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Evolutionary Portfolio Optimization During the COVID-19 Crisis: An Empirical Analysis of the Indonesian LQ45 Index Using NSGA-II

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A B S T R A C T

Background: The global financial capital markets have faced unprecedented volatility during the COVID-19 pandemic which severely questions the validity and practicality of the classic portfolio optimization. Method: This research studies the capacity to optimise the capital allocation in the Indonesian LQ45's stock index using Non-dominated Sorting Genetic Algorithm II (NSGA-II) in pandemic era. Method A bi-objective mathematical model specifically with the goal to maximize expected return and decrease portfolio variance was created, not requiring developing a full-scale data-driven software application, in order to be able to generate a non-dominated Pareto front. Results: The results from experiment show that the evolutionary algorithm managed to determine highly efficient portfolios and obtained an exceptional Sharpe Ratio of 1.034 under extreme economic stress. The best asset allocation offered to provide insight into a mode of strategic allocation which actively mixed high-yield equities with low variability defensive stocks - it eliminated the shortcoming of naive diversification. In conclusion, evolutionary algorithms offer a better and more efficient decision support system for institutional investors coping with severe macroeconomic shocks, computationally compared to traditional analytical techniques.

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INTRODUCTION

Portfolio optimization represents a fundamental decision-making process in investment management, primarily aimed at identifying the most efficient allocation of capital to maximize expected returns while systematically minimizing financial risk (Elton, Gruber, Brown, & Goetzmann, 2014). Since the seminal introduction of Modern Portfolio Theory (MPT) (Markowitz, 1952), institutional and individual investors have heavily relied on the mean-variance framework to construct their portfolios. This classical approach utilizes quadratic mathematical programming to find an optimal balance often referred to as the efficient frontier between the potential profitability of a given asset and its price volatility (Kolm et al., 2014; Salo et al., 2024). Over the past several decades, MPT has served as the bedrock of quantitative finance, influencing everything from individual asset pricing to the development of complex mutual funds (Fama & French, 2004).

However, despite its theoretical elegance, the classical mean-variance model operates under highly idealized mathematical assumptions. It presumes that asset returns follow a normal distribution, that investors have unrestricted access to capital, and that the financial environment remains relatively stable and linear over time (Sharpe, 1964). Consequently, these rigid models frequently face significant limitations when applied to highly dynamic, real-world environments. During periods of severe market stress, the covariance matrices which the model relies upon to estimate risk tend to break down, leading to highly concentrated and suboptimal asset allocations (Ang & Bekaert, 2002; Das & Uppal, 2004). This systemic fragility necessitates a transition from static mathematical programming to more adaptive financial methodologies.

The outbreak of the COVID-19 pandemic provided an extreme stress test for global financial ecosystems, introducing unprecedented volatility and non-linear fluctuations (Salisu & Vo, 2020; Zhang et al., 2020). Emerging markets, characterized by higher information asymmetry and distinct liquidity constraints, experienced profound uncertainty during this period (Bekaert et al., 2007; Lesmond, 2005). Within the context of the Indonesian capital market, the pandemic triggered sudden market drawdowns that rendered traditional investment strategies highly vulnerable (Ali et al., 2020; Rizwan et al., 2020). The Indonesian stock exchange, particularly its premier LQ45 index which tracks the 45 most liquid and highly capitalized corporations witnessed drastic sectoral divergence. For example, while defensive sectors such as consumer goods maintained relative stability, cyclical sectors like finance and commodities suffered from severe liquidity crunches and demand shocks. In such complex scenarios, financial markets behave as adaptive systems where traditional, rigid formulas struggle to process extreme anomalies (Arthur, 1999; Lo, 2004).

To fully comprehend the magnitude of this systemic fragility, one must examine the specific historical disruptions that paralyzed the Indonesia Stock Exchange (IDX) during the onset of the pandemic (Panjaitan & Novel, 2021). In March 2020, the macroeconomic shock was so severe that the IDX Composite Index (IHSG) experienced a precipitous free-fall, forcing the exchange to trigger unprecedented circuit breakers and halt trading activities multiple times within a single month. This catastrophic decline was significantly exacerbated by massive foreign capital outflows, as panicked international and domestic investors aggressively liquidated their holdings, severely draining market liquidity (Ali et al., 2020). During this exact window of extreme market distress, the foundational assumptions of classical portfolio optimization collapsed. The drastic spike in cross-asset correlations meant that traditional diversification completely failed to protect capital. In such an intensely chaotic and liquidity-constrained environment, relying on static mathematical equations becomes practically obsolete, underscoring the critical necessity for advanced, algorithmically driven decision-support systems that can dynamically adapt to extreme, real-time macroeconomic anomalies.

Previous empirical studies have attempted to navigate this turbulent period using conventional tools. For instance, portfolio strategies during the COVID-19 pandemic were examined using traditional Markowitz optimization models on Indonesian equities (Hanif et al., 2021). While their research provided valuable insights into market behavior during crises, it also highlighted the structural limitations of classical approaches. The traditional mean-variance framework frequently fails to adapt its search mechanisms when faced with sudden, extreme data outliers, often resulting in portfolios that look optimal on paper but perform poorly in out-of-sample stress conditions.

To address the inherent limitations of classical mathematical programming, modern computational finance has increasingly adopted machine learning and evolutionary algorithms (Habbab & Kampouridis, 2024; Krink & Paterlini, 2011; Metaxiotis & Liagkouras, 2012). These algorithms, inspired by the biological principles of natural selection and genetics, are specifically designed to solve complex, multi-objective problems that traditional solvers cannot efficiently compute (Hu et al., 2024; Ma et al., 2021; Metaxiotis & Liagkouras, 2012). They are particularly adept at handling real-world trading frictions, such as cardinality constraints (limiting the maximum number of assets in a portfolio) and strict weight boundaries, without requiring the mathematical search space to be convex (El Kharrim, 2023).

