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A comprehensive system to support decision making in highly complex project portfolio situations

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ABSTRACT This paper describes a new approach in project portfolio selection (PPS) problems, emphasizing the need to overcome traditional deficiencies with respect to multicriteria decision-making and multiobjective optimization. While existing methods typically allow the solving of partial aspects of the PPS problem, the proposed approach seeks to provide a holistic framework dealing with aspects like interdependence between projects, interaction among criteria, the incorporation of both cardinal and ordinal information, and a hierarchical multiobjective optimization. Unlike approaches that optimize portfolios neglecting superiority of some projects, or those that only assess individual projects without considering overall portfolio performance, the proposal allows for a compromise between both objectives. A case study is given, proving the application of the proposal for developing well-balanced portfolios aligned with strategic organizational goals and stakeholder preferences. The results point to significant improvements in the efficiency and effectiveness of decision-making, especially in complex project environments. This research contributes not only to the advancement of the theoretical framework of PPS but also to practical implications for portfolio management in a wide variety of organizational contexts.

INDEX TERMS Decision making, Evolutionary algorithms, Multicriteria analysis, Multiobjective optimization, Outranking methods, Project portfolio selection.

I. INTRODUCTION

Generally, the senior management of an organization (which may be a group of individuals or a decision-maker representing senior management), hereafter referred to as the decision-maker (DM), is responsible for determining how to allocate its resources among a set of project proposals. In general, the quality of most proposals is acceptable, and the DM would like to support most of them; however, resource constraints make this impractical, so a multi-criteria decision-making process must be undertaken to determine the subset of proposals to support [1]. This

subset is known as the project portfolio. The determination of the most appropriate portfolio of projects is referred to as the project portfolio selection (PPS) problem. Numerous researchers have been proposing dozens of methods for solving this type of problem for decades [2]. PPS intends to direct an organization's scarce resources toward projects that promise the greatest alignment with its objectives and operational viability. Despite decades of research and application, traditional PPS methodologies often fail, particularly when faced with real features of

modern enterprises that require simultaneous handling of diverse data types and intricate project interdependencies. Recent studies reveal significant shortcomings in existing PPS frameworks, in particular their failure to effectively incorporate cardinal and ordinal information and to account for the synergistic and hierarchical nature of project criteria [3], [4], [5], [6]. These gaps not only limit decision-making capability, but also potentially bias the strategic alignment of portfolios toward suboptimal configurations.

The proposal presents a comprehensive methodology to address these critical shortcomings and to bridge the gap between both project and portfolio levels of decision-making. Furthermore, by integrating hierarchical decision-making processes with this dual data handling mechanism, our proposal improves the accuracy of project evaluations and ensures that portfolios are not simply collections of high-performing projects but are cohesive units that advance organizational goals. The application of this methodology to a complex, real-world case study underscores its practical importance and the substantial improvements it offers over traditional methods, marking a significant advancement in PPS research and application. Multi-criteria decision making (MCDM) and multi-objective optimization (MOO) approaches constitute the most prominent family of methods to address this problem, mainly in complex PPS scenarios [7]. MCDM has been applied primarily to evaluate and rank projects; in many methods and applications, the portfolio value is achieved by summing the values of the projects in the portfolio; the best portfolio is achieved from a portfolio value optimization process. In methods using MOO, the portfolio is replaced by a vector of objectives; in most MOO approaches, the values of the portfolio objectives come from aggregating (possibly considering synergistic effects) the “impacts” of the projects in the portfolio; the best portfolio is a Pareto point of the corresponding multi-objective problem [3]. By analyzing how input variations like cost and duration impact portfolio stability and performance, some studies have enabled strategic prioritization and optimization of resources. They also demonstrate how sensitivity analysis supports strategic decision-making, by preparing portfolios to adapt to future uncertainties and ensuring investments yield the highest returns with manageable risk levels [3].

While many existing methods effectively address specific aspects of PPS, our review has identified areas where these approaches may face challenges under certain conditions. It is important to note that while some methods do provide solutions for specific issues, a comprehensive approach that addresses all these aspects simultaneously has been less explored. The following are some of these aspects:

- a) Difficulty handling high dimensionality, that is, many project proposals and/or criteria.
- b) Inability to consider interdependence between projects (e.g., synergistic projects).

- c) Inability to consider interaction between criteria.
- d) Problems in handling information that is presented in ordinal or qualitative form in certain criteria, and in cardinal scales in other criteria.
- e) Challenges or incapacity in addressing uncertain, unclear, or potentially absent values related to criteria scores, resource needs, and preference parameters. Managing such scenarios becomes especially pronounced when the decision-maker comprises a diverse group or an individual who is not easily accessible, such as a CEO of a large enterprise.
- f) Inability to cope with PPS problems where criteria are organized as a hierarchy structure, i.e., where the score of a (non-elementary) criterion depends on the scores of other criteria (called descendants), and the evaluation of projects and portfolios is performed on different non-elementary criteria.
- g) The optimization process produces unbalanced portfolios (see e.g., [8], [9]). A portfolio is unbalanced when relatively poor performance of the portfolio on some non-elementary criteria coexist with very good performance on other non-elementary criteria. For example, when tackling a public project selection problem, the DM may be interested in ensuring an appropriate environmental benefit (composed of several sub-criteria), as well as acceptable economic and social impacts.
- h) Incapability to manage specific criteria that impact the portfolio's quality, yet these criteria do not stem from the aggregation of project scores. Achieving the optimal portfolio goes beyond simply optimizing the combined project scores; there are additional criteria that the decision-maker may wish to take into account when evaluating portfolio quality. For instance, the decision-maker might seek to maximize the number of supported R&D projects categorized as “Good” in terms of their probability of success. Alternatively, there may be an interest in minimizing the number of unsupported projects that rank higher than other supported projects. It's important to note that these criteria are utilized to assess the constructed portfolio, contrasting with the more traditional criteria used for individual projects. The former is often employed to gauge the decision-maker's alignment with the portfolio, referred to as “conformity criteria,” while the latter are simply termed “criteria.” Disregarding the conformity criteria can result in the decision-maker being dissatisfied with the portfolio, especially when the portfolio's outcome is derived from optimizing a single quantity representing its value or a vector of portfolio scores.

An effective decision support method should have the capability to handle various subsets of these constraints based on the specific context. However, to the best of our knowledge, no existing approach has been published that accomplishes this feat [1], [3], [10].

The novelty of the proposed system consists of a comprehensive approach able to give an effective solution to complex PPS challenges. The proposal can innovatively aggregate the decision maker's objectives into a single objective and integrate cardinal and ordinal data in PPS, enhancing decision-making through a comprehensive, hierarchical approach that includes conformity criteria and dynamic data aggregation. In more detail:

1. The proposed approach innovatively transforms a multi-objective optimization problem into a single-objective one by effectively incorporating the decision-maker's preferences. Typically, project selection and portfolio optimization involve juggling multiple objectives, a task that becomes cognitively burdensome due to human limitations in handling more than seven conflicting objectives simultaneously, as identified by [11]. To address this challenge, our strategic transformation simplifies complexity by focusing selective pressure on a specific region of interest. This targeted approach efficiently narrows the search to the most preferred portfolio, ensuring that the decision-making process remains manageable and aligned with human cognitive capacities.
2. We propose a new approach, which for the first time handles both cardinal and ordinal information innovatively and specifically in Project Portfolio Selection. Specific treatments for each type of information are indeed required, because they usually entail different mathematical and logical treatments to be possibly integrated effectively. The proposed system has enabled the aggregation of mixed data types under a compensatory framework, which is carefully regulated through thresholds by the decision-maker to avoid overcompensation. This enhances both the precision and flexibility of the decision-making process, hence marking a significant advancement in accommodating the complex data scenarios typical in strategic project evaluations.
3. This proposal represents an evaluative method that reflects the preference of decision-makers for rigorous project evaluations from any perspective, for example, "determine the scientific impact of the project", or "determine the overall quality of the project". This evaluative technique applies to portfolio-level evaluations in that it offers an analytical framework that guarantees strategic congruence at the level of both individual projects and the portfolio in general.
4. We introduce conformity criteria and conformity constraints. Conformity criteria are standards or

benchmarks against which the fit of a portfolio is measured. Unlike the traditional criteria that evaluate individual projects on the aspects of, for example, cost, risk, and potential return, the conformity criteria assess the portfolios on how well the collective group of selected projects conforms to broader, often qualitative organizational objectives; for example, "Maximize the number of projects in the category Excellent". Conformity criteria ensure that, beyond the traditional performance metrics, the portfolios will excel and suit other strategic objectives, including sustainability, diversity, and long-term organizational goals. The proposed approach can ensure that chosen portfolios have the potential for broader acceptance and support by embedding criteria reflecting the preferences and values of key stakeholders. Conformity constraints may be imposed in the form of, for example, "reject projects that are Bad or Below Average".

5. In this regard, the proposed system bases its approach on a two-layer assessment process that evaluates on one hand, individual projects, and on the other, assesses each project portfolio as a whole. This approach ensures that the evaluation addresses individual projects and their integration into a single portfolio, taking into account not just the value of an individual project but also the interaction between projects within the portfolio. Traditional PPS methods often do not consider the assessment of both perspectives, and to the best of our knowledge, there are no published approaches providing explicitly a mechanism where the decision-maker can express his/her preferences about the compensation between both perspectives.
6. We present a novel strategy for assembling balanced portfolios in a way that their performance will be uniformly distributed across criteria. For no single criterion or a group of criteria to strongly dominate or affect overall effectiveness in the portfolio. This approach is cognitively straightforward for the decision-maker, as he/she is allowed to easily articulate his/her preferences in the form of simple expressions about acceptable portfolios. Those are used as benchmarks within the system to guide the selection process. This will simplify the selection and also allow for closer outcomes to what is actually perceived by the decision-maker as balanced.
7. Combining the outranking approach, the functional paradigm, and evolutionary algorithms may enable performing hierarchical decision-making. Though these methodologies are all well-established in their respective areas, their integration in the context of PPS for a hierarchical environment is new. PPS deals with many decision criteria that can be interrelated and vary in importance; when treated

linearly, such treatment tends to be problematic for the decision-makers. A hierarchical framework in organizing these criteria at different levels provides for a systematic evaluation that clearly outlines the relationship and impact from the lower level operational goals to the higher level strategic objectives. The proposed approach is thus exploiting the strengths of evolutionary algorithms to handle large solution spaces and taking advantage of the ability of the outranking method to handle qualitative and conflicting criteria, whereas the characteristics of the functional paradigm are used to deal with cardinal information. Hierarchical structuring of the evaluation enhances clarity and efficacy in the decision-making process.

