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COMPARISON OF MEAN-VARIANCE MODEL AND FIREFLY ALGORITHM PERFORMANCE: BIST 30 INDEX APPLICATION

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Abstract

Market participants manage their portfolios with the aim of maximizing profits and minimizing risks, and portfolio optimization plays a crucial role in this process. Markowitz's (1952) mean-variance model provides a new perspective to portfolio optimization by mathematically quantifying risk. However, in recent years, advances in finance and many other fields are driven by artificial intelligence algorithms. Motivated by the Firefly Algorithm's dynamic focus on solving optimization problems, this study aims to compare the performance of Markowitz's mean-variance model with that of the Firefly Algorithm. In this direction, the performance metrics of portfolios—expected return, risk, Sharpe ratio, coefficient of variation, and downside risk—are calculated on a yearly basis using data obtained from companies operating in the BIST 30 Index between January 1, 2018, and December 31, 2023, according to the traditional mean-variance model. Subsequently, considering the 2023 data, which yields the most successful results, these metrics are recalculated using the Firefly Algorithm, a meta-heuristic artificial intelligence method, and the performances of both models are compared. The results reveal that the higher Sharpe ratio and expected return obtained from the Firefly Algorithm indicate a more successful performance than the mean-variance model. However, when interpreting the results, it should be considered that the higher downside risk identified compared to the mean-variance model may present certain disadvantages for the Firefly Algorithm in terms of risk management constraints.

Keywords: Portfolio Optimization, Mean Variance, Firefly Algorithm
JEL Classification: JEL 10, JEL 11

ORTALAMA-VARYANS MODELİ İLE ATEŞ BÖCEĞİ ALGORİTMASININ PERFORMANS KARŞILAŞTIRMASI: BIST 30 ENDEKSİ UYGULAMASI

Öz

Piyasa katılımcıları portföylerini, karlarını maksimize etme ve riskten kaçınma hedefiyle yönetirler ve bu süreçte portföy optimizasyonu büyük önem taşır. Markowitz (1952)'in ortalama-varyans modeli riski matematikselleştirerek portföy optimizasyonuna yeni bir bakış açısı kazandırmıştır. Ancak son birkaç yılda finans ve diğer birçok alandaki ilerlemeler yapay zeka algoritmaları tarafından oluşmuştur. Ateş böceği algoritmasının dinamik bir şekilde optimizasyon problemlerine odaklanarak, sorunları çözmek için kullanılan tekniklerden biri olması motivasyonu altında bu çalışmanın amacı Markowitz'in ortalama-varyans modeli ile Ateş böceği algoritmasının performans karşılaştırmasının yapılmasıdır. Bu doğrultuda 01/01/2018 ile 31/12/2023 tarihleri arasında BİST30 Endeksinde faaliyet gösteren firmalardan elde edilen verilerle yıl bazında portföylerin performans metrikleri (beklenen getiri, risk, sharpe oranı, değişim katsayısı ve downside riski) geleneksel model olan ortalama varyans modeline göre hesaplanmıştır. Ardından en başarılı sonuçların alındığı 2023 yılı verileri dikkate alınarak Meta-Sezgisel bir yapay zekâ yöntemi olan Ateş böceği algoritmasıyla söz konusu metrikler tekrar hesaplanarak her iki modelin performans karşılaştırması yapılmıştır. Yapılan analizler neticesinde ateş böceği algoritmasının performansından elde edilen yüksek sharpe oranı ve beklenen getiri ortalama-varyans modelinden daha başarılı performans sergilediğini gözler önüne sermektedir; ancak sonuçlar değerlendirilirken ortalama varyans modeline göre tespit edilen daha yüksek downside riski ateş böceği algoritmasının risk yönetimi açısından kısıtlar dahilinde bazı dezavantajlar sağlayabileceği de göz önünde bulundurulmalıdır.

Anahtar kelimeler: Portföy Optimizasyonu, Ortalama Varyans, Ateş Böceği Algoritması.
JEL Sınıflaması: JEL 10, JEL 11

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1. Introduction

One of the most crucial topics in contemporary financial management is portfolio optimization, which deals with the challenge of allocating financial resources to a group of assets in a way that maximizes return and minimizes risk. Investors use the notion of diversification to guide their financial decisions by allocating their cash across a range of asset classes. Instead of focusing on a single asset, investing in a portfolio diversifies assets, lowering risk without compromising projected profits. The fundamental form of portfolio optimization is defined as an optimization problem where the goal is to minimize risk and maximize anticipated return, as indicated by return variance and mean return, respectively. The choice of a securities portfolio that minimizes risk subject to return is the focus of this topic (Bacanin and Tuba, 2014).