A prominent example of such an advancement is the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002). Recent literature, notably the EvoFolio framework (Guarino et al., 2024), demonstrates that NSGA-II can effectively manage multi-objective portfolio formations by exploring a vast space of possible asset combinations without being trapped by localized market anomalies (Lwin et al., 2014; Zou et al., 2011). Despite its theoretical promise and computational sophistication, there is a persistent gap in the literature regarding the empirical validation of this evolutionary engine against classical models, specifically within the context of a severe, real-world crisis in an emerging market (Masmoudi & Abdelaziz, 2018; Rouwenhorst, 1998).

Therefore, this study aims to bridge this research gap by developing a computational simulation that directly applies the NSGA-II evolutionary algorithm to optimize a portfolio of highly liquid blue-chip stocks (the LQ45 index) in Indonesia during the peak of the COVID-19 pandemic. The primary objective is to empirically evaluate whether the evolutionary approach can produce a more robust and efficient set of optimal portfolios (represented by the Pareto front) compared to the classical mean-variance benchmark under conditions of extreme market stress. By avoiding the complexities of building a full-scale software application, this research focuses strictly on the algorithmic validity and financial efficiency of NSGA-II. Ultimately, this study seeks to provide a reliable, adaptive decision-support framework for institutional investors navigating high-risk environments, contributing to both the theoretical discourse on computational finance and the practical implementation of crisis-resilient investment strategies.

LITERATURE REVIEW

This section establishes the theoretical foundation of the study by navigating through the evolution of portfolio management theories. It first critically examines the classical principles of Modern Portfolio Theory (MPT) and its inherent mathematical vulnerabilities during severe macroeconomic crises. Subsequently, it explores the mechanics of evolutionary computation, specifically the Non-dominated Sorting Genetic Algorithm II (NSGA-II), as a modern alternative to traditional solvers. Finally, it reviews recent empirical studies to highlight the innovative gap this research aims to fill. By contrasting adaptive evolutionary models with traditional mathematical frameworks, this review justifies the necessity of deploying advanced decision-support systems in turbulent emerging markets.

Modern Portfolio Theory and Market Crises

The foundation of modern quantitative investment strategy is heavily rooted in the Modern Portfolio Theory (MPT) (Markowitz, 1952). The core principle of MPT dictates that rational investors seek to maximize their expected returns for a given level of risk, or conversely, minimize risk for a targeted level of return. In this strictly mathematical framework, risk is quantitatively defined as the variance (or standard deviation) of historical asset prices, while the return is the historical average of price changes. By diversifying investments across a basket of assets that are not perfectly positively correlated, MPT generates an "efficient frontier" a theoretical set of optimal portfolios that offer the best possible risk-return trade-offs (Elton et al., 2014; Salo et al., 2024).

Despite its profound and lasting impact on financial economics, classical MPT relies on strict, idealized mathematical assumptions. It presumes that asset returns follow a normal (Gaussian) distribution, that markets are perfectly frictionless without transaction costs or liquidity constraints, and that the financial environment remains static over time (Fama & French, 2004; Sharpe, 1964). In reality, these assumptions frequently break down, particularly during periods of severe economic distress or "black swan" events. During such crises, asset correlations tend to converge toward one, meaning that previously diversified assets begin to fall simultaneously, effectively neutralizing the risk-reducing benefits of standard diversification (Ang & Bekaert, 2002; Das & Uppal, 2004; Rizwan et al., 2020).

Demonstrating this vulnerability, an empirical study was conducted utilizing the classical Markowitz mean-variance model to optimize stock portfolios within the Indonesian LQ45 index during the early phases of the COVID-19 pandemic (Hanif et al., 2021). Their research provided a crucial baseline for understanding how the Indonesian stock market reacted to macroeconomic shocks. However, their findings also implicitly highlighted a fundamental computational flaw in traditional mathematical programming: classical quadratic models struggle to adapt to extreme volatility and non-linear market behaviors. Traditional exact solvers (such as linear or quadratic programming) become computationally intractable and easily get trapped in suboptimal solutions when evaluating a highly chaotic data landscape, especially when real-world trading limits, such as cardinality constraints (restricting the maximum number of assets in a portfolio), are introduced (Lwin et al., 2014; Masmoudi & Abdelaziz, 2018).

Multi-Objective Evolutionary Algorithms (MOEAs)

To overcome the rigid limitations of classical static models, researchers in computational finance have shifted their focus toward meta-heuristics, specifically Multi-Objective Evolutionary Algorithms (MOEAs). The inclusion of real-world trading constraints transforms the standard portfolio allocation model from a simple quadratic programming problem into a mixed-integer, non-linear, and non-convex NP-hard problem (Metaxiotis & Liagkouras, 2012). Unlike traditional mathematical solvers that process equations sequentially and require continuous, convex search spaces, MOEAs are stochastic search techniques inspired by the biological process of natural selection and genetics.

Evolutionary algorithms generate a "population" of random portfolio combinations and iteratively "breed" the best-performing portfolios over multiple generations (Metaxiotis & Liagkouras, 2012). Through genetic mechanisms such as crossover (mixing parts of two successful portfolios to create potentially superior offspring) and mutation (randomly altering specific asset weights to maintain genetic diversity and prevent the algorithm from stagnating in local optima), the algorithm efficiently navigates highly complex and discontinuous search spaces (Krink & Paterlini, 2011; Ma et al., 2021).

While various meta-heuristic algorithms have been deployed in financial literature, they are not uniformly effective when confronted with the intricate, multi-dimensional constraints of real-world portfolio optimization. Alternative optimization techniques, such as Simulated Annealing (SA) and Particle Swarm Optimization (PSO), are frequently employed due to their relative ease of implementation and rapid computational execution. However, these algorithms exhibit critical vulnerabilities when applied to non-convex financial environments during periods of systemic crisis. PSO, for example, relies heavily on the social and cognitive learning of particles converging toward a singular global optimum. When navigating highly restricted mathematical spaces such as portfolio selection governed by strict cardinality bounds and minimum weight thresholds PSO frequently suffers from premature convergence. Consequently, the swarm tends to become permanently trapped in local optima, failing to discover the true global frontier. Furthermore, traditional swarm and trajectorybased algorithms typically struggle to preserve population diversity over successive iterations, significantly limiting their capacity to generate a comprehensive suite of viable trade-off options.