This paper is structured as follows. Section II provides a review of the characteristics of some published approaches, their contributions and limitations. Section III presents an extensive example in R&D projects illustrating the complexity of the problem and the need for a new method. Section IV describes the proposed approach. Section V shows how the proposal is used to address an example with real-world features related to R&D projects, and Section VI concludes this paper.

II. RELATED WORKS

The novelty of the proposal lies in an overall improvement of a traditionally two-step process, individual project selection and portfolio optimization [3]. During the assessment at the individual project level the proposal handles both cardinal and ordinal information, allowing for a review of each project's potential performance, strategic fit, risk, and resource need and any other criteria that the decision maker considers relevant. This ensures that specific projects are analysed based on their stand-alone benefits and in relation to the organization's objectives.

The second stage is portfolio construction, where the proposal optimizes synergy between projects while considering some high-level DM's objectives regarding the composition of the portfolio. It involves more than just project selection; there is interaction in resource sharing, risk distribution, and overall portfolio balancing. The proposal ensures that the portfolio maximizes collective value and adheres to several types of constraints by addressing the dynamic nature of strategic objectives and interdependencies between projects. This new approach facilitates the process of selecting the most preferred projects while improving the strategic congruence and operational viability of the overall portfolio.

A. ASSESSMENT OF INDIVIDUAL PROJECTS

The initial phase involves evaluating individual projects based on multiple criteria. Typically, the impacts assessed by a project across these multiple criteria are: i) consolidated using a Multi-Criteria Decision Making (MCDM) approach to

generate a singular value representing the project's quality, ii) utilized to categorize the project within a set of ordered classes, iii) employed to rank the projects from best to worst; or iv) employed to ascertain the project's contribution to the portfolio. When feasible, the latter can be accomplished straightforwardly by summing the scores of the projects endorsed by the portfolio.

A common approach to produce a single value of the project's quality is the weighted sum function (e.g., [12], [13], [14]). It has been widely used to create a ranking of the projects or to assign projects to preferentially ordered classes. The main reason to use this approach is its simplicity; it only requires defining the importance and the value that the DM assigns to each criterion. Moreover, it fulfills several appealing theoretical properties such as independence with respect to irrelevant alternatives, comparability, and transitivity. Nevertheless, this approach does not allow the explicit consideration of interactions among criteria, veto situations, or other threshold effects that are very important for a holistic project evaluation. Additionally, it requires cardinal information and enforces constant tradeoff rates between criteria. The latter requires that any decrease in one criterion be exactly offset by a proportional increase in another direction, which often does not align with real-world projects. Another multiple criteria decision-making approach employed to derive values representing the quality of projects or their rankings is PROMETHEE (Preference Ranking Organization METHod for Enrichment of Evaluations) [6], [10], [15]. PROMETHEE, an outranking-based method, is not confined to working exclusively with cardinal information; it can also accommodate qualitative data and non-compensatory effects. Nevertheless, the rankings generated by this method are susceptible to be influenced from irrelevant alternatives.

Other outranking methods can be used to assign projects to classes or to generate a ranking. Outranking methods represent one of the main schools of thought of MCDM. Such methods build and exploit an outranking relation between pairs of decision alternatives (also called actions in the related literature). Given alternatives x and y , the outranking relation considers arguments to approve and disapprove the assertion " x is at least as good as y ". When this assertion is accepted, it is said that " x outranks y ". Exploitation of the outranking relation can be performed for choosing, ranking and for ordinal classification purposes.

The ELECTRE family contains most of the outranking methods used to address the PPS problem (e.g., [16], [17], [18], [19], [20], [21]). ELECTRE methods can handle ordinal information, threshold effects, incomparability and non-transitivity situations when aggregating the criteria scores. ELECTRE methods can also cope with imperfect knowledge (zones of uncertainty) in the preferences of the DM through several ways, such as discriminating thresholds (so-called pseudo-criteria) (e.g., [22]) and interval numbers (e.g., [23]). However, traditional ELECTRE methods are limited in that they do not accommodate interacting criteria or criteria that

are hierarchically structured. These limitations can hinder the decision-making process in complex scenarios where the interplay between criteria and their structural dependencies significantly impact outcomes. For a detailed exploration of these challenges, refer to the illustrative example in Section III.

ELECTRE methods for addressing interacting criteria have been expanded upon in [24], criteria have been organized hierarchically in [25], and hierarchical assessments of alternative performances on interacting criteria are discussed in [26]. Corrente et al. [27] introduced a multiple criteria hierarchy process for categorizing alternatives into preferentially ordered classes (i.e., sorting alternatives). Drawing inspiration from ELECTRE, Fernández et al. [28] presented two multi-criteria sorting methods capable of handling imperfect knowledge regarding the preferences of the decision-maker, imprecise, vague, or even missing values in criteria scores, and resource requirements. Moreover, this proposal is adept at evaluating alternatives (projects or portfolios) based on hierarchically structured criteria and assigning alternatives to ordered classes at the level of any non-elementary criterion [29]. In spite of the benefits of ELECTRE, it hardly handles compensatory preferences and situations where the intensity of the preference in favour of the outranking relation is relevant; furthermore, it is not able to consider situations where only cardinal information is treated, and compensation is allowed in a wide range.

Some other well-known methods for dealing with interacting criteria have also been proposed outside of the outranking approach (Choquet, 1954; Sugeno, 1974; Ramedani et al., 2024; Xing et al., 2022), the same is true for handling uncertainty [31].

B. BUILDING PROJECT PORTFOLIOS

The second stage involves constructing the project portfolio, determining which projects will receive support. In this phase, considerations extend beyond the criteria used in the first stage to build the portfolio. New criteria related to the decision-maker's alignment with the portfolio (conformity criteria) are taken into account, along with various constraints. The available options for executing this stage are contingent upon the actions undertaken in the preceding stage, such as how project impacts were aggregated in the initial phase.

If a single value representing each project's quality was determined, then the portfolio value can be calculated as the aggregated value of its supported projects, and an optimization of the portfolio value should be performed. This approach is very simple and easy to explain, however, it neglects that criteria can be hierarchically structured, that there can be interactions between criteria and between projects, and it requires cardinal information which may be a serious practical limitation.

If an MCDM approach is utilized in the initial stage (e.g., [21], [32], [33]), the projects can be arranged in a ranking or a set of ordered categories. In this manner, the most preferred

projects are supported until resources are depleted. Alternatively, the requirements of the projects in the top classes can be adjusted to align with the available resources (e.g., [34]). This approach to building portfolios is straightforward and ensures support for the highest-quality projects. However, it does not consider interdependence between projects. The interactions (synergies) between projects were studied more intensively from the work of Stummer and Heidenberger [35] (see e.g., [36], [37], [38], [39], [40]) and continue to be addressed by recent papers [5], [41]. Typical implications of project interaction often include increasing/decreasing the criteria scores of synergetic projects and modifying the total resources consumed by these projects. Typically, this cannot handle segmentation constraints directly. Such constraints require, for example, that specific proportions of resources be allocated or restricted to segments of the portfolio. For example, "no more than 15% of the total budget should be allocated to projects from private organizations".

Another option is to aggregate the criteria scores of the supported projects to produce criteria scores now at portfolio level. After defining the, say, N scores of the projects in the first stage, the scores of the potentially supported projects can be combined (e.g., through summation) to define the N scores at portfolio level. Assessing portfolios this way provides the DM with an easy way to measure the levels of impact on his/her objectives; thus, allowing the DM to create balanced portfolios with acceptable impact levels on objectives. Nevertheless, in this scenario, the intricacy of the problem can pose a significant challenge, particularly when handling even a few objectives and several dozen projects due to the following reasons: i) the cognitive limitations of the decision-maker in expressing preferences, which may restrict them to working with only a few objectives [11], ii) the computational complexity, making it highly challenging to employ exact methods, and iii) the vast number of non-dominated portfolios (in accordance with Pareto optimality), making the identification of the portfolio that best represents a compromise among objectives a challenging task.

Strong and complex nonlinear combinatorial optimization search spaces often characterize project portfolio selection problems. Many authors have advanced in the design of metaheuristics to address these problems (e.g., [38], [42], [43], [44], [45], [46]). Of these works, evolutionary algorithms, particularly genetic algorithms (GAs), stand out mainly because of their robustness to deal with diverse shapes of complex nonlinear search spaces [45], [47] and because their characteristics (selection, crossover and mutation operators) make them able to explore the search space reducing risks of getting stuck in local optimums [48], [49]. Furthermore, they allow for flexible representations of solutions, which is very convenient to deal with a 1–0 combinatorial approach as the required to represent projects in or out the portfolio. GAs support hierarchical decision-making, integrating both cardinal and ordinal data, essential for reflecting varied project

information accurately [29], [50], [51]. Their iterative nature adapts to changes in strategic priorities or project environments, making it indispensable for dynamically optimizing portfolios to align closely with organizational goals and decision-maker preferences [49].

All the cited works focus only on some of the characteristics of the PPS problem, lacking the flexibility and robustness to deal with more complex and realistic scenarios. Furthermore, they suffer from several limitations, since they do not allow to:

- Contemplate many criteria and/or projects, which avoids contemplating conformity criteria.
- Reflect synergies between projects.
- Build the portfolio by optimizing objectives at different levels of a hierarchical structure.
- Handle uncertainty on the criteria scores caused by imprecision, vagueness, arbitrariness, or even missing values.
- Consider ill-defined preferences of the DM caused, for example, by a fuzzy entity representing the real DM or because the DM is a rather heterogeneous group.
- Deal with interacting criteria.
- Ponder and select tradeoffs between improving the overall quality of the portfolio and supporting better projects.
- Provide information to the DM regarding the classification of the projects/portfolios on other criteria besides the overall criterion.
- Incorporate preferences regarding the balance of the portfolio.