The goal of an optimization issue is to identify the best possible solution from all potential options. Stated differently, the optimization issue consists of locating a solution with the minimum (or maximum) value of the objective function inside the feasible zone. The sorts of mathematical connections that exist between the objective, constraints, and decision variables in an optimisation issue influence its difficulty as well as the types of approaches or algorithms that may be used to optimisation in order to obtain the genuinely optimum solution (Johari et al, 2013).

In financial mathematics, portfolio optimization has grown in interest since the groundbreaking work of Markowitz (1952). Variance is a metric used by him in "Portfolio Selection" to express how risky an investment is. Markowitz's method is sometimes referred to a mean-variance portfolio optimization. The ideal portfolio is defined as the least variance portfolio given the amount of expected return (Setiawan, 2020).

A review of the literature can yield several solutions to the portfolio dilemma. In Markowitz's classic mean-variance model, the remaining objective functions are presented as constraints, and an important objective function is chosen and submitted to optimization. Using a portfolio's anticipated returns as the return on investment and its return variance as the investment risk is the fundamental idea behind the mean-variance formulation. The current portfolio theory has benefited greatly from the widespread adoption of this strategy (Markowitz, 1952; Anagnostopoulos and Mamanis, 2011; Wang, et al, 2013).

The conventional theory of portfolios suggests a number of tactics to help investors strike a balance between risk and return. In addition to conventional approaches, more sophisticated algorithms are required due to the portfolio optimization problem's great dimensionality and complexity.

Since the majority of real-world issues can be modeled as optimization tasks, several approaches and strategies are being developed to deal with these kinds of issues. As a result, one of the most useful areas in computer science and mathematics is becoming optimization. Accordingly, problem-specific search strategies are needed to produce optimal or nearly optimal solutions (Bacanin and Tuba, 2014). One of them is the firefly algorithm, a nature-inspired algorithm that efficiently searches the solution space influenced by natural systems in an effort to identify the best outcomes. The firefly algorithm is said to be more effective than other traditional algorithms, and to outperform them in terms of statistical performances as determined by standard stochastic test functions. The basis for this algorithm's operation is the worldwide communication of fireflies. As a result, it is able to simultaneously locate the local and global optima. Fireflies operate autonomously, and are positioned to be implemented in parallel (Yang, 2010; Zhang et al, 2013; Johari et al, 2013). According to this viewpoint, the primary driving force behind this investigation is the assertion that the firefly algorithm is one of the methods that academics have lately employed to address optimization issues in dynamic environments. The objective of this research is to evaluate the performance of the mean variance model and the firefly algorithm in calculating the annual performance measures of the companies traded in the Borsa Istanbul 30 Index. In order to determine whether artificial intelligence model will perform better, the conventional model and a meta-heuristic model in portfolio development are compared. From an analytical standpoint, the Markowitz Mean Variance model is utilized to compute share weights and portfolio performance metrics based on the returns derived from the stock prices of the companies quoted in the BIST 30 Index between January 1, 2018, and December 31, 2023. Next, using the Firefly algorithm, the ideal portfolio was determined. Following a comparison between the derived portfolio performance measures and the conventional mean-variance model's output, the optimal model was identified. All these applications are carried out using Pyhton Jupyter Notebook.

Following the literature review, data set and methodology details are provided in the remaining portions of the research. Comprehensive details on the Firefly Algorithm, which serves as the research's basis, are provided, particularly in the next section. The results of this algorithm's analysis are subsequently shown and explained in tables, which are included in the section on the results and analysis. In the conclusion part, the research is finally given a broad assessment and discussion.

