

# ESG integration in portfolio selection: A robust preference-based multicriteria approach

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## ABSTRACT

We present a framework for multi-objective optimization where the classical mean–variance portfolio model is extended to integrate the environmental, social and governance (ESG) criteria on the same playing field as risk and return and, at the same time, to reflect the investors' preferences in the optimal portfolio allocation. To obtain the three-dimensional Pareto front, we apply an efficient multi-objective genetic algorithm, which is based on the concept of  $\epsilon$ -dominance. We next address the issue of how to incorporate investors' preferences to express the relative importance of each objective through a robust weighting scheme in a multicriteria ranking framework. The new proposal has been applied to real data to find optimal portfolios of socially responsible investment funds, and the main conclusion from the empirical tests is that it is possible to provide the investors with a robust solution in the mean–variance–ESG surface according to their preferences.

## 1. Introduction

Investment decisions and the methods that justify them remain one of the main topics of study in finance. Since Markowitz's seminal work [1] in 1952, many approaches have been developed, especially in the field of multicriteria decision making analysis (MCDM) to advance the design of investment strategies that respond to the emerging challenges of the financial sector [2–4]. One of the current challenges facing the financial sector is the integration of ESG considerations into investment decisions. In the last two decades, purely financial two-dimensional models based on profitability and risk have begun to incorporate new criteria in line with the high percentages of investors favorably disposed towards environmental or social issues. The attempt to reconcile financial objectives with ethical objectives has generated several labels for this new trend such as socially responsible investment (SRI), sustainable finance or environmental, social or governance (ESG) investments [5]. These new management models have adopted the “Principles for Responsible Investment” of the United Nations, so that in recent years there has been a growing trend to develop emerging approaches, both theoretical and applied, which are concerned with incorporating classic financial criteria together with ESG criteria.

Among the models that have been proposed to date for considering sustainability aspects into investment decisions, the most common ones are those that first integrate ESG-related issues as a constraint to

perform an initial screening of securities, and then apply the traditional bi-criteria mean–variance (M–V) framework of [1] for the survivors. In this way, sustainable investors become *satisfiers*, as the universe of stocks to be optimized is restricted to an approved list and the selection is made in terms of standard financial objectives. Once a certain level of sustainability has been achieved, the interest of investors levels off. Some seminal contributions in this area are due to [6–10], who provide the first operational research-oriented approaches to integrate sustainability criteria into portfolio selection. A recent contribution in this category is the work of [11] where, in addition to the classical terms of expected return and portfolio risk, transaction costs and the ESG score of the portfolio are also considered.

A major step forward in the move towards a stronger focus on sustainable decision-making has clearly been the pioneering contribution of [12] in which the ESG criterion competes on the risk/return playing field, turning the efficient frontier into an efficient surface in three dimensions. In this case, the investor becomes an *optimizer* concerned with the simultaneous consideration of the risk, return, and ESG objectives. In this perspective, investors are strongly driven by ESG considerations, and their commitment to ESG is such that they are willing to sacrifice profitability for sustainability. This new lens on the problem of ESG integration in portfolio selection has recently been reflected in some pioneering studies. For example, in [13] a tri-criterion portfolio

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optimization model, formulated as a convex quadratic program, is proposed to investigate the impact of the ESG rating on the portfolio selection process. In [14] a multiobjective minimax-based portfolio optimization model is applied to extra-financial criteria, namely, the ESG risk scores and the controversy level. Also, it is worth noting the work of [15], in which a special technique called Non-contour efficient fronts is developed to solve the portfolio problem of sustainable investors and to assess the best return/risk/ESG trade-offs.

Another strand of the literature stems from integrating sustainability related issues using heuristic approaches which are inspired by biological processes. These approaches include Multiobjective Evolutionary Genetic Algorithms (MOGAs) which, while not providing an exact solution, are capable of generating approximate solutions efficiently. For example, the contributions of [16,17], and [18] use several heuristic approaches to provide satisfactory approximations of the efficient frontier incorporating the ESG concern either as an objective or as a constraint. As a first stage of the methodology, our work attempts to implement a MOGA approach to obtain the mean-variance-ESG non-dominated surface. In particular, we use an elitist multi-objective evolutionary genetic algorithm based on the concept of  $\epsilon$ -dominance, called ev-MOGA, developed by [19]. With limited memory resources, this algorithm dynamically evolves to ensure convergence towards uniformly distributed solutions on the  $\epsilon$ -Pareto front.

In the case of considering sustainability as a third criterion, it is not enough to understand what an investor is asking for in terms of return and risk. Besides, financial advisors must be able to delve deeper into what their clients are trying to achieve in terms of ESG integration and then convey the consequences of those preferences by finding a solution that suits their interests. Therefore, the need to find an optimal portfolio allocation that simultaneously reflects investor's preferences and takes into account the three criteria, adds additional complexity, especially in the field of professional financial advice. For each investor profile, this entails the search for a subset of  $\epsilon$ -Pareto front. Consequently, to find these solutions we introduce an a posteriori multicriteria decision aiding approach based on the SMAA-TOPSIS framework in a second stage of our proposal. This approach integrates the "Stochastic Multi-criteria Acceptability Analysis" (SMAA; [20]) into the "Technique for Order Preferences by Similarity Solutions" (TOPSIS; [21]) to provide robust recommendations as for the final portfolio allocation on the mean-variance-ESG surface. As in many ranking methodologies, TOPSIS implies the definition of a weight vector denoting the importance of each criterion. The implementation of the SMAA approach allows the analyst to sort the non-dominated solutions of the  $\epsilon$ -Pareto front through a probabilistic ranking where the weights that each investor profile assigns to the objectives are obtained through a Monte Carlo simulation. Thus, it avoids the choice of a single weight vector, and addresses robustness concerns regarding the preference choice of the investors. It is important to highlight that this approach is different from classical robust portfolio optimization models, which involves considering uncertainty in the input data. According to [22], models grounded on robust strategies are preferable to classical methodologies in terms of stability of selected portfolio returns, and of out-of-sample performance.

