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Environmental corporate responsibility for investments evaluation: an alternative multi-objective programming model

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Abstract Current financial and economic crisis, as well as growing environmental pressures put seriously under question traditional development patterns. The need to develop alternative models able to address current economic situation through the exploitation of sustainable patterns is of crucial importance. The innovation of this current study is the incorporation of energy and environmental corporate responsibility (EECR) in decision making, supporting particularly the development of a new model for investment evaluation. A bi-objective programming model is introduced in order to provide the Pareto optimal portfolios (Pareto set) based on the net present value of projects and the EECR score of firms. A systematic decision making approach using Monte Carlo simulation and multi-objective programming is also developed in order to deal with the inherent uncertainty in the objective functions' coefficients. The robustness of the Pareto set as a whole, as well as the robustness of the individual Pareto optimal portfolios is also assessed. The proposed approach facilitates banking organizations and institutions to the selection of firms applying for financial support and credit granting, within the frame of their EECR. Finally, an illustrative real-world application of the proposed model is presented.

Keywords Multi-objective programming · Economic crisis · Corporate social responsibility · Energy and environment · Project portfolio selection · Uncertainty · Robustness

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1 Introduction

One of the major reasons for economic crises is the irrational distribution of resources. The problem of project selection deals with exactly this kind of problems. Project selection is one of the most common and oldest problems in operations research (OR). Financial organizations often face the problem of selection within a set of projects to fund. Several OR techniques are involved in this kind of problems like e.g. multiple criteria decision analysis (MCDA), mathematical programming (MP). These techniques are widely exploited in relevant decision problems, such as portfolio selection, choice among alternative projects or investment opportunities, student selection, military applications, capacity expansion (see e.g. Golabi et al. 1981; Mavrotas and Rozakis 2009; Salo et al. 2011; Martínez-Costa et al. 2014).

Project portfolio selection problem is defined as the problem of selecting a subset of projects usually based on one or more criteria that have to fulfill specific constraints. In the presence of the imposed constraints (e.g. policy, segmentation) a simple MCDA method does not suffice. Combinatorial character of the problem implies the use of optimization methods aiming at the portfolio of projects that satisfy constraints and achieves the "best" performance. A combination of projects is defined as project portfolio. Usually the "best" performance is expressed emphasizing on economic and financial criteria. Criteria related with the promotion of sustainable practices, fostering green growth, were not taken into consideration in traditional models (Hobbs and Meier 2000).

However, current financial and economic crisis, as well as growing socio-economic and environmental pressures, including climate change, put seriously under question traditional development patterns. The need to develop alternative models able to address current economic situation through the exploitation of sustainable patterns is of crucial importance (Hobbs and Meier 2000; Doukas et al. 2012). Companies are at the heart of the Europe 2020 Strategy, taking into consideration their vital role towards national prosperity and sustainable development (SD). Enterprises have to integrate social and environmental concerns in their business operations and in their interaction with stakeholders on a voluntary basis, within the framework of the corporate social responsibility (CSR) concept.

Companies, more than other stakeholders, have to address the problem in a long term plan, and become a driving force for adoption of relative initiatives towards "green" development and promotion of energy efficiency and environmentally friendly practices, within the CSR framework (Doukas et al. 2013). CSR has been incorporated recently in decision models using Data Envelopment Analysis (Lee and Farzipoor Saen 2012), inventory policy (Barcos et al. 2013) and supply chain (Hsueh 2014) among others. The penetration of energy and environmental policies, as an aspect of CSR is definitely small and CSR does not appear to be a systematic activity in new conditions of European market, a conclusion further confirmed by Apostolakou and Jackson (2009) and Gjølberg (2009a, b) studies. However, relevant works in various fields have been detected recently like e.g. in supplier selection (Hashemi et al. 2014). In this context, new tools and methods are required to foster green entrepreneurship and green energy growth.

The innovation of the current study is the incorporation of energy and environmental corporate responsibility (EECR) in decision making, supporting particularly the development of a new model for investment evaluation. This model can assist financial institutions (green loans) and governmental bodies funding energy—environmental friendly investments. The EECR performance of a firm is considered as an evaluation criterion of the submitted project. Therefore, in our study the drivers of optimization are two objective functions: (1) The net present value (NPV) that represents the economic dimension and characterizes each project and (2) the EECR index that represents the CSR and characterizes each firm that submits the project. In this way, firms with increased EECR are rewarded without ignoring the economic performance of relevant projects.

The resulting multi-objective model (specifically bi-objective) does not provide an optimal portfolio but a set of Pareto optimal portfolios among which the most preferred one is selected by the decision maker (DM). In general, multi-objective optimization increases degrees of freedom within decision making process providing not an optimal solution (as in single objective optimization) but a set of candidate solutions among which the DR chooses. Therefore, the set of Pareto optimal solutions (Pareto set) is essential information in an integrated decision making approach. It must be noted that we deal with multi-objective integer programming (MOIP) models and we can produce the exact Pareto set (i.e. all the Pareto optimal solutions). It is also important to note that, especially the last years, the multi-objective character of project portfolio selection is addressed with multi-objective metaheuristic methods that produce an approximation of the Pareto set (see e.g. Yu et al. 2012; Tavana et al. 2013; Hassanzadeh et al. 2014a).

This work is going one step further, considering also the uncertainty characterizing basic parameters of the model, which are the coefficients of objective functions, namely the NPV of each project and the EECR score of each firm. Given that these values are actually estimations, we follow a systematic approach to deal with the inherent uncertainty. The latter is considered to be of stochastic nature, i.e. we have a probability distribution instead of a crisp number for the values of objective functions' coefficients. It must be noted that a similar approach for project selection problems with multiple criteria that deals with stochastic uncertainty in projects' evaluation is stochastic multiobjective acceptability analysis (SMAA) introduced by Lahdelma et al. (1998). However, SMAA cannot handle the case of multiple constraints that are imposed to the constraints but is used only with independent alternatives in a MCDM context.