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2. Literature Review

Yang (2009) tries to evaluate how well the Firefly method performed in comparison to other comparable techniques and particle swarm optimization. The fingings indicate that when it comes to the optimization of the Firefly method and its capacity to handle multimodal functions in a more efficient and natural manner, better outcomes are reached than with particle swarm optimization. Wang (2019) offers an enhanced Firefly method known as the Discrete Firefly Algorithm (DFA) algorithm from a new angle. The experimental findings demonstrate that the DFA method has greater convergence accuracy and faster convergence speed than the genetic algorithm, particle swarm optimization algorithm, differential evolution algorithm, and firefly algorithm. Similarly, using the entropy-constrained Cardinality Constrained Mean-Variance (CCMV) portfolio model, Bacanin and Tuba (2014) present a modified version of the firefly algorithm (FA). To address the lack of exploratory power in the initial iterations, the algorithm is adjusted and evaluated using industry-standard portfolio benchmark datasets. The suggested modified firefly method is found to perform better than alternative algorithms.

By converting the fuzzy mean-variance-skewness model into a fuzzy mean-variance-skewness kurtosis model, Salehi (2019) suggests the Firefly Algorithm's use to solve the model. The suggested algorithm's efficiency and performance are evaluated in terms of fitness value and computing time required against the precise method (LINGO software). The findings demonstrate how attractive the suggested Firefly algorithm is and how quickly it may produce excellent outcomes for fuzzy portfolio selection.

By combining a machine learning model with stock return forecasts, Hongjoong (2021) seeks to ascertain how effectively a portfolio optimization model performed. Portfolio selection in the research is done using the mean variance model. Stock return forecasting is with the XGBoost algorithm. Analysis reveals that compared to the old model, the machine learning method produces superior outcomes.

In order to achieve the best possible portfolio construction, Chaweewanchon and Chaysiri (2022) suggest a novel method based on a hybrid machine learning model that combines the Markowitz mean-variance (MV) model with a Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM). The proposed strategy outperforms the benchmark models in terms of Sharpe ratio, average return, and risk, according to assessments done using data from the Stock Exchange of Thailand 50 Index (SET50) between January 2015 and December 2020. A sequential Quadratic Programming (QP) technique is presented by Xiu

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et al. (2023) to optimize the overall mean variance problem. The analysis's findings demonstrate that, in comparison to cutting-edge techniques, the suggested algorithm has a greater rate of convergence and better scalability.

Li (2023) seeks to optimize the financial investment risk prediction model through the use of the Firefly Algorithm and Graph Convolutional Network (GCN). By fine-tuning the Firefly algorithm in the financial investment risk prediction model, they increase the prediction model's accuracy and conducted studies to confirm the model's efficacy. According to the study, the optimized model outperforms the standard models in feature selection, with an optimal accuracy of 91.9%, which is much more effective. Nugraha et al. (2024) employ a distinct methodology, utilizing Markowitz's mean-variance model to determine the optimal portfolio for their research. Companies that traded in the Indonesia Stock Exchange 30 (IDX30) Index in 2022 and 2023 were included in the analysis. Seven equities with an estimated rate of return of 65.776% and a portfolio risk of 20.0008% were determined to be the ideal mix for the portfolio as a consequence of the Python calculations.

Dadfar et al. (2024) a study was conducted to optimize banks' resource allocation processes within the scope of credit risk management. In the research, Sina Bank's credit portfolio was analyzed using Markowitz's modern portfolio model along with meta-heuristic methods such as Genetic Algorithm and Firefly Algorithm. The performance comparison of the models shows that the Genetic Algorithm model provides the highest efficiency in optimizing the bank's credit portfolio. According to the results, while the services and trade (52.4%) and housing and construction (40.7%) sectors constitute the largest share of the portfolio; industry and mining (3.5%) and agriculture and water (3.4%) sectors were evaluated as riskier assets. These findings reveal that the bank's credit allocation process is far from optimal and that sector-based rebalancing is necessary to reduce risk.

Jaiswal et al. (2025) compared a Monte Carlo simulation-based probabilistic algorithm with a deterministic method based on Markowitz Portfolio Theory using data from eight pharmaceutical companies traded in India between 2020-2023. In the study, an AdaBoost model developed with the Firefly Algorithm (FA) was used to predict stock returns, achieving a 14.6% reduction in prediction error. The portfolio optimized with the Mean-Value-at-Risk (Mean-VaR) model showed better performance by achieving a 12.3% higher Sharpe ratio compared to the traditional Mean-Variance model. These findings demonstrate that artificial intelligence and meta-heuristic methods can be effectively used in portfolio optimization. Türkoğlu and Kutlu (2025) using the price data of stocks included in the BIST Dividend 25 Index between 2018-

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2023, the study compared the traditional Mean-Variance model with the Firefly and Simulated Annealing algorithms in terms of portfolio performance. Expected return, portfolio risk, Sharpe ratio, coefficient of variation, and downside risk were used as performance metrics in the study. The findings show that the Firefly and Simulated Annealing algorithms provided higher returns than the average return but carried more risk. In particular, the Firefly algorithm demonstrated better performance in terms of Sharpe ratio and downside risk, revealing that investors could achieve above-market returns by diversifying with these methods in Borsa Istanbul.

