Multi-Objective Portfolio Optimization Towards Sustainable Investments

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ABSTRACT

The process of financial portfolio optimization involves choosing the most suitable mix of assets to meet a particular investment goal. Conventional portfolio optimization primarily focuses on maximizing returns and minimizing risks while overlooking the importance of social responsibility or sustainability in financial investments. In this paper, we present a Python-based multi-objective portfolio optimization library for sustainable investments (MOPO-LSI). MOPO-LSI is able to take Environmental, Social and Governance (ESG) factors into consideration in financial portfolio, where investors' assets can be well allocated to mutual funds towards the ESG optimization along with their financial goals in the investment. MOPO-LSI is easy to be configured and used, and it is capable of production solutions in two scenarios – when client preferences are known or unknown. The developers can also easily customize the library to adapt it to their own financial objectives.

CCS CONCEPTS

• **Social and professional topics → Sustainability**.

KEYWORDS

ESG, portfolio optimization, multi-objective, sustainable investment

ACM Reference Format:
Yong Zheng, Kumar Neelotpal Shukla, Jasmine Xu, David Xuejun Wang, and Michael O'Leary. 2023. Multi-Objective Portfolio Optimization Towards Sustainable Investments. In *ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS '23), August 16–19, 2023, Cape Town, South Africa.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3588001.3609373

1 INTRODUCTION & BACKGROUND

Financial portfolio optimization, as discussed in several studies [9, 11], entails the careful selection of financial assets to align with an investor's objectives while taking into account their risk tolerance. An integral component of this process is asset allocation, which involves dividing an investor's portfolio among different asset classes (e.g., stocks, bonds, cash) based on their risk tolerance and investment objectives. The primary aim of traditional portfolio optimization is to construct a portfolio that maximizes expected returns for a specified level of risk or minimizes risk for a given level of expected returns.

There has been a growing interest in sustainable investments, as indicated by various studies [3, 12, 13]. Investors are increasingly realizing the significance of considering Environmental, Social, and Governance (ESG) factors [1, 7] in their investment decision-making processes. Sustainable investments, also referred to as socially responsible investing [12] or ESG investing [10], involve an investment approach that not only focuses on financial returns but also takes into account the impact of investments on the environment, society, and corporate governance practices. At the current stage, there are no unified framework to capture the ESG factors, while the financial companies or fund managers can define their own ESG dimensions. However, all of these ESG factors or dimensions should capture the following three characteristics or concerns.

Environmental (E): The environmental component of ESG refers to factors related to the impact of a company's operations on the environment. This includes assessing a company's performance in areas such as carbon emissions, energy efficiency, waste management, water usage, pollution prevention, and climate change adaptation. Environmental considerations aim to evaluate a company's commitment to sustainable practices, resource conservation, and mitigating environmental risks.

Social (S): The social component of ESG focuses on evaluating a company's impact on society and its stakeholders. This encompasses various factors such as labor practices, human rights, employee relations, diversity and inclusion, community engagement, consumer protection, and product safety. Social considerations assess how a company manages relationships with its employees, customers, suppliers, communities, and other societal stakeholders.

Governance (G): The governance component of ESG centers around the governance structure and practices within a company. This involves evaluating the company's leadership, board structure, executive compensation, shareholder rights, transparency, ethical standards, and anti-corruption measures. Good governance ensures

COMPASS '23, August 16–19, 2023, Cape Town, South Africa

ACM ISBN 979-8-4007-0149-8/23/08.
https://doi.org/10.1145/3588001.3609373

that a company operates in an ethical and responsible manner, with appropriate accountability, oversight, and integrity.

By integrating ESG factors into portfolio optimization, we aim to generate long-term financial returns while promoting sustainable and responsible practices. Accordingly, we present themulti-objective portfolio optimization library for sustainable investments (MOPO-LSI) [14, 15] which is an open-source and Python-based tool specifically designed for sustainable investment in mutual funds.