One of the most robust and widely recognized MOEAs in contemporary computer science that successfully resolves these specific algorithmic deficiencies is the Non-dominated Sorting Genetic Algorithm II (NSGA-II), originally developed (Deb et al., 2002). Rather than aggregating all goals into a single composite score to find one "perfect" answer, NSGA-II simultaneously evaluates multiple conflicting objectives such as maximizing expected returns while simultaneously minimizing portfolio variance. The algorithm utilizes a fast non-dominated sorting mechanism to rank portfolios based on their Pareto efficiency, combined with a crowding distance metric to ensure a diverse spread of solutions. This crowding distance mechanism directly mitigates the premature convergence seen in algorithms like PSO by actively forcing the genetic population to maintain diversity across the search space. Consequently, NSGA-II outputs a well-distributed Pareto front. This front represents a diverse set of optimal decision choices, allowing institutional investors to select a portfolio configuration that precisely matches their specific risk appetite without compromising mathematical efficiency (Arthur, 1999; Lo, 2004; Zou et al., 2011).

The EvoFolio Framework and Research Novelty

The application of evolutionary algorithms in finance has gained significant global traction, prominently illustrated by the EvoFolio framework (Guarino et al., 2024). EvoFolio demonstrated that utilizing NSGA-II for multi-objective portfolio optimization provides superior adaptability compared to classical Markowitz models, particularly when handling real-world trading constraints (such as enforcing cardinality bounds to avoid over-diversification and mitigating insignificant fractional allocations). While the computational viability of NSGA-II was successfully proved, the study primarily focused on building a comprehensive software architecture, graphical user interface, and interactive decision-support application (Guarino et al., 2024). The underlying computational engine NSGA-II proved to be exceptionally powerful, yet its empirical robustness was generally tested under normal or broad market conditions rather than isolated extreme shock scenarios.

This current study builds upon the theoretical foundations established (Markowitz, 1952), the empirical crisis context mapped in the Indonesian market (Hanif et al., 2021), and the sophisticated algorithmic engine proposed (Guarino et al., 2024). The fundamental difference between this manuscript and prior studies lies in its targeted empirical application and stress-testing methodology. Rather than developing a software application or a user interface like EvoFolio, this research abstracts and isolates the NSGA-II algorithmic engine to rigorously test its mathematical superiority against the classical Markowitz baseline in a real-world, high-stress environment (the COVID-19 pandemic). By strictly enforcing a bi-objective optimization model on the highly liquid LQ45 index during a period of unprecedented market drawdown, this study provides an innovative synthesis. It leverages advanced machine learning heuristics to solve the exact empirical vulnerabilities identified by conventional financial researchers, offering a scientifically validated framework for crisis-resilient asset allocation in emerging markets.

METHODOLOGY

This research employs a quantitative computational methodology. The study is designed to simulate a portfolio optimization process by applying an evolutionary algorithm to historical stock market data. The framework evaluates the trade-off between maximizing expected returns and minimizing portfolio variance without the development of a dedicated software application.

Sample / Participants

The population of this study comprises the constituents of the LQ45 index listed on the Indonesia Stock Exchange (IDX). The LQ45 index was selected because it represents the 45 most liquid and highly capitalized companies in the Indonesian market, serving as an appropriate proxy for institutional investment opportunities. Purposive sampling was used to select companies that remained consistently listed in the index throughout the observation period to avoid survivorship bias. The list of companies included in this study is presented in Table 1.

Table 1. Research Sample: LQ45 Constituents

No	Code	Issuer Names
1	AKRA	AKR Corporindo Tbk.
2	ANTM	Aneka Tambang Tbk.
3	BBCA	Bank Central Asia Tbk.
4	BBNI	Bank Negara Indonesia Tbk.
5	BBRI	Bank Rakyat Indonesia Tbk.
6	BBTN	Bank Tabungan Negara Tbk.
7	BMRI	Bank Mandiri Tbk.
8	BRPT	Barito Pacific Tbk.
9	ERAA	Erajaya Swasembada Tbk.
10	EXCL	XL Axiata Tbk.
11	HMSP	H.M Sampoerna Tbk.
12	INDF	Indofood Sukses Makmur Tbk.
13	ITMG	Indo Tambangraya Megah Tbk.
14	KLBF	Kalbe Farma Tbk.
15	SCMA	Surya Citra Media Tbk.
16	SMGR	Semen Indonesia Tbk.
17	UNVR	Unilever Indonesia Tbk.

Instrument(s)

The primary analytical instrument used in this study is a Python-based computational script utilizing the yfinance library for data acquisition and the pymoo framework for executing the evolutionary algorithm. The optimization problem is mathematically modeled based on the classic Markowitz Mean-Variance framework, translated into a bi-objective minimization problem.Let w_i

represent the weight of the capital allocated to asset i, and let N represent the total number of assets in the portfolio. The first objective is to minimize the portfolio risk, defined as the portfolio standard deviation:

$$f_1(w) = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}} \quad (1)$$

where $\sigma_{ij}$is the covariance of returns between asset i and asset j. The second objective is to maximize the expected portfolio return. Within the algorithmic framework, which traditionally minimizes functions, this is formulated as minimizing the negative expected return:

$$f_2(x) = -\sum_{i=1}^{N} w_i \mu_i \quad (2)$$

where μ_i is the vector of expected returns for the individual assets. The mathematical model is subjected to a strict budget constraint, ensuring a fully invested portfolio without short-selling, represented by:

$$\sum_{i=1}^{N} w_i = 1 \quad (3)$$

and $0 \leq w_i \leq 1$.

Data collection procedures

To capture the market dynamics during a period of high volatility, the observation window was set from January 1, 2019, to July 31, 2020. This specific timeframe directly aligns with the emergence and peak impact of the COVID-19 pandemic on global and domestic financial markets, providing a stress-test environment similar to the conditions observed (Hanif et al., 2021). Daily closing prices for the selected equities were collected from Yahoo Finance and converted into daily logarithmic returns to calculate the expected return and covariance matrices.