The current paper introduces an innovative approach that deals with parameters' uncertainty in a MOIP model and eventually converges to the final Pareto set. It uses the main idea of the iterative trichotomic approach (ITA) (Mavrotas and Pechak 2013a, b). ITA was originally designed for single objective problems of project portfolio selection. It gives information about the degree of certainty for the inclusion or rejection of a specific project in the final portfolio. The version of ITA described in the current paper deals with multi-objective problems of project portfolio selection and provides information about the degree of certainty for inclusion of a specific portfolio in the final Pareto set, expanding thus its application area from project level to portfolio level. This kind of information is essential for the DR to be more confident to select project portfolios that have high degree of certainty regarding their Pareto optimality. In this respect, the DR has a sufficient tool to measure the robustness of the final Pareto set as well as the robustness of specific portfolios that appear in the final Pareto set. Robustness in project portfolio selection has also been addressed in a different way in the works of (Liesiö et al. 2008; Hassanzadeh et al. 2014a, b).

The remainder of the paper is structured as follows: In Sect. 2 the methods, concepts and terminology that will be used in the proposed model are briefly presented, with the focus on adaptation of ITA for the multi-objective case. In Sect. 3 the development of the MOIP model is being elaborated, along with the way the EECR scores are calculated and the relevant constraints. In Sect. 4 the application of the proposed model is presented and the results of multi-objective ITA are discussed, giving emphasis to the kind of additional information that is available to the DR. Finally, in Sect. 5 the main concluding remarks are summarized.

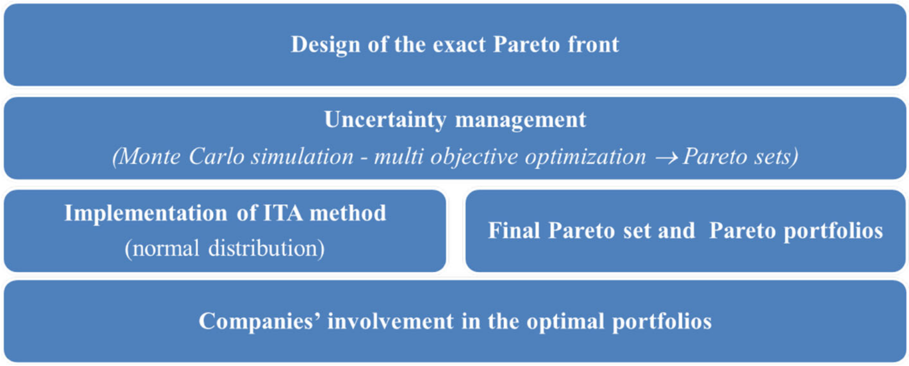

Fig. 1 The adopted procedure

2 Methods, concepts and terminology

The overall procedure that was adopted for the addressed multi-objective project portfolio selection problem is graphically illustrated in Fig. 1.

In the following sections, a more detailed description of the methods deployed will be presented.

2.1 Iterative trichotomic approach (ITA) to multi-objective project portfolio selection problems

The basic idea of current work is to extend the applicability of ITA to the case of multi-objective optimization. ITA was originally designed for project portfolio selection under the framework of MP and more specifically integer programming (IP). It was used with a single objective function reflecting the optimization criterion. The uncertainty associated with objective function coefficients has a stochastic nature (probability distributions instead of crisp numbers).

The term "trichotomy" refers to the separation of a set into three parts. In this context, the proposed decision making process ITA is based on the fact that projects are assigned to one of three groups based on their performance and current level of uncertainty. The latter is incorporated using probability distributions for coefficients of the objective function, which usually express projects' performance. Individual projects' performances are summed up in the objective function, which is the driver of optimization. Monte Carlo simulation is performed using sampling from these distributions. Subsequently with the sampled objective function's coefficients the IP model is solved leading to an optimal portfolio. This pair of sampling and optimization is the core of calculations. The number of Monte Carlo simulations is set to a large number T (e.g. $T = 1000$) which means that the sampling and optimization cycle is performed T times. The output of this process is 1000 optimal portfolios based on the sampling of model's parameters (in this case—projects' performance). Eventually, the set of projects is divided into three subsets (classes): green projects that are present in the final portfolio under all circumstances (i.e. in all Monte Carlo simulations), red projects that are absent from the final portfolio under all circumstances, and grey projects that are included in part of final portfolios. The classification in three subsets is not new in the literature. Liesiö et al. (2007, 2008) used a similar approach in the framework of robust programming. However, the way projects are assigned to each set is different. In addition, Mavrotas and

Rozakis (2009) applied similar concepts in a student selection problem for a post graduate program.

The term “iterative” indicates that the proposed process is developed in a series of computation rounds (or cycles). A predetermined number of computation rounds is defined from the beginning and every round feeds its subsequent until a convergence to the final portfolio is attained. From round to round the uncertainty is reduced for grey projects, and some of them are forced to become either green or red. The uncertainty reduction can be performed either by inclusion of more information or by an automatic uniform narrowing of grey projects’ probability distributions.

The concept behind the trichotomic approach is that a DM can focus on projects at stake. The “sure” projects (either in or out of the portfolio) are determined and the DM can shift his attention to “ambiguous” projects (e.g. the grey set). The method provides quantitative and qualitative information that cannot be acquired using e.g. the expected values of distributions. In the latter case, the DM is provided with a unique optimal portfolio or, in other words, which are “go” and “no go” projects, without any discrimination about the degree of certainty for each one of them. On the contrary, in trichotomic approach, DM is provided with fruitful information about certainty degree of each project in the portfolio.

Project portfolio selection is by definition a multi-objective problem. Different points of view should be taken into account. One approach is to aggregate these points of view to a single metric through multicriteria analysis and subsequently optimize the resulting single objective problem where coefficients of objective function are multicriteria scores (Mavrotas et al. 2008). Alternatively, one can use a goal programming approach aggregating the objective functions based on their distance from individual goals (see e.g. Zanakis et al. 1995; Santhanam and Kyparisis 1996).

