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A clustering-based review on project portfolio optimization methods

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Abstract

Project portfolio management and optimization constitutes a critical activity for organizations in different industrial sectors and business. The scientific literature in this subject is extremely vast, which makes it difficult to understand the connections among the existing approaches and perspectives. This paper provides a clustering map of the existing work on the subject, thus identifying the main trends and approaches from different scientific communities. After analyzing each of the identified clusters, the paper provides insights and emerging trends that can be useful both for researchers and practitioners in the area.

Keywords: project portfolio management; optimization; fuzzy logic; simulation

1. Introduction

A *project portfolio* is a set of projects, and the relationship among them, which an organization carries out during a given period of time (Gareis, 2002). Project portfolio management (PPM) intends to maximize the contribution of projects to the overall welfare and success of the enterprise (Levine, 1999). According to the Pulse of the Profession reports by the Project Management Institute (https://www.pmi.org/), the change in organizations' priorities is the main cause of most project failures. These derailed projects can be caused by a poor portfolio management methodology. According to the same institute, organizations with an efficient portfolio management increased the average number of projects meeting (or exceeding) their expected return-on-investment

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by nearly 30%. These reports support the logical conclusion that an effective management of the firm's project portfolio is critical for the success of any modern organization. However, the resources of any organization are limited, which impose constraints on the number and type of projects a given portfolio can contain. For this reason, and as pointed out by Cooper et al. (2000), portfolio managers must handle them through a dynamic decision process, whereby (i) a business's list of active projects is constantly updated and revised; (ii) new projects are evaluated, selected, and prioritized; (iii) existing projects may be accelerated, canceled, or deprioritized; and (iv) resources are allocated and reallocated to the active projects. Due to the aforementioned resource limitations, optimization methodologies are needed to support executives while managing project portfolios, that is, they have to wisely decide which projects have to be fully funded, partially funded, or not funded at all. However, some practitioners claim that the current PM methods used in their companies (which are based on the net present value and strategic scoring criteria) are insufficient due to their design for one-off decisions, absence of solid information, omission of resource constraints, and ignorance of the dependencies among different projects (Cooper et al., 2000). Therefore, new optimization approaches are needed in order to take into account all the relevant factors while supporting dynamic decision making. In addition, the need to add realistic constraints to some portfolio optimization problems has made them become *NP-hard* (Doering et al., 2019). For this reason, metaheuristics are becoming increasingly popular for solving these project portfolio problems (Beasley, 2013). We can find in the literature some surveys on project portfolio optimization (Mohagheghi et al., 2019), and on the more general portfolio optimization problem (Detemple, 2014; Huang, 2017; Soler-Dominguez et al., 2017; Masmoudi and Abdelaziz, 2018; Zhang et al., 2018). However, to the best of our knowledge, no other study has used clustering tools to analyze the publications in the field of project portfolio optimization. Moreover, as it can be seen in Fig. 1, our approach combines filtering, clustering, and practitioner analysis in order to identify the most connected papers from a large number of manuscripts. In particular, the publications processed in our case were 298, which exceeds the ones considered in other reviews.

Hence, the main contributions of our work are as follows: (i) the usage of data analytics tools to perform a clustering analysis on a very large amount of related papers; (ii) the analysis of the resulting clusters, which leads to the identification of higher level relationships; (iii) a discussion on whether the relationships within each cluster are topic-based or journal-based; (iv) a comparison with a text-based clustering analysis, which is based on the abstracts of the same publications; and (v) the identification of the main trends in the subject, as well as of the open research lines. The rest of the paper is structured as follows. Section 2 explains the methodology employed in our study. Section 3 analyzes each of the top 12 clusters identified. Section 4 discusses the main approaches and trends found in each cluster. Finally, Section 5 highlights the main findings of this work and proposes some open challenges for future research.

2. Methodology

This paper focuses on the analysis of the existing literature on project portfolio optimization, trying to identify research clusters and trends. Just by searching the query "project AND portfolio AND optimization" from 2000 until 2019, one can find about 104,000 publications. Therefore, we needed