Data analysis

The data analysis was systematically conducted utilizing the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002), which serves as the core evolutionary engine inspired by the EvoFolio method (Guarino et al., 2024). To ensure a robust search mechanism while maintaining computational efficiency, the evolutionary engine was configured with specific hyperparameters derived from preliminary convergence testing. The population size was initialized at 100 individuals, representing 100 distinct portfolio weight configurations. This specific population size provides sufficient genetic diversity to explore the complex solution space without inducing excessive computational overhead. The algorithm was set to evolve over 200 generations, which empirical tests indicated as the optimal threshold where the Pareto front stabilizes and further iterations yield negligible improvements.

During the evolutionary process, the algorithm employed Simulated Binary Crossover (SBX) and Polynomial Mutation as its primary reproductive operators. The SBX operator facilitates the exchange of asset weight combinations between high-performing parent portfolios, generating offspring that inherit superior risk-return traits. Concurrently, Polynomial Mutation introduces deliberate stochastic perturbations to individual asset weights. This mutation phase is critical in preventing the algorithm from converging prematurely on local optima, a common vulnerability observed in traditional quadratic solvers when evaluating highly chaotic and volatile datasets.

At the conclusion of each generational cycle, the population was evaluated using non-dominated sorting to rank portfolios based on their strict Pareto efficiency. A crowding distance metric was simultaneously applied to preserve genetic diversity, ensuring that the surviving solutions are evenly distributed across the efficient frontier rather than densely clustered in a single risk-return region. Following the completion of the 200th generation, the algorithm successfully mapped the optimal, non-dominated Pareto front. Finally, to provide a clear and actionable metric for institutional investors, the resulting non-dominated portfolios were ranked computationally based on their Sharpe Ratios, explicitly identifying the configurations that offer the highest excess return per unit of total risk.

To systematically evaluate and rank these final optimal portfolios generated by the NSGA-II algorithm, the Sharpe Ratio was employed as the primary performance metric. The Sharpe Ratio quantifies the risk-adjusted return of a portfolio, defined mathematically as:

$$S_p = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

where S_p denotes the Sharpe Ratio of the portfolio, R_p represents the expected return of the portfolio, R_f is the risk-free rate of return, and σ_p is the standard deviation (total risk) of the portfolio's returns. For the purpose of this empirical study, the risk-free rate (R_f) was calibrated using the Bank Indonesia 7-Day Reverse Repo Rate (BI7DRR) prevailing during the 2020 COVID-19 crisis window. Utilizing the historical BI7DRR provides a highly accurate, domestic macroeconomic baseline for the risk-free yield in the Indonesian capital market. By applying this specific ratio, the methodology rigorously isolates portfolios that do not merely offer absolute returns, but efficiently compensate investors for the specific, elevated volatility endured during the pandemic.

RESEARCH RESULT

Following are some empirical results obtained from the computation simulation on NSGA-II algorithm used to the LQ45 index in the context of COVID-19 pandemic. The information is presented objectively and factually, guiding the reader through the statistical profiles and the resulting optimal portfolios.

Descriptive Statistics of the Market Sample

Prior to executing the optimization algorithm, the risk and return profiles of the selected equities during the observation period are established. Table 2 summarizes the annualized expected returns, standard deviations (risk), and variances for the analyzed stocks.

Table 2. Descriptive Statistics of the Selected Assets

No	Code	Exp Return	Risk (Std)	Var
1	AKRA	-0.0918	0.4919	0.2419
2	ANTM	0.1046	0.4960	0.2460
3	BBCA	0.1737	0.2873	0.0825
4	BBNI	-0.2866	0.4215	0.1777
5	BBRI	0.0315	0.3994	0.1595
6	BBTN	-0.2991	0.5041	0.2542
7	BMRI	-0.0132	0.4184	0.1751
8	BRPT	0.6292	0.6383	0.4074
9	ERAA	0.0166	0.6965	0.4851
10	EXCL	0.2805	0.5164	0.2667
11	HMSP	-0.3376	0.4216	0.1777
12	INDF	0.0248	0.3865	0.1494
13	ITMG	-0.3612	0.4482	0.2009
14	KLBF	0.1103	0.3802	0.1446
15	SCMA	-0.0842	0.5070	0.2571
16	SMGR	0.0066	0.5178	0.2681
17	UNVR	0.0265	0.3453	0.1192

Source: Processed data (2026).

As indicated in Table 2, the pandemic induced significant dispersion in asset performances. Certain stocks exhibited severe vulnerabilities to macroeconomic shocks, as seen in ITMG and BBTN, which recorded annualized expected returns of -36.12% and -29.91%, respectively, accompanied by high volatility. On the contrary, some assets showed a high level of resilience. BBCA maintained a stable positive return of 17.37% with the lowest standard deviation in the sample (28.72%). Meanwhile, BRPT recorded the highest annualized return at 62.92%, albeit with the highest corresponding risk level (63.82%). This heterogeneity justifies the necessity of applying an advanced evolutionary algorithm to identify optimal combinations.

Evolutionary Optimization Outcomes and the Pareto Front

Applying the NSGA-II algorithm to the empirical data resulted in a set of non-dominated solutions. These solutions represent portfolios where no further improvement in expected return can be achieved without concurrently increasing the risk. This set of optimal portfolios forms the Pareto front, as visualized in Figure 1.

