Assisting Multi-Objective Portfolio Selection and Enhancing Transparency by An Interactive Visualization Platform

Yong Zheng[1(✉)[0000−0003−4990−4580]], Kumar Neelotpal Shukla[2[0009−0006−4221−7314]], Michael O'Leary[2[0009−0006−3560−4367]], David Xuejun Wang[2[0000−0003−0724−7615]], and Jasmine Xu[2[0009−0003−3595−7304]]

[1] Center for Decision Making and Optimization,
Illinois Institute of Technology, Chicago, 60616, USA
`yzheng66@iit.edu`

[2] Morningstar, Inc., Chicago, 60602, USA
{`kumarNeelotpal.shukla,michael.oleary,david.wang,jasmine.xu`}`@morningstar.com`

Abstract. Financial portfolio optimization is a widely studied task, wherein researchers have endeavored to construct optimization models that account for the risks and returns and even metrics related to environmental, social, and corporate governance. Many methods for scalarization in multi-objective portfolio optimization rely on clients' preferences for the objectives. However, obtaining and interpreting these preferences can be challenging, as they might change over time. The study in this paper introduces a novel approach that combines multi-objective evolutionary algorithms with an interactive visualization platform to facilitate multi-objective portfolio selection and improve the transparency of optimization outcomes. Unlike traditional methods of collecting preferences through questionnaires, this approach leverages an interactive platform, allowing financial advisers or clients to actively engage with and understand the impact of their preferences on their investment portfolios. The efficacy of this interactive platform is underscored by positive feedback received from financial experts in our company, demonstrating its effectiveness in enhancing the decision-making process.

Keywords: Multi-Objective · Portfolio Optimization · decision making

1 Introduction & Motivations

The optimization of financial portfolios encompasses the meticulous curation of financial assets to align with the investment objectives of an investor, while considering their risk tolerance [15,12,21]. A pivotal facet of this optimization process involves asset allocation, a strategic maneuver involving the distribution of an investor's portfolio across diverse asset classes such as stocks, bonds, and cash. This allocation is intricately tailored to the investor's risk tolerance and overarching investment objectives. The fundamental objective of conventional portfolio optimization resides in the construction of a portfolio designed to maximize anticipated returns for a specified level of risk. In addition to the risks and returns, Investors are increasingly recognizing the paramount importance of incorporating Environmental, Social, and Governance (ESG) [9,1] into financial portfolio optimization. It leads to the popularity of sustainable investments where socially responsible investing [16,13,21] was promoted. Presently, a standardized framework for encompassing ESG factors is notably absent, permitting financial entities to delineate their unique ESG dimensions.

ESG factors are considered in financial investments alongside traditional metrics like risks and returns because they offer insights into long-term sustainability, reputational risks, and regulatory compliance. Integrating ESG criteria enables investors to align their investments with values, mitigate risks, and capitalize on opportunities associated with environmental, social, and governance performance. As a result, achieving optimal financial portfolio optimization involves employing a multi-objective optimization process, where traditional goals like risks and returns, alongside ESG factors, are considered as objectives.

Multi-objective optimization (MOO) [11,4,6], a prominent field within optimization theory, focuses on solving problems that involve conflicting objectives or criteria. Unlike traditional optimization, which typically seeks a single optimal solution, multi-objective optimization aims to find a set of solutions known as the Pareto front, where improving one objective comes at the expense of worsening another. This approach offers decision-makers a range of trade-off options, enabling them to make informed choices based on their preferences and priorities. MOO has been applied to multiple areas or domains (e.g., financial applications [15], recommender systems [22], education [24], etc.) to help achieve balances among multiple objectives.

There are two main categories of MOO approaches: one involves *scalarization* [7,8,11], transforming the MOO task into a single-objective task through various scalarization formulas (e.g., weighted sum of objectives); the other employs *multi-objective evolutionary algorithms* (MOEAs) [15,4], capable of generating a set of Pareto-optimal solutions. A Pareto-optimal solution, also well-known as a non-dominated solution, refers to a solution that excels in all objectives without being surpassed by any alternative feasible solution. Namely, a non-dominated solution implies that further improvement in one objective cannot be achieved without compromising at least one of the other objectives.

