B.Tech Capstone Project
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Green Portfolio Optimization

Submitted by

Parth Parker
20BCB0061

Pranav Bhagwat
20BCB0074

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Aim

To develop a Python model for ESG-integrated portfolio optimization, employing four algorithms to predict stock weights, aiming to empower investors with socially responsible investment decisions.

Objectives

The objectives of this project are as follows: (for a given portfolio)

- Maximize dividend yield.
- Minimize price-earnings ratio.
- Maximize clean energy use.
- Maximize expected return.
- Maximize environmental, social, and corporate-sustainability.
- Optimize portfolio volatility.

MOTIVATION

- Environmental sustainability, social responsibility, and effective governance are now seen as critical factors for long-term success.
- Investors look beyond purely financial metrics, there's a rising demand for tools that can integrate these considerations into investment decisions.
- Our project aims to meet this demand by developing a Python model that incorporates ESG criteria into portfolio optimization.
- By promoting the consideration of ESG factors in investment decisions, we're trying to make a shift towards more responsible and sustainable business practices.
- By optimizing portfolios with both financial returns and ESG considerations in mind, we're demonstrating that responsible investing doesn't mean sacrificing profitability.

LITERATURE REVIEW - I

Title: Sustainable Portfolio Optimization with Higher-Order Moments of Risk [1].

Dataset Preprocessing Methods:
The paper does not provide detailed information on the dataset preprocessing methods used in this study. However, it does mention that the study used Morgan Stanley Capital International's (MSCI) emerging and developed market categorization to select six Asian emerging markets and two developed Pacific stock markets for analysis.

Concepts:
In terms of machine learning concepts, the study employed the Polynomial Goal Programming (PGP) approach, which is a multi-objective optimization technique that can find optimal portfolios based on various criteria, including investors' preferences. The PGP approach is a flexible method of including higher moments of risk (variance, skewness, and kurtosis) and helps optimize portfolios according to investors' risk preferences without an explicit specific utility function.

Performance Measures:
The study used several performance measures to evaluate the performance of the optimized portfolios, including the Sharpe ratio, Sortino ratio, Omega ratio, and Kappa ratio. The Sharpe ratio measures the excess return per unit of risk, the Sortino ratio measures the excess return per unit of downside risk, the Omega ratio measures the probability-weighted return distribution, and the Kappa ratio measures the consistency of returns. The study also used the mean-variance framework to compare the performance of the optimized portfolios with the traditional approach.

LITERATURE REVIEW - II

Title: The Role of ESG in Sustainable Development: An Analysis Through the Lens of Machine Learning [2].

Dataset Preprocessing Methods:
A dataset was generated by compiling the names and ticker symbols of top companies from stock indices worldwide, using web scrapers built with Python programming language and its libraries. Two separate web scrapers were developed and deployed to collect data in two parts, which were then merged to create a final dataset containing both ESG and financial parameters.

Concepts:
Machine learning techniques were used to gauge the importance of ESG parameters for investment decisions and their impact on the financial performance of firms.
Linear and random forest regression models were employed to predict growth variables, such as 'profit margin' and 'return on assets', with improved accuracy when ESG data was included as input.

Performance Measures:
Companies with the best ESG ratings were found to have a greater 'return on equity' compared to other companies. The study focused on the prediction accuracy of growth variables, specifically 'profit margin' and 'return on assets', which increased when ESG data was incorporated into the models.

LITERATURE REVIEW - III

Title: Incorporating environmental and social considerations into the portfolio optimization process [3].

Dataset preprocessing:
The authors use a dataset of 1,000 companies from the MSCI World Index, which is a widely used benchmark for global equity performance.

Concepts:
The paper employs a machine learning approach to optimize portfolios for socially responsible investors. The authors use a combination of clustering and portfolio optimization techniques to identify the most promising assets within a set of companies.

Performance measures:
The paper evaluates the performance of the optimized portfolios using the following measures:
-Risk-adjusted return: The authors calculate the Sharpe ratio, which is the ratio of the portfolio's return to its risk, to assess the risk-adjusted performance of the portfolios.
-Diversity: The authors measure the diversity of the portfolios by calculating the Herfindahl-Hirschman Index (HHI), which is a measure of market concentration.
-ESG scores: The authors incorporate Environmental, Social, and Governance (ESG) scores into the optimization process to ensure that the portfolios are socially responsible.