III. AN ILLUSTRATIVE EXAMPLE IN R&D PROJECT PORTFOLIO SELECTION

In the PPS problem, a first assessment is performed at a project level where the criteria scores are defined for each project. Subsequently, some (most) of the criteria used at project level can now be considered at a portfolio level. At this new level, the criteria scores of the projects supported by the portfolio are aggregated to produce the criteria scores now at a portfolio level. Additional criteria and constraints may be considered when assessing portfolios (such as conformity criteria and conformity constraints).

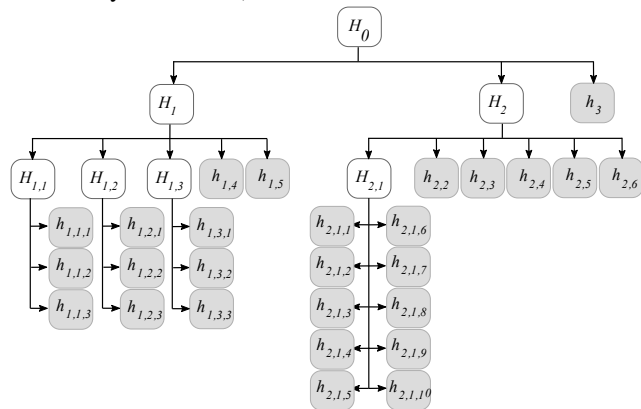


FIGURE 1. Hierarchy of the criteria used to assess projects. H_0 is the overall quality of the project but, since it is a complex (also called non-elementary) criterion, it is decomposed on several other criteria which, in turn, can also be complex.

We present an example that uses the two levels of assessment. The example, while illustrative and not directly extracted from real-world data, is meticulously constructed based on scenarios discussed in published research [29]. Note that the ‘experts’ in this example should be understood as hypothetical, since they are not real individuals but are instead fabricated personas created to demonstrate the application and potential outcomes of the proposed methodology in a simulated scenario.

A. ASSESSING R&D PROJECTS

Let’s assume the case of a large organization interested in supporting Research and Development projects. A set of criteria has been defined and structured as a hierarchy. Given the number of project proposals and criteria, a group of expert evaluators has been consulted to define the criteria scores of the projects and resource requirements; imprecise and vague information was provided by several evaluators. Multiple interactions have been found between pairs of criteria and between pairs of projects. Also, the DM is interested in supporting the best projects but does not discard supporting some average projects if doing so implies improving portfolio-level objectives (see next subsection). However, the DM is unwilling to support bad projects regarding some non-elementary criteria.

The root node of the hierarchy represents the overall quality of the project (H_0), comprised of three direct sub-criteria (refer to Figure 1): project impact (H_1), probability of success of the project (H_2), and cost of the project (h_3). Some of these criteria, referred to as non-elementary criteria, are composed of sets of criteria, while others are considered elementary criteria. For instance, the cost of projects (h_3) is directly measured in monetary terms, while the project impact (H_1) and the probability of success (H_2) are complex and require definition in terms of other sub-criteria. (Note that the use of upper- and lower-case notation corresponds to non-elementary and elementary criteria, respectively.)

The project impact (H_1) is dependent on five direct sub-criteria: economic impact ($H_{1,1}$), scientific impact ($H_{1,2}$), development of human resources ($H_{1,3}$), capacity to make positive synergy with other projects ($h_{1,4}$), and the quality of the project’s deliverables ($h_{1,5}$). Economic impact ($H_{1,1}$) consists of three criteria: the number of patents generated ($h_{1,1,1}$), the number of innovative processes generated ($h_{1,1,2}$), and the number of prototypes generated ($h_{1,1,3}$). Scientific impact ($H_{1,2}$) is based on three criteria: the number of papers to be published by first quartile JCR journals ($h_{1,2,1}$); the number of papers to be published by other JCR journals ($h_{1,2,2}$); and the number of papers contributed to international conferences ($h_{1,2,3}$). Lastly, the development of human resources ($H_{1,3}$) includes three criteria: the number of new

PhDs to be generated by the project ($h_{1,3,1}$); the number of post-PhDs ($h_{1,3,2}$ and the number of new master graduates ($h_{1,3,3}$).

The probability of success of the project (H_2) relies on six direct sub-criteria: quality of the leader's curriculum ($H_{2,1}$), likelihood of meeting the deadline ($h_{2,2}$), difficulty of the research problem ($h_{2,3}$), strength of the research collaborator group ($h_{2,4}$), appropriateness of the institutional environment ($h_{2,5}$), and quality of the research design ($h_{2,6}$). The quality of the leader's curriculum ($H_{2,1}$) is influenced by ten elementary criteria: number of relevant awards obtained by the leader ($h_{2,1,1}$), number of papers published by 3-top rated journals ($h_{2,1,2}$), number of papers published by JCR first quartile journals ($h_{2,1,3}$), numbers of papers published by JCR journals ($h_{2,1,4}$), number of books published by top-rated editorials ($h_{2,1,5}$), number of PhD students advised by the leader ($h_{2,1,6}$), number of citations to his/her scientific works ($h_{2,1,7}$), number of projects successfully led ($h_{2,1,8}$), national level of collaboration ($h_{2,1,9}$), international level of collaboration ($h_{2,1,10}$).

Tables I-III show the non-elementary criteria and their direct sub-criteria for the different levels of the hierarchy. These tables also show the impact scales used by the elementary criteria and the preference direction of these impacts. The impact scales are cardinal (CS) or a six-level ordinal scale (OS), except for the case of criterion $h_{1,5}$ whose values are binary denoting relevance (1) or not (0). Note that, if evaluated, the impact scales of non-elementary criteria would always be ordinal. The criteria scores in the case of the six-level OS are denoted by 0-5 where: Nothing = 0, Very low = 1, Low = 2; Medium = 3, High = 4, Very high = 5. The preference direction can be decremental (DP) or incremental (IP). Of course, the experts' opinions often diverge creating imperfect knowledge about the actual impacts of the projects. This knowledge can be effectively managed through the use of pseudo-criteria or interval numbers. Utilizing pseudo-criteria may be more suitable when the criterion is represented by an ordinal scale (e.g., $h_{1,4}$ and $h_{2,2}$). On the other hand, employing interval numbers may be more fitting for cardinal scales (e.g., h_3 and $h_{2,1,7}$).

TABLE I
NON-ELEMENTARY CRITERIA AND THEIR DIRECT SUB-CRITERIA IN THE
FIRST LEVEL OF THE HIERARCHY

Overall quality of the project (H_0)		
Project impact (H_1)	Probability of success of the project (H_2)	Cost of the project (h_3): DP, CS

TABLE II
NON-ELEMENTARY CRITERIA AND THEIR DIRECT SUB-CRITERIA IN THE
SECOND LEVEL OF THE HIERARCHY

Project impact (H_1)		
Economic ($H_{1,1}$)	Scientific ($H_{1,2}$)	Human resources ($H_{1,3}$)

Positive synergy
($h_{1,4}$): IP, OS

The deliverables
are relevant
($h_{1,5}$): IP, OS

Probability of success of the project (H_2)

Leader curriculum ($H_{2,1}$)	Likelihood of meeting the deadline ($h_{2,2}$): IP, OS	Difficulty of the research problem ($h_{2,3}$): DP, OS
Research group ($h_{2,4}$): IP, OS	Institutional environment ($h_{2,5}$): IP, OS	Research design ($h_{2,6}$): IP, OS

TABLE III
THIRD LEVEL OF THE HIERARCHY

Economic impact ($H_{1,1}$)		
Patents generated ($h_{1,1,1}$): IP, CS	Innovative processes generated ($h_{1,1,2}$): IP, CS	Prototypes generated ($h_{1,1,3}$): IP, CS
Scientific impact ($H_{1,2}$)		
Papers to be published in Q1 JCR journals ($h_{1,2,1}$): IP, CS	Papers to be published in other JCR journals ($h_{1,2,2}$): IP, CS	Papers contributed to international conferences ($h_{1,2,3}$): IP, CS
Development of human resources ($H_{1,3}$)		
Number of PhD generated ($h_{1,3,2}$): IP, CS	Number of post-PhD ($h_{1,3,2}$): IP, CS	Number of master ($h_{1,3,3}$): IP, CS
Quality of the leader curriculum ($H_{2,1}$)		
Number of awards ($h_{2,1,1}$): IP, CS	Number of papers in 3-top journals ($h_{2,1,2}$): IP, CS	Number of papers in Q1 JCR journals ($h_{2,1,3}$): IP, CS
Number of papers in other JCR journals ($h_{2,1,4}$): IP, CS	Number of books in top-rated editorials ($h_{2,1,5}$): IP, CS	Number of PhD students advised ($h_{2,1,6}$): IP, CS
Number of citations ($h_{2,1,7}$): IP, CS	Number of projects led ($h_{2,1,8}$): IP, CS	National level of collaboration ($h_{2,1,9}$): IP, OS
International level of collaboration ($h_{2,1,10}$): IP, OS		

Several pairs of criteria show some kind of interaction (cf. [52]). For instance, since it is expected that good leaders design good proposals, quality of the leader curriculum ($H_{2,1}$) and research design ($h_{2,6}$) exhibit an antagonism interaction; that is, when comparing two projects, say a and b , to assess the credibility of “ a is at least as good as b ”, the credibility that

$H_{2,1}$ can generate in favor of that assessment when the quality of the leader curriculum of a is high enough is reduced when the research design ($h_{2,6}$) of a is bad enough.

A strengthening interaction (positive synergy) is appreciated between quality of the leader curriculum ($H_{2,1}$) and the research problem difficulty ($h_{2,3}$), between quality of the leader curriculum ($H_{2,1}$) and the strength of the research group ($h_{2,4}$), and between research problem difficulty ($h_{2,3}$) and the strength of the research group ($h_{2,4}$); thus, for example, a high enough quality of the leader curriculum ($H_{2,1}$) makes more credible the assertion “ a is at least as good as b ” when the difficulty of the research problem ($h_{2,3}$) is low enough. Finally, since higher ranked journals and editorials usually imply a higher number of citations of published works, some redundancy (that is, weakening interaction or negative synergy) is identified between numbers of papers in other JCR journals ($h_{2,1,4}$) and number of citations ($h_{2,1,7}$), also between number of papers in 3-top journals ($h_{2,1,2}$) and number of citations ($h_{2,1,7}$).