The purpose of this study is to find an optimal portfolio in which the sustainability criterion is included as an additional objective for those investors who are concerned about ESG issues. To address this problem, we propose a methodology consisting of three stages. In the first stage, we obtain the M-V-ESG efficient frontier using the ev-MOGA algorithm, where the investor can determine the efficient portfolios purely on the basis of their financial and sustainable features, i.e., without taking into account the investor's preferences. Next, in the second stage, we narrow down the region of interest according to the information that the investors have provided on their preferences by applying the SMAA-TOPSIS approach to help the investors reach the final robust portfolios allocation. Finally, in the third and final stage, we assess the

quality of these solutions through a performance analysis. While the ev-MOGA and SMAA-TOPSIS methods used in this paper are not new and have also been independently applied to similar problems, the novelty of our contribution lies in their innovative combination and adaptation to develop a preference-adapted decision tool for generating robust recommendations in a three-criteria sustainability portfolio selection problem, as highlighted by extensive empirical results on real-world data. Furthermore, we emphasize the advantages of employing these methods over existing approaches:

- ev-MOGA is often preferred over other multiobjective genetic algorithms used in portfolio optimization such as NSGA-II [23] due to several key advantages it offers. One significant benefit of ev-MOGA is its ability to dynamically adapt and evolve towards uniformly distributed solutions along the Pareto front. Unlike traditional MOGAs that may struggle with achieving balanced and diverse solutions, ev-MOGA efficiently explores the solution space, providing a broader range of optimal outcomes. Additionally, ev-MOGA tends to be less mathematically challenging compared to exact optimization methods, making it more accessible and practical for real-world applications. This algorithm achieves a balance between solution quality and computational efficiency, making it a suitable choice for solving complex multi-objective optimization problems, particularly in areas like sustainable portfolio selection, where balancing risk, return, and sustainability criteria is essential for decision-making.
- SMAA-TOPSIS integrates the principles of both stochastic dominance analysis and similarity to ideal solutions, allowing decision makers to comprehensively assess the acceptability and performance of alternatives. By considering multiple scenarios and possible outcomes, SMAA-TOPSIS provides a more accurate assessment that captures the inherent complexity and uncertainty of real-world decision environments. Another advantage of SMAA-TOPSIS is its flexibility in handling diverse sets of criteria and preferences. We believe this approach can be a valuable tool to deliver guidance to investors when exploring different weighting schemes for the three objectives and to understand the impact of criteria preferences on the ranking of portfolios.

The remaining sections are structured as follows. Section 2 describes how the methodologies can be implemented in the problem of three-criterion portfolio selection. This is followed by a description of the datasets used in the empirical analysis in Section 3. Section 4 presents the results of the application to three datasets employed by real fund managers. Finally, Section 5 provides some conclusions and further research proposals.

## 2. Methodology

In multi-objective optimization, the problem is solved in two steps. First, using optimization to find Pareto optimal solutions, and second, applying a decision-making approach to choose a single preferred solution. In the latter step it is necessary to incorporate information about the preferences of the decision-maker or an analyst [24]. In this section, we provide a detailed description of the stages of the model proposed in this paper, as outlined in Fig. 1.

Starting with the optimization phase for the in-sample dataset (Stage I), by means of the ev-MOGA algorithm we obtain the M-V-ESG efficient frontier, in which the investor can choose the portfolio's placement based solely on the financial and sustainable characteristics of the portfolio, that is, regardless of the investor's preferences. Next, using information about investor's preferences (Stage II) and applying the SMAA-TOPSIS approach we narrow down the region of interest and help the investors to come up with the final portfolio robust allocation. To evaluate the quality of this final solution we compute some relevant performance measures of these portfolios for the in-sample and out-of-sample window periods (Stage III). A detailed description of each of the stages is set out below.

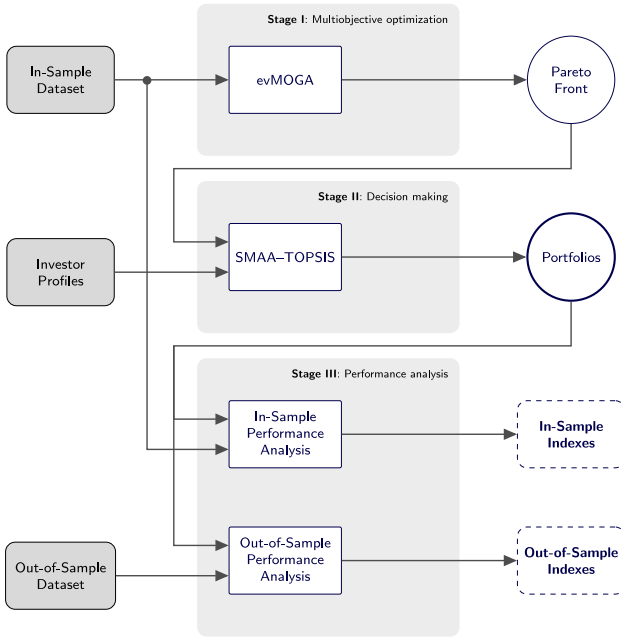


Fig. 1. Flowchart of the proposed methodology.

### 2.1. Stage I: Tri-criterion mean–variance–ESG multiobjective optimization

To deal with the first stage in our proposal, we join the latter trend of ESG integration [13,15,25], making ESG a criterion competitive on the playing field of risk and return, but using the ev-MOGA algorithm [19] to derive the approximate non-dominated M–V–ESG surface. This procedure, which is an elitist multiobjective genetic algorithm based on the concept of  $\epsilon$ -dominance, allows us to approximate uniformly distributed solutions of the 3D Pareto front. A detailed description of the adapted ev-MOGA to derive the M–V–ESG frontier can be found in [16]. In this work, our goal is to find a portfolio allocation that provides an optimal trade-off between expected financial returns, risk, and ESG related issues. Thus, departing from the in-sample data-set, the tri-criterion portfolio selection problem is mathematically formulated as follows:

$$\begin{aligned} \min_{\mathbf{x}} \mathbf{f}(\mathbf{x}) \\ \text{s.t.: } \mathbf{x} \in S = \{ \mathbf{x} \in \mathbb{R}^m : \mathbf{1}^T \mathbf{x} = 1, x_i = q \lambda_0, q \in \mathbb{Z}^+, x_i \leq x_{\max} \} \end{aligned} \quad (1)$$

where  $x_i$  denotes the proportion of asset  $i$  in the portfolio  $\mathbf{x}$  and

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} -\boldsymbol{\mu}^T \mathbf{x} \\ \mathbf{x}^T \boldsymbol{\Sigma} \mathbf{x} \\ \boldsymbol{\rho}^T \mathbf{x} \end{bmatrix} \quad (2)$$

The first component of the objective vector function is  $f_1(\mathbf{x}) = -\boldsymbol{\mu}^T \mathbf{x}$  representing the portfolio expected return, where  $\boldsymbol{\mu}$  is the expected return vector for each asset. The second component  $f_2(\mathbf{x}) = \mathbf{x}^T \boldsymbol{\Sigma} \mathbf{x}$ , models the financial risk, where  $\boldsymbol{\Sigma}$  is the covariance matrix. Finally, the third component of the objective vector function,  $f_3(\mathbf{x}) = \boldsymbol{\rho}^T \mathbf{x}$ , represents the sustainability for the portfolio, where  $\boldsymbol{\rho}$  denotes the vector of ESG risk scores, which according to Sustainability methodology, is rendered on a 0–100 scale where lower scores are better [26]. By integrating ESG risk scores into the mean–variance analysis, investors can make more informed decisions that not only optimize financial returns, but also align with their ESG-related values and goals. This approach helps create a portfolio that balances both financial and ethical considerations.

