalization in the world.			✓	✓
Fernández & Gómez, 2007	Weekly prices listed from Hang Seng in Hong Kong, DAX 100 in Germany, FTSE 100 in the U.K., S&P 100 in USA and Nikkei 225 in Japan with price data of 31, 85, 89, 98 and 225 assets respectively from March 1992 to September 1997.	✓		✓	✓

Notes: *SA = Simulated Annealing, HC = Hill-Climbing, GA = Genetic Algorithm, TS = Tabu Search*

benchmark data that have been used in T. J. Chang et al. (2000). Although the results showed that none of the four has clearly outperformed the others, when dealing with problem demanding portfolios with low investment risk, the proposed method provides better solutions than the other heuristics (Mokhtar et al., 2014). There are several works not mentioned that have already taken steps in the direction of what the authors called the Research Gap section.

Research Gap

There are some missing elements in the discussion on stock portfolio optimization. First, the exploration of Shariah stock market is still limited. Ho et al. (2014) has exposed that the increase on the number of global Shariah stock indices in the world is evidence of relatively large growth potential and profitability. Moreover, some scholars also claimed that the performance of the Shariah stock market has a tendency to be preferable with regard to return and stable in defiance of financial crisis compared to the conventional ones (Abu Bakar & Ali, 2014; Karim et al., 2014; Reddy & Fu, 2014). In more detail, Lusyana and Sherif (2017) said that Indonesia, with the largest Muslim population in the world, was favorable by reason of the increasing number of investors who are concerned in the ethical investment. Indeed, the quantity of these works, which mainly refer to the Islamic stock market, is still less frequent than the research results related to data from conventional platforms.

Second, the gap in methodology, particularly on how to select the promising portfolio. The study on blending between fundamental and technical analysis is still lacking and has never even been discussed. Many researchers stick just to one of either fundamental or technical. Some believed that fundamental analysis is the only proper instrument that can comprehensively capture the intrinsic value of a company (Jakpar et al., 2019; Mustilli et al., 2018; Silva et al., 2014; Suresh, 2013). On the contrary, others claimed that technical analysis is more powerful because it can predict future risks or returns that are not yet known on the day of the investment decision (AlHalaseh et al., 2016; Kulali, 2016; Lee & Eid, 2018; Mangram, 2013; Rockafellar & Uryasev, 2016).

Third, the quadratic programming as a standard form in portfolio optimization still has drawback and require some form of modification or improvement for solving stock portfolio problem. Researchers have tried to modify quadratic programming with their respective findings, which have proven difficult to complete large-scale portfolio optimization (Best & Kale, 2000; Cesarone et al., 2013; Zhang & Zhang, 2011).

Finally, another gap in methodology, especially on portfolio optimization. The comparative study between exact and approximation methods, that is, standard quadratic programming, modified quadratic programming, and heuristic approaches has never been studied. In handling portfolio optimization, some scientists only focus on the heuristic approach (Chang et al., 2009; Crama & Schyns, 2003; Kapiamba et al., 2015), while others concentrate on the exact approach (Ibrahim et al., 2008; Kulali, 2016; Yousfat, 2015).

Conclusion

Stock investment has become an interesting topic not only in economics but also in mathematics. This review provided the current situation on stock investment, particularly the stock market, along with its dynamics. It is also considered a new trend of investments based on ethical so-called Shariah stock investment. Such a concept has grown to become one of the world's profitable economic forces so that many well-known stock markets in the U.S., Europe, and Asia are involved in this investment. Moreover, Shariah stock has also been proven to be better than conventional, especially related to the rate of return and stability in a crisis. Nevertheless, the main drawback of investing in Shariah stocks is the limited options due to the screening of trade mechanisms and halal products. Investors in conventional stocks have so many options that they can tailor their portfolios to meet any investment objective, whereas investors in Shariah stocks have fewer options to pick from.

The review highlighted techniques on stock portfolio selection, that is, technical analysis and fundamental analysis. By exploring each of the advantages and disadvantages of the two analyzes based on previous research, the stock portfolio assessment can be evaluated better. In view of that, the stock portfolio selection might be executed by considering the properties on fundamental analysis as a base choice, but it seems that it needs to be verified by technical analysis. Therefore the combination of two altered methods would rather give a more comprehensive decision.

The findings in this review shown that stock portfolio optimization eventually turns into an alternative tool for both theorists and practitioners in dealing with a financial decision. It deliberated two common approaches used by researchers. The exact approach seems to be the popular method for solving stock portfolio optimization rooted in Markowitz properties. However, based on the review, the heuristic approach could approximate the solution of problems as an exact solution for a large scale of portfolios and has less execution time. Therefore, this review led to the further development of stock portfolio optimization by comparing the models of the two approaches and their results in the real case of stock market.

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