In the above mentioned approaches, the DR has to assign weights to criteria or goals in order to aggregate them to a single objective function (scalarization). Another approach is to keep individual criteria as separate objective functions and proceed to a multi-objective optimization generating the Pareto set of the problem (or the Pareto front in criteria space). The Pareto set comprises Pareto optimal solutions (or Pareto portfolios in our case). The DR then examines the Pareto front before reaching his final choice. These methods are called “a posteriori” or “generation” methods in the popular Hwang and Masud (1979) terminology for multi-objective optimization methods (first generate Pareto front, examine it, and then select the most preferred Pareto portfolio). Their aim is not just to provide the most preferred solution but also to generate the Pareto set (either exactly or its approximation).

In the current work, we adapt ITA to the multi-objective case. While in original ITA we provide the certainty degree of a specific project to be member of the optimal portfolio given underlying uncertainty, in multi-objective ITA we provide the degree of certainty of a specific portfolio of projects to be member of the Pareto set. A schematic representation of the multi-objective ITA is shown in Fig. 2.

Unlike original ITA, in multi-objective ITA the first iteration has no red set as we don’t have any portfolios to be excluded. In the first iteration we have the maximum number of generated portfolios as candidate final Pareto optimal portfolios (POPs). In subsequent iterations some of these portfolios are not present anymore in any Pareto set so they join the red set. As we move from round to round, the uncertainty of parameters (objective functions’ coefficients) is reduced (e.g. reduce the standard deviation of a normal probability distribution or shrink the interval of a uniform probability distribution). As we reduce the uncertainty, more portfolios from grey set move to green (appear in all Pareto sets). The red set is implied indirectly by the initially generated portfolios that are not present in any current Pareto set.

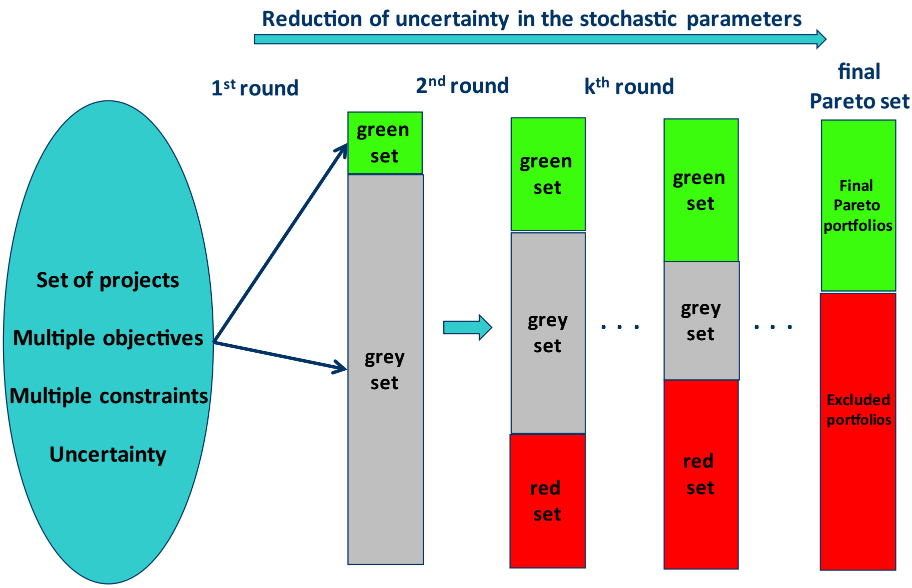

Fig. 2 Graphical representation of multi-objective ITA

In order to describe our model we first present the relevant concepts and terminology, then the mathematical definitions of the robustness measures and then the algorithm that can be used to compute these measures in the framework of ITA.

2.2 Concepts and terminology

We will start with some terminology. The POPs of projects are actually the Pareto optimal solutions of the multi-objective integer problem with binary variables:

$$\begin{aligned}
&\max\ Z_1 = \sum_{i=1}^{N} c_{i1} X_i \\
&\ldots \\
&\max\ Z_K = \sum_{i=1}^{N} c_{iK} X_i \\
&st \\
&\mathbf{X} \in S \\
&X_i \in \{0, 1\}
\end{aligned} \tag{1}$$

where N is the number of candidate projects, c_{ik} is the objective function coefficient of i-th project in k-th objective function, X_i is a binary decision variable indicating if the i-th project from initial set is selected ($X_i = 1$) or not ($X_i = 0$), and S represents the feasible region formulated by all the imposed constraints. Apart from the usual budget constraints, segmentation and policy constraints, interactions and interdependencies among projects can be also taken into account in the formulation of decision space S (Mavrotas et al. 2003; Liesiö et al. 2007). Eventually, a POP is represented by a vector of “0” and “1” of size N. According to the multi-objective version of ITA method each one of the initial POPs is eventually characterized as red or green as we gradually decrease the uncertainty in model's parameters. The reduction of uncertainty in the model's parameters is performed in *computation rounds*.

In each computation round we solve a great number ($t = 1, \ldots, T$ with e.g. $T = 1000$) of problems like model (1), with different model's parameters, specifically different objective function coefficients using a Monte Carlo simulation approach (see e.g. Vose 1996).

$$\begin{aligned}
&\max \ Z_1^{(t)} = \sum_{i=1}^{N} c_{i1}^{(t)} X_i \\
&\ldots \\
&\max \ Z_K^{(t)} = \sum_{i=1}^{N} c_{iK}^{(t)} X_i \\
&st \\
&\mathbf{X} \in S \\
&X_i \in \{0, 1\}
\end{aligned} \tag{2}$$

where $c_{ik}^{(t)}$ is the objective function coefficient of i-th project in k-th objective function during t-th Monte Carlo iteration. The values of $c_{ik}^{(t)}$ are sampled from the selected probability distributions (uniform, normal, triangular etc). Therefore, in each computation round T Pareto sets ($PS_t, t = 1, \ldots, T$) are produced. The generation of each one of the T Pareto sets is performed using the AUGMECON2 method (Mavrotas and Florios 2013). AUGMECON2 is an improved version of the well known ε-constraint method, especially appropriate for MOIP problems like model (1). It must be noted that AUGMECON2 is capable of generating the exact Pareto set in MOIP problems which means that no Pareto optimal solution is left undiscovered.