Additionally, we include the discretization of portfolio weights  $x_i$ , so that the analyst has to specify: (i) the value of  $\lambda_0$  to set the discrete step between two investment shares, being  $\lambda_0$  the same for all assets; and

(ii) the maximum asset weight  $x_{\max} = q_{\max} \lambda_0$ , to indicate the maximum amount of investment in an asset. Thus, the portfolio is defined by a set of weights that are zero or multiples of  $\lambda_0$  with a maximum level of  $x_{\max}$ .

The feasible region in the objective space is defined as follows:

$$Z = \{ \mathbf{z} \in \mathbb{R}^3 : \mathbf{z} = \mathbf{f}(\mathbf{x}), \mathbf{x} \in S \}$$

Note that by solving the multi-objective optimization problem (1) by means of the ev-MOGA approach, we obtain the approximate M–V–ESG Pareto front. As we have mentioned, the ev-MOGA is an elitist MOEA based on the concept of  $\epsilon$ -dominance proposed by [27]. Within the concept of  $\epsilon$ -dominance, a solution dominates the solution inside a distance that is less than parameter  $\epsilon$ . Thus, the objective function space is split into a fixed number of boxes forming a grid. This grid preserves the diversity of the non-dominated solutions since each box can be occupied by only one solution. The size of the boxes is determined by the value of  $\epsilon_i$ , which is calculated as follows:

$$\epsilon_i = \frac{f_i^* - f_{i*}}{n_{\text{box}}}$$

where,  $f_i^*$  and  $f_{i*}$  correspond to the maximum and minimum value of the objective function  $f_i$  for all the solutions in the Pareto front, and  $n_{\text{box}}$  is the number of boxes. Next, we recall some relevant concepts of  $\epsilon$ -dominance and  $\epsilon$ -Pareto front.

**Definition 1.**  $\epsilon$ -dominance: Let  $\mathbf{x}^1, \mathbf{x}^2 \in S$  be two feasible solutions, and let  $\mathbf{z}^1 = \mathbf{f}(\mathbf{x}^1), \mathbf{z}^2 = \mathbf{f}(\mathbf{x}^2) \in Z$  be their image solutions in the objective space. Then, assuming that the objective functions have to be minimized,  $\mathbf{x}^1$  is said to  $\epsilon$ -dominate  $\mathbf{x}^2$  for some  $\epsilon > 0$ , denoted as  $\mathbf{z}^1 <_{\epsilon} \mathbf{z}^2$ , iff:

$$z_i^1 - \epsilon_i \leq z_i^2, \quad i \in \{1, 2, 3\} \quad (3)$$

**Definition 2.**  $\epsilon$ -Pareto front: Let  $Z$  be the set of feasible solutions in the objective space. Then, we call  $\epsilon$ -approximate Pareto front  $\hat{Z} \subset Z$  the set of all solutions that are  $\epsilon$ -non dominated by any other feasible solution:

$$\hat{Z} = \{ \mathbf{z} \in Z : \nexists \mathbf{z}' \in Z, \mathbf{z}' <_{\epsilon} \mathbf{z} \} \quad (4)$$

In addition, ev-MOGA is able to adjust the width of  $\epsilon_i$  dynamically and prevent solutions belonging to the extremes of the front from being lost. The main advantage of ev-MOGA is that the algorithm generates good approximations of a well-distributed Pareto front in a single run and within limited computational time. The original ev-MOGA algorithm is available in [28]: [ev-MOGA in Matlab Central](#).

### 2.2. Stage II: Incorporating investor's preferences using the SMAA-TOPSIS approach

Over the past twenty years, many techniques have been proposed to consider the preferences of the decision maker in MOEAs, thus narrowing down the solution search to a subset of Pareto optimal solutions, the so called region of interest. The integration of these preferences can be performed in one of the following three directions: a-priori, interactive or progressive, and a-posteriori, corresponding to the point in time at which the decision maker informs of his/her preferences [29,30].

In our proposal, the integration of ESG preferences in the decision stage is based on an a posteriori multicriteria approach implemented within the SMAA-TOPSIS framework. The main underlying idea of this methodology is to consider a plurality of weighting vectors on the relative importance of each objective (return, risk, sustainability) which are obtained through simulation approaches according to SMAA. Finally, these preferential weights are integrated into the TOPSIS methodology to derive a robust probabilistic ranking. The idea of integrating the SMAA methodology into the TOPSIS method has been initially proposed by [31] and used in many studies to elicit a plurality of weight vectors compatible with the preference information provided by the decision maker [32].

### 2.2.1. Implementing TOPSIS in our proposal

In general, TOPSIS is based on a set of alternatives which are evaluated on a group of criteria. In our case, the set of alternatives corresponds to the number  $N$  of solutions on the  $\varepsilon$ -Pareto front,  $\hat{Z} = \{\hat{z}^1, \hat{z}^2, \dots, \hat{z}^N\}$ , which are evaluated on the investor's preferences for the mean, variance and ESG risk criteria. From now on, and following the classical terminology in TOPSIS, each of these solutions will be denoted as an element of the set of alternatives  $A = \{a_1, a_2, \dots, a_n\}$ , while the set of criteria will be denoted by  $G = \{g_1, g_2, \dots, g_m\}$ . Then, the assessment of alternative  $a_i \in A$  on criterion  $g_j \in G$  will be denoted by  $a_{ij}$ , where, in our three objective problem,  $j = 1, 2, 3$ . Therefore, the values of the three criteria for each non-dominated solution are collected in a decision matrix  $A \in \mathbb{R}^{n \times 3}$ .

