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Application of Computational Intelligence in the Financial Market

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Abstract. The financial market involves a complex dynamic of assets and investments, where shares and other financial instruments are bought and sold in order to obtain profit. Shares are equivalent to a portion of a company's capital and are one of the most common investment methods in the capital market. Financial research seeks to understand the processes that govern these transactions, as well as the tactics to maximize the return on investments, taking into account the risk associated with each decision. This work focuses on the optimization of investment portfolios, concentrating on shares of electric power companies, examining the behavior of assets, and maximizing the return within a risk reduction strategy. The study investigates computational techniques, such as Sequential Least Squares Programming (SLSQP), Nelder-Mead, and Powell algorithms, to construct effective portfolios, employing Markowitz theory and the Sharpe ratio to assess performance. The assessment was carried out on a group of stocks representative of the Brazilian financial market, in particular PETR4 (Petrobras), PRIO3 (PetroRio), ELET3 (Eletrobras), and TAEE3 (Electric Energy Alliance Transmission Company - Taesa), providing perspectives for investors seeking to enhance their portfolios amid high volatility in the energy sector.

Keywords: Stocks, Stock Exchange, Finance, Computational Intelligence, Optimization.

1 Introduction

The relationship between man and money dates back to ancient times. Nowadays, financial power provides security and well-being to the individual. Any object that has value and can be traded in the financial market is called an asset. Some examples of assets are stocks, currencies, and government bonds, among others. A set of assets intended for investment is known as an investment portfolio. Assets can be evaluated individually based on their history or expected future performance. Thus, those with a recent positive history tend to be more attractive and desired [1].

Investing in the financial market is a challenging activity, especially when it comes to variable income assets. Due to the high instability of the market, stock buying and selling operations are marked by high volatility, exposing investors to significant risks. In addition to the lack of guaranteed returns, there is also the possibility of losing the invested capital. For this reason, many investors seek to predict market movements and find ways to optimize their investments [2].

Stock portfolio optimization consists of the process of determining the best asset allocation to achieve a specific objective [3]. Depending on each investor's profile, this objective can range from maximizing expected returns to minimizing financial risk. In order to ensure profits, regardless of market conditions, and to reduce losses in periods of economic recession, the careful selection of financial assets becomes essential [4]. The most widely adopted strategy for this selection is portfolio diversification, composed of different assets, aiming at risk distribution [5].

The portfolio optimization problem involves defining which assets, from a set of available assets, should make up the portfolio and how much to invest in each of them [6]. The objective is to maximize the return on investment while seeking to minimize the associated risk. This portfolio must consider both the conditions imposed by the financial market and the particularities and preferences of the investor [1]. To optimize the construction of an investment portfolio, investors often resort to computational intelligence techniques, with techniques for optimization and forecasting [7]. These tools help investors analyze the risk-return relationship and predict market prices, facilitating more informed decisions about the composition of their portfolios [8].

According to Pereira et al. [9], the study on portfolio selection and optimization remains relevant and has a great impact today. Therefore, this work will address the problem of investment portfolio optimization, considering real characteristics, such as the number of assets, maximum return, and minimum risk expected in each investment. The energy sector, with emphasis on the electricity segment, has recorded a significant increase in average volatility since 2012. This is a broad sector that is highly vulnerable to variations, influenced by high-impact factors, such as tariff flags applied to electricity bills and the growing adoption of clean energy sources [10].

Given this context, this work aims to analyze the Brazilian financial market with a focus on historical data from the electric power sector, specifically exploring the shares of PETR4 (Petrobras), PRIO3 (PetroRio), ELET3 (Eletrobras), and TAEE3 (Alliance Electric Energy Transmission Company - Taesa) from the IBOVESPA Index. For this, the optimization algorithms Sequential Least Squares Programming (SLSQP), Nelder-Mead, and Powell were used to optimize the weights for the investment portfolio, seeking to maximize return and minimize risk in the energy sector.

The remainder of the manuscript is structured as follows: Section 2 describes the bibliographical review. Section 3 describes the study and the methodology used. In addition, Section 4 describes the conducted experiments and the achieved results. In Section 5, conclusions are presented.

2 Bibliographical Review

According to Guo [11], Markowitz is one of the main references for understanding the process of constructing an optimal portfolio. Through the mean-variance model, he defines the expected return as the measure of portfolio performance and the variance as the measure of risk. Markowitz's portfolio composition model [12] involves the optimization of two objective functions, in which the first aims to maximize the expected return, and the second seeks to minimize the risk, measured by the portfolio volatility [13]. These functions are subject to the constraints that the allocation of each asset must be between 0 and 1 and that the total available budget must be completely allocated among the assets.