Like in original ITA, in each computation round we have three sets where all the POPs p are allocated: The green set (G), the red set (R) and the grey set (Y). The membership relation for each portfolio p in G, R and Y are shown below.

$$\begin{aligned}
&p \in G : \forall t \in \{1, \ldots, T\}, \quad p \in PS_t \\
&p \in R : \forall t \in \{1, \ldots, T\}, \quad p \notin PS_t \\
&p \in Y : \exists t \in \{1, \ldots, T\}, \quad p \in PS_t
\end{aligned} \tag{3}$$

In other words the green set includes the portfolios p that are present in all Pareto sets ($PS_1, \ldots, PS_T$) of the computation round, the red set includes the portfolios that were produced in the initial computational round but are not present in any of T Pareto sets in current computational round and the grey set includes portfolios that are present in some of T Pareto sets. In order to be more specific about the round r that a green, red and grey set refers to we use the notation G_r, R_r and Y_r. To facilitate the decision process, we can define membership thresholds for the green set by relaxing membership requirements. For example, we may set a "green" threshold of 95 % which means that a portfolio is considered to be a member of green set if it is present in the Pareto set for at least 95 % of iterations.

2.3 Robustness measures

Robustness of the POPs in multi-objective ITA is associated with how sure we are about the membership of a specific portfolio in the final (definitive) Pareto set, which is obtained in the last computation round. As uncertainty is reduced going from one computation round to the next, the sooner a POP enters the green set, the more sure we are about its participation

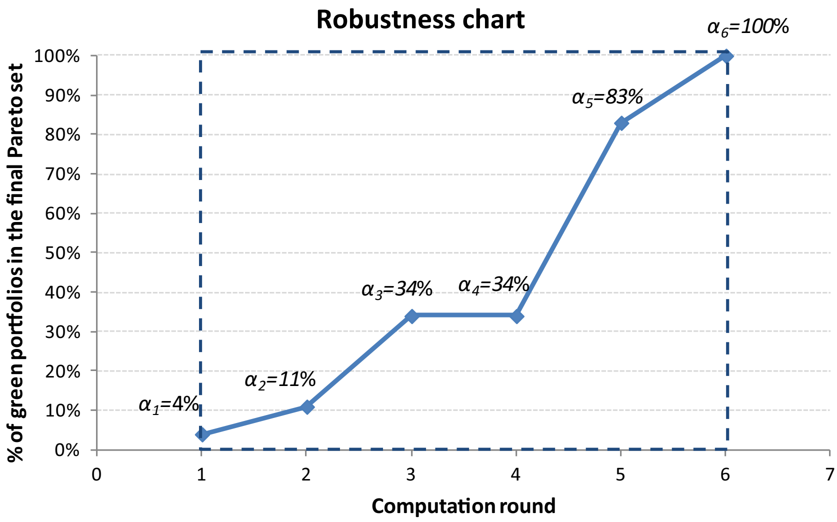

Fig. 3 Example of Robustness Chart with R = 6

in the final portfolio. Therefore, for the POPs, the measure of robustness can be quantified with the *Robustness Degree* for each POP (RD_p) which is defined as follows:

$$RD_p = \frac{R - r_p}{R} \tag{4}$$

where r_p is the computation round that p-th portfolio enters the green set (i.e. becomes member of the final Pareto set) and R the total number of computation rounds. As it is obvious from Eq. (4) Robustness Degree of p-th portfolio varies in $[0, (R-1)/R]$ and the closer it is to 1 the more robust is the specific portfolio.

We have also developed a measure of robustness for the final Pareto set according to how early in the decision process the final POPs are entering the green set. The more green portfolios we have from early rounds (i.e. when we have greater uncertainty), the more robust is the final Pareto set. On the contrary, if the majority of green portfolios is identified in last rounds, it means that the final Pareto set is not so stable.

For the robustness of the final Pareto set we introduce the *Robustness Index (RI)*. In order to calculate the RI we need to draw the so called *Robustness Chart* where the percentages of green portfolios that are available on r-th round (denoted as a_r) are plotted as a function of the computation round. The resulting curve is called *Robustness Curve*. In Fig. 3 we can see an example of a Robustness Chart with the corresponding Robustness Curve. We can observe that from round 2 to round 3 there are no new portfolios added in the green set. This may happen especially when the maximum number of rounds (R) is relatively high.

The RI of the final Pareto set is calculated as the area below the robustness curve, divided by the rectangle area denoted by the dashed rectangular in Fig. 2. The dashed rectangular actually expresses the maximum robustness ($RI = 1$) that occurs when already from the first computation round (i.e. when we have the maximum uncertainty), only one Pareto set is produced from all Monte Carlo iterations. The minimum robustness occurs when all green portfolios are added in the final Pareto set on the last round ($RI = 0$). *RI* takes values between 0 and 1 and it is calculated using the trapezoid rule for piecewise linear functions according to the following equations:

$$
\begin{aligned}
RI &= \left(\frac{a_1+a_2}{2}+\frac{a_2+a_3}{2}+\cdots+\frac{a_{R-1}+a_R}{2}\right)\Big/(R-1)\\
RI &= \left[\frac{a_1}{2}+\sum_{r=2}^{R-1}a_r+\frac{a_R}{2}\right]\Big/(R-1)\\
RI &= \left[\frac{a_1}{2}+\sum_{r=2}^{R-1}a_r+\frac{1}{2}\right]\Big/(R-1) \qquad (5)
\end{aligned}
$$

For example, from Fig. 2 we can calculate the corresponding *RI* as:

$$
RI=\left[\frac{0.04}{2}+0.11+0.34+0.34+0.83+\frac{1}{2}\right]\Big/5=42.8\,\%
$$

2.4 The algorithm

As it was mentioned, ITA proceeds with computation rounds (or cycles). The DR initially determines the number R of computation rounds. In the first round, the Monte Carlo sampling is performed using appropriate probability distributions for the uncertain parameters. The results define the green and grey set denoted as G_1 and Y_1. On second round the variance of Y_1 projects' parameters is reduced proportionally to the number of total rounds R. This reduction depends on the form of distribution. For example, for a normal distribution we reduce the standard deviation by $1/(R-1)$, or, for a uniform distribution, we cut $1/(2(R-1))$ from both edges of the range.