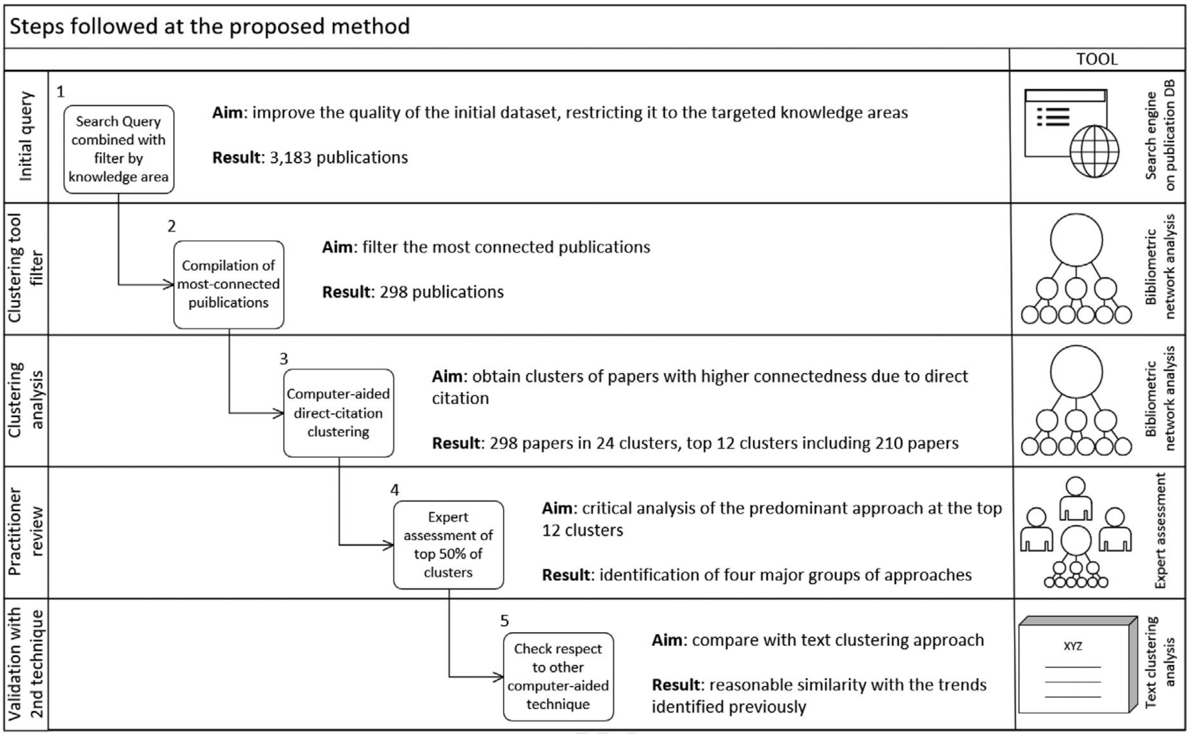

Fig. 1. An overview description of the methodology employed.

additional techniques and tools to filter out the publications that are more likely to be relevant. They have been detailed in Fig. 1. Each step is explained in the following paragraphs.

In Step 1 we have performed the following search query in order to obtain the set of publications to be analyzed: "(project AND portfolio AND optimization) OR (project AND portfolio AND selection) OR (project AND selection AND problem)". The search has been limited to the title and abstract, and only to publications dated 2000 or later. Also, it has been limited exclusively to the following fields of research, which have been considered as the most likely to include relevant publications: *01 Mathematical Sciences*, *08 Information and Computing Systems*, *09 Engineering*, *14 Economics*, and *1503 Business and Management*. The query has returned 3183 results. From this subset, we performed two more filters using the options offered by the clustering tool (Step 2): minimum of five citations and connections with other publications (many of the publications are not connected to others). As a result, we obtained the 298 publications that, according to our criteria, are likely to be more relevant. Then, we performed a clustering analysis on those publications. The clustering analysis has grouped these publications into 24 clusters, which are shown in Fig. 2. After analyzing the papers included in the top 12 clusters, which comprise 70% of the 298 short-listed publications, we were able to identify and analyze some predominant approaches in most of these clusters (Step 3).

This bibliometric analysis has been aided by two tools: (i) a publication database and search engine for extracting the publication and citation data; and (ii) a network analysis tool, developed