The Markowitz model is expressed as follows:

$$\max \overline{R} = \sum_{i=1}^{N} X_i \overline{R}_i, \tag{1}$$

$$\min \sigma^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \left(X_i X_j \sigma_{ij} \right), \tag{2}$$

Subject to:

$$0 \leq X_t \leq 1; \sum_{t=1}^{N} X_t = 1. \tag{3}$$

where N is the number of assets considered, X_i is the share (in percentage) of asset i in the portfolio, $\overline{R}_i$ is the expected return of asset i, σ_{ij} is the covariance between asset i and asset j. Equation 3, which indicates the constraints, establishes that the allocation of each asset must be between 0 and 1, and that the total available budget must be completely allocated among the assets.

The variance σ^2 is calculated based on the covariance of the return series σ_{ij} between all pairs of assets that make up the portfolio. This covariance is estimated from the historical returns of the assets over a specific period T:

$$\sigma_{ij} = \sum_{k=1}^{T} \frac{(R_{ik} - \overline{R}_i)(R_{jk} - \overline{R}_j)}{T}, \tag{4}$$

where $\overline{R}_i$ and $\overline{R}_j$ are the average return for assets i and j, respectively, and R_{ik} the return of asset i in period k.

Another relevant metric is the Sharpe Ratio [14], an indicator used to measure the relationship between return and risk of an investment. This ratio allows us to calculate the extent to which a portfolio's return offsets the risk assumed, evaluating the investment's return compared to a risk-free rate. In addition to considering return, the ratio also takes into account the investment's risk or volatility, allowing us to combine both concepts into a single value. This metric allows investors to compare different funds, helping them choose the best one in terms of risk and return [15]. The Sharpe Ratio equation can be expressed as:

$$\max S_p = \frac{\overline{R} - R_f}{\sigma^2}, \tag{5}$$

where R_f is the risk-free rate.

The Markowitz model adopts portfolio variance as a measure of risk, marking the beginning of quantitative finance and underpinning Modern Portfolio Theory [5]. Neto [16] contributed to Modern Portfolio Theory by stating that the risk of an asset, when considered in isolation, is distinct from the risk it represents in a portfolio. Portfolio risk is determined not only by the combination of individual assets but also by the correlation between them. Assets with negative correlation, for example, reduce portfolio risk. Neto [16] assertion is fundamental to the financial market and impacts how investors assess and manage the risk of their portfolios.

In recent years, portfolio optimization studies have focused on maximizing return, minimizing risk, and price prediction. The Markowitz model pioneered this field, inspiring innovative approaches. Hellström [17] proposed portfolio selection based on return and the Sharpe Ratio, outperforming the market index as a benchmark. Moretti [18] applied modern portfolio theory to combine solar and wind power plants, seeking to optimize energy generation and reduce risks in the Brazilian electricity sector, highlighting the relevance of the intermittency of these sources. Linear programming models were used to minimize the risk of downside exposure in short-term markets. Other works in the literature applied computational methods to price forecasting and portfolio optimization, such as the works of Santos et al. [19], Saba [20], Kalayci et al. [5] and Melo and Cardoso [21].

3 Materials and Methods

3.1 Dataset

This study analyzed historical financial data from January 1, 2019, to July 25, 2025, for the shares of Petrobras, PetroRio, Eletrobras, and Taesa, all of which are in the electric power sector. The period was chosen because it encompasses significant economic and geopolitical events, such as the COVID-19 pandemic and fluctuations in the energy market, allowing us to capture relevant variations and trends. PETR4 is the ticker symbol for Petrobras, one of the largest companies in the oil sector, operating in the petrochemical, transportation, refining, and fuel segments. PRIO3 corresponds to PetroRio, a company specializing in oil reservoir management. ELET3 refers to Eletrobras, the leading company in Brazil's electric power sector, responsible for approximately one-third of the country's electricity generation. TAEE3 refers to the shares of Electric Energy Alliance Transmission Company (Taesa), an energy transmission company that currently operates in 17 Brazilian states.

3.2 API Yahoo Finance

The Yahoo Finance API is a tool used to programmatically access financial data, providing information on stocks, indices, currencies, commodities, and other assets. Supporting historical (daily, weekly, monthly) and real-time data, dividend information, and other financial indicators, it enables quantitative analysis through the extraction of adjusted time series and financial metrics, as well as risk, return, and portfolio optimization studies. Furthermore, the API integrates with libraries such as Python's pandas_datareader and yfinance, automating the data collection process [22].

3.3 Sequential Least Squares Programming Method

Sequential Least Squares Programming (SLSQP) is a nonlinear optimization algorithm used to find solutions with both linear and nonlinear constraints. It is an optimization method using sequential quadratic program-

ming. The SLSQP algorithm adopts a quadratic approximation approach of updating the objective function and constraints at each iteration, ensuring that the solutions remain within the established bounds. This is achieved through a set of Lagrange multipliers, which adjust the objective function and constraints, enabling the solution to the original problem [23].