LITERATURE REVIEW - IV

Title: On ESG Portfolio Construction: A Multi-Objective Optimization Approach [4].

Dataset Preprocessing:
The dataset preprocessing methods involve normalizing ESG risk scores and controversy levels for each firm separately. This normalization is expressed as a ratio of the rating of the security to the maximum and minimum ratings among available securities. Decision variables are identified, and hard constraints are listed for the optimization process. The model aims to minimize deviations from ESG targets while respecting identified hard constraints, allowing for the optimization of each security's weight within the portfolio.

Performance measures:
The performance measures used to assess the financial and extra-financial performances of the proposed model include volatility, total return, average weekly return, risk-adjusted return (Sharpe ratio), and novel ESG metrics. These metrics are employed to evaluate the ESG risk performance, social risk performance, governance risk performance, and controversy performance of the portfolios. The EURO STOXX 50 exhibits a concentration of mid to high-ERP and high-SRP stocks, with varying levels of GRP. The customizable parameters' values used in the empirical testing of the proposed model are specified, and the results obtained by applying the methodology to the EURO STOXX 50 are described, indicating the concentration of different risk performances within the index components.

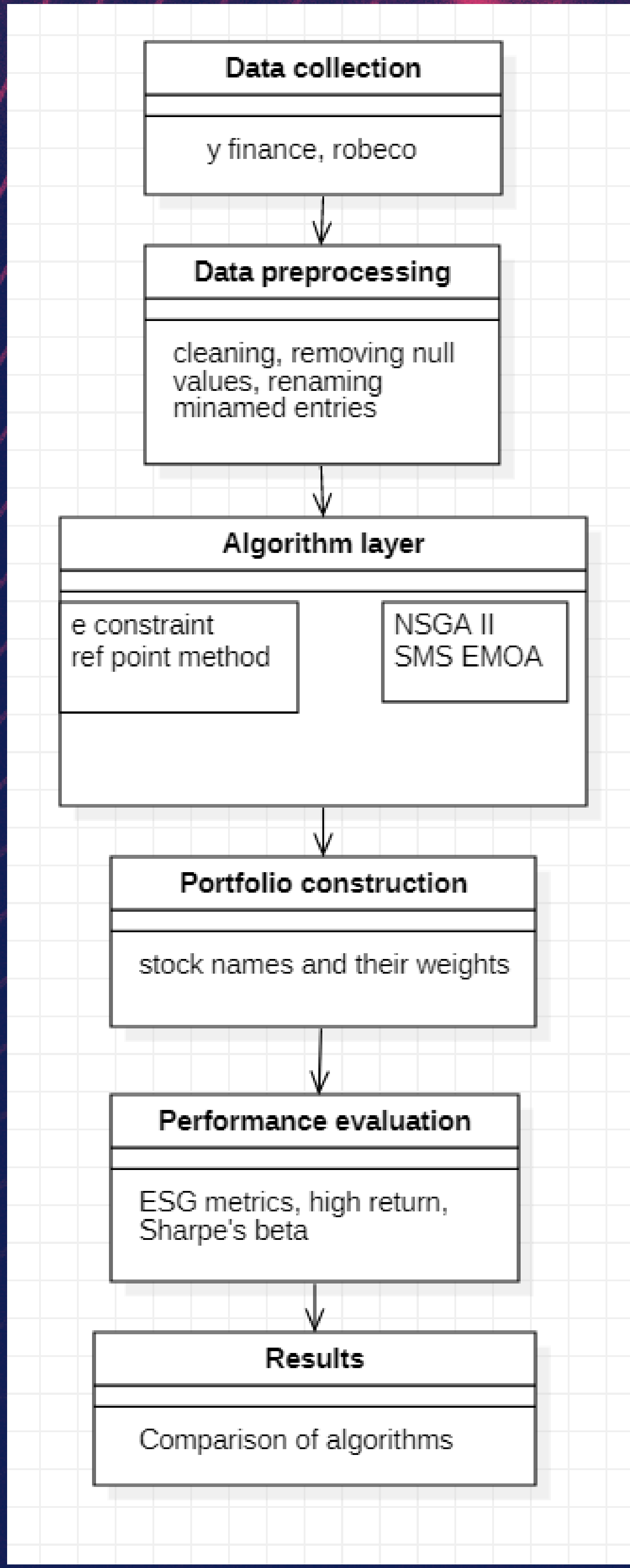
LITERATURE REVIEW - IV

The proposed model provides higher returns without implying higher volatility and future research could focus on testing the model with Monte Carlo simulation. The document also discusses the impact of ESG on corporate financial performance, ethical goals, and objectives without suffering from a financial backlash. It further explores the differences between socially responsible and conventional investing during crises, the impact of climate change on market volatility, and the measurement of ESG risks by ESG ratings.