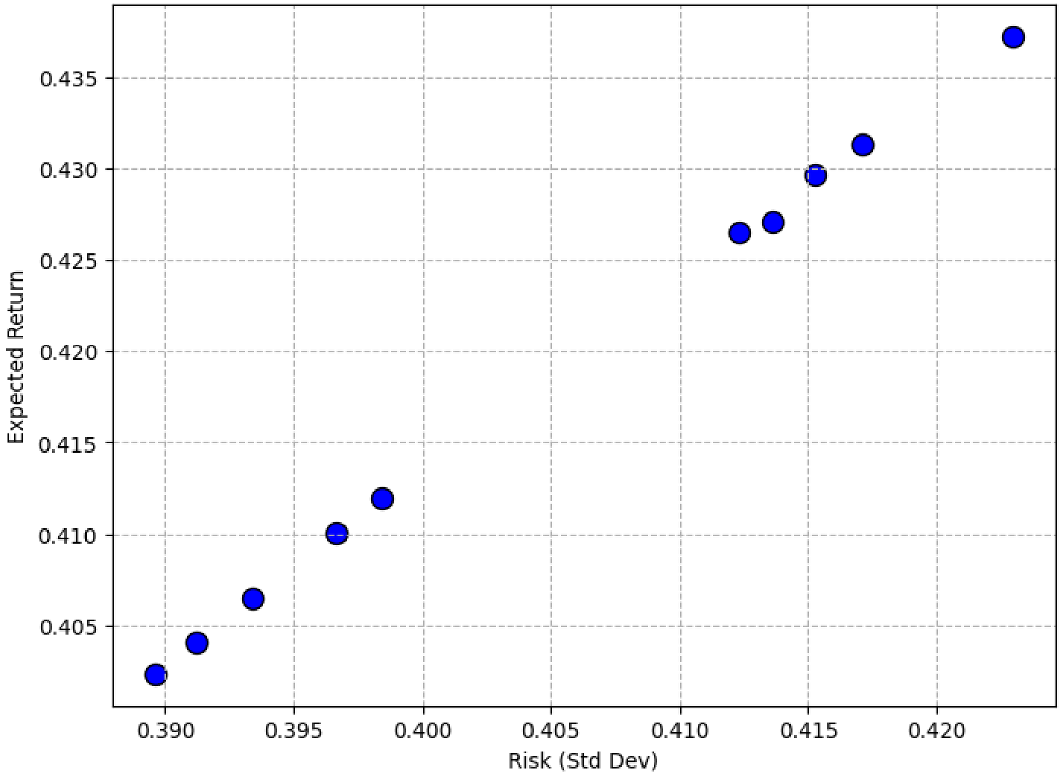

Figure 1. Pareto Front of the Top 10 Optimal Portfolios
Source: Processed data (2026).

Figure 1 illustrates a clear, upward-sloping trade-off between portfolio risk and expected return. To quantitatively evaluate these non-dominated solutions, the portfolios were ranked based on their Sharpe Ratios. Table 3 presents the top 10 portfolio configurations generated by the evolutionary engine.

Table 3. Top 10 Optimal Portfolios Generated by NSGA-II

Scenario	AKRA (%)	ANTM (%)	BBCA (%)	BBNI (%)	BBRI (%)	BBTN (%)	BMRI (%)	BRPT (%)	ERAA (%)	EXCL (%)	HMSP (%)	INDF (%)	ITMG (%)	KLBF (%)	SCMA (%)	SMGR (%)	UNVR (%)	Return	Risk	Sharpe
Portfolio 1	0.02	0.04	39.03	0.01	0.00	0.01	0.04	55.06	0.01	5.45	0.01	0.14	0.00	0.13	0.01	0.01	0.03	0.4296	0.4153	1.0346
Portfolio 2	0.03	0.05	39.38	0.01	0.00	0.01	0.04	54.31	0.01	5.78	0.00	0.16	0.01	0.14	0.03	0.00	0.04	0.4265	0.4123	1.0344
Portfolio 3	0.03	0.17	38.56	0.01	0.00	0.01	0.04	55.48	0.01	5.31	0.01	0.16	0.00	0.14	0.03	0.00	0.04	0.4313	0.4171	1.0340
Portfolio 4	0.06	0.01	45.15	0.01	0.00	0.01	0.00	51.93	0.00	2.33	0.00	0.02	0.00	0.37	0.02	0.01	0.08	0.4120	0.3984	1.0340
Portfolio 5	0.06	0.02	45.45	0.01	0.00	0.01	0.00	51.49	0.00	2.45	0.00	0.02	0.00	0.38	0.02	0.01	0.08	0.4101	0.3966	1.0339
Portfolio 6	0.03	0.05	37.17	0.01	0.00	0.00	0.04	56.70	0.01	5.61	0.01	0.15	0.01	0.13	0.03	0.01	0.04	0.4372	0.4229	1.0339
Portfolio 7	0.04	0.02	46.34	0.01	0.03	0.04	0.01	50.76	0.01	2.32	0.00	0.03	0.00	0.31	0.04	0.03	0.01	0.4065	0.3934	1.0333
Portfolio 8	0.08	0.02	45.48	0.05	0.03	0.00	0.05	49.86	0.00	4.05	0.00	0.02	0.03	0.29	0.03	0.01	0.00	0.4041	0.3912	1.0330
Portfolio 9	0.09	0.05	45.50	0.01	0.00	0.04	0.00	49.45	0.04	4.27	0.00	0.03	0.00	0.45	0.03	0.03	0.01	0.4024	0.3896	1.0327
Portfolio 10	0.02	0.04	38.78	0.01	0.00	0.01	0.04	54.71	0.01	5.42	0.01	0.77	0.00	0.13	0.01	0.01	0.03	0.4271	0.4136	1.0325

Source: Processed data (2026).

As reported in Table 3, the NSGA-II algorithm successfully identified portfolios with highly efficient risk-adjusted performances. Portfolio 1 achieved the highest Sharpe Ratio of 1.034, yielding an expected annualized return of 42.96% against a standard deviation of 41.52%. The consistency of the Sharpe Ratios among the top 10 scenarios indicates strong mathematical convergence.

Optimal Asset Allocation

To understand the internal mechanics of the optimization output, Figure 2 illustrates the specific capital allocation for Portfolio 1, which represents the mathematical pinnacle of the generated Pareto front.