B. ASSESSING PORTFOLIOS

As stated above, most of the criteria used to assess projects are also used to assess portfolios; thus, some scores of the projects supported by a portfolio need to be aggregated to define the scores on these portfolio-level criteria; moreover, additional criteria are also used to encompass a wider perspective on the overall quality of a portfolio. Let us mention the criteria considered here to assess portfolios.

The quality of the portfolio (G_0) is assessed considering the portfolio impact (G_1) and the DM's conformity with the

relevant deliverables ($g_{1,4}$). Economic impact ($G_{1,1}$) is further broken down into the number of patents to be generated ($g_{1,1,1}$), the number of innovative processes to be generated ($g_{1,1,2}$), and the number of prototypes to be generated ($g_{1,1,3}$). Scientific impact ($G_{1,2}$) is dependent on three criteria: the expected number of papers that the projects in the portfolio will publish in first quartile JCR journals ($g_{1,2,1}$); number of papers to be published in other JCR journals ($g_{1,2,2}$); number of papers contributed to international conferences ($g_{1,2,3}$). Development of human resources ($G_{1,3}$) consists of the number of new PhDs to be generated ($g_{1,3,2}$); the number of post-PhDs to be generated ($g_{1,3,2}$); and the number of new master graduates to be generated ($g_{1,3,3}$).

The DM's conformity with the supported portfolio (G_2) is assessed through three sub-criteria: the number of projects with good scientific impact ($g_{2,1}$), the total cost incurred by the portfolio ($g_{2,2}$), and the quantity of supported projects with a quality lower than that of non-supported projects ($g_{2,3}$). The portfolio score on $g_{2,3}$ is measured by comparing the class of overall quality to which each supported project was assigned with that of each non-supported project. If the supported project was assigned to a class worse than that of at least one of the non-supported projects, then this is counted as an inconsistency for the supported project (i.e., each supported project can increase the number of inconsistencies in one). We denote by $g_{2,3}$ the number of inconsistencies for all the projects supported by the portfolio.

Note that the scores on all elementary criteria descending from G_1 are imprecise, as well as $g_{2,2}$.

Also note that, to assess $g_{2,3}$, the projects must be assigned to preferentially ordered classes of overall quality a priori (H_0). Assume that there are three possible classes of overall quality: Bad, Acceptable, and Good. Furthermore, a project can also be assigned to any set of preferentially ordered classes regarding any of the other non-elementary criteria. Assume that each project is also sorted regarding its impact (H_1), its probability of success (H_2), and its scientific impact (H_{12}). Therefore, a set of constraints that the portfolios must fulfill is that the supported projects are at least Acceptable regarding their overall quality and their impact, and that they have a Good probability of success.

Finally, the supported portfolio must be balanced; that is, the DM requires the supported portfolio to create Acceptable scientific, economic and human resources impact.

IV. THE PROPOSED METHODOLOGY

As stated before, the proposal aims to consider the two stages of portfolio management, individual project selection and portfolio construction. The proposed methodology introduces a new approach to represent the preferences of the decision-maker, utilizing the HI-INTERCLASS-nC method for sorting alternatives. This comprehensive framework enhances PPS by characterizing and selecting the best compromise portfolio, aligning individual project evaluations with strategic objectives to optimize portfolio synergy. The proposal

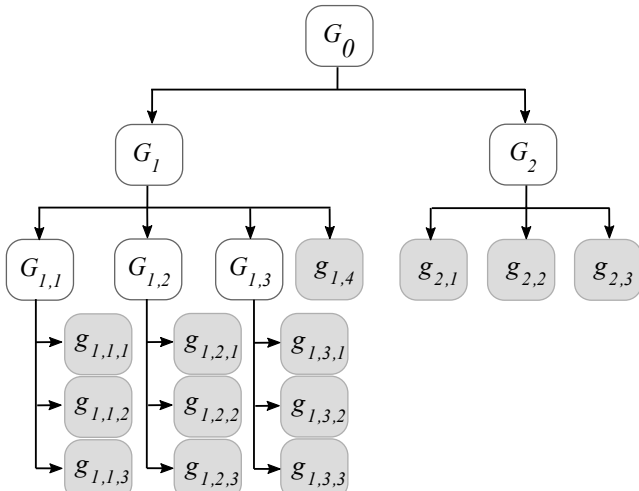


FIGURE 2. Hierarchy of the criteria used to assess portfolios portfolio (G_2), as seen in Figure 2. The portfolio impact (G_1) is assessed by aggregating the scores of the projects supported by the portfolio, while the DM's conformity with the portfolio (G_2) is assessed by considering other criteria that are not impact measures.

G_1 comprises economic impact ($G_{1,1}$), scientific impact ($G_{1,2}$), development of human resources ($G_{1,3}$), and number of

addresses complex interdependencies and ensures operational efficacy and strategic congruence.

This section presents first the notation and a succinct explanation of the proposed methodology mentioning its main components; after that, a deeper description of the methodology is provided.

For homogeneity purposes, we will use here part of the notation adopted by Fernández *et al.* [29].

- Let A be the set of alternatives (potential actions).
- Let I_g be the set of indices of all criteria in the hierarchy.
- Let $\chi = \{g_0, g_1, \dots, g_{\text{card}(I_g)}\}$ be the set of all the criteria in the hierarchy. Without loss of generality, we assume that the preference increases in the sense of the values of the criteria.
- Let EL be the set of indices of all elementary criteria.
- Let N_h be the number of immediate sub-criteria of a non-elementary criterion g_h .
- Let $G_h = \{g_{h1}, \dots, g_{hN_h}\}$ be the set of immediate sub-criteria of a non-elementary criterion g_h . If $g_j \in G_h$, then it is said that g_j is an immediately descending criterion from g_h , and this one is an immediately ascending criterion of g_j .
- Let I_{G_h} be the set of indices of all the criteria in G_h .
- Let $W_h = \{(i,j) \in I_{G_h} \times I_{G_h} \text{ such that the pair } (g_i, g_j) \text{ produces mutual weakening effect with respect to } g_h\}$, that is, the pair of criteria where the DM would consider the combined importance to be smaller than the sum of the individual contributions, which indicates certain redundancy between both criteria;
- Let $St_h = \{(i,j) \in I_{G_h} \times I_{G_h} \text{ such that the pair } (g_i, g_j) \text{ produces mutual strengthening effect with respect to } g_h\}$, that is, the DM would consider that the combined importance of these two criteria is greater than the total importance of the criteria when they are considered separately; this means that there is cooperation between these cri- teria;
- Let $Ant_h = \{(i,j) \in I_{G_h} \times I_{G_h} \text{ such that } g_j \text{ produces antagonistic effect to } g_i \text{ with respect to } g_h\}$, that is, the impact of a given action is high on a given criterion (say, g_j), but the importance of the criterion is actually decreased in the mind of the DM when the impact of that action on another criterion (say, g_i) is low enough;
- Let $EL(h)$ be the set of indices of all elementary criteria which influence a non-elementary criterion g_h ;
- Let $D(h)$ is the set of indices of all criteria which influence a non-elementary criterion g_h from a lower hierarchical level;

When $j \in D(h)$, then it is said that g_j is descending from g_h .

For more detailed information about the interactions among criteria, the reader is referred to [53].

A. OVERALL FRAMEWORK

Figure 3 shows the overall framework of the proposed methodology.

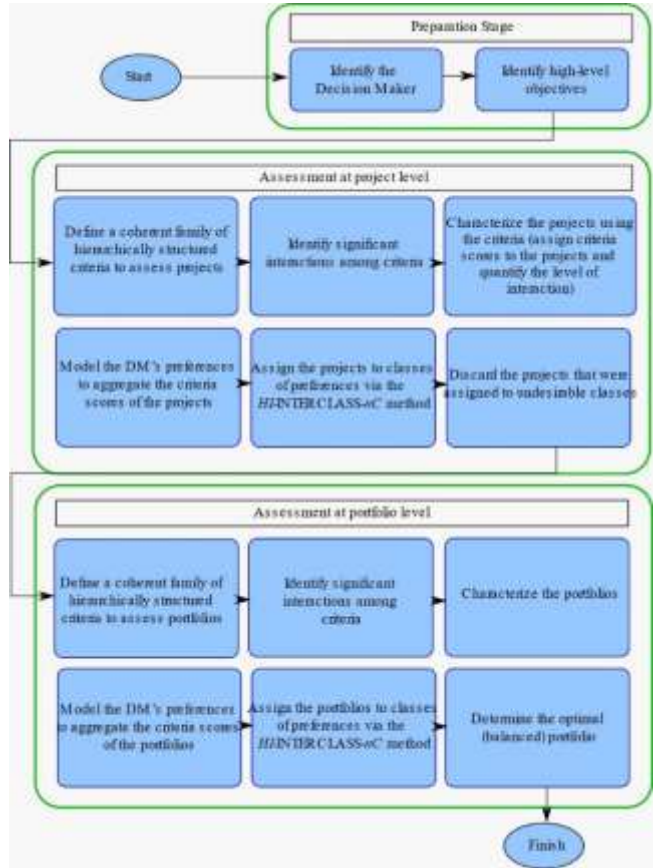


FIGURE 3. Framework of the proposed methodology

Once the problem is defined, the proposed methodology models the decision-maker's preferences by a novel eclectic approach that merges hierarchical interval outranking with the value function method. This new framework aggregates the criteria scores for comparing i) individual projects or ii) projects against reference profiles. This is the process that involves the DM's preferences and, therefore, dictates the projects' evaluation to assign them into preferentially ordered classes.

Furthermore, this approach transforms a multi-objective optimization problem into a single-objective one by using the DM's preferences, in a novel manner. This transformation uses selective pressure to focus the search for the most preferred portfolio within a region of interest. A canonical genetic algorithm is adapted, aimed at identifying the best project portfolio.