3. Dataset and Methodology

The purpose of this study is to evaluate the effectiveness of the Firefly Algorithm model vs Markowitz's mean variance model. The closing stock prices and yearly risk-free interest rates and 28 out of the 30 companies listed in the BIST 30 Index are included in the data set utilized for this purpose. The research's data, which covered the months of January 1, 2018, and December 31, 2023, was acquired from Yahoo Finance. On an annual basis, risk-free interest rates are examined using data from Government Domestic Debt Securities (GDDS) for the years 2018–2023. Considering the data set's daily stock closing prices, annual returns are computed. By normalizing stock returns for each year, annual performance statistics are generated. Annual risks are calculated using standard deviation and covariance matrices. The weights of the stocks and the expected return of the portfolio between 2018 and 2023 are calculated according to Markowitz's mean variance method. Immediately afterwards, this study presents the optimal portfolio created with the Firefly Algorithm with 2023 data. Closing prices of 28 BIST 30 constituents were used for 1,523 trading days covering the 2018–2023 period. The analysis was conducted based on daily returns, while the yearly summary tables were presented solely for comparative performance analysis purposes. To reduce potential reliability concerns arising from data density, a cross-year validation approach was implemented. Each year's data was individually tested using the calculate_yearly_metrics() function to ensure the consistency and robustness of the model's performance across different periods. By comparing the performance metrics of the obtained portfolios, the performance of the mean variance method, which is a traditional method, and the performance of the Firefly algorithm, a meta-heuristic artificial intelligence model, were compared. Performance metrics include expected return, Sharpe ratio, coefficient of variation and downside risk. All these analyses were performs all these analyses Pyhton Jupyter Notebook.

Mallieswari et al. (2024) use information from eight pharmaceutical companies that listed in India between 2020 and 2023 to do portfolio optimization two algorithms: a probabilistic

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optimization algorithm that makes use of Monte Carlo simulation and a deterministic optimization method that applies Markowitz Portfolio Theory. The results obtained through Monte Carlo simulation analysis indicate that the NIFTY Pharma Index exhibits substantially higher volatility.

3.1. Mean Variance Model

While constructing a portfolio, investors give consideration to both risk and return considerations. While there is a correlation between risk and return, an investor's potential return is higher when the risk is higher. In the absence of this, the investor will have modest expectations for the return. To maximize their returns, investors must, therefore, choose their stocks wisely. The Markowitz model is one of the methods available for creating an ideal portfolio. The mathematical framework that Markowitz (1952) devised for portfolio optimization is known as Markowitz Theory, or Modern Portfolio Theory. This theory emphasizes the value of diversity and the ways in which returns may be increased while risk is decreased. Markowitz theory is still analyzed, and has had a significant influence on the domains of finance and portfolio management. The link between risk and return is at the center of the Markowitz model. Random diversification, defined as building a portfolio by choosing securities at random, irrespective of the qualities of the assets involved, is something that this model can handle (Edy Suprianto and Akt, 2008). To put it briefly, the Markowitz model analyzes returns and risks for different assets using statistical analysis, and it then uses that information to identify the best way to allocate assets within a portfolio (Nugrahaa et al., 2024).

The mean-variance methodology has been the most widely used approach for resolving the portfolio selection problem since the groundbreaking work of Markowitz (1952). The mean-variance model's primary concept is to use expected value and variance to quantify investment return and risk while treating the returns of individual securities as random variables.The fundamental components of the ideal portfolio selection are represented by this model.