The application of TOPSIS consists of the following steps:

1. **Normalization.** This is a preliminary step required to express all the objectives in a common scale. In our case we use the min-max normalization to derive  $z_{ij}$ , the normalized values of  $a_{ij}$ .
2. **Weighting.** As for the elicitation of the weights we use the SMAA approach explained below. We denote by  $w = [w_1, \dots, w_m]$  the vector composed of randomly derived weights on criteria  $G$ , such that  $w_j > 0$  for all  $g_j \in G$  and  $\sum_{j=1}^3 w_j = 1$ . Once they are computed, we obtain the normalized weighted values  $v_{ij} = w_j \cdot z_{ij}$ .
3. **Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS).** We denote by  $G_I$  the subset of increasing criteria, and by  $G_D$  the subset of the decreasing ones, so that the Positive Ideal Solution  $PIS = V^+ = [v_1^+, v_2^+, \dots, v_m^+]$  and the Negative Ideal Solution  $NIS = V^- = [v_1^-, v_2^-, \dots, v_m^-]$  are computed as follows:

$$V^+ = v_j^+ = \begin{cases} \max_i v_{ij} & \text{if } g_j \in G_I \\ \min_i v_{ij} & \text{if } g_j \in G_D \end{cases} \quad (5)$$

$$V^- = v_j^- = \begin{cases} \min_i v_{ij} & \text{if } g_j \in G_I \\ \max_i v_{ij} & \text{if } g_j \in G_D \end{cases} \quad (6)$$

4. **Distances from PIS and NIS.** For a given alternative  $a_i$ , the Euclidean distances from PIS and NIS, denoted respectively by  $d^+(a_i)$  and  $d^-(a_i)$ , are computed as:

$$d^+(a_i) = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^+)^2} \quad (7)$$

$$d^-(a_i) = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^-)^2} \quad (8)$$

5. **Relative closeness to the PIS and NIS.** Finally, we derive for each alternative  $a_i$  the relative closeness  $C(a_i)$  to the positive solution as follows:

$$C(a_i) = \frac{d^-(a_i)}{d^+(a_i) + d^-(a_i)} \quad (9)$$

Thus, after computing this ratio, the non-dominated solutions of the  $\varepsilon$ -Pareto front will be ranked from best to worst with respect to the decreasing values of the ratio  $C(a_i) \in [0, 1]$ .

### 2.2.2. Implementing SMAA in our proposal

If preference information about the importance of the criteria is collected from investors or decision-makers using weights, it is important to be clear about how these preferential weights are interpreted. For cardinal criteria and a linear value function, the weights are just interpreted as "price coefficients" and the ratios between the preferential weights can be interpreted as trade-off ratios between the criteria.

To manage the preference information regarding the significance that each investor profile places on financial and non-financial attributes, we can establish an initial set of criteria weights using the

Analytic Hierarchy Process (AHP) methodology introduced by Saaty [33]. AHP is a widely adopted multicriteria approach for determining weights for various criteria. It involves constructing a decision matrix, wherein investors perform pairwise comparisons employing Saaty's 1–9 fundamental scale. In this scale, a rating of 1 signifies equal importance assigned to both criteria, 3 indicates moderately greater importance, 5 implies significantly greater importance, 7 denotes very strong greater importance, 9 represents extremely greater importance, and 2, 4, 6, 8 are used as intermediate values between two adjacent judgments.

From the initial vector of AHP-derived weights relative to investor's priorities for the M–V–ESG criteria and using a Monte Carlo simulation approach, the SMAA framework is applied to derive a set of favorable preferred weights. Therefore, the feasible space of preferred weights is given by:

$$W = \left\{ w \in \mathbb{R}^3 : w \geq 0 \quad \sum_{j=1}^3 w_j = 1 \right\} \quad (10)$$

The SMAA methodology was originally formulated on the assumption that the distributions of the alternatives  $f_A$  or the distribution of the weights  $f_W$  could be regarded as uncertain values. However, in our proposal, the values of the alternatives come from the non-dominated solutions of the Pareto front  $a_i \in A$ , and the uncertainty only applies to the case of the generation of weights  $w \in W$  following distribution  $f_W$ .

While the most frequently used value function in SMAA is the linear one, in our proposal we use these weights in the aggregation step of a value function  $u(a, w)$  based on the TOPSIS framework just described in Section 2.2.1. Therefore, the rank of each non-dominated solution according to the ratio  $C(a_i)$  is defined so that:

$$\text{rank}(a_i, w) = 1 + \sum_{k=1}^N \rho(u(a_k, w) > u(a_i, w)) \quad (11)$$

where  $\rho = 1$  if  $u(a_k, w) > u(a_i, w)$  and  $\rho = 0$  otherwise. For each rank position  $r \in \{1, \dots, n\}$  of the non-dominated solutions, we obtain the stochastic set of favorable rank preferential weights as:

$$W_i^r = \{w \in W : \text{rank}(a_i, w) = r\} \quad (12)$$

Finally, the recommendations of the SMAA are provided in statistical terms through the *rank acceptability index*  $b_i^r$ , as a measure of the frequency with which a non-dominated solution  $a_i$  reaches position  $r$ . It is computed as a multidimensional integral over the  $a_i$ , and the favorable rank of preferential weights are computed as:

$$b_i^r = \int_{w \in W^r(a_i)} f_W(w) dw \quad (13)$$

The range of the acceptability indices is between zero and one, i.e.,  $b_i^r \in [0, 1]$ . This means that the best solutions are those with values higher and close to 1, while the worst positions in the ranking imply a lower value of this index close to zero.

### 2.3. Stage III: Performance analysis

In this final stage, the performance analysis of the resulting portfolios is assessed using various financial metrics commonly employed in the literature, including mean, variance, Sharpe ratio [34], and Sortino ratio [35]. Additionally, we monitor the ESG performance of selected portfolios by calculating the ESG risk for each investor's profile.

The Sharpe ratio is commonly used to gauge the performance of an investment by adjusting for its risk. Although it is a well-known performance metric, we here provide its formula:

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p} \quad (14)$$

where,  $R_p$  is the return of the portfolio,  $R_f$  is the return of the risk-free asset (in our case we consider  $R_f = 0$ ), and  $\sigma_p$  denotes the standard deviation, as a measure of risk. The Sharpe ratio quantifies risk and



**Table 1**  
Summary of real-world SRI datasets analyzed.

Fund Manager	SRI funds	Time interval (In-Sample)	Time interval (Out-Sample)
FM1	35	Jan 2011–Dec-2016	Jan 2017–Dec 2019
FM2	16	Jan 2011–Dec-2016	Jan 2017–Dec 2019
FM3	14	Jan 2011–Dec-2016	Jan 2017–Dec 2019

reward using two-sided measures, so positive and negative deviations from the benchmark are weighted equally. A variant of the Sharpe Ratio is the Sortino Ratio, which removes upside volatility from the equation and takes only the downside standard deviation  $\sigma_d$  into consideration, as shown in:

$$\text{Sortino ratio} = \frac{R_p - R_f}{\sigma_d} \quad (15)$$

The performance analysis could be carried out for in-sample and out-of-sample periods previously stated by the analyst. The results can be provided to the analyst or the investor in summary tables showing the values of the performance measures for each investor profile to assess the trade-off between the selected strategies.

### 3. Empirical analysis

The application of our methodology in a real scenario is based on three real-world datasets comprising socially responsible mutual funds offered by different fund managers. The numerical information used in these datasets consists of monthly returns and ESG risk scores of the mutual funds obtained from January 2011 to December 2019. The three real-world datasets are publicly available on [36]. The details about the datasets are summarized in Table 1.