The balance in the selected portfolio is maintained through a two-step process. Firstly, the DM creates a portfolio prototype by either directly inputting acceptable scores for the criteria based on his/her experience or, otherwise, through some interaction process. This prototype plays the role of a benchmark with respect to balance that needs to be outperformed. Secondly, the outranking of this prototype will guarantee the balanced criteria scores of the portfolio in

situations where some of the criteria have veto power. A portfolio that does not outrank this prototype will be vetoed. The need for outrank ensures that the integrity and balance of the supported portfolio are maintained.

B. A NEW APPROACH TO REPRESENT THE PREFERENCES OF THE DECISION-MAKER

Here, we introduce a generalization of the method proposed in [29]. This novel method adheres to the same principle for comparing alternatives as its predecessor: evaluating the credibility of “a is at least as good as y” on a given non-elementary criterion necessitates an assessment of such an assertion on the criterion’s immediate descendants. However, recognizing that descendants are occasionally measured on a cardinal scale and may require compensation, the new method incorporates capabilities to aggregate scores on the corresponding non-elementary criterion using a function value. The function value employed in this method can also accommodate imperfect knowledge, similar to the approach in [54], by utilizing interval numbers. Additionally, based on the preferences of the decision-maker, it can limit compensatory effects by considering veto thresholds.

1) Handling qualitative and ordinal criteria scores with the outranking approach

If the information that must be handled at the level of a given non-elementary criteria is qualitative and/or ordinal, the aggregation should be done through the outranking approach. We now explain how it can be done.

The following concepts are added to the notation:

- Let $EL_p \subseteq EL$ be the set of indices of all the criteria which are pseudo-criteria.
- Let $EL_i \subseteq EL$ be the set of indices of all the criteria which are interval numbers.

Interval numbers also allow dealing with ill-defined scores. They are defined using an upper and a lower bound that identify the range where an imprecise quantity is believed to be [55]. Thus, a quantity i believed to be in the range i^- (lower bound) and i^+ (upper bound) can be denoted by the interval number $i = [i^-, i^+]$. We will use **boldface** to denote an interval number. Interval numbers extend real numbers in the sense that any real number r can be defined as an interval number as $r = [r^-, r^+]$, which is known as a degenerate interval number. On the other hand, some mathematical properties have been developed in the context of interval numbers; these properties allow to address an important question in the context of interval numbers: how to determine if an interval number is not lower than another, even when their ranges intersect. Fernández *et al.* [56] used the following function to define the possibility that the interval number i is not lower than j :

$$p(i \geq j) = \begin{cases} 1 & \text{if } p_{ij} > 1, \\ 0 & \text{if } p_{ij} < 0, \\ p_{ij} & \text{otherwise.} \end{cases} \quad (1)$$

Where $p_{ij} = \frac{i^+ - j^-}{(i^+ - i^-) + (j^+ - j^-)}$.

Furthermore, if $i^+ = i^-$ and $j^+ = j^-$, then

$$p(i \geq j) = \begin{cases} 1 & \text{if } i^- \geq j^-, \\ 0 & \text{otherwise.} \end{cases}$$

Fernández *et al.* [29] suggest employing a partial outranking relation. $S_j \subset A \times A$ associated to each criterion $g_j \in EL$ to denote that “a is at least as good as b from the perspective of g_j ” ($a, b \in A \times A$), and a degree of the credibility that $aS_j b$ is fulfilled, $\delta_j(a, b)$. Calculating $\delta_j(a, b)$ depends on g_j being a pseudo-criterion or an interval number. Thus, when g_j is an interval number, i.e. $g_j \in EL_i$:

$$\delta_j(a, b) = P(g_j(a) \geq g_j(b)).$$

And when $g_j \in EL_p$:

$$\delta_j(a, b) = \begin{cases} 1 & \text{if } g_j(b) - g_j(a) \geq p_j, \\ \frac{g_j(a) - g_j(b) + p_j}{p_j - q_j} & \text{if } g_j(b) - p_j \leq g_j(a) < g_j(b) - q_j, \\ 0 & \text{if } g_j(a) - g_j(b) \geq -q_j. \end{cases}$$

where p_j and q_j represent the preference and indifference thresholds for criterion g_j . The former builds a range where the DM has a strict preference for one of the alternatives; the latter builds a range where the DM is indifferent given that the performances of the alternatives are similar enough.

Now, the credibility degree of $aS_h b$ when $h \notin EL$, denoted by $\sigma_h(a, b)$, can be recursively calculated by aggregating all the $\sigma_j(a, b)$ values for $g_j \in G_h$ (note that $\sigma_j(a, b) = \delta_j(a, b)$ when $g_j \in EL$). Such an aggregation requires a criterion weight (considered as a coefficient of relative importance) to be defined for each $g_j \in G_h$; let us denote by k_{jh} this weight. Other parameters associated to $g_j \in G_h$ can also be defined; these parameters are (i) a veto threshold¹, v_{jh} (rejecting any credibility of $aS_h b$ if $g_j(b)$ exceeds $g_j(a)$ by an amount greater than v_{jh}); (ii) a value to be subtracted from k_{jh} to model the mutual weakening effect between g_j and g_i in G_h , $k_{ij}^{W,h}$; (iii) a value to be added to k_{jh} to model the mutual strengthening effect between g_j and g_i in G_h , $k_{ij}^{S,h}$; (iv) a value to be subtracted from k_{jh} to take into account the antagonistic effect between g_j and g_i in G_h , $k_{ij}^{A,h}$. Parameters (ii)-(iv) allow to model interactions between criteria and, together with the criteria weights k_{jh} , they allow to calculate a γ -Concordance index related to S_h , $c_h(a, b, \gamma)$. This value represents the support of the coalition of criteria in concordance with $aS_h b$, where γ is the highest credibility value of these criteria supporting the assertion. The credibility degree of the statement “the considered γ -concordance coalition is sufficiently strong” is then calculated as $P(c_h(a, b, \gamma) \geq \lambda_h)$, where λ_h is a threshold set

¹ Other veto thresholds, v_{jr} , can also be defined for criteria g_j that do not immediately descend from g_r , that is, $j \in D(r)$. These must fulfill that $v_{jr} \leq v_{jr}$ for $g_j \in G_h$.

by the DM for establishing what a strong majority is. The reader is referred to [56] to see the details in the calculation of $c_h(a, b, \gamma)$, as well as some constraints that the parameters mentioned above must fulfill.

Regarding the veto power that $g_j \in G_h$ may exert to $aS_h b$, if $j \in EL_l$ or if v_{jh} is an interval number, $d_{jh}(a, b)$ is calculated by $P(g_j(a) \geq g_j(b) + v_{jh})$; if $g_j \in EL_p$ and v_{jh} is a well-defined value, $d_{jh}(a, b)$ is calculated by:

$$d_{jh}(a, b) = \begin{cases} 1 & \text{if } g_j(b) - g_j(a) \geq v_{jh}, \\ \frac{g_j(b) - g_j(a) - u_{jh}}{v_{jh} - u_{jh}} & \text{if } u_{jh} < g_j(b) - g_j(a) < v_{jh}, \\ 0 & \text{if } g_j(b) - g_j(a) \leq u_{jh}. \end{cases}$$

The credibility index of “ a is at least as good as b with respect to g_h ” is then defined for a given γ as $\sigma_{h\gamma} = \min\{\gamma, P(c_h(a, b, \gamma) \geq \lambda_h), 1 - \max_{j \in D(h)} d_{jh}(a, b)\}$ and, comprehensively, as $\sigma_h(a, b) = \max\{\sigma_{h\gamma} \mid \gamma \in D(h)\}$ with $\gamma \in \Gamma$ and $\Gamma = \{\sigma_j(a, b) > 0; g_j \in G_h\}$. Note that this form of calculating $\sigma_h(a, b)$ assumes that at least one of the following conditions is fulfilled:

- i) At least one criterion in G_h is ordinal or qualitative.
- ii) There is interaction between some criteria in G_h .
- iii) The preferences of the DM over the criteria in G_h are non-compensatory.

Now, let β be a real number in $(0.5, 1]$ considered as a credibility threshold to establish the flowing crisp preference relations:

Hierarchical outranking: $aS(\beta)b \Leftrightarrow \sigma_h(a, b) \geq \beta$.

Hierarchical preference: $aP(\beta)b \Leftrightarrow \sigma_h(a, b) \geq \beta$ and $\sigma_h(b, a) < \beta$.

Hierarchical indifference: $aI(\beta)b \Leftrightarrow \sigma_h(a, b) \geq \beta$ and $\sigma_h(b, a) \geq \beta$.

Hierarchical incomparability: $aR(\beta)b \Leftrightarrow \sigma_h(a, b) < \beta$ and $\sigma_h(b, a) < \beta$.

Finally, it is said that a dominates b if $g_j(a) \geq g_j(b)$ for all $g_j \in EL_p$ and $P(g_j(a) \geq g_j(b)) \geq 0.5$ for all $g_j \in EL_l$.

2) An interval value function to aggregate cardinal immediate descending criteria

On the other hand, if the immediate descendants of a given non-elementary criterion g_h fulfill the following characteristics:

- i) are elementary criteria measured on a cardinal scale,
- ii) preference intensity is important on them,
- iii) compensation between their scores is possibly allowed, and
- iv) there is no interaction between them,

then a value function $\sigma_h(a, b)$ should be used to assess the credibility of “ a is at least as good as b ”. Now $\sigma_h(a, b)$ can be exploited by the procedure described in the previous section to assess $\sigma_r(a, b)$ such that $g_h \in G_r$.

Value functions constitute a traditional paradigm to address multi-criteria decision problems; they are of special

significance in the presence of cardinal information. A value function maps the objective space to the expected reward.

One of the most popular forms of value functions, $U(a)$, is the normalized weighted sum, which is defined as follows:

$$U(a) = \sum k_{ih} (g_i(a) - g_i^{\min}) / (g_i^{\max} - g_i^{\min})$$

where g_i^{\max} (resp. g_i^{\min}) is the maximum (resp. minimum) value attainable by alternatives on criterion g_i (or an estimate of it), and k_{ih} is the weight of criterion i . Each weight expresses the importance of its related criterion.