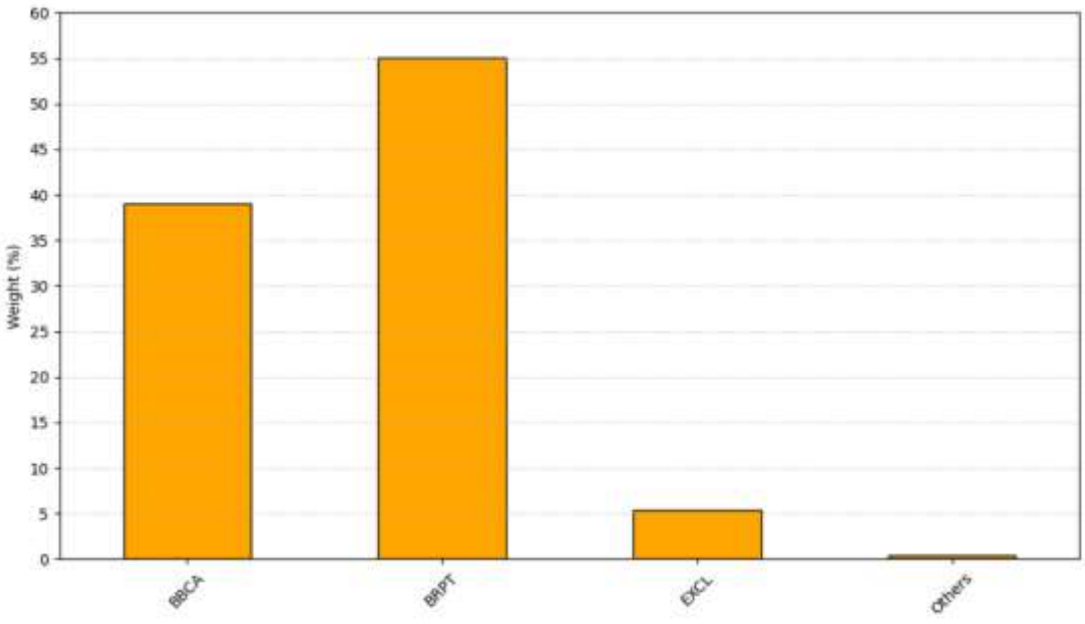

Figure 2. Asset Allocation of the Optimal Portfolio (Portfolio 1)
Source: Processed data (2026)

The visualization demonstrates that the evolutionary algorithm did not rely on a naive, equally-weighted diversification strategy (the traditional $1/N$ approach). Instead, it systematically concentrated capital into a highly strategic "barbell" allocation to maximize risk-adjusted returns amidst a highly chaotic market environment. The analytical breakdown of this allocation reveals a profound alignment between the algorithm's mathematical selections and the fundamental macroeconomic realities of Indonesia during the COVID-19 pandemic.

The core of the optimal portfolio is anchored by a massive 39.03% allocation to BBCA (Bank Central Asia Tbk.). In the context of the 2020 economic downturn, liquidity and institutional trust were paramount. BBCA is historically recognized for its exceptionally strong fundamentals, dominant Current Account Saving Account (CASA) ratio, and stringent risk management, which kept its Non-Performing Loans (NPL) well below the industry average during the crisis. The algorithm autonomously identified BBCA's historically low variance (28.73%) and positive expected return, utilizing it as the primary defensive shock-absorber to stabilize the entire portfolio against market-wide drawdowns.

Conversely, to drive the portfolio's profitability, the algorithm allocated the majority of the capital (55.06%) to BRPT (Barito Pacific Tbk.). While BRPT exhibited the highest risk in the sample (63.83%), it also generated an unprecedented expected return of 62.92%. Rather than rejecting BRPT due to its extreme volatility a common flaw in traditional, highly constrained quadratic solvers the NSGA-II algorithm successfully mathematically paired BRPT's high-yield potential with BBCA's stability. This structural pairing effectively neutralized the excessive risk of BRPT while capturing its upside, resulting in the mathematically superior Sharpe Ratio of 1.034.

Furthermore, the minor yet highly strategic allocations toward EXCL (XL Axiata Tbk., 5.45%) and KLBF (Kalbe Farma Tbk., 0.13%) underscore the algorithm's capability to capture structural thematic shifts caused by the pandemic. During this period, the Indonesian government implemented the Large-Scale Social Restrictions (Pembatasan Sosial Berskala Besar or PSBB). The sudden shift to Work-From-Home (WFH) and distance learning triggered an exponential surge in cellular data traffic, structurally benefiting telecommunication infrastructures like EXCL. Simultaneously, heightened public awareness regarding health and immunity drove massive demand for pharmaceuticals and consumer health supplements, bolstering KLBF.

Remarkably, the evolutionary algorithm was entirely agnostic to these qualitative narratives; it evaluated the assets purely on quantitative price behaviors and covariance matrices. Yet, its optimal output perfectly mirrored the fundamental economic thematic winners of the PSBB era. Equally important is what the algorithm chose to exclude. It aggressively penalized and assigned zero or near-zero weights to cyclical and commodity-driven stocks like ITMG (coal) and vulnerable financial sectors like BBTN, which suffered heavily from disrupted cash flows and mortgage defaults during the economic standstill. This advanced filtering corroborates the fact that NSGA-II can provide autonomous function as an applied, context understanding, decision support during serious macroeconomic crises.

DISCUSSION

The empirical results of our research provide strong evidence that NSGA-II evolutionary algorithm is reliable in building the optimal portfolio under the scenario of extreme market adverse, as we have observed recently during the period of COVID-19 outbreak. Traditional portfolio optimization models, particularly the classical Markowitz mean-variance framework, often exhibit significant limitations when applied to highly volatile datasets. These classical models are acutely sensitive to input estimations such as historical covariance matrices which tend to destabilize during systemic economic shocks (Ang & Bekaert, 2002; Das & Uppal, 2004). Furthermore, traditional mathematical solvers demonstrate an inability to efficiently map non-convex constraints, such as the cardinality limits enforced in this study, causing them to frequently collapse into suboptimal, highly concentrated portfolios (Hu et al., 2024; Lwin et al., 2014). In stark contrast, the evolutionary approach utilized in this study successfully navigated the chaotic market environment of 2019–2020 without succumbing to these computational traps.