The variance reduction follows a uniform pattern across rounds. For example, in case of normal distribution, we reduce the standard deviation sd by $1/(R-1)$ after each round. This means that after round r, the reduction of standard deviation is $sd \times (r-1)/(R-1)$. Thus, in the final round projects' parameters (objective function coefficients) are considered as deterministic (have no variance at all). Therefore the final round produces only one Pareto set which is the final Pareto set that comprises the final Pareto portfolios. The flowchart of the decision making process is depicted in Fig. 4.

After the end of the multi-objective—ITA algorithm we have all the information for computing the Robustness Degree of each one of the POPs, for creating the Robustness Chart and computing the RI of the Pareto set. In addition we can provide the DR with informative charts that illustrate the Pareto front with additional information about the robustness of each POP. The latter is explicitly shown in the application in the next section.

3 Model building

This idea of incorporating energy and environmental issues in CSR is rather recent (Doukas and Psarras 2010; Doukas et al. 2012, 2014). In the present application a multi-criteria project portfolio selection problem is addressed taking into account both economic and environmental criteria. Given the uncertainty in quantifying the economic as well as the environmental performance of projects, multi-objective ITA method is an appropriate choice to extract results about the robustness of obtained project portfolios.

As it was mentioned before, the MP model that represents the optimization problem is a MOIP problem with the following characteristics:

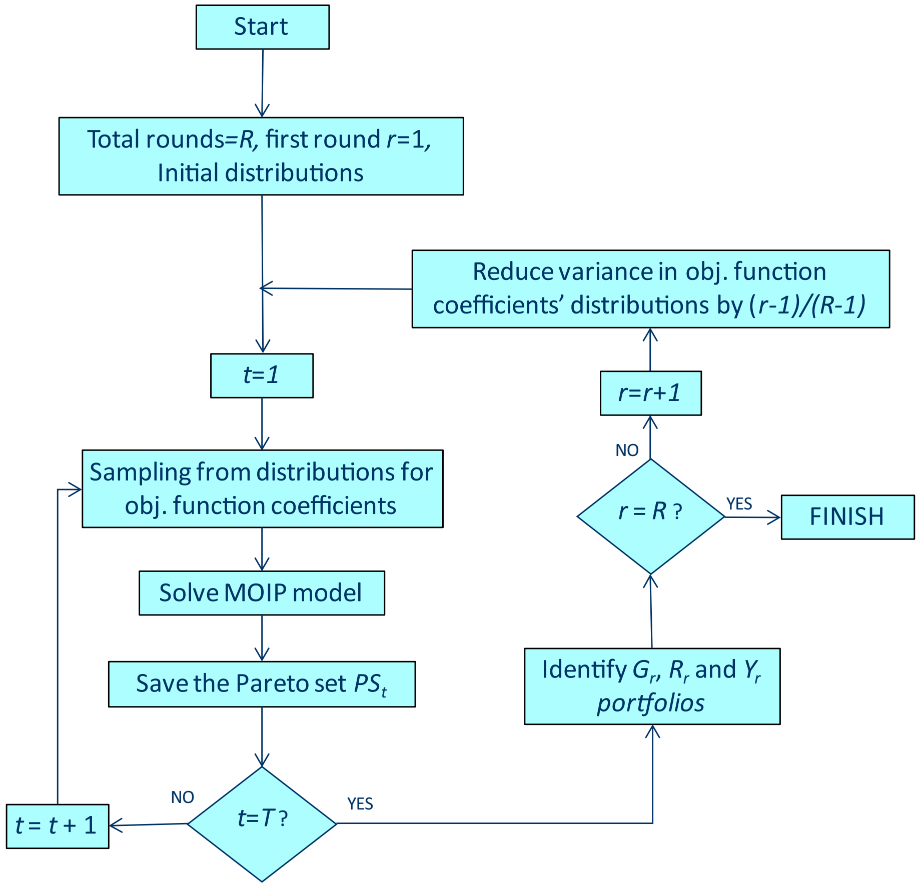

Fig. 4 Illustration of the multi-objective—ITA algorithm

3.1 Decision variables

In the specific case, firms' applications are expressed with 0–1 decision variables, with X_i denoting the i-th firm or application.

More specifically:

- If $X_i = 1$, then the corresponding application is approved.
- Otherwise, if $X_i = 0$, the corresponding application is rejected.

3.2 Objective functions

In the specific model we have two objective functions, namely the NPV of a portfolio and the EECR index of a portfolio. They are both additive functions of individual projects' relevant values.

$$\text{portfolio's } EECR\text{:} \quad max\ Z_1 = \sum_{i=1}^{N} eecr_i X_i$$

$$\text{portfolio's } NPV: \quad max\ Z_2 = \sum_{i=1}^{N} npv_i X_i \tag{6}$$

The parameters npv_i and $eecr_i$ are the NPV of the specific project application and the EECR score of the specific applied company.

3.3 EECR calculation

The adopted procedure used for calculation of the EECR scoring was based upon the ordered weighted average (OWA) operator. According to the literature, OWA operators were introduced by Yager (1988). An aggregation operator is a function $F : I^n \rightarrow J$ where I and J are real intervals. I denotes the set of values to be aggregated and J denotes the corresponding result of aggregation. The set of aggregation operators is denoted as $A_n(I, J)$.

An OWA operator is an aggregation operator from $A_n(I, J)$ with an associated vector of weights $w \in [0, 1]^n$, such that:

$$Fw(x) = \sum_{i-1}^{n} w_i \times b_i, \quad \text{where} : \sum_{i-1}^{n} w_i = 1 \tag{7}$$

and b_i denoting the performance of the alternative in the criteria $x_1, \ldots, x_n$.

The criteria to be selected have to be operational, exhaustive in terms of containing all points of view, monotonic and non-redundant since each criterion should be countered only once, as pointed out by Bouyssou (1990). With respect to this, the research focuses on the provision of a small but clearly understood set of evaluation criteria, which can form a sound basis for the comparison of the examined firms in terms of their systematic energy and environmental policy integration as a part of CSR and SD. Concisely, all six criteria are presented in Table 1. The data from these firms were mainly collected from the global reporting initiative disclosure database (GRI 2013).