To deal with continuously changing financial markets, for instance, multi-period portfolio selection should be taken into account. Practical constraints, such as transaction costs, restrictions on trading rules, restrictions on security types, restrictions on market security, and others, should also be taken into account. Optimal portfolios are frequently susceptible to estimation errors of the mean value and deviation of sample parameters, and when there is insufficient sample, it is difficult to predict future returns and risks of a security with high

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accuracy (Zhang et al., 2018). The mean-variance model's central formula for risk and anticipated return is as follows (Kardiyen, 2008):

anticipated return is as follows (Kardiyen, 2008):

$$E(r_p) = \sum_{i=1}^{n} E(r_i)\, x_i \tag{1}$$

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} cov(r_i, r_j) x_i x_j \tag{2}$$

x_i: the proportion of security i in the portfolio

$E(r_p)$: expected return of the portfolio

Σ^2_p: portfolio variance (risk)

$E(r_i)$= expected return of security i

$cov(r_i,r_j)$= : covariance of returns of securities i and j

n : is expressed as the number of available securities.

The objective function and constraints for obtaining the Markowitz efficient frontier are given in equations (3).

$$Min \sum_{i=t}^{n} \sum_{j=1}^{n} x_i x_j \,\sigma_{ij}$$

Constraints

$$\sum_{i=1}^{n} x_i E(r_i) \geq \text{R} \tag{3}$$

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

$$0 \leq x_i \leq 1, i = 1,2, \dots, n$$

R: targeted expected return level

In the model, portfolio risk is minimised under the constraints that the expected return of the portfolio is equal to or greater than a certain target return level, the weights given to the securities in the portfolio are between zero and one and the sum of these weights is equal to one.

3.2. Firefly Algorithm

A generic algorithmic basis for handling challenging situations is offered by metaheuristics. Learning techniques are used to efficiently structure information to identify near-optimal

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solutions, whereas metaheuristics are an iterative generation process that integrates many ideas to explore and exploit the search space, leading a subset of heuristics (Johari et al., 2013).

According to Yang (2009), fireflies may distinguish their neighbors because their close proximity attracts them more strongly than a distance can. Empirically, the Firefly algorithm offers a superior success rate and efficiency when comparing the test functions of several issues with swarm intelligence claiming global optimal solutions and genetic algorithms. Certain academics assert that the Firefly algorithm is an effective method for resolving even certain Non-deterministic Polynomial time (NP) hard problems in light of this outcomes.

Winged insects known as fireflies emit light and flicker during the night. Bioluminescence is the term for the light that is created chemically from the lower abdomen and lacks both ultraviolet and infrared frequencies. They mostly use the flash light to entice potential mates or food. According to Johari et al. (2013), flash lights are also employed as a warning system to safeguard fireflies from possible predators. It is feasible to develop novel optimization methods by associating flashing lights with the objective function that has to be optimized (Yang, 2009).

A novel population-based meta-heuristic method called the firefly algorithm performs exceptionally well in a variety of optimization tasks (Wang, 2019). This well-liked and effective algorithm was inspired by firefly behavior and light flashing. At a certain distance r from the light source, the light intensity is controlled by the inverse square law. Put otherwise, the light intensity I diminishes as I, I ∝ 1/r2 and the distance r grows (Zare et al., 2023).

The algorithm's parameter values, including population size, density, attraction coefficient, and light absorption coefficient, are calculated. A random selection is made from the lower and upper limit values to create the beginning population. Every value in the identified population has its goal function values computed (Doğru & Eren, 2020):

$$x_i = x_{min} + r(x_{max} - x_{min}) \tag{4}$$

In Equation 4, r is a randomly selected number between 0 and 1, $xmin$ and $xmax$ are the lower and upper bound values. In the next process, the distance between any two individuals at points i and j is calculated using equation 5.

$$r_{ij} = \left\| x_i - x_j \right\| \tag{5}$$

After the distance between the two individuals is calculated, the new position of the firefly is calculated according to equation 6.

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$$x_i^{t+1} = x_i^t + \beta_o e^{-yr^2 xj}(x_j^t - x_j^t + a_t \varepsilon_i^t \quad (6)$$

In the equation β_0 is the attractiveness coefficient, γ is the light absorption coefficient, $x_j{}^t$ and $x_i{}^t$ are the individuals located at points i and j, at is a random number between 0 and 1, $\varepsilon_i\ t$ is a variable determined according to the lower upper limits. $x_i{}^t$+is the new location of the individual and the objective function value is recalculated and assigned as the new location if a better result is achieved compared to the first location.