We believe that portfolio construction with ESG considerations supports the growth of sustainable societies, from the perspective of financial investments. More specifically, investors can identify companies that are better equipped to manage environmental and social risks and recognize opportunities within companies that are leading the way in adopting more sustainable practices. By using the library, investors can select their desired financial portfolio by their own definition of the risk level (e.g., aggressive, moderate, conservative) and their preferences on ESG factors. Moreover, through investing in companies with strong ESG performance, investors can provide support and encouragement for these companies to continually enhance their sustainability practices over time. With more investors paying attention to financial portfolio with ESG optimization, companies in different industries will be encouraged to disclose their ESG insights, development and plans, especially for the ones which have not started ESG development yet.

MOPO-LSI offers solutions for two scenarios: one where the client's preferences for ESG factors are predetermined and another where these preferences are currently unknown. Additionally, the MOPO-LSI library is featured with several advantages, including flexible configurations, multi-thread running, visualizations and explanations of the outputs, and so forth. Moreover, MOPO-LSI also allows users or developers to easily extend the library in order to adapt to their own financial optimization problems.

2 THE MOPO-LSI LIBRARY

2.1 Multi-Objective Optimization

The MOPO-LSI library works for asset allocations to a list of mutual funds, where the ESG scores associated with each mutual fund are available in the data set. The ESG factors are categorized into positive and negative ones. The positive ESG factors refer to the ones that are considered beneficial for society, such as clean energy, well-beings, people's health, and so forth. The negative ESG variables are consider harmful, e.g., environmental pollution, regulatory violations, human rights abuses, etc. Therefore, the general objectives in MOPO-LSI refer to producing a financial portfolio by maximizing positive ESG scores, minimizing negative ESG scores and tracking error. The tracking error is used to measure the deviation from standard benchmarks in a specific risk level (e.g., aggressive, moderate, conservative). The risk level can be viewed as a joint factor which captures risks, returns and volatility. The tracking error should be small, in order to guarantee that the portfolio is still in a user-specified risk level (e.g., aggressive, moderate, conservative).

MOPO-LSI is able to produce portfolio solutions in the following two scenarios – one where client preferences are known, and another where client preferences are unknown. In the first case, client preferences can be considered as the weights on different objectives. If they are known, the optimization task can be easily converted to a single-objective optimization by using the weighted sum method, as shown by Equation 1.

$$\max(POS_s - NEG_s - p_m \times TE) \tag{1}$$

In the equation above, s refers to a portfolio solution, and TE denotes tracking error (as shown by Equation 5), where p_m refers to the client preference or weight on the tracking error. POS_s and NEG_s represent the weighted sum of ESG scores on positive and negative ESG dimensions, respective, where the weights here refer to client preferences on ESG factors.

$$POS_s = \frac{\sum\limits_{i \in ESG+} p_i \times Score_i}{\sum\limits_{i \in ESG+} p_i} \tag{2}$$

$$NEG_s = \frac{\sum\limits_{j \in ESG-} p_j \times Score_j}{\sum\limits_{j \in ESG-} p_j} \tag{3}$$

In the equations above, i and j are used to denote a positive and negative ESG factor, respectively. p_i and p_j refer to client preferences on dimension i and j. The score shown in Equation 4 describes the calculation of ESG score on a single ESG factor or dimension, where w is the vector of fund weights or allocations – that's the parameter or solution we would like to learn. E denotes the ESG matrix, where each row is a mutual fund, and each column denotes an ESG factor. E^i is used to represent the i^{th} column in E. We use $|w|$ to indicate summation of fund weights (i.e., elements in w). TE is as shown by Equation 5, where V refers to the covariance matrix and b indicates the benchmark fund weights.

$$Score_i = \frac{w \cdot E^i}{|w|} \tag{4}$$

$$TE = (w - b)^T V (w - b) \tag{5}$$

In addition to the setup of the objectives, we also assign multiple constraints in order to obtain more feasible and practical solutions:

- The summation of fund allocations (i.e., $|w|$) is close to 1.
- Tracking error must be smaller than a pre-defined threshold which can be easily configured in the library.
- Positive ESG scores in the solution should be no smaller than the ones in the benchmark, and negative ESG scores in the solution should be no larger than the ones in the benchmark. The benchmark is determined by a selected risk level.
- The portfolio should be diverse, e.g., we cannot assign most of the assets to a same type of the mutual funds. To do so, we can set a threshold for each asset class, and this threshold can be easily defined in the configuration file of the library.

By combining the objectives and constraints above, we are able to utilize the embedded conic solver (ECOS) [6] in the CVXPY [5] library to solve the quadratic convex optimization problem in our library. The output in this scenario will be a single optimal solution.

Alternatively, client preferences on the objectives may not be known beforehand. In this scenario, we utilized several multi-objective evolutionary algorithms (MOEAs) [4] from the Pymoo [2] library to optimize specific objectives, including maximizing the

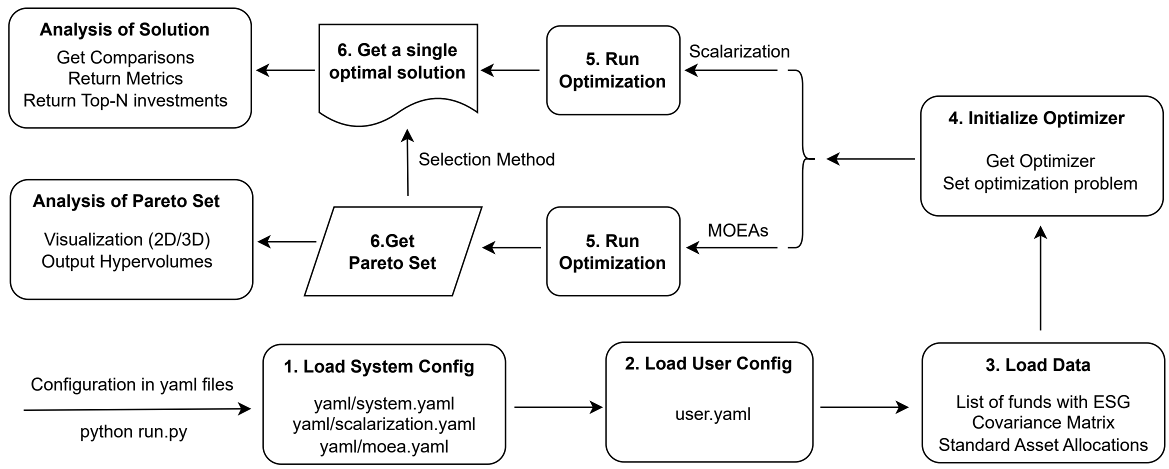

Figure 1: The Framework and Workflow in MOPO-LSI [15]

positive ESG scores, minimizing the negative ESG scores and tracking error. However, MOEAs may spend longer time to find the optimal solutions, if there are more number of ESG dimensions. To better help clients identify their desired solutions, we allow clients to specify individual positive and/or negative ESG factors which they expect to be maximized or minimized. By this way, we can additionally assign constraints on these selected ESG dimensions, and make sure the solution can achieve better ESG scores in these dimensions in comparison with the benchmark. MOEAs will provide Pareto set which is a set of non-dominated solutions. MOPO-LSI allows users to give extra inputs in order to utilize multi-criteria decision making methods [8] to select a single optimal solution from the Pareto set. Also, we provide 2D/3D visualizations to help user observe and understand the selected solution.

2.2 Workflow

The workflow by MOPO-LSI can be depicted by Figure 1, with descriptions as follows.

Configurations. At the beginning, users should well-define hyperparameters in different configuration files, e.g., yaml files. Regarding these parameters, refer to the user guide on the coding repository on Github.