A preference function defined this way models fully compensatory and transitive preferences. Nevertheless, it can be extended to handle partially compensatory preferences and veto effects as suggested by Fernández et al [57]. Let v_i be the veto threshold associated to criterion g_i , and S be the binary reflexive preference relation defined below:

$$aSb \Leftrightarrow U(a) \geq U(b) \wedge g_i(b) - g_i(a) < v_i \text{ for all } g_i.$$

The presence of veto conditions converts S into a non-transitive relation. Compensation is possible within the ranges allowed by the veto thresholds.

Imprecisions in setting the weights in U and the veto thresholds are, to a great extent, unavoidable. Sometimes, the DM should handle imprecisions in criteria performance levels and parameters $g_{i\min}$ and $g_{i\max}$. Here, following [57], we will use interval numbers to model such imprecisions:

$$U(a) = \sum w_i (g_i(a) - g_i^{\min}) / (g_i^{\max} - g_i^{\min})$$

The outranking relation is:

$$aSb \Leftrightarrow U(a) \geq U(b) \wedge \text{there is no veto}$$

The credibility degree of the assertion “ a is at least as good as b ” is calculated as the degree of truth of a conjunction of two predicates. So, using $\sigma_h(a, b)$ to denote this credibility degree and with $g_i \in G_h$, we have:

$$\sigma_h(a, b) = \text{Min} \{P(U(a) \geq U(b)), [1 - \text{Poss}(g_i(b) - g_i(a) \geq v_i)]\}$$

C. SORTING ALTERNATIVES USING THE HI-INTERCLASS-nC METHOD

Fernández et al. [56] also presented a novel method to assign alternatives to preferentially ordered classes called *HI-INTERCLASS-nC*. Such assignments can be performed at the level of any non-elementary criterion g_h . Let C^h be a finite set of classes $C^h = \{C_1, \dots, C_{ki}, \dots, C_M\}^h$, $M \geq 2$, ordered with increasing preference concerning g_h . Let $R_k = \{r_{kj}, j = 1, \dots, \text{card}(R_k)\}$ denote the subset of reference alternatives introduced to characterize C_k , $k = 1, \dots, M$. Let $\{r_0, R_1, \dots, R_M, r_{M+1}\}$ be the set of all reference alternatives, where r_0 and r_{M+1} are the anti-ideal and the ideal alternatives. See [56] for the conditions that should be fulfilled by the reference set.

The credibility indices between alternative a and the class C_k are defined as:

$$\sigma_h(\{a\}, R_k) = \max_{j=1, \dots, \text{card}(R_k)} \{\sigma_h(a, r_{kj})\}$$

$$\sigma_h(R_k, \{a\}) = \max_{j=1, \dots, \text{card}(R_k)} \{\sigma_h(r_{kj}, a)\}.$$

Therefore, the hierarchical categorical crisp outranking relations are defined as:

- a) $aS_h(\beta)R_k \Leftrightarrow \sigma_h(\{a\}, R_k) \geq \beta$;
- b) $R_k S_h(\beta)a \Leftrightarrow \sigma_h(R_k, \{a\}) \geq \beta$.

The selection function is defined as $i_h(\{a\}, R_k) = \min\{\sigma_h(\{a\}, R_k), \sigma_h(R_k, \{a\})\}$.

Similarly to ELECTRE TRI-nC, to suggest assignments, the *HI-INTERCLASS-nC* uses two joint rules, namely the descending rule and the ascending rule, which should be employed conjointly. Each of these rules selects only one class for a potential assignment of an alternative.

Descending assignment rule:

Set β and λ . Define the set of classes C^h and the representative subsets of alternatives $\{r_0, R_1, \dots, R_M, r_{M+1}\}$.

- i. Compare a to R_k for $k = M, \dots, 0$, until the first value, k , such that $aS_h(\beta)R_k$.
- ii. For $k = M$, select C_M as a possible category to assign alternative a .
- iii. For $0 < k < M$, if $i_h(\{a\}, R_k) \geq i_h(\{a\}, R_{k+1})$, then select C_k as a possible category to assign a ; otherwise, select C_{k+1} .
- iv. For $k = 0$, select C_1 as a possible category to assign a .

Ascending assignment rule:

Set β and λ . Define the set of classes C^h and the representative subsets of alternatives $\{r_0, R_1, \dots, R_M, r_{M+1}\}$.

- i. Compare a to R_k for $k = 1, \dots, M+1$, until the first value, k , such that $R_k S_h(\beta)a$.
- ii. For $k = 1$, select C_1 as a possible category to assign alternative a .
- iii. For $1 < k < M+1$, if $i_h(\{a\}, R_k) \geq i_h(\{a\}, R_{k-1})$, then select C_k as a possible category to assign a ; otherwise, select C_{k-1} .
- iv. For $k = M+1$, select C_M as possible category to assign a .

D. CHARACTERIZING THE BEST COMPROMISE PORTFOLIO

The intricacy of the problems outlined in Section II renders it impractical for exhaustive optimization methods to determine the best portfolio. Therefore, resorting to evolutionary algorithms seems plausible to tackle the problem. However, the many-objective nature inherent in portfolios (as depicted in Fig. 2) causes evolutionary algorithms to generate numerous non-dominated Pareto optimal solutions, which can be counterproductive for decision support. Hence, we present a novel approach to leverage the preferences of the decision-maker, modeled by the hierarchical interval outranking approach, to exert selective pressure towards the so-called region of interest within the Pareto front. This selective pressure aims to yield a more focused set of recommended solutions.

Let Ω be the set of feasible portfolios and A a given subset of portfolios (e.g., the population of an evolutionary

algorithm). Following recommendations from Balderas et al. [18], we consider that the best compromise portfolio (in terms of the DM's preferences) within A must be a feasible portfolio a^* such that: i) there is not $b \in \Omega$ that is preferred to a^* (see the definition of hierarchical preference above), and ii) the number of portfolios b for which $a^* S_0 b$ holds is high enough. Measuring the credibility degree that " a is preferred to b ", $\theta(a, b)$, as the conjunction of " a is at least as good as b " and " b is not at least as good as a " in terms of the hierarchical interval outranking approach and assuming that $\sigma(b, a) = 0$ when a dominates b , we have $\theta(a, b) = \sigma(a, b) \wedge (1 - \sigma(b, a))$. Therefore, the best compromise portfolio in A is defined by maximizing the truth degree that a is preferred to all $b \in A$, denoted by $\Theta(a, A)$ and calculated by:

$$\Theta(a, A) = \forall b_i \in A: \theta(a, b_i) \Leftrightarrow \theta(a, b_1) \wedge \theta(a, b_1) \wedge \dots \quad (2)$$

E. SELECTING THE BEST COMPROMISE PORTFOLIO

We will now outline our approach for selecting the best portfolio concerning the DM's preferences as expressed in Eq. (7). Our proposal relies on a canonical genetic algorithm, with the initial population being augmented with specific knowledge pertaining to the problem. Through preliminary experiments, we observed a substantial enhancement in the algorithm's performance by incorporating this knowledge into the search procedure. The primary aim of this genetic algorithm is to identify the region of interest within the Pareto front.

1) Components of the search procedure

We describe here the input and output required and generated by the proposal.

Input data

The input data for the search procedure must be provided for both project and portfolio levels. For both levels it is necessary to specify the parameters of the hierarchical interval outranking approach. These parameters are:

- A threshold for the crisp outranking relations, β . It sets the minimum threshold for determining when one alternative is considered at least as good as another in outranking relations.
- A threshold for defining what a strong majority is λ . It defines the level of agreement that the criteria must fulfill for the superiority of one action over the other to be sufficiently supported.
- The hierarchy of criteria.
- The performance matrix that contains the scores of the projects on the elementary criteria.
- The set of non-elementary criteria $g_h \in \chi/EL$ where the project scores on $g_j \in G_h$ must be aggregated through a value function.
- For each non-elementary criterion $g_h \in \chi/EL$:
 - The criteria weights k_{jh} ($j = 1, 2, \dots, \text{card}(G_h)$); these weights are coefficients of relative importance in the context of the outranking approach, and compensatory factors in the context of value functions.

- The pairs of criteria (g_i, g_j) showing weakening effect and the weight of such an effect $k_{ij}^{W,h}$. This weight quantifies the important of the antagonistic effect, which is vital for managing trade-offs and conflicts within the portfolio.
- The pairs of criteria (g_i, g_j) showing strengthening effect and the weight of such an effect $k_{ij}^{S,h}$.
- The pairs of criteria (g_i, g_j) showing antagonistic effect and the weight of such an effect $k_{ij}^{A,h}$.
- An indifference threshold q_j for each elementary pseudo-criterion $g_j \in G_h$. This threshold determines the level at which differences between project scores on criterion g_j are considered negligible, effectively making them indifferent in terms of impact on the decision-making process.
- A preference threshold p_j for each elementary pseudo-criterion $g_j \in G_h$. This sets the level at which differences between scores on criterion g_j are significant enough for one alternative to be considered preferable over others.
- A (possibly empty) set of veto and pre-veto thresholds v_{jh} and u_{jh} ($j = 1, 2, \dots, \text{card}(G_h)$). These thresholds represent conditions under which a particularly high difference between scores on one criterion can completely override (veto) or significantly influence (pre-veto) the decision-making process about two alternatives, despite other criteria scores.
- For each non-elementary criterion $g_h \in \chi/\text{EL}$, where sorting must be performed:
 - A set of classes $C^h = \{C_1, \dots, C_{k_i}, \dots, C_M\}^h$, $M \geq 2$, ordered with increasing preference.
 - The set of all reference alternatives, $\{r_0, R_1, \dots, R_M, r_{M+1}\}$ used to characterize the classes.

Output of the search procedure

The output of the search procedure is a single (or sufficiently small set of) portfolio(s). The output portfolio represents the best compromise portfolio in the sense that it maximizes the DM's overall satisfaction by fulfilling all the constraints that the portfolio must satisfy; the output portfolio gives priority to the most important criteria considering some relevant thresholds and interactions.

2) A genetic algorithm to select the best compromise portfolio

The canonical version of the genetic algorithm (GA) has been adjusted here to address the project portfolio optimization problem. This choice is strategic, given the GA's

robustness in managing vast and intricate search spaces, crucial for evaluating numerous project combinations and criteria interdependencies in PPS [49]. The GA supports hierarchical decision-making, integrating both cardinal and ordinal data, essential for reflecting varied project information accurately [29], [50], [58]. Its iterative nature, which exploits crossover and mutation, adapts to changes in strategic priorities or project environments, making it indispensable for dynamically optimizing portfolios to align closely with organizational goals and decision-maker preferences [5], [49]. Hereon, we will use the concepts "portfolio", "solution", "individual" and "chromosome" interchangeably.