The scalarization method is widely favored for its simplicity in comprehension and implementation, but it requires obtaining clients' preferences in advance. While it is feasible to collect clients' preferences ahead of financial portfolio optimization, there are two potential drawbacks: firstly, clients' preferences may undergo changes over time, necessitating a resource-intensive process of repeatedly collecting preferences; secondly, clients may lack clarity regarding the impact of their preferences of objectives on their portfolio, resulting in a lack of transparency and the potential misconfigurations of financial portfolios.

In contrast, MOEAs operate without requiring clients' predetermined preferences on the objectives. Nevertheless, MOEAs may yield a set of Pareto-optimal solutions (i.e., Pareto set), requiring clients to choose one for their investments. Researchers in the field of MOEAs have suggested leveraging knee points (i.e., an ideal approximation based on mathematical approaches) or employing multi-criteria decision-making (MCDM) methods [10,23] to aid in selecting the optimal solution from the Pareto set. However, there is a lack of transparency in the process of financial decision making. To address this challenge, we develop a prototype for a 3-dimensional (3D) interactive visualization platform. This platform enables financial advisers to guide clients through visualizations, facilitating decision-making in financial portfolio selection.

2 Multi-Objective Portfolio Optimization by MOEAs

2.1 Multi-Objective Portfolio Optimization

We endeavor to identify the most advantageous portfolio for investing in mutual funds. Financial experts in our company, Morningstar, Inc.[3], have predefined 15 ESG factors. These factors include five positive ESG (PosESG) dimensions, such as climate actions and healthy ecosystems, alongside other negative ESG (NegESG) factors like tobacco, gambling, alcohol, and arms. Each mutual fund in our dataset is associated with ESG scores across these 15 dimensions, wherein the scores, ranging from 0 to 100, were assigned by financial experts. We have three types of objectives in our portfolio optimization:

- **Tracking error**. In contrast to stock investments where precise returns and risks are computed, clients engaging in mutual funds prefer opting for portfolios within a designated risk range. Our company provides three benchmarks of different risk levels – conservative, moderate, and aggressive, each serving as a comprehensive factor encompassing risks, returns, and volatility. The tracking error (TE) is employed to gauge the deviation from established benchmarks within a specified risk level. The benchmark refers to a standard portfolio associated with a specific risk level without considering ESG factors. Clients are required to choose their preferred risk level, following which our optimization process generates portfolios with tracking errors below 5%.
$$TE = (w - b)^T V (w - b) \tag{1}$$
The computation of TE can be described by Equation 1, where w refers to the fund weights or allocations in a solution, b denotes the fund weights from the standard benchmark associated with a specific risk level, and V represents the covariance matrix of mutual funds.
- **Overall ESG scores**. Revisiting the context, we have five PosESG and ten NegESG dimensions. In our MOO process, we aim to maximize PosESG scores and minimize NegESG scores. Given the absence of client preferences on individual ESG factors, we employ the average PosESG and NegESG scores as calculations for PosESG and NegESG, respectively. For instance,

[3] https://www.morningstar.com/company/about-us

the average PosESG score is calculated by determining the mean score across the five PosESG dimensions.

$$Score_i = \frac{w \cdot E^i}{|w|} \quad (2)$$

The computation of the ESG score on the i^{th} ESG factor by given a solution can be described by Equation 2. E denotes the ESG score matrix, where each row is a mutual fund, and each column denotes an ESG factor. E^i is used to represent the i^{th} ESG column in E. We use $|w|$ to indicate summation of fund weights (i.e., elements in w) in a solution.

- **User-Specified ESG scores**. Each client may present a distinct set of mutual funds considered as potential candidates for constructing the optimal portfolio. Consequently, the distributions of ESG scores among these candidates may vary. In conjunction with the overarching ESG scores serving as objectives, we enable clients to specify up to two PosESG and up to two NegESG factors of interest. The optimization process ensures that the ESG scores pertaining to these selected dimensions surpass the corresponding benchmarks, i.e., higher PosESG scores and lower NegESG scores.