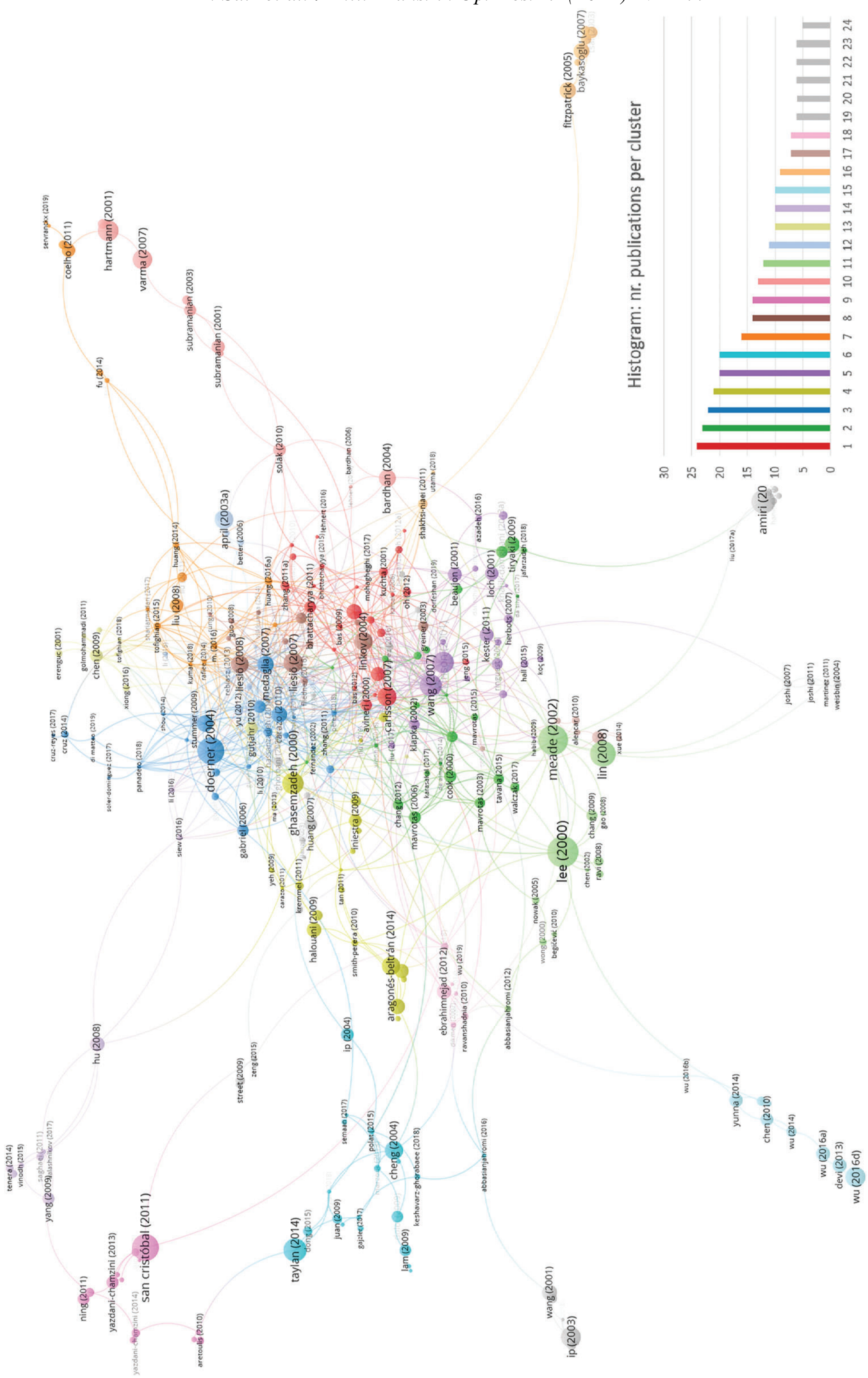

Fig. 2. Cluster map and histogram of the 298 filtered publications.

by the Erasmus University of Rotterdam and the Leiden University. This paper helps to visualize the citation links and clusters associated with project portfolio optimization. In this context, the connections have to be understood as citations, that is, a connection between two publications *A* and *B* exists if publication *A* is citing *B* or vice versa. By checking all those connections, it is possible to identify clusters of publications. The clustering algorithm is mapping the relationship among all the studied publications. When there is a direct citation between two papers, a link is considered between both publications (which are the nodes in the graph). The more links a publication has in common with others, the higher the likelihood that they are included in the same cluster. Specifically, the clustering technique is a variant based on a modularity maximization algorithm. As described in Newman et al. (2004), modularity is the fraction of connections within the clusters minus the expected fraction of connections if the clustering structure were randomly generated. The higher this modularity score is, the higher the difference with a random formation and the higher the likelihood that there is a relevant connection within each cluster. The parametrization of the algorithm features as few additional assumptions as possible, that is, we do not force the algorithm to employ a minimum number of clusters or a minimum amount of papers per cluster. This approach has resulted in 298 papers distributed across 24 clusters. From those, the top 12 clusters include the 210 most connected papers and, for this reason, they have been selected for a further qualitative analysis (Step 3). The interested reader can find more information on this variant of modularity maximization algorithms in Waltman et al. (2010) and Van Eck and Waltman (2017). Additionally, we have compared the results of our analysis with a text-based clustering algorithm, which was applied on the abstracts of the same papers (Step 4). Since the aforementioned methodology is based on the number of citations a paper has already received, very recent articles have less options of being included in any of the citation-based clusters. However, some of these recent papers offer new approaches or promising methodologies and, for this reason, they should be mentioned as promising new contributions. Hence, we have added a special cluster considering those papers published on or after 2018 that are already receiving a considerable number of citations per year.