The generation of a stable, well-distributed Pareto front (as depicted in Figure 1) and the attainment of a high Sharpe Ratio of 1.034 (Table 3) provide compelling evidence of the algorithm's capability to avoid local optima. The ability of NSGA-II to maintain a diverse population of solutions through its non-dominated sorting and crowding distance mechanisms is critical in a crisis scenario. When asset correlations shift unpredictably, having a frontier of diverse, risk-adjusted options allows institutional investors to pivot their strategies rapidly rather than being locked into a single, fragile "optimal" allocation predicted by a static quadratic equation (Deb et al., 2002; Guarino et al., 2024).

Furthermore, the asset allocation strategy of the optimal portfolio reveals a highly sophisticated balancing mechanism that challenges conventional diversification heuristics. Rather than suggesting a uniform distribution (the naive $1/N$ strategy) or concentrating solely on historical winners, the algorithm demonstrated strategic asset clustering. It concentrated significant capital in resilient, defensive equities (e.g., BBCA) to suppress overall portfolio variance, while strategically allocating heavy weights to high-growth, high-risk assets (e.g., BRPT) to drive expected returns. It is noteworthy that the algorithm autonomously allocated zero or near-zero weights to severely distressed assets (e.g., ITMG and BBTN), effectively functioning as a computational risk-mitigation filter.

Theoretical Implications

This dynamic adaptability aligns seamlessly with the Adaptive Markets Hypothesis (AMH) (Lo, 2004, 2005), fundamentally extending its empirical application within emerging markets. The AMH posits that financial markets evolve similarly to biological ecosystems, where market efficiency is not a static state but a highly fluid condition dependent on environmental factors. During the COVID-19 shock, the financial environment fundamentally changed, rendering historical pricing models obsolete. The NSGA-II algorithm, which itself is predicated on biological principles of survival of the fittest (mutation, crossover, and selection), mirrors the mechanics of the AMH. By continuously "breeding" better portfolios, the algorithm adapted to the new market regime faster and more efficiently than a static mathematical formula could (Arthur, 1999; Lo, 2004).

Comparing these findings directly with prior regional studies, such as the work (Hanif et al., 2021), underscores the theoretical novelty of this research. While their application of the classical Markowitz model provided a foundational understanding of the Indonesian market during the pandemic, their methodology lacked the computational flexibility to simultaneously enforce realistic trading constraints while seeking an absolute global optimum across conflicting objectives. The findings of the current study explicitly demonstrate that integrating evolutionary computation into financial modeling bridges a critical gap between computer science metaheuristics and financial economics, providing a vastly more resilient theoretical alternative to conventional analytical methods during periods of systemic crisis.

Managerial and Practical Implications

Beyond its theoretical contributions, this study provides profound and highly actionable managerial implications for institutional investors, specifically mutual fund managers and pension fund administrators operating within the

Indonesia Stock Exchange (IDX). The primary operational challenge during a black swan event such as a global pandemic or a sudden macroeconomic collapse is the rapid breakdown of asset correlations. During these systemic shocks, the assumption of normal distribution inherent in the Markowitz model fails entirely, as market returns exhibit "fat tails" and extreme downside risks.

In such chaotic environments, human fund managers are frequently paralyzed by cognitive overload and emotional biases, leading to irrational "panic selling" or the detrimental holding of depreciating assets. By integrating an evolutionary engine like NSGA-II into their algorithmic trading desks or robo-advisory systems, portfolio managers can establish an automated, data-driven rebalancing mechanism. When the market crashes, the algorithm does not rely on outdated assumptions of normality; instead, it aggressively recalculates the covariance matrices based on immediate volatility data and recalibrates the Pareto front overnight. This gives fund managers a quick mathematically sound dashboard of new risk-return trade-offs so they can make defensive reallocations before human sentiment can get in the way negatively.

Moreover, Indonesia's institutional investors are held responsible by regulatory bodies such as the Financial Services Authority (OJK) that are in particular strict in enforcing compliance rules and regulations about asset concentration and risk exposure. Traditional mathematical programming struggles to incorporate these complex, real-world constraints without the equations becoming mathematically intractable. NSGA-II, however, thrives in non-convex spaces. Fund managers can seamlessly program the algorithm to respect maximum investment limits per sector, minimum liquidity requirements, and specific cardinality bounds (e.g., holding no more than 15 assets to reduce transaction costs).

This study concludes that for modern portfolio managers working in emerging markets, adopting machine learning and heuristic algorithms is far from still being an academic novelty. And that's why it's a key operational requirement. Transitioning traditional mathematical models into an adaptive evolutionary framework enables financial institutions to navigate severe market turbulence, protects institutional capital and optimizes risk-adjusted returns in the setting of high-level global risk.

CONCLUSIONS AND RECOMMENDATIONS

The objective of this study was to evaluate the efficacy of the NSGA-II algorithm for portfolio optimization by incorporating Indonesia’s LQ45 index constituents during the COVID-19 pandemic. The computational simulation produced a Pareto-optimal frontier that proves that the algorithm can effectively maximize expected returns and minimize portfolio variance in a highly volatile market. The optimal portfolio configuration resulted in an efficient Sharpe Ratio of 1.034 due to such an allocation pattern that combined high-yield equities with low-variance defensive stocks.

Theoretically, this research contributes to the computational finance research by demonstrating empirical benefits of evolutionary heuristics to classical mean-variance models in time of extreme macroeconomic distress. By the method of efficient mapping of nonconvex mathematical space, the work validates evolutionary algorithm as the building block for adaptive decision-support system, which may help in integrating the advanced algorithm prediction and real portfolio management for emerging markets environment.

ADVANCED RESEARCH

However, this study has several limitations. The empirical tests were mainly limited to a time-window during crisis periods of peak severity that may not correspond to the algorithm's performance over multiple economic cycles. The model is also based on a bi-objective design only considering return and variance, which excludes important market frictions including transaction costs as well. These limitations, however, should be expanded in future studies, testing the algorithm to further understand the performance of the scheme in the broader economic timespan, including the post-pandemic era of market recovery. Moreover, the implementation of such an evolutionary methodology to Sharia-compliant market segments, such as the Jakarta Islamic Index (JII), could yield further comparative information. Ultimately, in order to define a robust adaptive decision-support system, future studies have to adopt a multi-faceted approach by adding other factors such as the Amihud illiquidity measure or ESG (Environmental, Social, and Governance) scores, so that the optimization model is robust to the liquidity reality.