The optimization objectives within our framework are articulated through Equation 3. Here, $\overline{Score}_{NegESG}$ signifies the average ESG score across all NegESGs, and $\overline{Score}_{PosESG}$ represents the mean ESG score across all PosESGs. The indices of two selected NegESGs are denoted by m and n, while p and q are used to represent the indices of two selected PosESGs. All objectives will be normalized to a same score to be considered in the optimization process. Note that clients are allowed to declare up to two PosESGs and NegESGs. The limitation is used to control the quality of Pareto set. With more objectives, MOEAs can produce more non-dominated solutions, which results in more difficulties for selections.

$$\min(TE + \overline{Score}_{NegESG} - \overline{Score}_{PosESG} + \sum_{i \epsilon \{m,n\}} Score_i - \sum_{j \epsilon \{p,q\}} Score_j) \quad (3)$$

In our experiments, we adopt the MOPO-LSI library [20,19] to produce multi-objective solutions. MOPO-LSI[4] is an open-source multi-objective portfolio optimization library for sustainable investments, where it implements the technologies of both scalarization and MOEAs for finding multi-objective solutions in mutual fund investments. More specifically, we utilized the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [5] as the MOEA algorithm in the MOO process. NSGA-II is a popular and widely employed MOEA known for its effectiveness in addressing optimization problems with multiple conflicting objectives. It utilizes non-dominated sorting and genetic operators to iteratively generate a diverse population of solutions, ultimately producing a Pareto-optimal front.

[4] `https://github.com/irecsys/MOPO-LSI`

2.2 Sample Data and Scenarios

We utilized a sample data where there are 119 mutual funds. This sample data is one of the most popular candidate sets for our clients. Recall that we will design the 3D interactive visualization platform and send it to be reviewed by financial experts in our company. To simplify the process, we assume that the clients specified two PosESGs (i.e., climate action and healthy ecosystems) and two NegESGs (i.e., thermal coal and fossil fuel) to be considered in the optimization process. Note that we just assume all these four dimensions are user-specified ESG factors. All 15 ESG factors were considered to calculate the overall ESG scores as mentioned in Section 2.1.

3 Prototype of the 3D Interactive Visualization Platform

3.1 The Visualization Platform

Based on the sample data discussed above, we apply NSGA-II to produce 150 non-dominated solutions, and visualize them in our 3D interactive visualization platform. Next, we introduce these important components one by one.

Part 1. 3D and 2D Plots. A 3D plot is used to visualize all 150 non-dominated solutions. The three dimensions to be visualized can be selected from Part 2. In addition to the 3D plot, there are three 2D plots which are projections from the 3D plot. In the 3D plot, each axis presents normalized scores in the objectives. It is worth noting that we used reversed scores to represent the dimensions to be maximized (such as PosESG), and then normalized theses scores to [0, 1]. By this way, the optimal solution refers to a data point which minimizing all dimensions in the 3D plot. The point "+" denotes the coordinates (0, 0, 0), and it is considered as the ideal point. Namely, the point closer to this ideal point may be the optimal solution.

The interactive features of the 3D plot include functionalities like rotation, zooming in and out. When hovering over a point, the point will be colored orange, and this coloring will extend to the corresponding points in the 2D plot, highlighting them in orange as well. The red and green points refer to optimal solutions by different approaches, where we will discuss them in Part 3 and 4. Users can also click a data point, which results in adding one row in the click history shown in the table at the bottom (i.e., Part 5).

Part 2. Dimensions to be visualized. The platform provides a list of objectives in the process, including the tracking error, the overall ESG scores (i.e., PosESG and NegESG) and user-specified positive and negative ESG dimensions. Users can deselect current options and select other dimensions to be visualized.