To examine the portfolio performance we have split the entire analysis period into two different experimental setups, where the in-sample time interval includes an opportunity set of 72 monthly returns over six years, and the out-of-sample time interval comprises three years with 36 observations. The dataset information corresponding to the in-sample period is used to derive the M–V–ESG approximate efficient frontier in the first and second stage of the proposed methodology. The out-of-sample period is used in the third stage of our proposal to test the performance of the optimal portfolio.

As a representative of investors, we consider four types of profiles that are grouped in two main categories: Financial First and ESG First. Thus the information on preferences about the importance of return, risk or ESG criteria is formulated taking into account the following investor's profiles:

1. In the Financial First group the investors attempt to optimize financial returns with social or environmental objectives. This group is composed of commercial investors who seek financial vehicles that offer them returns in line with the market, but with a combination of social and environmental objectives. Within this category we distinguish between the conservatives (FIN-con) and the aggressive (FIN-agg) investors, depending on their risk aversion.
2. On the other hand, we have the ESG First investors who primarily focus on the ESG criterion while preserving financial returns to a greater or lesser extent. This latter category has been inspired by the type of investors proposed in the work of [25]. In this group we include the ESG aware (ESG-awa) investors, whose motivation is social and environmental impact but without affecting the profitability of the investment. Finally, the ESG motivated (ESG-mot) investors are those who are willing to accept lower returns for more responsible stocks.

The corresponding AHP pairwise comparison matrices for the above investor's profiles and the resulting initial vectors of criteria weights are provided in Tables 2 and 3. As required in AHP the consistency indices for all the matrices are smaller than 0.10.

**Table 2**  
M–V–ESG priorities for the Financial First investor's profile using Saaty's 1–9 scale.

	Fin-agg			Fin-con		
	M	V	ESG	M	V	ESG
M	1	5	7	1	1/2	4
V	1/5	1	3	2	1	5
ESG	1/7	1/3	1	1/4	1/5	1
$w$	0.724	0.193	0.083	0.334	0.568	0.098

**Table 3**  
M–V–ESG priorities for the ESG First investor's profile using Saaty's 1–9 scale.

	ESG-awa			ESG-mot		
	M	V	ESG	M	V	ESG
M	1	1	1	1	1	1/5
V	1	1	1/2	1	1	1/3
ESG	1	2	1	5	3	1
$w$	0.328	0.261	0.411	0.158	0.187	0.655

### 4. Results

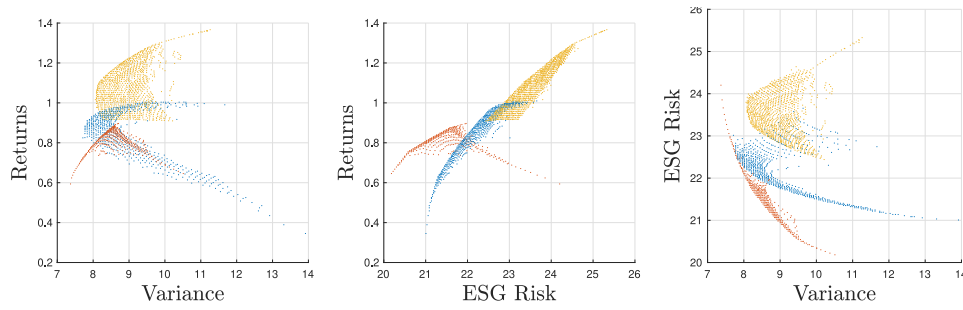
This section presents the results and analyzes the consequences of including investor's preferences in the decision stage using the SMAA-TOPSIS framework to increase the robustness of the final portfolios obtained with the ev-MOGA algorithm in the three-criterion problem. This robustness has been achieved by converting all investor's preferences for return, risk and sustainability into a system of randomly derived weights that are integrated into a multicriteria ranking method in order to sort the efficient portfolios obtained in the first stage (see Section 2.1). For each fund manager, the results of the four investor profiles are compared in terms of the performance indicators specified in Section 2.3.

In the optimization stage using the algorithm, an initial population of 50000 and an auxiliary population of 500 with a crossover and mutation probability of 0.5 have been considered. The number of boxes defining the space of each function is 100. As a preliminary remark on the comparison of the three approximated Pareto fronts, it is noted that including an additional objective increases the complexity of the analysis of the results as we obtain 606, 356 and 1145 non-dominated solutions respectively. For this reason, a pairwise grouped visualization of the Pareto front is provided to better assess the trade-offs between each pair of objectives in Fig. 2.

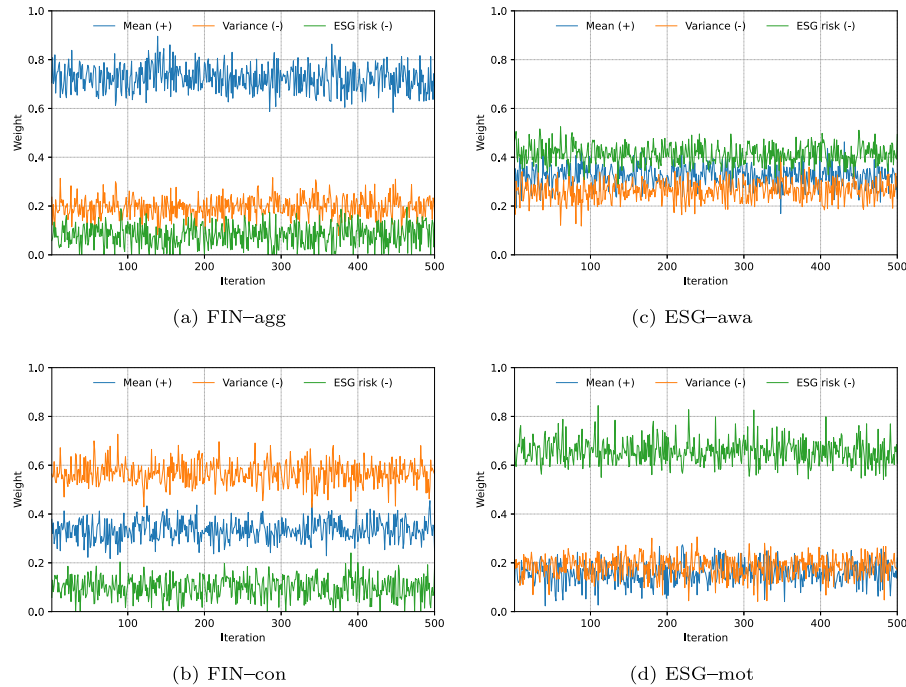
Let us observe that in the Returns-Variance plane corresponding to the first figure, the third fund manager (colored in yellow) is the one that includes the most profitable assets, followed by the first fund manager (colored in blue), while fund manager 2 is the worst in terms of profitability (colored in red). The Returns-ESG risk projection in the central chart looks very different, whose higher return is associated with smaller sustainability performance (higher ESG risk). Finally, the ESG Risk-Variance projection does not suggest a clear trade-off between the objectives. Indeed, each fund manager represents a set of funds with different features so that applying the proposed methodology may be more meaningful than looking at a single dataset.