In general, the basic steps of the Firefly algorithm can be summarised as the pseudo code shown in Figure 1:

Figure 1. Basic codes of the firefly algorithm

Objective function *f(x), x=(x₁,…,x_d)*
Generate initial population of fireflies x_i (I,2,…,n)
Light intensity Ii at xi is determined by *f(x_i)*
Define light absorption coefficient γ
while (*t <MaxGeneration*)
for *i = 1 : n all n* fireflies
for *j = 1 : i all n* fireflies
if $(I_j > I_i)$, Move firefly i towards j in d-dimension; **end if**
Attractiveness varies with distance r via exp[−r]
Evaluate new solutions and update light intensity
end for *j*
end for *i*
Rank the fireflies and find the current best
end while
Postprocess results and visualization

Source: Salehi, K. (2019). Firefly Algorithm (FA) for solving extended fuzzy portfolio selection problem. International journal of industrial engineering and operational research, 1(1), 39-50.

The attraction and movement among the fireflies aim at global optimisation by moving towards better solutions. This algorithm explains the working principle of the Firefly Algorithm, a nature-inspired optimisation method. Table 1 presents hyperparameters of the firefly algorithm applied in this study are presented in Table 1.

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Table 1. Hyperparameters of the Firefly Algorithm

Hyperparameter	Description	Value in Practice
dim	The size of the position vector of the firefly	self.dim
alpha	The traction of the firefly	0.5
beta	Reduction rate of firefly light	0.2
gamma	Traction	1.0
n_iterations	Number of iterations	100
n_fireflies	Number of fireflies	30

The hyperparameters employed in the Firefly Algorithm research are highlighted in Table 1. In the present research, default values were used to prevent issues like local maximum stuttering and overfitting with the assumption that marginal benefit will decrease, complexity will increase, and more parameter interactions may complicate the algorithm's dynamics. It may be possible to increase the number of iterations and fireflies in the analysis application.

4. Analysis and Findings

The goal of this study is to generate an optimal portfolio employing the firefly algorithm as a meta-heuristic model, and the mean variance modelThis study aims to compare the performance of two models—the Firefly Algorithm and the Mean-Variance Model—by considering the daily returns, risks, and return characteristics of 28 companies continuously listed in the BIST 30 Index between January 1, 2018, and December 31, 2023. To achieve this, portfolio weights and annual weights were calculated using Markowitz's Mean-Variance framework, based on the daily closing prices of these 28 companies. The performance parameters of the BIST 30 Index portfolio, including anticipated return, sharpe ratio, coefficient of variance, and downside risk, were also computed. The risk-free interest rate, or GDDS, was determined throughout the computations using data from the Yahoo Finance database for the equities. Following these computations, the Firefly Algorithm is used to estimate the most ideal portfolio, which is most likely to comprise the BIST 30 Index portfolio. The performance metrics are shown beside the conventional model.

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Table 2. Stock Weights and BIST 30 Performance Metrics Calculated by Mean-Variance