Solution representation

Given the specific characteristics of the project portfolio selection problem, the genetic algorithm utilizes a straightforward yet powerful representation where the genotype and phenotype are identical. Each chromosome within the genetic algorithm is structured as a binary string, each position of which directly corresponds to a potential solution to the problem. In this binary representation, a '1' in the i th position of the string indicates the inclusion of the i th project in the portfolio, whereas a '0' denotes its exclusion. This direct mapping simplifies the genetic manipulation processes such as crossover and mutation, enhancing the algorithm's efficiency in evaluating and evolving the portfolio configurations.

Initialization scheme

The random initialization of the canonical genetic algorithm has been adapted to consider some context-specific knowledge.

First, since the preferences of the DM have already been modeled, it is relatively straightforward to produce a ranking of the projects; for example, using the so-called net flow score [59]. If $\sigma(a, b)$ is a fuzzy relation on a set A , the net flow score related to $a \in A$ is defined as $\text{NFs}(a) = \sum_{b \in A/\{a\}} [\sigma(a, b) - \sigma(b, a)]$. This ranking of course will present many of the problems described in the introductory sections. However, it can ensure that some aspects required by the DM are fulfilled while defining the best overall projects. Then, by following the paradigm of supporting the best projects, an accumulation of the required budgets is performed until exhausting the monetary resources. Now the supported projects form a portfolio that is introduced as part of the initial population of the genetic algorithm, while the rest of the individuals in that population are randomly created. Experimentally, we noted that the performance of the algorithm is evidently increased when introducing this "seed" into the initial population. For assessing this genetic algorithm (see Section V), we used two hundred individuals.

Fitness function

In Subsection IV.D, we explore the adaptability of the genetic algorithm to the project portfolio selection problem by identifying the best compromise portfolio within a set A of portfolios. This optimal portfolio is defined as the one that maximizes its credibility of being preferred to all other

portfolios in the set, as specified by Equation (2). This fitness function highlights the genetic algorithm's flexibility in adapting to varying decision criteria and complex portfolio configurations.

Parent selection

A binary tournament selection is employed here to determine the parents to be crossed and form the child population. In this approach, each individual in the population is randomly selected to compete against another individual. Following the recommendation of Deb et al. [60], a constraint handling approach is utilized with the following rules:

- i) If both parents are feasible, then choose the one with the highest fitness.
- ii) If only one parent is feasible, choose this one.
- iii) If both parents are infeasible, choose the parent with the lowest constraint violation value.

Crossover operator

The best individual in a tournament is chosen to be crossed with another best individual and produce two offspring individuals. The offspring individuals are created by exploiting the single-point crossover operator. So, the algorithm takes a random value $s \in [1, m]$ (where m is the number of projects and length of the chromosome) that will be the crossover point. Then, from a pair of fitted parents, form one child individual by taking genes from 1 to s of parent 1 and genes from $s + 1$ to m of parent 2 to combine the genetic information from both parents and create the first child. Similarly, the second new child is created with the union of the second part of parent 1 and the first part of parent 2. The crossover operation is performed for each pair of criteria with a given p_cross probability. In the experiments described in Section V, we used $p_cross = 0.8$.

Mutation operator

The mutation operator simply consists of interchanging an allele for its complement. That is, if the randomly selected allele is zero, then it is changed to one and viceversa. The mutation operation is performed for each individual with a given p_mut probability. In the experiments of Section V, we used $p_mut = 0.1$.

Restart of the generational process

The algorithm intends to exploit elitism and reduce randomness effects by restarting its generational process. This process is composed of the initialization scheme, the parent selection method, and crossover and mutation operators. Thus, after evolving the initial solutions during several generations, the best solution is determined for the generational process; this best solution is now considered as a new "seed" for the initial population of the following generational process. The best overall solution is determined as the best solution of the final generational process. We used two hundred individuals per generational process and thirty generational restarts in the experiments in the following section.

V. EXPERIMENTAL DESIGN

In this section, we demonstrate the capability of the proposed approach to tackle the entire complexity of a realistic illustrative example. To achieve this, we revisit the problem of R&D project portfolio selection outlined in Section III. It is crucial to emphasize that, to the best of our knowledge, no published work has comprehensively addressed the entire complexity of this problem.

A. INPUT DATA

We follow the specifications of Subsection IV.E.1 and describe the data used as input for the experiments. As specified in that subsection, first we provide the input data at a project level and, later, at a portfolio level.

1) Project level

- The threshold for the crisp outranking relations is defined as $\beta = 0.75$.
- The strong majority threshold is defined as $\lambda = [0.51, 0.75]$.
- The hierarchy of criteria is given in Fig. 1.
- The project scores for the elementary criteria described in Subsection III.A are randomly created for one thousand projects according to the domains shown in the third column of Table IV.
- Only the project's economic (H_{11}) and scientific (H_{12}) impacts are defined by aggregating their sub-criteria scores through a value function. Note that these sub-criteria are all defined using a cardinal scale.
- The criteria weights are shown in the fourth column of Table IV for all criteria but H_0 .
- As stated in Section III, (h_{214}, h_{217}) and (h_{212}, h_{217}) show weakening effects; the weights reflecting such effects are $k_{214,217}^{W,h_{21}} = [0.04, 0.06]$, and $k_{212,217}^{W,h_{21}} = [0.06, 0.08]$, respectively.
- Also stated in Section III, (h_{21}, h_{23}), (h_{21}, h_{24}) and (h_{23}, h_{24}) show strengthening effects; the weights reflecting such effects are $k_{21,23}^{S,h_2} = [0.02, 0.05]$, $k_{21,24}^{S,h_2} = [0.05, 0.08]$, and $k_{23,24}^{S,h_2} = [0.1, 0.15]$, respectively.
- The pair of criteria (h_{21}, h_{26}) shows an antagonistic effect whose weight is $k_{21,26}^{W,h_2} = [0.05, 0.08]$.
- The indifference thresholds for those elementary criteria defined as pseudo-criteria are shown in column five, while the preference thresholds are shown in column six of Table IV.
- The criteria exerting veto power regarding their immediate ascending criterion are shown in column seven of Table IV.
- According to the discussion in Section III, each project will be assigned to one of three classes: Bad (C_1), Average (C_2), and Good (C_3) regarding each of four non-elementary criteria, H_0, H_1, H_2 , and H_{12} .
- Each class will have one characteristic alternative according to Table V.

TABLE IV

PROBLEM INFORMATION AT PROJECT LEVEL

Criterion	Not.	Domain	w_j	q_j	p_j	v_{jh}
Overall quality	H_0					
Project impact	H_1		[0.25, 0.4]			
Economic impact	H_{11}		[0.2, 0.4]			
Number of patents to be generated	h_{111}	[0, 4]	[0.3, 0.45]	-	-	[2, 3]
Number of innovative processes to be generated	h_{112}	[0, 4]	[0.125, 0.35]	-	-	[2, 3]
Number of prototypes to be generated	h_{113}	[0, 4]	[0.25, 0.4]	-	-	[2, 3]
Scientific impact	H_{12}		[0.25, 0.45]			
Number of papers to be published by first quartile JCR journals	h_{121}	[0, 10]	[0.35, 0.45]	-	-	[3, 5]
Number of papers to be published by other JCR journals	h_{122}	[0, 10]	[0.3, 0.4]	-	-	[3, 5]
Number of papers to be contributed to international conferences	h_{123}	[0, 10]	[0.2, 0.25]	-	-	[3, 5]
Development of human resources	H_{13}		[0.15, 0.3]			
Number of new PhD to be generated by the project	h_{131}	[0, 5]	[0.35, 0.45]	-	-	[2, 3]
Number of post-PhD to be generated by the project	h_{132}	[0, 4]	[0.2, 0.25]	-	-	-
Number of new master graduates to be generated by the project	h_{133}	[0, 8]	[0.3, 0.4]	-	-	[3, 5]
Capacity to make positive synergy with other projects (ordinal)	h_{14}	[1, 5]	[0.1, 0.2]	-	-	-
If the project's deliverables are relevant or not (ordinal)	h_{15}	{0, 1}	[0.15, 0.2]	0	0	-
Probability of success	H_2		[0.3, 0.4]			
Quality of the leader curriculum	H_{21}		[0.2, 0.25]			
Number of relevant awards obtained by the leader	h_{211}	[0, 30]	[0.05, 0.1]	-	-	-
Number of papers published by 3-top rated journals	h_{212}	[0, 50]	[0.15, 0.2]	5	8	-
Number of papers published by JCR first quartile journals	h_{213}	[0, 100]	[0.12, 0.15]	10	15	-
Numbers of papers published by JCR journals	h_{214}	[0, 200]	[0.08, 0.12]	20	31	-
Number of books published by top-rated editorials	h_{215}	[0, 10]	[0.05, 0.1]	1.2	1.8	-
Number of PhD students advised by the leader	h_{216}	[0, 50]	[0.1, 0.15]	5	7.5	-
Number of citations to his/her scientific works	h_{217}	[0, 20000]	[0.15, 0.2]	20	30	-
Number of projects successfully led	h_{218}	[0, 20]	[0.2, 0.3]	2.2	3.3	-
National level of collaboration (ordinal)	h_{219}	[1, 5]	[0.01, 0.05]	0.4	0.6	-
International level of collaboration (ordinal)	h_{2110}	[1, 5]	[0.02, 0.08]	0.4	0.6	-
Likelihood of meeting the deadline (ordinal)	h_{22}	[1, 5]	[0.1, 0.2]	-	-	[2, 3]
Difficulty of the research problem (ordinal & to minimize)	h_{23}	[1, 5]	[0.15, 0.25]	-	-	-
Strength of the research collaborator group (ordinal)	h_{24}	[1, 5]	[0.15, 0.2]	-	-	-
Appropriateness of the institutional environment (ordinal)	h_{25}	[1, 5]	[0.05, 0.15]	-	-	[2, 3]
Quality of the research design (ordinal)	h_{26}	[1, 5]	[0.15, 0.2]	-	-	[2, 3]
Cost of the project (dollars)	h_3	[100 000, 400 000]	[0.2, 0.3]	-	-	[46 000, 68 000]

TABLE V

CRITERIA SCORES OF THE CHARACTERISTIC ALTERNATIVES USED FOR SORTING.