3.4 Constraints

The model includes constraints, imposed by each banking institution's specific credit policy. First of all, a budget constraint is used in order to secure that the cumulative cost of approved applications does not exceed the overall budget.

$$\sum_{i=1}^{N} \cos t_i \mathrm{X}_i \leq avb \tag{8}$$

where avb is the total available budget and $cost_i$ the cost of i-th project application. In the specific application the available budget is 3 M€ while the total cost of all 40 projects is 9.4 M€.

Specific bounds are imposed to control the distribution of projects according to their category, across various sectors. In particular, we don't want a specific project category to dominate in portfolio which is expressed as "no sector or region is allowed to have more than half of the total approved applications". This condition is expressed with the following constraints:

Table 1 The criteria

Criteria	Description
C1: Management commitment	The degree to which Management of a firm prioritizes actions related to the energy and environmental corporate policy, sets specific targets and corresponding time schedule for their accomplishment
C2: Monitoring progress and related impact	The degree to which a firm adopts procedures and protocols for monitoring the set of targets, specific progress made in each related activity and the corresponding impact in companies operation and activation in the market
C3: Participation in dissemination activities	Reflects firms' participation in dissemination activities in broader community, including among others, educational and information activities regarding environmental practices, organization of workshops, conferences and other events, and sponsorships
C4: Promotion of renewable energy	Refers to the firms' involvement for investment in projects and initiatives related to renewable energy sources—wind power, solar power (thermal, photovoltaic and concentrated), hydro-electric power, tidal power, geothermal energy and biomass
C5: Promotion of energy efficiency	The extent to which a firm incorporates initiatives to provide energy-efficient products and services, to reduce direct and indirect energy consumption and other energy conservation practices and technological improvements
C6: Waste and water management	This criterion demonstrates the effort of firms in reducing total water use or discharge and the adoption of waste management activities

$$\sum_{i \in S} X_i \leq 0.5 \times \sum_{i=1}^{N} X_i \quad \text{for } S = \mathit{Sector}\, 1, 2, 3, 4 \tag{9}$$

$$\sum_{i \in R} X_i \leq 0.5 \times \sum_{i=1}^{N} X_i \quad \text{for } R = \mathit{Region}\, 1, 2, 3, 4 \tag{10}$$

In order to assure that all sectors and regions will be present in final portfolios we also add the following condition: "all sectors and areas will be funded with at least 10 % of the total cost". This condition is expressed with the following constraints:

$$\sum_{i \in S} \cos t_i X_i \geq 0.1 \times \sum_{i=1}^{N} \cos t_i X_i \quad \text{for } S = \mathit{Sector}\, 1, 2, 3, 4 \tag{11}$$

$$\sum_{i \in R} \cos t_i X_i \geq 0.1 \times \sum_{i=1}^{N} \cos t_i X_i \quad \text{for } R = \mathit{Region}\, 1, 2, 3, 4 \tag{12}$$

In the framework of ITA, the uncertainty characterizing the estimation of projects' NPV as well as the calculation of firm's EECR score is expressed with normal distributions for relevant projects' values. Specifically we take as mean value for the normal distributions the estimated value presented in Table 4 of the appendix and as standard deviation of the initial round the 5 % of the mean. This is done for the NPV as well as the EECR values. From round to round we reduce the standard deviation of corresponding normal distributions to 4, 3, 2, 1 and 0 % in the final round. The whole process (model building, random sampling, Pareto set generation) is implemented within GAMS platform (GAMS 2010).

4 Application and results discussion

For the application we have 40 projects from 40 different firms, with a geographical, sectoral distribution as follows in Table 2:

The parameters' values of the model as well as the membership of projects in various sets (sectoral and geographical) are shown in Table 4 of the Appendix. It must be noted that more types of constraints may be considered in the MP framework like e.g. the specific number (or range) of accepted applications (projects to be finally funded), or constraints for mutually exclusive projects etc.

We performed 1000 Monte Carlo iterations in each computation round and the computation time varied between 7181 and 9150 s from round to round in a core i-5 running at 2.5 GHz. It must be noted that in the specific application, we set a 99 % acceptance threshold for the green set (if a portfolio is present in 99 % of Pareto sets i.e. in 990 out of 1000).

The results of multi-objective ITA are shown in Table 3. There are in total 398 POPs that participate in 1000 Pareto sets of the initial round. Among them only four were present in all Pareto sets. At subsequent iterations we reduce the standard deviation of sampling distributions as shown in the first column of Table 3. Eventually, on the last round we obtain the final Pareto set that comprises 31 POPs of projects. These portfolios contain from 18 to 28 projects.

The additional information that we have from ITA is that we are aware which of these 31 portfolios can be considered more certain than others. The degree of certainty for each portfolio is directly related to the corresponding round that it enters the green set. In Fig. 5 we can see this picture very clear. The darker the portfolio's background the more certain we are about its Pareto optimality. From Fig. 4 we have at a glance which portfolios are more robust given the uncertainty in the model's parameters. The DR can exploit this information in his final selection.

A challenging task is to incorporate the robustness information in the Pareto front. As it is well known, Pareto front of a multi-objective problem is a graph of the Pareto set in criteria space. When we have 2 or 3 objective functions the Pareto front can be easily visualized. The

Table 2 Characteristics of the 40 projects

Geographical regions	Sectors
11 southern European enterprises	11 energy enterprises
10 northern European enterprises	9 industrial enterprises
13 central European enterprises	7 electrical equipment enterprises
6 Greek enterprises	13 enterprises from other sectors

Table 3 The results of multi-objective ITA from round to round

		Computation time (sec)	Green	Red	Grey
σ = 5 %	Round 1	9178	4	0	394
σ = 4 %	Round 2	8247	4	109	285
σ = 3 %	Round 3	8592	5	215	178
σ = 2 %	Round 4	7811	9	275	114
σ = 1 %	Round 5	8685	16	324	54
σ = 0 %	Round 6	7.3*	31	367	0

* For just one iteration as there is no uncertainty quantified by standard deviation

Fig. 5 Coloring code for the 31 portfolios

1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16
17	18	19	20	21	22	23	24
25	26	27	28	29	30	31	

robustness of each portfolio can be expressed with a bubble chart, where the size of bubble being the portfolio's Robustness Degree (see Sect. 2).