Part 3. Solution selection by using Knee points. Knee points [3] denote specific solutions on the Pareto front characterized by a notable shift in the trade-off

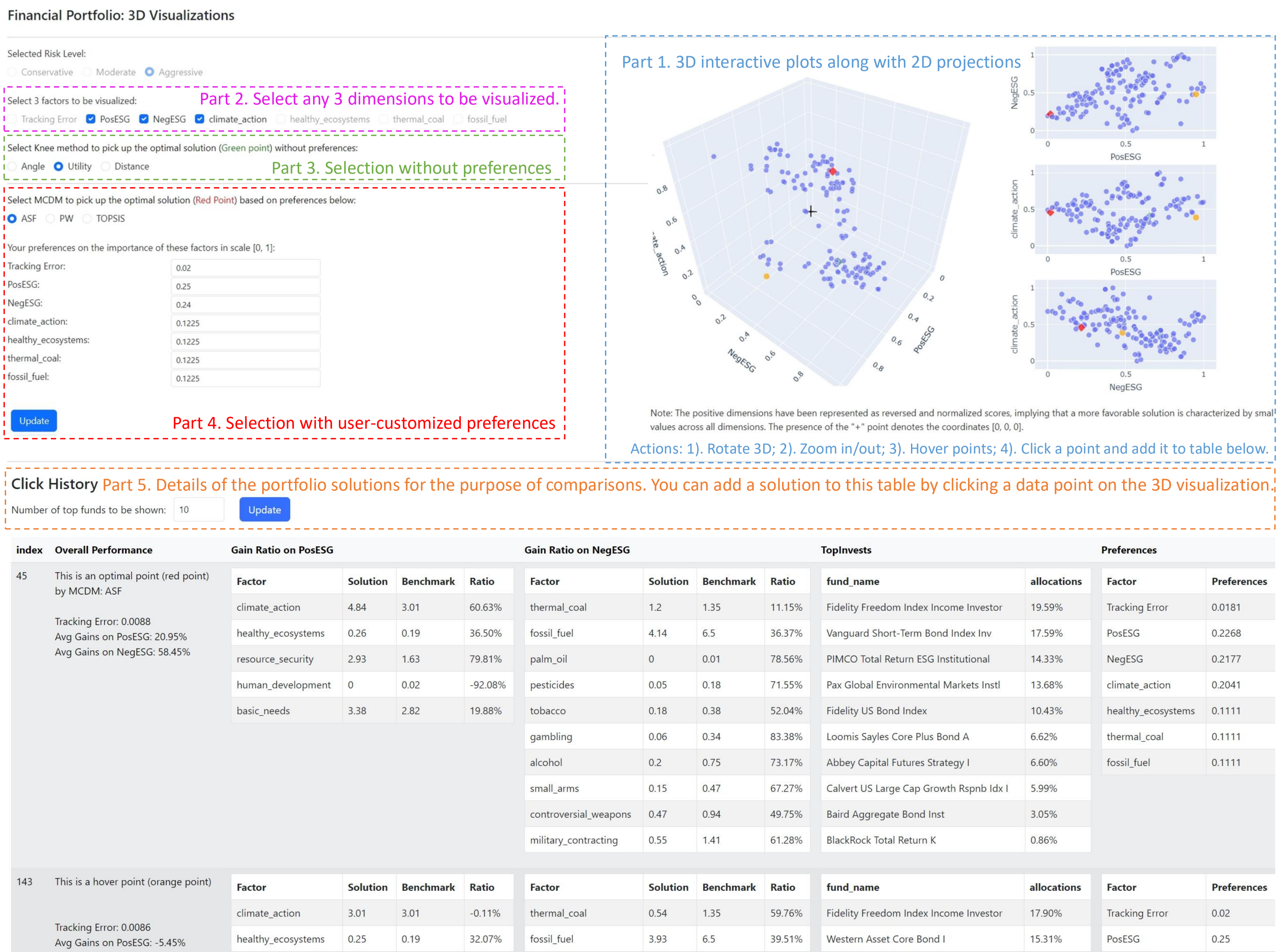

Fig. 1. Prototype of 3D Interactive Visualization Platform

between different objectives. At a knee point, certain objectives exhibit improvement, whereas others experience a substantial degradation. Therefore, knee points can be considered as approximation of the optimal solution from Pareto set, and this selection method based on knee points does not require clients' preferences. We adopted three popular ways to find the knee point highlighted as a green point in the 3D plot - the angle-based approach [3], the method based on marginal utility [3] and the distance-based approach [18].