3.4 Nelder-Mead Method

The Nelder-Mead method is an unconstrained iterative nonlinear optimization algorithm that does not require the computation of derivatives. It is especially useful for non-differentiable, non-linear, or noisy objective functions. Based on the concept of geometric simplex, the method uses points in the search space to iteratively advance toward the optimal solution [24]. It minimizes a function $f(x)$, with $x \in \mathbb{R}^n$, requiring only that $f(x)$ be defined and measurable in the domain.

3.5 Powell Method

Powell's method [25] is an iterative algorithm for nonlinear optimization that does not rely on the calculation of derivatives and is used for objective functions that are non-differentiable or noisy. It performs one-dimensional searches along conjugate directions, which are dynamically adjusted during the process, providing efficient convergence for a variety of problems.

4 Results and Discussions

The computational experiments were performed using the Python programming language and implementations based on the Pandas [26], Matplotlib [26], SciPy [27] and yfinance [28] framework libraries. All experiments were run on a computer with the following specifications: Intel(R) Core(TM) i5-1135G7, 8 GB RAM, and Windows 10 operating system.

Figure 1 corresponds to the stock market performance of the selected companies in the period from 01/01/2019 to 25/07/2025. With this graph, it can be seen that Eletrobras obtained a better performance in relation to the other three companies until 2023, but from the year 2023 onwards, the company PetroRio starts to have the best performance.

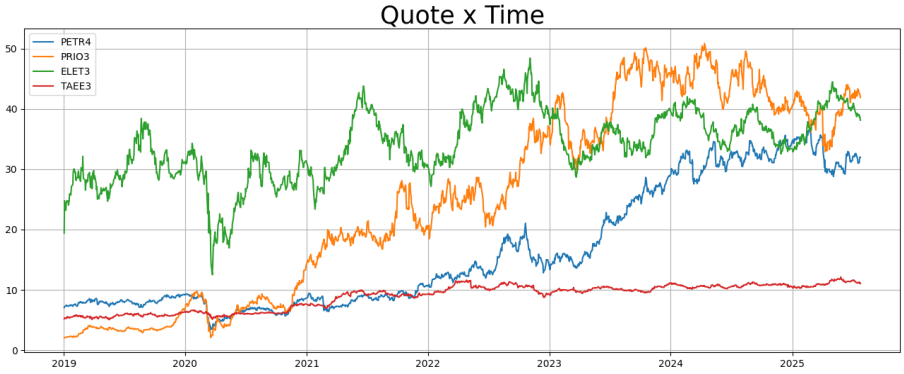
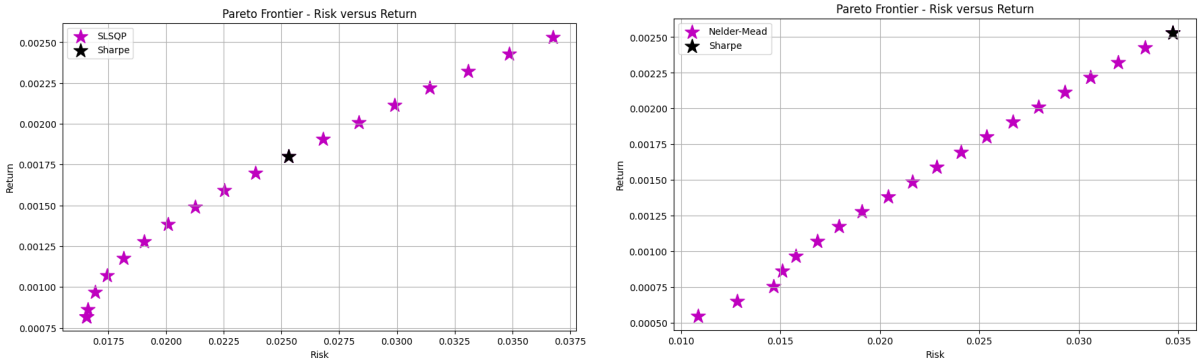


Figure 1. Price of selected shares, between 01/01/2019 and 25/07/2025.

The Pareto frontier represents the efficient combinations of risk and return, identifying portfolios that maximize return for a given level of risk or minimize risk for a desired return [12]. Figure 2 presents the Pareto frontier obtained using the SLSQP and Nelder-Mead methods. The Pareto frontier obtained by the SLSQP method presents a consistent alignment between risk and return, reflecting the method's efficiency in constructing optimized solutions. However, the concentration of points along the curve suggests a possible limitation in capturing diversified solutions in highly complex scenarios or with multiple nonlinear constraints. Although the point with the highest Sharpe ratio stands out as the most efficient solution, its intermediate position on the curve may indicate that the method prioritizes the balance between risk and return to the detriment of exploring more aggressive returns. For the real investor, this means that the choice of optimization method directly influences the type of portfolio

obtained: SLSQP allows for a more balanced distribution of assets, which can be safer in scenarios of economic instability.