At the decision-making stage, once the efficient solutions have been obtained, the preferences of the four investor's profiles considered to be representative are taken into account. From the AHP-derived weights in Tables 2 and 3, and implementing the SMAA-TOPSIS framework, we first derive the values of the randomly generated preferential weights.

The set of randomly generated preferential weights for the first 500 out of 10000 Monte Carlo iterations are shown in Fig. 3. This figure illustrates how, for the Financial First aggressive investor, the weight range that captures the preference about the importance of return (colored in blue) is always above that of the importance given to risk (colored in orange) or sustainability (colored in green). In contrast, for a more conservative investor, the priority for variance (less risk) is



**Fig. 2.** Mean-Variance-ESG approximate Pareto fronts computed with ev-MOGA algorithm for each fund manager and their projections in the Variance-Returns plane, ESG risk-Returns plane and Variance-ESG risk plane. (The meaning of the colors in this figure is explained within the context of the text and corresponds to each of the fund managers.).



**Fig. 3.** Randomly generated weights for the first 500 Monte Carlo iterations and for the four types of investor profile.

above that for profitability and sustainability. Once, in the sustainable investor category, it can be seen, that while sustainability is the main concern of investors (the green band falls above the orange and blue one), the valuation of how important sustainability is for the ESG aware investor is much smaller than for an ESG motivated one. Moreover, we can check how these preferential weights are located in the feasible weight space of our three-criterion problem in Fig. 4.

Once the random weights are obtained, they are integrated into the TOPSIS approach to obtain a probabilistic ranking. Fig. 5 shows the rank acceptability indices for the best non-dominated solution  $a_i$  for both, the corresponding investor profile and each fund manager. The probabilistic ranking has been ordered according to the value of the barycenter denoted as  $\mu$ , so that the best solution is the one with the lowest barycenter. We also show the probability of this best solution being in the first position  $P(r = 1)$  and the probability of being in the first ten positions  $P(r \leq 10)$ . For example, if we look at Fund Manager 2, for an investor FIN-agg (Fig. 5(b)), the portfolio that best matches his/her preferences is the one that corresponds to the non-dominated solution  $a_{17}$ , with a barycenter of  $\mu = 2.7$ , a probability of ranking first of  $P(r = 1) = 30.7\%$ , and of being in the top 10 of  $P(r \leq 10) = 98.8\%$ .

In order to provide an overview of the quality of the results it would be appropriate to analyze the performance of the selected portfolios

both in the in-sample time window and also for the out-of-sample period, as described in Tables 4 and 5, respectively. Of the four investor's profiles, those who prefer sustainability first over financial objectives have lower returns and higher risks for all three datasets. Graphically, these results can be further analyzed in the projections depicted in Figs. 6–8. For example, for the first fund manager (see Fig. 6), it is clear that the trade-off between the three objectives is much larger for profiles that are defined as sustainable, as the distances between the target values for an ESG-awa and an ESG-mot investor are larger than those between an FIN-agg and a FIN-con profile. On the other hand, for the second fund manager, whose funds show the best levels of sustainability as a whole, the results are noteworthy (see Fig. 7). We find that an ESG-awa investor delivers higher returns than a FIN-con investor, but yet the former assumes higher levels of risk than a FIN-agg investor. Finally, for the third fund manager, while an FIN-agg investor presents a risk close to that of an ESG-mot investor, the differences in terms of returns are substantial (see Fig. 8).

In summary, stronger preferences for ESG criteria lead to a drop in the scores for the financial criteria as well as for the Sharpe and Sortino ratios.

Finally, the portfolio that each fund manager would recommend as a first choice for investors according to their preferences is displayed in Tables 6–8.

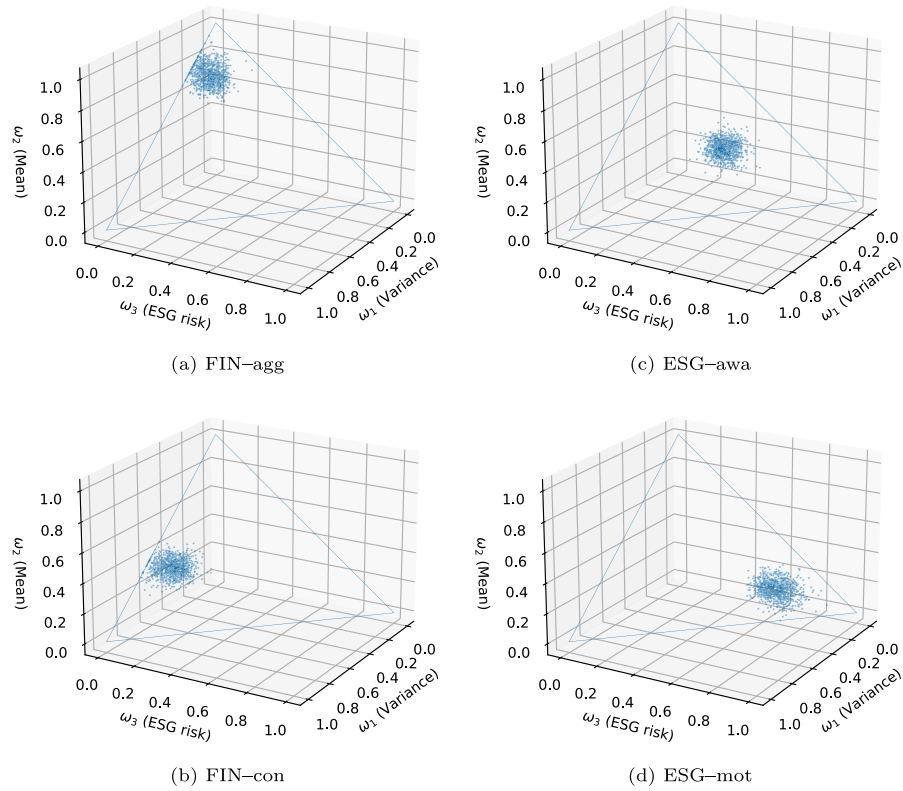


Fig. 4. Set of favorable preferential weights for each investor's profile and their placement in the feasible weight space of M-V-ESG risk criteria.