Criterion	r_0	R_1	R_2	R_3	r_4
h_{111}	[0, 0]	[0, 1]	[1, 2]	[2, 3]	[4, 4]
h_{112}	[0, 0]	[0, 1]	[1, 2]	[2, 3]	[4, 4]
h_{113}	[0, 0]	[0, 1]	[1, 2]	[2, 3]	[4, 4]

h_{121}	[1, 1]	[1, 2]	[4, 6]	[7, 8]	[10, 10]
h_{122}	[2, 2]	[3, 4]	[5, 6]	[8, 9]	[10, 10]
h_{123}	[1, 1]	[2, 3]	[4, 5]	[7, 8]	[10, 10]
h_{131}	[0, 0]	[0, 1]	[2, 3]	[3, 4]	[5, 5]
h_{132}	[0, 0]	[0, 1]	[1, 2]	[2, 3]	[4, 4]
h_{133}	[1, 1]	[1, 2]	[3, 4]	[4, 7]	[8, 8]
h_{14}	[1, 1]	[1, 2]	[2, 3]	[3, 4]	[5, 5]
h_{15}	0	0	1	1	1
h_{211}	[1, 1]	[6, 7]	[12, 18]	[18, 27]	[30, 30]
h_{212}	0	5	19	36	50
h_{213}	2	11	36	62	100
h_{214}	10	26	72	135	200
h_{215}	0	1	3	6	10
h_{216}	1	8	15	26	50
h_{217}	20	1250	4250	15250	20000
h_{218}	0	5	10	15	20
h_{219}	1	2	3	4	5
h_{2110}	1	2	3	4	5
h_{22}	[1, 1]	[1, 2]	[2, 3]	[3, 4]	[5, 5]
h_{23}	[5, 5]	[3, 4]	[2, 3]	[1, 2]	[1, 1]
h_{24}	[1, 1]	[1, 2]	[2, 3]	[3, 4]	[5, 5]
h_{25}	[1, 1]	[1, 2]	[2, 3]	[3, 4]	[5, 5]
h_{26}	[1, 1]	[0, 1]	[2, 3]	[3, 4]	[5, 5]
h_3	[400 000, 400 000]	[370 000, 380 000]	[250 000, 260 000]	[195 000, 210 000]	[180 000, 180 000]

2) Portfolio level

The specific information used in the experiments is as follows:

- The threshold for the crisp outranking relations is defined as $\beta = 0.75$.
- The strong majority threshold is defined as $\lambda = [0.51, 0.75]$.
- The hierarchy of criteria is given in Fig. 2.
- The criteria scores of each portfolio are calculated from the portfolio's supported projects according to Subsection III.A.
- At this level, no criteria score is aggregated through a value function.
- The criteria weights are shown in the fourth column of Table VI for all criteria but G_0 .
- No criteria pair shows interaction effect.
- The indifference thresholds for those elementary criteria defined as pseudo-criteria are shown in column five, while the preference thresholds are shown in column six of Table VI.
- The criteria exerting veto power regarding their immediate ascending criterion are shown in column seven of Table VI.

TABLE VI

PROBLEM INFORMATION AT PORTFOLIO LEVEL

Criterion	Not.	Weight	q_j	p_j	v_{jh}
Overall quality	G_0				
Portfolio impact	G_1	[0.4, 0.6]			

Economic impact	G_{11}	[0.2, 0.4]			
Number of patents to be generated	g_{111}	[0.2, 0.3]	-	-	[25, 35]
Number of innovative processes to be generated	g_{112}	[0.5, 0.6]	-	-	[25, 35]
Number of prototypes to be generated	g_{113}	[0.2, 0.3]	-	-	[25, 35]
Scientific impact	G_{12}	[0.25, 0.45]			
Number of papers to be published by first quartile JCR journals	g_{121}	[0.6, 0.6]	-	-	[80, 115]
Number of papers to be published by other JCR journals	g_{122}	[0.25, 0.3]	-	-	[80, 115]
Number of papers to be contributed to international conferences	g_{123}	[0.1, 0.15]	-	-	[80, 115]
Development of human resources	G_{13}	[0.15, 0.3]			
Number of new PhD to be generated by the project	g_{131}	[0.45, 0.6]	-	-	[30, 45]
Number of post- PhD to be generated by the project	g_{132}	[0.15, 0.3]	-	-	-
Number of new master graduates to be generated by the project	g_{133}	[0.1, 0.3]	-	-	-
Number of relevant deliverables	g_{14}	[0.1, 0.2]	0	0	[15, 20]
DM's conformity with the portfolio	G_2	[0.35, 0.55]			
Number of projects with high scientific impact	g_{21}	[0.2, 0.4]	0	0	-
Total cost incurred by the portfolio	g_{22}	[0.2, 0.4]	-	-	[1 000 0000, 1 500 0000]
Number of supported projects with a quality inferior to that of non-supported projects	g_{23}	[0.4, 0.6]	-	-	-

B. RESULTS AND DISCUSSION

The results of the experiments performed in this work can be accessed in the supplementary material provided [here](#). The criteria scores of the thousand simulated projects are shown in the supplementary material. This material also shows the class to which each project was assigned regarding some non-elementary criteria of interest.

Subsection III.B mentions that the supported projects must be at least Acceptable regarding their overall quality (H_0) and their impact (H_1), and that they must have a Good probability of success (H_2). 189 projects fulfill these constraints as shown in the online supplementary material.

An additional constraint, now at portfolio level, considered by the genetic algorithm during optimization is that the required budget of the portfolio must not be greater than \$35,000,000. Considering this amount, a ranking is built using the net flow score according to the description of the *Initialization scheme* in Subsection IV.E.2. This ranking of projects is used as a “seed” for the initial population of the algorithm and is considered as a benchmark for the results of the proposal. Another benchmark portfolio was built by supporting the projects with the best overall quality until exhausting resources (if two projects are equal regarding their

quality, we chose the cheapest one). Note that these benchmarks form part of a paradigm when building project portfolios. The benchmark portfolios as well as the portfolio recommended by the proposal are shown in the online supplementary material. Table VII shows the criteria scores for these portfolios.

TABLE VII
PERFORMANCE OF THE BENCHMARK AND PROPOSED PORTFOLIOS

Criterion	Net flow score (y)	Best overall quality (z)	Our proposal (x)
g_{111}	[152, 237]	[176, 280]	[166, 266]
g_{112}	[149, 237]	[167, 269]	[204, 314]
g_{113}	[130, 217]	[153, 257]	[143, 243]
g_{121}	[418, 647]	[494, 766]	[545, 838]
g_{122}	[473, 709]	[593, 891]	[593, 890]
g_{123}	[453, 697]	[530, 816]	[554, 846]
g_{131}	[166, 272]	[223, 359]	[225, 358]
g_{132}	[132, 211]	[144, 236]	[154, 246]
g_{133}	[333, 536]	[406, 648]	[417, 664]
g_{14}	78	74	69
g_{21}	19	25	38
$g_{22}(M)$	[2.3, 3.5]	[2.3, 3.5]	[2.3, 3.5]
g_{23}	[-88, -88]	[0, 0]	[0, 0]

Except for g_{14} (which has the lowest weight in its corresponding non-elementary criterion), the proposed portfolio dominates the portfolio built by using the net flow score. On the other hand, both the portfolio built considering the projects that were assigned to the best overall category and the proposed portfolio provide more competitive scores throughout the criteria; however, taking into consideration the preferences expressed by the DM, the proposed portfolio is superior as shown below.

Assessing the credibility of outranking between the benchmark and proposed portfolios for the different non-elementary criteria, we obtain the results shown in Table VIII.

TABLE VIII
CREDIBILITY DEGREES OF THE OUTRANKING RELATION BETWEEN SOLUTIONS

Criterion	$\sigma(x, y)/\sigma(y, x)$	$\sigma(x, z)/\sigma(z, x)$
G_0	0.75/0.2	0.58/0.39
G_1	0.75/0.2	0.58/0.39
G_2	0.95/0	0.94/0.5
G_{11}	0.75/0	0.58/0.31
G_{12}	0.8/0	0.61/0.39
G_{13}	0.74/0	0.51/0

Note that if a marginal asymmetric preference relation is defined on each criterion with a threshold $\beta = 0.51$, we have “ x is preferred to y ” and “ x is preferred to z ” for all criteria in Table VIII.

VI. CONCLUSIONS

The proposed approach allowed detailed project evaluations consistent with strategic goals and reflecting decision-maker's preferences for individual projects, as well as the whole portfolio. Also, with the addition of both

conformity criteria and conformity constraints, the portfolios will not just meet traditional performance metrics but also satisfy broader qualitative organizational objectives vital in stakeholder buy-in and eventual successful implementation of projects.

The proposal uses a dual assessment approach where both individual projects and overall portfolio impacts are assessed, which is not present in traditional PPS methods. This dual assessment ensures a more complete analysis, as the synergies of projects are considered, and overall optimal performance of the portfolio is not compromised by leaving out high-potential projects. It resolves interrelated and differing importance of decision criteria, incorporating well-known methodologies such as the outranking approach, functional paradigms, and evolutionary algorithms within a hierarchical decision-making framework to enhance clarity and efficacy.

Extensive experiments in the context of R&D proposals demonstrated the method's ability to consider hundreds of projects, constructing portfolios with zero project quality violations and achieving positive impacts on other critical objectives. The method optimizes project status information at various levels, such as overall quality, probability of success, and individual project impact. Results surpass benchmarks that support the best projects directly, indicating the effectiveness of the proposed methodology in addressing this complex project portfolio selection problem comprehensively.

Future research directions include evaluations in real scenarios with sophisticated optimization techniques, scalability studies, and robustness assessments. Additionally, exploring indirect elicitation procedures to define parameter values more intuitively is considered a necessary complement to this work.

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