	2018	2019	2020	2021	2022	2023
AKBNK.IS	0,0589	0,0292	-0,0056	0,0079	0,0314	0,0665
ALARK.IS	0,1154	0,0934	0,0323	0,0356	0,0548	0,0220
ASELS.IS	0,0508	-0,0057	0,0420	0,0164	0,0319	0,0381
BIMAS.IS	-0,0397	0,0114	0,0384	-0,0082	0,0232	0,0691
BRSAN.IS	0,0673	0,0490	0,0724	0,0080	0,0334	0,1806
DOAS.IS	0,1210	0,0754	0,0890	0,0547	0,0473	0,0444
EKGYO.IS	0,1210	0,0041	0,0312	0,0000	0,0419	-0,0096
ENKAI.IS	0,0324	0,0316	0,0227	0,0667	0,0267	0,0113
EREGL.IS	0,0444	0,0330	0,0410	0,0688	0,0156	0,0051
FROTO.IS	0,0051	0,0328	0,0505	0,0668	0,0240	0,0371
GARAN.IS	0,0393	0,0304	0,0012	0,0136	0,0303	0,0685
GUBRF.IS	0,0727	0,0882	0,1653	0,0093	0,0364	-0,0267
HEKTS.IS	-0,0909	0,0679	0,0651	0,1307	0,0656	-0,0353
ISCTR.IS	0,0777	0,0308	0,0093	0,0088	0,0422	0,0634
KCHOL.IS	0,0486	0,0312	0,0087	0,0317	0,0306	0,0510
KOZAL.IS	-0,1003	0,0329	0,0212	0,0141	0,0497	-0,0176
KRDMD.IS	0,0686	0,0291	0,0587	0,0437	0,0231	0,0350
OYAKC.IS	0,0314	0,0629	0,0353	-0,0069	0,0288	0,0880
PETKM.IS	0,0477	-0,0003	0,0359	0,0419	0,0279	0,0016
PGSUS.IS	0,0697	0,1063	0,0065	0,0211	0,0492	0,0299
SAHOL.IS	0,0785	0,0246	0,0180	0,0174	0,0361	0,0330
SASA.IS	-0,0563	0,0268	0,0754	0,1139	0,0439	-0,0051
SISE.IS	-0,0744	0,0007	0,0293	0,0549	0,0336	0,0121
TCELL.IS	0,0238	0,0169	0,0143	0,0194	0,0224	0,0381
THYAO.IS	-0,0342	-0,0036	-0,0019	0,0435	0,0537	0,0452
TOASO.IS	0,1371	0,0459	0,0304	0,0781	0,0239	0,0293
TUPRS.IS	-0,0345	0,0180	-0,0060	0,0332	0,0343	0,0689
YKBNK.IS	0,1190	0,0371	0,0195	0,0151	0,0382	0,0561
Expected return	-0,17	0,55	0,67	0,51	1,54	0,59
Sharpe ratio	-1,28	1,71	1,64	1,08	1,93	0,88
Coefficient of variation	-1,47	0,42	0,50	0,62	0,23	0,80
Downside risk	0,02	0,02	0,02	0,02	0,03	0,03

The mean-variance approach, which is the foundation of contemporary portfolio theory, was used to compute the weights of the firms included in the analysis for the portfolio between 2018 and 2023 as well as the performance measures of the present portfolio. The results are displayed in Table 2. 2018, with a negative anticipated return and Sharpe ratio, performed the worst. 2019 through 2021 have strong performance with high Sharpe ratios and favorable anticipated returns. The greatest performance, as measured by the highest Sharpe ratio and predicted return, 2023. Particularly in 2018, the coefficient of variation has a negative value, suggesting that the year had a significant level of volatility. On the other hand, downside risk remained quite modest and stable throughout the course of all years, indicating that the portfolio has managed risk successfully.

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Table 3 illustrates the portfolio created using the Firefly Algorithm with the data from 2023, based on the optimal weights. This yielded the most effective outcome when it turned out to be variance optimization.

Table 3. Optimal Portfolio Constructed with Firefly Algorithm

Stock	Weight	Stock	Weight
AKBNK.IS	0,1220	KCHOL.IS	0,3640
ALARK.IS	0,1888	KOZAL.IS	0,4362
ASELS.IS	0,3351	KRDMD.IS	0,8531
BIMAS.IS	0,7167	OYAKC.IS	0,3898
BRSAN.IS	0,3826	PETKM.IS	0,7057
DOAS.IS	0,6592	PGSUS.IS	0,7850
EKGYO.IS	0,6322	SAHOL.IS	0,2170
ENKAI.IS	0,2269	SASA.IS	0,8731
EREGL.IS	0,5864	SISE.IS	0,5100
FROTO.IS	0,6396	TCELL.IS	0,1876
GARAN.IS	0,2051	THYAO.IS	0,4349
GUBRF.IS	0,5736	TOASO.IS	0,4916
HEKTS.IS	0,6553	TUPRS.IS	0,4875
ISCTR.IS	0,3125	YKBNK.IS	0,4398
Optimal Portfolio Expected Return:		7,35	
Optimal Portfolio Sharpe Ratio:		1,82	
Optimal Portfolio Coefficient of Variation		0,53	
Optimal Portfolio Downside Risk		0,53	

The optimal portfolio generated by the Firefly Algorithm is predicted to have an expected return of 7.35. This figure indicates the anticipated future annual average rate of return for the portfolio. Since it indicates the expected profit that the portfolio will generate, expected return is a crucial indicator for investors. An anticipated return of 7.35% offers a respectable return at a manageable risk level. A statistic used to calculate a portfolio's risk-adjusted return is called the Sharpe ratio. The portfolio performed better the greater the Sharpe ratio. An excellent return per risk is provided by the portfolio, as seen by the Sharpe ratio of 1.82. The portfolio's return volatility gauged by the coefficient of variation, is 0.53. This number demonstrates that the portfolio's returns are generally consistent and do not exhibit high volatility. The likelihood that the portfolio's return will drop below a certain level and the extent of the loss in this scenario are measured by downside risk. With a downside risk value of 0.26, the portfolio is shielded from large losses and has a minimal chance of observing negative returns.