Table 4

Financial and ESG performance evaluation for each Fund Manager and investor's profile (in-sample).

Fund Manager	Investor profile	Mean	Variance	ESG risk	Sharpe	Sortino
FM1	FIN-agg	0.9503	8.24	22.74	1.147	1.732
	FIN-con	0.8847	7.83	22.59	1.095	1.559
	ESG-awa	0.7666	8.58	21.93	0.907	1.201
	ESG-mot	0.6364	10.07	21.48	0.695	0.874
FM2	FIN-agg	0.8890	8.61	21.83	1.050	1.649
	FIN-con	0.7455	7.81	22.53	0.924	1.497
	ESG-awa	0.8014	8.90	21.07	0.930	1.495
	ESG-mot	0.7394	9.50	20.54	0.831	1.314
FM3	FIN-agg	1.3000	9.85	24.57	1.435	2.423
	FIN-con	1.1297	8.30	24.01	1.358	2.234
	ESG-awa	1.0806	8.71	23.53	1.269	2.063
	ESG-mot	0.9163	9.30	22.70	1.041	1.643

Table 5

Financial and ESG performance evaluation for each Fund Manager and investor's profile (out-of-sample).

Fund Manager	Investor profile	Mean	Variance	ESG risk	Sharpe	Sortino
FM1	FIN-agg	0.7988	9.59	22.74	0.964	1.017
	FIN-con	0.8146	8.52	22.59	1.008	1.123
	ESG-awa	0.6743	8.84	21.93	0.798	0.967
	ESG-mot	0.6710	9.66	21.48	0.733	1.005
FM2	FIN-agg	0.9846	12.14	21.83	1.163	1.168
	FIN-con	0.9467	8.90	22.53	1.174	1.381
	ESG-awa	0.9890	12.25	21.07	1.148	1.182
	ESG-mot	0.9476	11.97	20.54	1.065	1.179
FM3	FIN-agg	1.0449	13.02	24.57	1.154	1.175
	FIN-con	0.9576	10.49	24.01	1.151	1.180
	ESG-awa	0.9305	9.98	23.53	1.092	1.183
	ESG-mot	0.8965	9.37	22.70	1.018	1.213

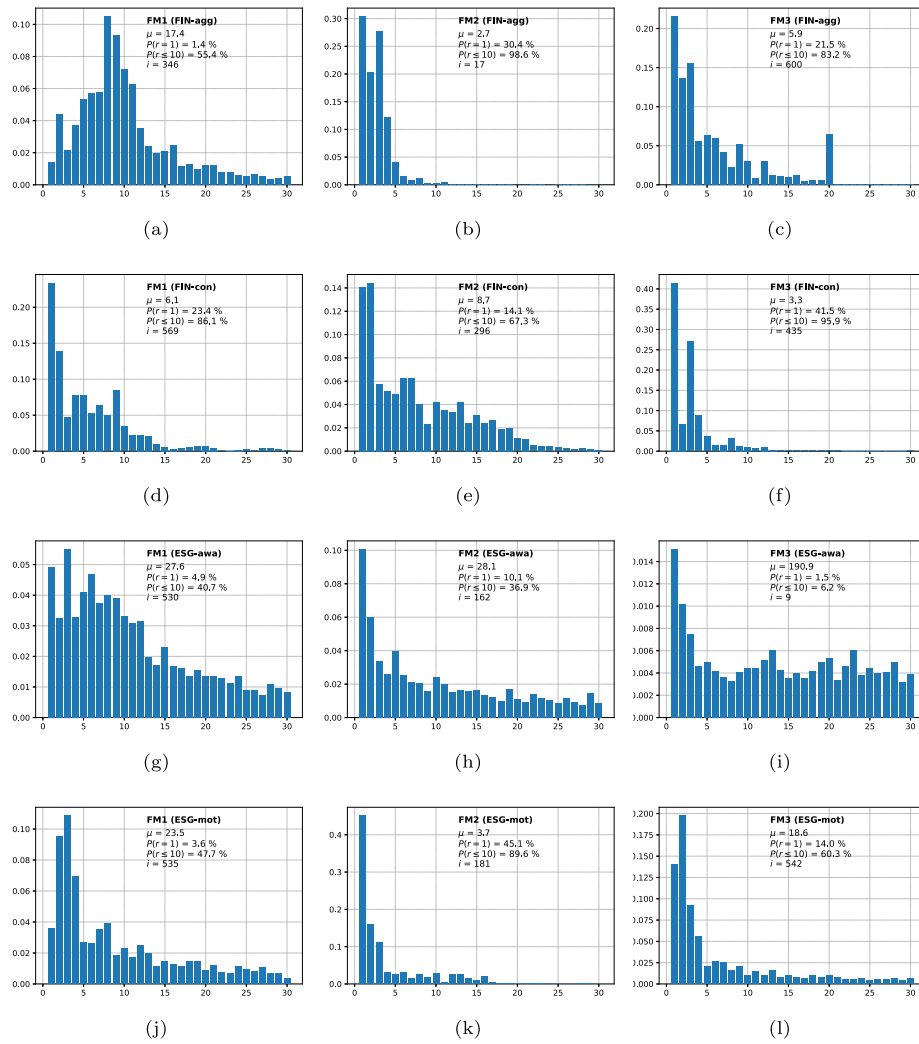


Fig. 5. Rank acceptability indices of the best solution according to the barycenter for each fund manager and investor's profile.

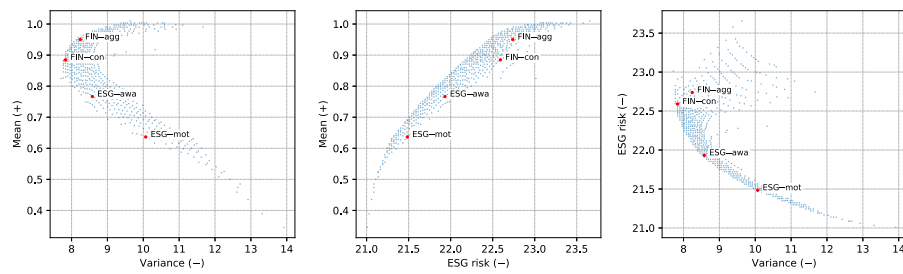


Fig. 6. Investor's profile projections in the Variance–Returns plane, ESG risk–Returns plane and Variance–ESG risk plane for Fund Manager 1.