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REFERENCES

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19) — An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, *27*, 100341. https://doi.org/10.1016/j.jbef.2020.100341

Ang, A., & Bekaert, G. (2002). International Asset Allocation with Regime Shifts. *The Review of Financial Studies*, *15*(4), 1137–1187. https://doi.org/10.1093/rfs/15.4.1137

Arthur, W. B. (1999). Complexity and the economy. *Science*, *284*(5411), 107–109. https://doi.org/10.1126/science.284.5411.107

Bekaert, G., Harvey, C. R., & Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies*, *20*(6), 1783–1831. https://doi.org/10.1093/rfs/hhm030

Das, S. R., & Uppal, R. (2004). Systemic Risk and International Portfolio Choice. *The Journal of Finance*, *59*(6), 2809. https://doi.org/10.1111/j.1540-6261.2004.00714.x

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. In *IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION* (Vol. 6, Number 2).

El Kharrim, M. (2023). Multi-period fuzzy portfolio optimization model subject to real constraints. *EURO Journal on Decision Processes*, *11*. https://doi.org/10.1016/j.ejdp.2023.100041

Elton, E. J., Gruber, M. J., Brown, S. J., & Goetzmann, W. N. (2014). *Modern Portfolio Theory & Investment Analysis* (9th ed.). John Wiley & Sons.

Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, *18*, 25–46. https://doi.org/10.1257/0895330042162430

Guarino, A., Santoro, D., Grilli, L., Zaccagnino, R., & Balbi, M. (2024). EvoFolio: a portfolio optimization method based on multi-objective evolutionary algorithms. *Neural Computing and Applications*, *36*(13), 7221–7243. https://doi.org/10.1007/s00521-024-09456-w

Habbab, F. Z., & Kampouridis, M. (2024). An in-depth investigation of five machine learning algorithms for optimizing mixed-asset portfolios including REITs. *Expert Systems with Applications*, *235*, 121102. https://doi.org/10.1016/j.eswa.2023.121102

Hanif, A., Hanun, N. R., & Febriansah, R. E. (2021). Optimization of Stock Portfolio Using the Markowitz Model in the Era of the COVID-19 Pandemic. *The International Journal of Applied Business)*, *5*(1), 37–50.

Hu, C., Gao, Y., & Guo, E. (2024). A Novel Improved Genetic Algorithm for Multi-Period Fractional Programming Portfolio Optimization Model in Fuzzy Environment. *Mathematics*, *12*(11). https://doi.org/10.3390/math12111694

Kolm, P. N., Tütüncü, R., & Fabozzi, F. J. (2014). 60 Years of portfolio optimization: Practical challenges and current trends. *European Journal of Operational Research*, *234*(2), 356–371. https://doi.org/10.1016/j.ejor.2013.10.060

Krink, T., & Paterlini, S. (2011). Multiobjective optimization using differential evolution for real-world portfolio optimization. *Computational Management Science*, *8*(1–2), 157–179. https://doi.org/10.1007/s10287-009-0107-6

Lesmond, D. A. (2005). Liquidity of emerging markets. *Journal of Financial Economics*, *77*(2), 411–452. https://doi.org/10.1016/J.JFINECO.2004.01.005

Lo, A. W. (2004). The adaptive markets hypothesis. *The Journal of Portfolio Management*, *30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. *The Journal of Investment Consulting*, *7*(2), 21–44.

Lwin, K., Qu, R., & Kendall, G. (2014). A learning-guided multi-objective evolutionary algorithm for constrained portfolio optimization. *Applied Soft Computing Journal*, *24*, 757–772. https://doi.org/10.1016/j.asoc.2014.08.026

Ma, Y., Han, R., & Wang, W. (2021). Portfolio optimization with return prediction using deep learning and machine learning. *Expert Systems with Applications*, *165*, 113973. https://doi.org/10.1016/j.eswa.2020.113973

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91.

Masmoudi, M., & Abdelaziz, F. Ben. (2018). Portfolio selection problem: a review of deterministic and stochastic multiple objective programming models. *Annals of Operations Research*, *267*(1–2), 335–352. https://doi.org/10.1007/s10479-017-2466-7

Metaxiotis, K., & Liagkouras, K. (2012). Multiobjective Evolutionary Algorithms for Portfolio Management: A comprehensive literature review. *Expert Systems with Applications*, *39*(14), 11685–11698. https://doi.org/10.1016/j.eswa.2012.04.053

Panjaitan, Y., & Novel, R. (2021). Volatility Spillover Among Asian Developed Stock Markets to Indonesia Stock Market During Pandemic Covid-19. *Jurnal Keuangan Dan Perbankan*, *25*(2), 342–354. https://doi.org/10.26905/jkdp.v25i2.5532

Rizwan, M. S., Ahmad, G., & Ashraf, D. (2020). Systemic risk: The impact of COVID-19. *Finance Research Letters*, *36*, 101682. https://doi.org/10.1016/j.frl.2020.101682

Rouwenhorst, K. G. (1998). Local return factors and turnover in emerging stock markets. *Working Paper, Yale University*.

Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis*, *71*, 101546. https://doi.org/10.1016/j.irfa.2020.101546

Salo, A., Doumpos, M., Liesiö, J., & Zopounidis, C. (2024). Fifty years of portfolio optimization. In *European Journal of Operational Research* (Vol. 318, Number 1, pp. 1–18). Elsevier B.V. https://doi.org/10.1016/j.ejor.2023.12.031

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. In *The Journal of Finance* (Vol. 19, Number 3).

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

Zou, W., Zhu, Y., Chen, H., & Zhang, B. (2011). Solving multiobjective optimization problems using artificial bee colony algorithm. *Discrete Dynamics in Nature and Society*, *2011*. https://doi.org/10.1155/2011/569784