Part 4. Solution selection by using MCDMs. MCDMs can be utilized to select the optimal solution, where clients' preferences need to be involved in the computations. In Part 4, users can input their preferences in the textboxes, and select any one of the three MCDMs, including the augmented scalarization function(ASF) [17], pseudo-weights (PW) [2] and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [14], to produce the optimal solution highlighted as a red point in the 3D plot.

Part 5. Click history. Users can click a data point from the 3D plot, and add details of this solution to the click history. Figure 1 presents an example where two solutions were added to the click history. The gain ratios refer to the improvement ratio in PosESGs or NegESGs in comparison with the ESG scores in the standard benchmark. The top investments present the fund allocations according to the specific solution. By observing the details of the portfolio and comparing different solutions, they are served as explanations to the clients, which results in improved transparency and ease for portfolio selections.

3.2 Questionnaire and Responses

We design a questionnaire and distribute it to the financial experts from the data science team at Morningstar, Inc., to learn their feedback on this prototype of 3D interactive visualizations. We received feedback from 19 financial experts, assessing their familiarity with portfolio optimization and ESG using a scale ranging from 1 (not familiar at all) to 5 (very familiar). Regarding portfolio optimization, their proficiency levels are distributed as 10.5%, 31.6%, 36.8%, and 21.1% for levels 2, 3, 4, and 5, respectively. In the context of ESG, 68.4% exhibit a knowledge level of 3, while 31.6% indicate a proficiency level of 4. The responses can be summarized as follows.

- *(Multi-choice question) Which interactive elements did you find most useful in the 3D/2D plots?* The three most favored options are plot rotations (chosen by 78.9% of respondents), click history (selected by 52.6%), and zoom in/out (preferred by 36.8%). The remaining two components, namely 2D projections and the flexibility to visualize any three dimensions, received responses of 31.6% and 36.8% respectively.
- *(Multi-choice question) Which solution selection methods are the best ones?* The methods using Knee points and MCDMs received 48% and 52% votes

respectively. Concerning the identification of knee points, votes were distributed as 45%, 35%, and 20% for utility-based, distance-based, and angle-based methods, respectively. Regarding MCDMs, preferences were divided with 50%, 25%, and 25% of votes for ASF, PW, and TOPSIS, respectively.
- *(Rating question) How effective do you think the tool is in helping you optimize financial portfolios based on ESGs?* 10.5%, 31.6%, 42.1% and 15.8% subjects gave their responses to 5 (very useful), 4, 3, 2, respectively.
- *(Single-choice question) Did you find the controls for selecting ESG dimensions and other parameters (such as clients' preferences on ESGs) user-friendly and intuitive?* 68.4%, 15.8% and 15.8% subjects gave their responses to Yes, Maybe and No, respectively.
- *(Single-choice question) Would you trust us more in terms of the asset allocations through this visualization platform?* 57.9%, 21.1% and 21.1% subjects gave their responses to Yes, Maybe and No, respectively.

4 Conclusions & Future Work

In this paper, we present a prototype of 3D interactive visualization platform to visualize non-dominated solutions generated from NSGA-II for the purpose of portfolio optimization. The majority of 19 financial experts participated in our questionnaire affirmed the utility of the visualization platform for enhancing financial transparency, expressing admiration for the efficacy of the solution selection methods. Anticipated users of this visualization system are expected to be individuals possessing expertise in portfolio optimization and ESG, such as financial experts or advisers, rather than end investors of mutual funds. Financial advisers are envisioned to play a pivotal role in assisting clients in navigating the visualizations, elucidating the repercussions of their selections, thereby streamlining the portfolio selection process. In our future work, we will explore more options or designs to reduce the workloads by financial advisers and make the visualizers easier for users with less knowledge in portfolio optimization or ESG.