The upper chart in Fig. 5 is the conventional Pareto front with 31 Pareto optimal solutions (different portfolios). The lower chart embodies also robustness information. The robustness information is visualized with the size of the bubble. The greater the Robustness Degree of a POP (i.e. the earlier it enters the green set), the greater the size of the bubble. This kind of information is essential for the DR as he can recognize regions of the Pareto front with higher or lower robustness.

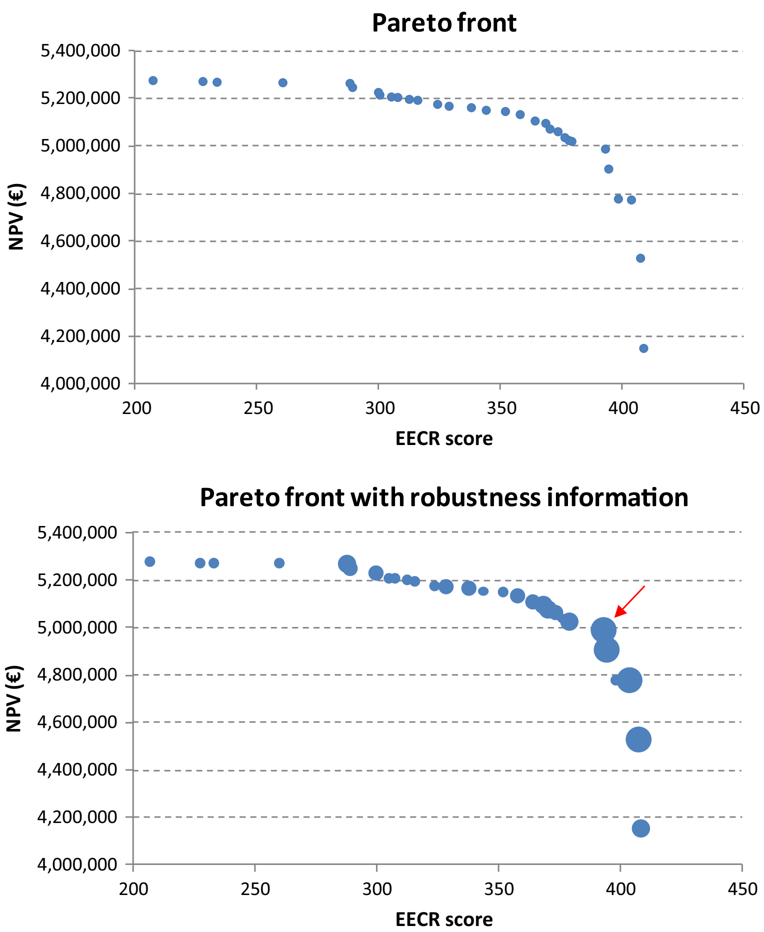

Fig. 6 Visualizing robustness with bubble charts

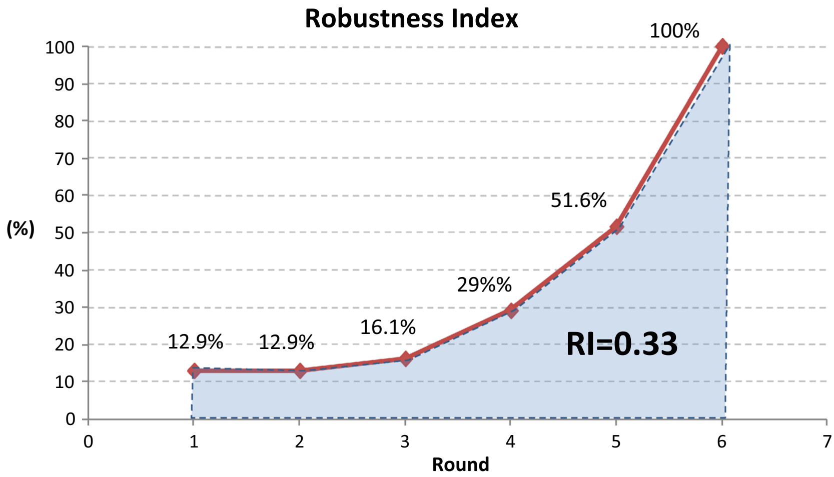

Fig. 7 The Robustness Chart

From this chart the DR can draw conclusions about criteria values of each solution (and therefore assess the trade-off) as well as about the robustness of solutions.

In the specific case, it seems that the robust Pareto optimal solutions are in the region of high EECR (horizontal axis). This also means that the values of EECR have less uncertainty, and this is true, into consideration the detailed and precise way of their calculations.

Promising solutions are on the knee of the Pareto curve where the slope changes sharply meaning that with a little sacrifice in one objective function we can achieve large improvement in the other. A promising solution (portfolio) in our case is the one pointed with an arrow. This means that a small compromise from the maximum EECR value leads to a great improvement in NPV. Besides, as it is evident from the size of the bubble, the specific solution is among the most robust. Conclusively, the robustness of the Pareto optimal solutions which is visualized in Fig. 6 can be regarded as an additional characteristic that helps the DR to evaluate the attractiveness of the obtained POPs.

The overall robustness of the final Pareto set can be measured using the RI. The Robustness Chart and the RI of specific case can be depicted in Fig. 7. Applying Eq. (2) we calculate the RI as the area underneath the Robustness Curve which is $RI = 0.33$.

Regarding all 40 projects, we can measure their presence in the Pareto front by counting how many times each one of them appears in 398 initial Pareto portfolios and how many in times in 31 final Pareto portfolios as shown in Fig. 8.

The initial Pareto portfolios correspond to maximum uncertainty. From Fig. 7 we can extract information about the robustness of the individual projects. The closer they are the two frequency rates (in the initial and in the final Pareto portfolios) for one project, the more robust are the conclusions for the participation frequency of the specific project. From Fig. 7 we can observe that there are projects included in more than 90 % of Pareto portfolios (even when maximum uncertainty is considered, i.e. in the initial round) like projects 7, 11, 13, 20, 21, 24, 35, 38, 39, 40) and other projects that never appear in Pareto portfolios (19, 23, 26, 29, 36, 37).