Run MOPO-LSI. A user can start running the library by using "python run.py" or "python run.py –config your.yaml". The default yaml to start running is the user.yaml file.

Load system configurations. The library will first load system configurations defined by yaml files in the folder "yaml", including system.yaml, scalarization.yaml, moea.yaml. The file "system.yaml" defines file paths, output path, risk levels (i.e., conservative, moderate, aggressive), ESG groups and dimensions, the optimization model to be used, and the general parameters for system constraints. The files, "scalarization.yaml" and "moea.yaml", define the MOO problems and corresponding hyperparameters related to the optimizers.

Load user configurations. The file, "user.yaml", is loaded, where the library will read user inputs, such as user option on the risk level, user preferences, and so on.

Load data. The library will then load the data sets indicated in "system.yaml", including the list of funds with their ESG scores, the covariance matrix and standard asset allocations for each risk level.

Initialize optimizer. The library initializes the optimizer by using the parameter "model" defined in "system.yaml". The MOO problem defined in corresponding yaml, either "scalarization.yaml" or "moea.yaml", will also be set up in this stage. A MOO problem defines the list of objectives and constraints to be considered in the optimization process.

Run optimization. The library will run optimization by using corresponding MOO algorithms (e.g., NSGA2) or optimization solvers (e.g., ECOS for the weighted sum method).

Get optimization results. The scalarization methods can return a single optimal solution directly, while the MOEAs will return a Pareto set which is a set of non-dominated solutions. There are several selection methods built in the library to help select a single optimal solution from the Pareto set.

Analysis of the solutions. By given a single optimal solution, the library can compare it with the standard benchmark (i.e., a non-ESG optimized solution associated with a specific risk level), output evaluation metrics (i.e., tracking error, improvement ratio on each ESG factor), and finally return the top-N mutual funds for investments. An example of the outputs by using the sample data and the weighted sum method in MOPO-LSI can be observed from Figure 2, where the gain values refer to the weighted average of the improvement ratios over each ESG groups (i.e., positive and negative ESGs). In terms of the analysis for Pareto set, the library has the option to visualize the non-dominated solutions and hypervolumes.

2.3 Innovations, Novelty and Major Features

The features and innovations can be summarized as follows.

We believe that MOPO-LSI is the first library to support sustainable investments in mutual funds. Existing ones either did not consider ESG factors, or are targeted for general investments, e.g., stocks or bonds.

MOPO-LSI supports MOO solutions for portfolio optimization in two scenarios – run scalarization when user preferences are known, and run MOEAs when user preferences are unknown.

MOPO-LSI offers flexible configurations, where all hyperparameters, data inputs/outputs, optimization constraints or threshold can be easily configure in different yaml files.

MOPO-LSI provides enriched outputs, including standard metrics (e.g., tracking error), metrics in comparisons (e.g. gains or improvement ratios in comparison with benchmarks) and the top-N mutual funds for investments, where the transparency and user trusts can be improved by using these outputs as explanations.

The 2D/3D visualizations can potentially further enhance transparency. The library currently supports the visualization of hypervolumes and non-dominated solutions, as well as the selected optimal solution by a specific multi-criteria decision making method.

MOPO-LSI allows users to extend the MOO problems (i.e., create subclasses of the pre-defined MOO problems, including the Python class *ScalarProblem* and *MOEAProblem*) and re-define the list of objectives and constraints, while users can run the library again without any changes to the optimizer or optimization process.

MOPO-LSI can assist investors and fund managers to start investing practice by considering ESG factors, and also encourage the sustainable investments in a long run.

3 USE CASES

A sample data is provided in the folder "data/SampleData/". This data was produced by simulations. The list of ESG factors and the ESG scores associated with each mutual fund are generated and simulated for the purpose of running tests only. Note that we do have a real-world data set sponsored by Morningstar, Inc. We are able to show and run results on this real data set in the demo session. However, we are not able to release this real-world data set in the open-source library. In this section, we present some examples of the outputs by running MOPO-LSI with the sample data.