The EURO STOXX 50's performance is compared to other indexes, showing its lagging performance across the entire time horizon. The document also provides raw data and normalized data for the DJIA's extra-financial ratings, as well as a comparative view of the level of success resulting from the manner of each index to take advantage of its best-rated components in terms of ESG and controversial risks through its weight allocation.

Optimization concepts:
The proposed multi-objective minimax-based portfolio optimization model employs a minimax objective to simultaneously maximize environmental, social, and governance (ESG) risk performances while applying a minimum threshold to controversy performance. The model includes customizable parameters to match investors' ESG preferences and portfolio constraints, addressing the lack of multi-objective models exclusively focused on ESG risk performance. It also utilizes decision variables, hard constraints, and a minimax objective to optimize security weights within the portfolio, aiming to minimize deviations from ESG targets while respecting identified constraints.

SYSTEM ARCHITECTURE



BLOCK WISE DESCRIPTION

1. **Data Collection**: Acquires relevant data inputs such as historical stock prices, ESG ratings, and financial metrics from external sources like APIs or databases.
2. **ESG Data Processing**: Processes and cleans the ESG data to ensure consistency and compatibility with the optimization model.
3. **Financial Data Processing**: Processes and cleans financial data including stock prices, market indices, and other financial indicators for use in the optimization model.
4. **Algorithm layer**: Implements the four independent multi objective optimization algorithm which aim to maximize portfolio returns while considering ESG constraints and objectives.
5. **Portfolio Construction**: Constructs the optimized portfolio based on the output of the optimization algorithm, allocating assets across various securities while adhering to ESG criteria.
6. **Performance Evaluation**: Evaluate the performance of the constructed portfolio using metrics such as return on investment, risk-adjusted return, and ESG performance indicators.
7. **Output/Results**: Presents the final optimized portfolio allocation along with performance metrics and other conclusion gathered from the optimization processes.

WORKING PRINCIPLE

- Portfolio optimization involves the process of selecting an optimal portfolio (asset distribution) to maximize factors such as expected return and minimize costs like financial risk, resulting in a multi-objective optimization problem.
- Our project operates on the foundation of four separate algorithms for portfolio optimization, each designed to maximize returns while simultaneously considering various other green objectives.
- Algorithms are—epsilon constraint, reference point method, NSGA2, and SMS EMOA
- Work independently to produce portfolios consisting of stock names and their respective weights.
- Within each algorithm, we implement multi-objective optimization strategies.
- We aim to maximize returns while adhering to ESG criteria, maintaining a desirable dividend yield, and minimizing volatility.
- To evaluate the performance of each algorithm, we use Sharpe's beta, a widely accepted measure of risk-adjusted returns.

OUTPUT - E CONSTRAINT

```
Objective function value

Beta
1.0999999999999999

Companies to invest in:
 Aegon NV 0.05
 American Airlines Group Inc 0.05
 Banco Santander Brasil SA 0.05
 Banco Santander Chile 0.00845426457548198
 British American Tobacco PLC 0.05
 Eni SpA 0.05
 Fabege AB 0.05
 Grupo Aval Acciones y Valores SA 0.05
 Honda Motor Co Ltd 0.05
 Jefferies Financial Group Inc 0.05
 Johnson Controls International plc 0.05
 Lloyds Banking Group PLC 0.05
 Mizuho Financial Group Inc 0.05
 POSCO 0.05
 Sasol Ltd 0.05
 SK Telecom Co Ltd 0.05
 Teck Resources Ltd 0.05
 Telefonica Brasil SA 0.05
 Ultrapar Participacoes SA 0.05
 Vedanta Ltd 0.0415457354245178
 WPP PLC 0.05
```