References

1. Amel-Zadeh, A., Serafeim, G.: Why and how investors use esg information: Evidence from a global survey. Financial Analysts Journal **74**(3), 87–103 (2018)
2. Blank, J., Deb, K.: Pymoo: Multi-objective optimization in python. IEEE Access **8**, 89497–89509 (2020)
3. Branke, J., Deb, K., Dierolf, H., Osswald, M.: Finding knees in multi-objective optimization. In: Parallel Problem Solving from Nature-PPSN VIII: 8th International Conference, Birmingham, UK, September 18-22, 2004. Proceedings 8. pp. 722–731. Springer (2004)
4. Coello, C.C.: Evolutionary multi-objective optimization: a historical view of the field. IEEE computational intelligence magazine **1**(1), 28–36 (2006)
5. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: Nsga-ii. IEEE transactions on evolutionary computation **6**(2), 182–197 (2002)

6. Deb, K., Sindhya, K., Hakanen, J.: Multi-objective optimization. In: Decision sciences, pp. 161–200. CRC Press (2016)
7. Eichfelder, G.: Adaptive Scalarization Methods in Multiobjective Optimization. Springer (2008)
8. Eichfelder, G.: Scalarizations for adaptively solving multi-objective optimization problems. Computational Optimization and Applications **44**, 249–273 (2009)
9. Friede, G., Busch, T., Bassen, A.: Esg and financial performance: aggregated evidence from more than 2000 empirical studies. Journal of sustainable finance & investment **5**(4), 210–233 (2015)
10. Greco, S., Figueira, J., Ehrgott, M.: Multiple criteria decision analysis, vol. 37. Springer (2016)
11. Gunantara, N.: A review of multi-objective optimization: Methods and its applications. Cogent Engineering **5**(1), 1502242 (2018)
12. Gunjan, A., Bhattacharyya, S.: A brief review of portfolio optimization techniques. Artificial Intelligence Review pp. 1–40 (2022)
13. Halbritter, G., Dorfleitner, G.: The wages of social responsibility—where are they? a critical review of esg investing. Review of Financial Economics **26**, 25–35 (2015)
14. Lai, Y.J., Liu, T.Y., Hwang, C.L.: Topsis for modm. European journal of operational research **76**(3), 486–500 (1994)
15. Ponsich, A., Jaimes, A.L., Coello, C.A.C.: A survey on multiobjective evolutionary algorithms for the solution of the portfolio optimization problem and other finance and economics applications. IEEE Transactions on evolutionary computation **17**(3), 321–344 (2012)
16. Renneboog, L., Ter Horst, J., Zhang, C.: Socially responsible investments: Institutional aspects, performance, and investor behavior. Journal of banking & finance **32**(9), 1723–1742 (2008)
17. Wierzbicki, A.P.: The use of reference objectives in multiobjective optimization. In: Multiple Criteria Decision Making Theory and Application: Proceedings of the Third Conference Hagen/Königswinter, West Germany, August 20–24, 1979. pp. 468–486. Springer (1980)
18. Zhang, X., Tian, Y., Jin, Y.: A knee point-driven evolutionary algorithm for many-objective optimization. IEEE Transactions on Evolutionary Computation **19**(6), 761–776 (2014)
19. Zheng, Y., Shukla, K.N., Xu, J., Wang, D.X., O'Leary, M.: MOPO-LSI: A user guide. arXiv preprint arXiv:2307.01719 (2023)
20. Zheng, Y., Shukla, K.N., Xu, J., Wang, D.X., O'Leary, M.: MOPO-LSI: An open-source multi-objective portfolio optimization library for sustainable investments. Software Impacts **16**, 100499 (2023)
21. Zheng, Y., Shukla, K.N., Xu, J., Wang, D.X., O'Leary, M.: Multi-objective portfolio optimization towards sustainable investments. In: Proceedings of the 6th ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies. pp. 124–128 (2023)
22. Zheng, Y., Wang, D.X.: A survey of recommender systems with multi-objective optimization. Neurocomputing **474**, 141–153 (2022)
23. Zheng, Y., Wang, D.X.: Multi-criteria decision making and recommender systems. In: Companion Proceedings of the 28th International Conference on Intelligent User Interfaces. pp. 181–184 (2023)
24. Zou, F., Wang, L., Hei, X., Chen, D., Wang, B.: Multi-objective optimization using teaching-learning-based optimization algorithm. Engineering Applications of Artificial Intelligence **26**(4), 1291–1300 (2013)