Figure 2 presents one of the key outputs in the MOPO-LSI library. Namely, the gains (i.e., improvement ratios in comparison with the benchmark associated with a specific risk level) are shown in the outputs, once a single optimal solution is selected.

Figure 3 shows an example of 2D visualization of the Pareto optimal solutions. More specifically, x-axis presents the negative value of positive ESG scores, and y-axis denotes the negative ESG scores. Note that, we would like to maximize positive ESGs and minimize negative ESGs. In this case, the point on the most left and low corner is expected to be the optimal solution. We utilize two markers to indicate two optimal solution selected by two approaches (i.e., ASF and pseudo weights), respectively. Clients can observe these visualizations, and either select the optimal solution or change their inputs in the ASF/pseudo weights in order to find a better solution. Once a single optimal solution is located, the improvement ratios/gains similar to Figure 2 can also be produced.

```
08 Mar 10:14    SUCCESS  Gains on PosESG: 78.96%
08 Mar 10:14    INFO  Details on PosESG:
                     Solution   Benchmark    Ratio
clean_energy        11.271718    7.809283   44.34%
energy_efficient    11.678043    4.500237  159.50%
recycle_material    12.920997    8.555833   51.02%
wellbeing            2.045654    2.051497   -0.28%
human_development    8.242344    7.905945    4.26%

08 Mar 10:14    SUCCESS  Gains on NegESG: 54.41%
08 Mar 10:14    INFO  Details on NegESG:
                  Solution   Benchmark     Ratio
carbon            3.204334    3.877207    17.35%
thermal_coal      6.342649    6.805105     6.80%
palm_oil          0.323982    2.563921    87.36%
ocean_pollution   0.438748    0.787276    44.27%
tobacco           0.000000    2.494546   100.00%
alcohol           0.433342    2.706351    83.99%
drugs             1.016219    3.380177    69.94%
arms              0.145263    2.924516    95.03%
military          0.000000    3.363846   100.00%
war_support       6.535923    6.529733    -0.09%
```

Figure 2: Improvement Ratios/Gains on Pos and Neg ESGs

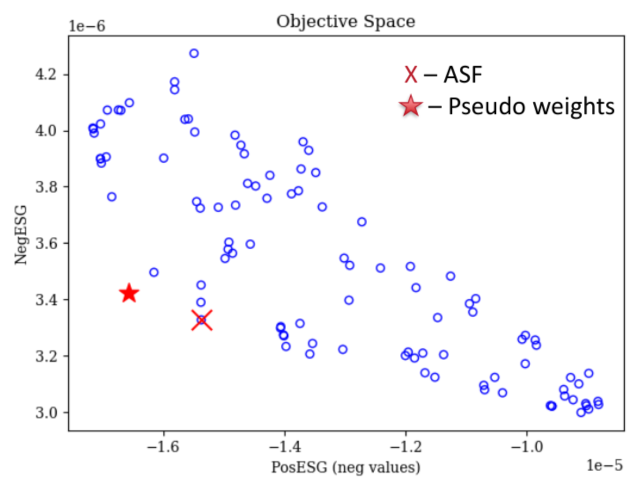

Figure 3: 2D visualization of Pareto solutions

4 CONCLUSIONS & FUTURE WORK

This paper presented an open-source library for sustainable investments in mutual funds. More specifically, the library provides multi-objective portfolio optimization by considering ESG factors. The library is able to help investors find ESG-optimized financial portfolio by given a specific risk level of the investments. The library provides easy configurations, enriched outputs, visualizations and explanations. We believe that it supports the growth of sustainable societies towards ESG optimization, from the perspective of financial investments. In our future work, we plan to develop an interactive visualization platform where both portfolio visualizations and explanations, as well as user interactions, can be fused into, so that the library can work together with the visualization platform to further enhance user experiences.

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