OUTPUT - REF POINT

```
%run optimization_ref_point_method.py

Ideal vector:
[0.11987025295830138, 0.8440032437224299, 5.002226416752611, 2.000000000000298, 6.258126011197561]

 === Estimation of Nadir vector ===

Payoff-table:
[0.11987025295830138, 0.3342824700624351, 2.007548687402179, 0.26669979663491605, 19.15022860094534]
[0.0977302069658828, 0.8440032437224299, 1.0539978375183945, 0.016657656326596517, 29.562502409660418]
[0.11987025295830869, 0.39716611987245465, 5.002226416752611, 2.3098353059016777e-14, 8.32126628861028]
[0.11914361664883318, 0.4900000000000843, 2.405000000000076, 2.000000000000298, 24.438068500000558]
[0.11987025295993088, 0.4296195188979856, 3.4143422669497077, 5.01388408944071e-12, 6.258126011197561]

Nadir vector is put together from each of the objective function's "worst"           value in the table
Nadir vector:
 [0.0977302069658828, 0.3342824700624351, 1.0539978375183945, 2.3098353059016777e-14, 29.562502409660418]

After normalizing the objective functions using ideal- and nadir-vectors:
normalized value for the problem at [0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.0
333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0
.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333,
0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333
, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.03333333333333333, 0.033333333333333
33, 0.03333333333333333, 0.03333333333333333] is
[0.004199666666671773, 0.9999002134628868, 0.7584565305656032, 0.8666666666666787, 0.5537604686268419]

=== SOLUTION ===
```

OUTPUT - REF POINT

```
            Iterations: 79
            Function evaluations: 2814
            Gradient evaluations: 77
Proportional amounts to invest in companies are:

 ABB Ltd  : 1.677788468511834e-07
 Abbott Laboratories  : 2.343048076223021e-08
 AbbVie Inc  : 0.10913090108000902
 Accenture PLC  : 0.5498885914284098
 Advance Auto Parts Inc  : 1.631342222353765e-11
 Aegon NV  : 0.3037835118118872
 Aflac Inc  : 4.654103488755085e-09
 AGCO Corp  : 1.1035372771084033e-10
 Agnico Eagle Mines Ltd  : 3.283272450530815e-12
 Alaska Air Group Inc  : 0.037195623387655516
 Albemarle Corp  : 9.41298685065129e-12
 Allegion PLC  : 6.82617879654177e-12
 Allison Transmission Holdings Inc  : 2.094258030374669e-12
 Ambev SA  : 5.112815977001423e-08
 Amdocs Ltd  : 4.592724019507145e-08
 Ameren Corp  : 5.274268839809064e-08
 American Airlines Group Inc  : 1.11901233170525e-07
 American Campus Communities Inc  : 1.0610437630556218e-10
 American Eagle Outfitters Inc  : 9.137669054851928e-07
 American Express Co  : 6.172480394360108e-12
 American Tower Corp  : 1.0506340194872849e-10
 American Water Works Co Inc  : 1.0498270974136263e-10
 Ameriprise Financial Inc  : 4.7202131257356006e-12
 Amgen Inc  : 2.0014029227448455e-12
 Amphenol Corp  : 7.243007309320486e-12
 Anheuser-Busch InBev SA/NV  : 7.413470325985543e-12
 Aon PLC  : 5.9414732736878314e-12
 Apple Inc  : 4.723825142071516e-12
 Aptiv PLC  : 4.499914355543423e-10
 Aramark  : 9.738644633386492e-12
```

OUTPUT - REF POINT

```
Objective function values are:

Expected return : 0.12582235257839292
Sustainability : 0.5374117272362777
Dividend yield : 3.247118473165489
Clean energy use : 1.0997785296868101
P/E ratio : 15.140087724056622
Portfolio beta :  1.1537677258857537
Ideal vector: [0.11987025295830138, 0.8440032437224299, 5.002226416752611, 2.0000000000000298, 6.258126011197561]
Sum of weights :  1.0
Solution is feasable
```

OUTPUT - NSGA 2

```
Allocation With Best Sharpe
WELL  0.6719722728594544
CHT   0.28220053442670734
TEF   0.045827192713838366
BNS   0.0
BTI   0.0
ETR   0.0
GM    0.0
GSK   0.0
TU    0.0
Sustainability  0.8134364244112402
Portfolio beta:  1.027115060540585
Total weight  1.0

Return     =  0.3202877665395075
Volatility =  0.1946915827962962
```

OUTPUT - SMS EMOA

```
Allocation With Best Sharpe
WELL  0.6873674104123579
CHT   0.2571955063846591
TEF   0.05543708320298294
AZN   0.0
BNS   0.0
BTI   0.0
ETR   0.0
GM    0.0
GSK   0.0
SKM   0.0
TU    0.0

Return     =  0.32569662054072357
Volatility =  0.19818200689282345
Sustainability  0.8495435087091942
Portfolio beta:  0.9674236597183108
Total weight  1.0
```

ANALYSIS OF RESULTS

From the outputs of each algorithm we can see that both the Meta Heuristic Algorithms; NSGA 2 and SMS-EMOA outperform Epsilon Constraint Method and Reference Point Method.