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Table 4. Optimal Portfolio Constructed with Firefly Algorithm

	Mean-Variance model	Firefly Algorithm
Expected return:	0,59	7,35
Sharpe Ratio:	0,88	1,82
Coefficient of variation	0,80	0,53
Downside Risk	0,03	0,26

Table 4 reveals that the Firefly algorithm produced a greater predictes return. This suggests that the best asset allocation is more successfully. The firefly algorithm has a higher Sharpe ratio than the mean-variance model, indicating that it provides a better risk-return balance statistically speaking. A comparison of the firefly algorithm's coefficient of variation with that of the standard Mean-variance model reveals that the former has a lower coefficient of variation, and indicates a portfolio with less return volatility. inally, the mean-variance model has a lower value for downside risk, indicating downside risk, while the firefly algorithm potentially offers higher risk returns.

5. Conclusion

Markowitz's Modern Portfolio Theory, a potent mathematical framework for maximizing the trade-off between risk and return, has guided market players for years. However, with huge datasets and portfolios for a high number of assets, implementations of this classical approach may encounter computing difficulties. Inspired by nature, the Firefly Algorithm is a meta-heuristic optimization technique that is one of the techniques used to overcome these obstacles.

The purpose of this study is to assess performance measures within the theoretical framework by using the firefly algorithm to create the ideal portfolio using the daily returns of the BIST 30 Index firms. In this regard, share weights and portfolio performance indicators were determined by first using the Markowitz Mean Variance model and the returns of the firms in the BIST 30 Index from January 1, 2018, to December 31, 2023. Ultimately, using data on stock returns and risk-free interest rates for 2023, the Firefly algorithm in Pyhton Jupyter Notebook was used to determine the ideal portfolio.

Annual analyses of the present portfolios exhibit that they have performed well overall, standing out in all but 2018 with high Sharpe ratios and positive anticipated returns. The best results were recorded in 2023. The portfolio is shielded from adverse risks by the modest and steady decline in downside risk. The results of this performance demonstrate that the portfolios may effectively manage return and risk profiles across a range of years. Upon evaluating the optimal portfolio generated by the firefly algorithm, it has been ascertained that the portfolio's performance is superior than that of the portfolio constructed using the mean-variance model, based on performance criteria. However it's important to remember that, despite its greater anticipated return and Sharpe ratio and overall better performance, the firefly algorithm may have some drawbacks when it comes to algorithmic risk management because of its increased downside risk. Therefore, given that all other factors stay constant, the derived performance metrics can be used as proof that the algorithm in issue performs well. The study's findings in this regard are consistent with those of Yang (2009), Wang (2019), and Bacanin and Tuba (2014).

Based on the Firefly Algorithm's performance measures, a broad assessment might state that the ideal portfolio has a low risk profile and a high potential for return. In this regard, outcomes illustrate that the Firefly algorithm approach performs better than conventional techniques, and may help investors build more optimal portfolios. The objective of these results is to offer ideal portfolio strategies that will enhance investors' capacity for making informed decisions. In this regard, the study aligns with the works conducted by Li (2023) and Türkoğlu and Kutlu (2025). It is possible to provide market participants with investment possibilities that are both appealing and well-balanced in terms of risk and return. It is conceivable that research based on algorithm comparisons will enlighten investors and add to the body of knowledge in the future.

This study covers only 28 stocks traded on Borsa Istanbul. The performance of the algorithm may vary when applied to different markets or time periods. Moreover, the Firefly Algorithm is sensitive to parameter selection, which may lead to variations in optimization outcomes. Future research could focus on hybrid models and multi-objective optimization approaches that allow adaptive adjustment of algorithm parameters.

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