Moreover, based on the results, it can be noted that companies requesting for larger loans, while having a low EECR index, tend to be rejected. On the other hand, companies asking for smaller loans and having a high NPV index, tend to be approved.

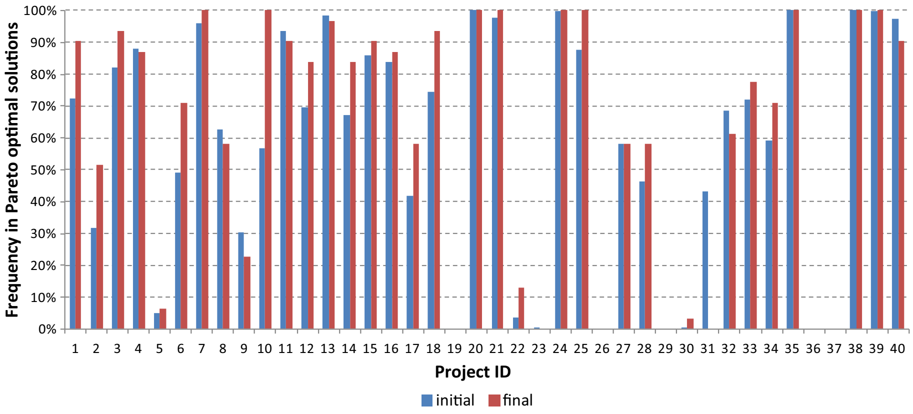

Fig. 8 Frequency of projects in the initial and final Pareto portfolios

5 Conclusions

Project portfolio selection is a challenging problem that sometimes involves multiple objectives and multiple constraints (budget, policy, allocation etc.) that should be satisfied. The combinatorial character of the problem implies the use of discrete optimization methods.

With the proposed methodology, banks and financial institutions do not take into consideration only usual and traditional economic performance in order to finance a project, but also additional ones, such as energy and environmental. The concept of this model can support fruitful decision making towards sustainable transition towards green growth, fostering green corporate responsibility. This is also in accordance with European Commission's objectives to foster firms to report related data in a transparent and explicit way. The proposed decision support model can also enhance the appropriate absorption of Structural and Cohesion Funds, assuring the energy and environmental responsibility of related firms.

In particular, in the presented case, two objective functions represent economic (NPV) and energy and environmental (EECR) dimensions of the submitted projects. A MOIP model is developed with these two objective functions and the exact Pareto set of project portfolios is generated. Moreover, we consider the underlying uncertainty of objective function coefficients (NPV of projects and EECR score of firms). For this reason, a multi-objective version of ITA is introduced so that it can convey useful information to the DR regarding the robustness of eventually obtained Pareto set.

The combination of Monte Carlo simulation and multi-objective programming via the systematic framework of ITA provides us with fruitful insights regarding the robustness of Pareto optimal solutions. The iterative approach gradually converges to the final Pareto set. Useful information emerged from this process is not just the Pareto optimality of project portfolios, but also their robustness in relation to perturbations in objective function coefficients (degree of robustness). Specific measures are developed in order to assess the robustness of the Pareto set as a whole as well as for each Pareto portfolio individually. We also obtain information regarding the specific projects and their frequency in POPs. The hybrid combination of two methodological tools (Monte Carlo simulation and multi-objective optimization) can effectively handle the specific green credit granting problem, where in addition to the consideration of multiple criteria, alternatives must obey to particular policy constraints.

Several issues can be considered for future research. Different probability distributions can be tested for the objective function coefficients. In addition, the underlying uncertainty may be extended to other model parameters beyond the objective function (i.e. to parameters associated with constraints). Moreover, the combination of Monte Carlo simulation and multi-objective optimization is a promising approach that may be used to address the robustness in multi-objective programming problems outside the ITA framework. For future research we can test the method in larger problems and with different probability distributions.

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Appendix

See Table 4.

Table 4 Projects' data

	EECR	NPV (€)	C ost (€)	Sector	Region
1	12.97	2500	5930	S1	R3
2	14.66	49,800	50,830	S1	R3
3	9.76	8300	5000	S1	R2
4	6.23	63,600	33,860	S1	R3
5	6.99	244,600	191,870	S2	R1
6	14.64	36,700	37,500	S2	R1
7	7.10	14,100	6070	S2	R1
8	11.92	22,500	23,030	S2	R4
9	11.81	261,300	190,000	S2	R1
10	21.59	455,000	422,670	S3	R2
11	13.64	696,800	415,000	S3	R1
12	13.59	53,900	39,330	S3	R1
13	3.86	238,900	95,330	S1	R4
14	9.62	3400	5630	S4	R1
15	40.00	600	7370	S4	R1
16	2.95	74,600	37,670	S4	R2
17	25.87	4900	30,100	S1	R4
18	5.25	12,500	5700	S4	R2
19	11.39	389,900	909,310	S4	R3
20	11.67	378,100	160,300	S4	R4
21	15.39	53,100	26,190	S4	R2
22	17.13	51,400	161,010	S4	R3
23	5.76	460,100	353,420	S3	R1
24	8.93	422,800	184,410	S1	R3
25	16.12	146,900	87,910	S4	R2

Table 4 continued

	EECR	NPV (€)	C ost (€)	Sector	Region
26	12.38	477,100	614,620	S1	R2
27	7.19	431,600	277,040	S1	R3
28	21.95	208,500	158,790	S3	R3
29	4.70	324,400	1,410,180	S2	R1
30	18.07	324,100	533,640	S3	R1
31	7.75	603,200	529,130	S4	R2
32	4.54	648,800	396,670	S2	R4
33	19.18	179,600	123,640	S1	R3
34	15.85	220,000	149,770	S1	R1
35	22.01	204,300	93,050	S4	R2
36	4.04	352,100	311,780	S4	R3
37	19.39	223,000	772,970	S3	R2
38	17.81	228,800	117,580	S2	R3
39	12.86	428,500	190,870	S4	R4
40	5.85	516,100	262,030	S2	R1

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