- These algorithms generate a more stable portfolio with lesser volatility as compared to the first two algorithms.
- Sharpes Beta values are closer to 1 (which is desired for volatile portfolios).
- Thus, Meta Heuristic algorithms generate similar financial returns but with much lesser risk while also adhering to ESG constraints as well.

CONCLUSION

- The project demonstrates the effectiveness of Meta Heuristic algorithms, specifically NSGA 2 and SMS-EMOA, in multi-objective portfolio optimization while considering ESG parameter constraints.
- The results show that these algorithms outperform traditional methods, such as the Epsilon Constraint Method and Reference Point Method, in generating more stable portfolios with lower volatility and similar financial returns.
- The Sharpe's Beta values closer to 1 indicate that the Meta Heuristic algorithms are better suited for managing risk in volatile portfolios.

FUTURE SCOPE

- **Robustness Analysis**: Perform sensitivity analysis to test the robustness of the Meta Heuristic algorithms to changes in market conditions, ESG parameters, and other factors that may affect portfolio performance.
- **Comparison with other Meta Heuristics**: Expand the comparison to include other Meta Heuristic algorithms, such as MOGA (Multi-Objective Genetic Algorithm), MOSA (Multi-Objective Simulated Annealing), and MOEA/D (Multi-Objective Evolutionary Algorithm based on Decomposition), to determine the most effective algorithm for multi-objective portfolio optimization.
- **Integration with Machine Learning**: Explore the integration of Machine Learning techniques, such as Neural Networks or Support Vector Machines, with Meta Heuristic algorithms to improve the accuracy of portfolio optimization and ESG parameter estimation.
- **Real-world Implementation**: Collaborate with financial institutions or asset management companies to implement the Meta Heuristic algorithms in real-world portfolio optimization scenarios, incorporating ESG constraints and evaluating their performance in live markets.

FUTURE SCOPE CONTD.

- **ESG Parameter Refining**: Refine the ESG parameter estimation process by incorporating more granular data, such as company-specific ESG metrics, and exploring alternative ESG scoring methods to improve the accuracy of the optimization process.
- **Multi-Period Optimization**: Extend the project to consider multi-period portfolio optimization, where the goal is to optimize portfolio performance over multiple time periods, incorporating ESG constraints and Meta Heuristic algorithms.
- **Visualization and Decision Support**: Develop interactive visualization tools and decision support systems to facilitate the interpretation and implementation of the optimized portfolios, enabling investors and portfolio managers to make more informed decisions.

By exploring these avenues, the project can further contribute to the development of more efficient and sustainable portfolio optimization methods that incorporate ESG considerations.

References

Journals:

[1] K. I. Khan, S. M. Naqvi, M. M. Ghafoor, and R. S. Akash, “Sustainable portfolio optimization with higher-order moments of risk,” Sustainability, vol. 12, no. 5, p. 2006, Mar. 2020. doi:10.3390/su12052006.

[2] A. Gupta, U. Sharma, and S. K. Gupta, “The role of ESG in sustainable development: An analysis through the lens of machine learning,” 2021 IEEE International Humanitarian Technology Conference (IHTC), Dec. 2021. doi:10.1109/ihtc53077.2021.9698939

[3] K. Liagkouras, K. Metaxiotis, and G. Tsihrintzis, “Incorporating environmental and social considerations into the portfolio optimization process,” Annals of Operations Research, vol. 316, no. 2, pp. 1493–1518, Mar. 2020. doi:10.1007/s10479-020-03554-3

[4] P. Xidonas and E. Essner, “On ESG portfolio construction: A multi-objective optimization approach,” Computational Economics, vol. 63, no. 1, pp. 21–45, Oct. 2022. doi:10.1007/s10614-022-10327-6

THANK YOU!