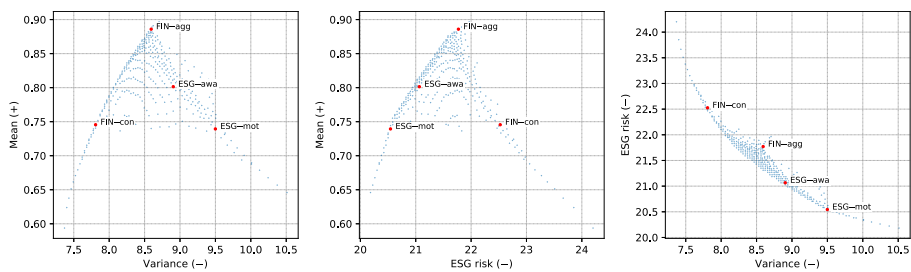


Fig. 7. Investor's profile projections in the Variance–Returns plane, ESG risk–Returns plane and Variance–ESG risk plane for Fund Manager 2.



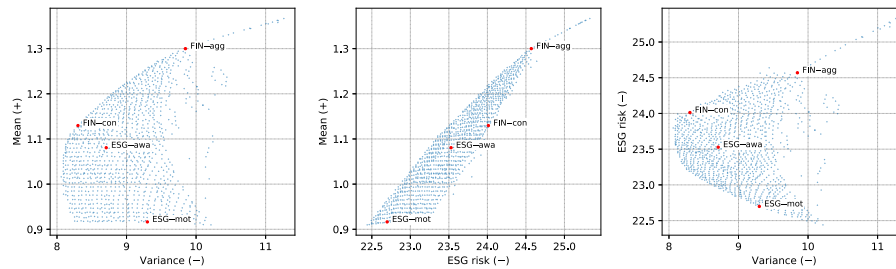


Fig. 8. Investor's profile projections in the Variance–Returns plain, ESG risk–Returns plain and Variance–ESG risk plane for Fund Manager 3.

Table 6

Fund Manager 1: Optimal robust portfolio according to each investor's profile.

Investor profile	$x_1$	$x_3$	$x_5$	$x_6$	$x_7$	$x_9$	$x_{16}$	$x_{18}$	$x_{19}$	$x_{22}$
FIN-agg			0.09		0.16	0.02	0.20	0.20	0.20	0.13
FIN-con			0.09	0.13	0.09	0.05	0.20	0.20	0.04	0.20
ESG-awa	0.03	0.08	0.18	0.20	0.07	0.09	0.20	0.15		
ESG-mot	0.15	0.12	0.20	0.19	0.09	0.09	0.16			

Table 7

Fund Manager 2: Optimal robust portfolio according to investor's profile.

Investor profile	$x_1$	$x_4$	$x_5$	$x_6$	$x_7$	$x_9$	$x_{10}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{15}$	$x_{16}$
FIN-agg		0.09	0.20				0.10	0.20	0.20	0.01	0.20	
FIN-con			0.20		0.02	0.09	0.06	0.20	0.09		0.18	0.16
ESG-awa	0.09		0.20	0.08			0.13	0.10	0.20		0.20	
ESG-mot	0.20		0.19	0.06			0.15		0.20		0.20	

Table 8

Fund Manager 3: Optimal robust portfolio according to investor's profile.

Investor profile	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_{10}$	$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$
FIN-agg			0.19			0.20	0.20	0.20	0.20	0.01
FIN-con			0.20	0.03	0.15	0.20	0.20	0.20	0.02	
ESG-awa		0.12	0.20		0.11	0.17	0.20	0.20		
ESG-mot	0.01	0.20	0.20	0.09	0.10		0.20	0.20		

## 5. Conclusions and further research

This paper is motivated by the growing concern in the financial industry about integrating ESG dimensions into the construction of optimal portfolios. The main original contribution of the proposed methodology is to improve the robustness of final portfolio recommendations according to investors' preferences when ESG criteria are placed on the same playing field as return and risk. This means that the optimal portfolio will not be in the M–V plane but has to be found in the M–V–ESG frontier as the investor is also interested in optimizing the sustainability criterion besides the classical financial criteria. After constructing the non-dominated set of solutions using a recent multi-objective genetic algorithm, our proposal provides investors with a decision tool to select portfolios according to their preferences.

We believe that the current proposal has merits both in theory and practice. Indeed, on the one hand, it addresses some concerns regarding two critical issues in sustainable portfolio selection. The first is integrating ESG criteria at the same level of risk and return and solving this three-criterion problem. To tackle this problem, we use the ev-MOGA algorithm as it has the advantage that it is less mathematically challenging than exact optimization approaches, and it provides uniformly distributed solutions along the Pareto front. The second is the issue of how to incorporate investor's preferences to express the relative importance of each criterion through a robust weighting scheme in a multicriteria ranking framework. Without an exact value to translate particular preferences into a single vector of criteria weights, the SMAA-TOPSIS approach provides rich probabilistic information to support decision-making. Regarding its applicability, the proposed methodology allows decision-makers, such as financial

consultants or fund managers, to assess the impact of integrating preference information into financial and sustainability objectives and to provide better advice according to the characteristics of each investor profile.

Our proposal has been applied to different sets of real-world socially responsible investments offered by three fund managers. Considering different investor's profiles, ranging from a traditional conservative financial profile to a motivated sustainable one, we have found that it is possible to achieve an optimal solution that matches their preferences. For each fund manager, the chosen portfolio is the one that is most likely to rank among the top positions according to the preferences expressed with a certain degree of uncertainty. Therefore, it can be stated that our proposal, based on many optimal solutions on a three-dimensional surface, can provide robust recommendations to a particular investor by considering a plurality of weights to represent his/her preferences for return, risk, and sustainability criteria.

However, a limitation of our study lies in the definition of investor profiles. The changing nature of investor preferences and market conditions adds another layer of complexity to this task. Consequently, the fact that our study is based on a fixed set of investor's profiles may not fully reflect the diverse and dynamic nature of real-world investor behavior and preferences when making portfolio decisions. More complex simulations of investors' behavior could be considered in future extensions of this study. For example, one could integrate the search for robust solutions into interactive multi-objective optimization frameworks that progressively allow decision-makers to provide information about their preferences. Once the non-dominated solutions have been generated, the SMAA-TOPSIS method could be applied many times and re-run to evaluate the final results including the updated preferences learned in the first process.

Another interesting topic left for future research is to explore the changes in the outcome of our approach when different risk measures, like, e.g., CVaR or expectiles, are used in the place of variance. As a final suggestion for application, it would be useful to develop a user-friendly expert system and visualization tools to select sustainable portfolios based on any investor's profile and not only on the four types proposed in our study.

## CRediT authorship contribution statement

**Ana Garcia-Bernabeu:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Adolfo Hilario-Caballero:** Software, Project administration, Methodology, Formal analysis. **Fabio Tardella:** Writing – review & editing, Validation, Supervision. **David Pla-Santamaria:** Resources, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Real-world datasets for sustainable portfolio selection en (Original data) (Riunet UPV)

## Acknowledgments

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