The Pareto frontier obtained by the Nelder-Mead method highlights an expected behavior between risk and return, with efficient solutions aligned with increasing risk. However, it is observed that the dispersion between the points may indicate the method's sensitivity to small variations in the initial parameters, which can compromise accuracy in highly volatile scenarios. Even so, the point with the highest Sharpe Index (in black) demonstrates the method's ability to identify the most efficient solution, but its location at the extreme of the curve reinforces the need for a cautious analysis of the trade-off between risk and return in practical applications.



(a) SLSQP.

(b) Nelder-Mead.

Figure 2. Efficient Frontier - Risk versus Return, from the SLSQP and Nelder-Mead method.

Figure 3 shows the Pareto frontier obtained by optimization with the Powell method. The Pareto frontier generated by the Powell method presents a coherent progression between risk and return, highlighting its ability to identify efficient solutions in optimization problems. However, it can be observed that the point corresponding to the highest Sharpe ratio is positioned in a region of relatively low risk, suggesting that the method may prioritize risk minimization over more aggressive returns. This characteristic indicates a potential bias in the algorithm in scenarios where the balance between risk and return is crucial, which may limit its applicability in contexts that require greater diversification of solutions or the exploration of higher-return strategies. In practice, an investor who wants to protect their capital without large exposures can benefit from Powell's approach, but should be aware that more aggressive returns may be sacrificed.

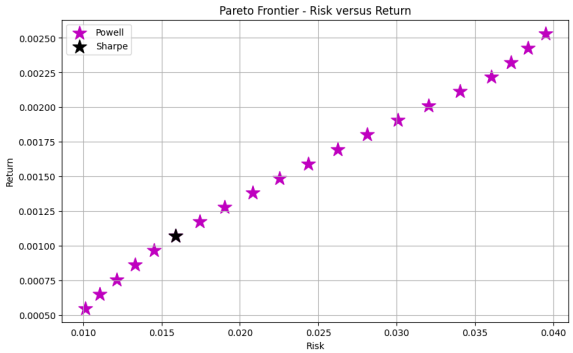


Figure 3. Efficient Frontier - Risk versus Return, from the Powell method.

Table 1 presents the Diversification Index (Herfindahl) for different optimization methods applied to the portfolio with the highest Sharpe Index. The Herfindahl Index [29] ranges from 0 to 1, with values closer to 1 indicating greater concentration in a few assets, that is, most investments are allocated to a few assets. This suggests less diversification and greater exposure to the specific risk of these assets. Meanwhile, lower values of the Herfindahl Index indicate greater diversification, with investments distributed more evenly across several assets. The SLSQP method presents an intermediate index (0.363), indicating moderate diversification and a relatively balanced distribution of weights. The Nelder-Mead has the highest index (0.769), suggesting greater

concentration in a few assets, which can increase specific risk. The Powell method, with the lowest index (0.194), generates the most diversified portfolio, favoring risk reduction, but with potential dispersion in returns. For an investor, this index can serve as an additional decision criterion: those seeking security and stability should favor methods with a lower Herfindahl, while experienced investors or those with a high risk tolerance may consider more concentrated methods.

Table 1. Diversification Index (Herfindahl) for the portfolio with the highest Sharpe.

Method	Diversification Index
SLSQP	0.363
Nelder-Mead	0.769
Powell	0.194

5 Conclusions

This study analyzed three optimization methods: SLSQP, Nelder-Mead, and Powell. The SLSQP method offers flexibility in constrained problems, while Nelder-Mead aims to maximize returns in more concentrated portfolios, and Powell seeks greater diversification and lower risk. The SLSQP method presents the best results, as it offers an efficient and well-distributed curve along the Pareto Frontier, with a point of highest Sharpe ratio balanced between risk and return. Powell, on the other hand, is more suitable for investors who prioritize diversification and low risk.

As future work, we intend to make forecasts of the stock prices of the companies PETR4 (Petrobras), PRIO3 (PetroRio), ELET3 (Eletrobras), and TAEE3 (Electric Energy Alliance Transmission Company - Taesa) of the IBOVESPA Index for the subsequent months using the neural network algorithm Long Short-Term Memory (LSTM), as it is an algorithm that has been used in works to predict financial market prices, such as in Moura [30] and Borges [31]. The predicted values will be analyzed to identify market trends, assisting in decision-making for investment strategies.

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