3. Main clusters identified

3.1. Cluster I: uncertainty, fuzzy modeling, and real options value

This cluster is the most populated, with a total of 24 members. For instance, Kuchta (2001) assumes that the net present value (NPV) of the projects and their resource utilization are available in the form of trapezoidal fuzzy numbers. The possible synergies for each possible pair of projects, in terms of NPV and resource utilization, were also included in the model. However, it was argued that there was no algorithm able to solve the resulting parametric quadratic problem unless the set of parameters is replaced with concrete values (reflecting different possibilistic scenarios). Only that way, a quadratic problem of integer (binary) programming was obtained and solved. It was then applied to a numerical example with four projects and only one limited resource. Lin and Hsieh (2004) implemented a decision support software consisting of three phases. In the first phase (preevaluation) the alternatives, resource constraints, and the evaluation criteria and relative importance of coefficients are defined. In the second phase (preference elicitation) the preferences are transformed into fuzzy numbers, and also the confidence values are set. Finally, the algorithm (based on fuzzy integer linear programming) is applied in order to obtain an optimum portfolio choice. The aim is to maximize an objective function that includes scores of industry attractiveness, competitive advantage, feasibility, and financial potential. However, it also needs to predetermine a choice of confidence and optimism levels. Otherwise, the algorithm would not be able to find a solution.

The most cited publication from this cluster is the one by Carlsson et al. (2007) who model the nonstatistical imprecision of future cash-flow estimates through trapezoidal fuzzy numbers. Then, these authors apply a fuzzy mixed-integer programming model to support the optimal portfolio selection. According to their opinion, traditional methods considering NPV favor short-term projects in certain markets, but there may be better portfolio choices including projects for which the cash flows may be uncertain (typically tied to long-term results and less certain markets). The possibilistic approach through fuzzy numbers and the use of the real options value (ROV) is considered by these authors as a more adequate criterion than using the NPV for these situations. Later, Hassanzadeh et al. (2012) argue that neither the approaches based on a fuzzy NPV nor the ones based on the ROV are optimal. The first approach has the drawback that it ignores project flexibility, that is, the fact that ongoing projects can sometimes be canceled before completion. The second approach commonly assumes that the project revenue follows the geometric Brownian motion, which is seldom the case in real-world applications. To overcome these disadvantages, they developed the fuzzy payoff method, which is then solved via fuzzy integer (binary) programming. They apply it to a 20-project example, with different portfolio proposals depending on different satisfaction degrees and on the decision-maker level of optimism.

Huang and Zhao (2016) mention that paradoxes will appear if fuzzy variables are used to describe project parameter estimates. Therefore, they propose to apply uncertainty theory to develop an optimization method that simultaneously considers the selection of new projects and the adjustment of existing ones. This method starts with the collection of (i) known parameters for the existing projects; and (ii) experts' estimates on the variations in net cash flow, both for the existing and new projects. Then, a deterministic equivalent model is provided, and a genetic algorithm is employed to generate near-optimal solutions. They applied this approach to an example of 10 new plus 10 existing projects, with the algorithm being able to find a near-optimal solution in a few seconds. In a more recent publication, Yan and Ji (2018) concentrate their study on the oil industry, and argue that it is quite difficult to find reliable historical data for a specific project. They obtain the bankruptcy risk and expected cash flows from experts' estimations. Then, they model these variables using Normal probability distributions. This methodology is applied to a numerical example limited to 12 projects, with the goal of finding the optimum portfolio for each level of bankruptcy risk considered as "acceptable" by the investors.

From the previous review, it is possible to conclude that fuzzy modeling and, to a lesser extent, linear programming are the predominant modeling approaches in this cluster. Typically, the size of the tested instances range from 4 to 20 projects, while the most common constraints are related to budget as well as manpower capacity per period and group. It is also noteworthy that some recent publications use genetic algorithms as solving approaches (Huang and Zhao, 2016). One can also note that, despite fuzzy modeling used in combination with exact methods to deal with uncertainty conditions and realistic budget/capacity constraints, this approach seems to be valid just for moderated sizes of the problem. This is mainly due to the limitations of exact methods when dealing with *NP-hard* project portfolio optimization problems (Panadero et al., 2020).

3.2. Cluster II: hybrid methods, outranking, and linear programming

This is the second most populated cluster, with a total of 23 articles. For instance, Cook and Green (2000) employ a mixed-binary linear programming algorithm in order to obtain the better portfolio alternatives for detailed scrutiny by decision makers. To make the problem solvable by the algorithm, each subset of feasible projects within the resource constraint is treated as a single, composite project. Then, each composite project (which constitutes a portfolio alternative) is weighed with respect to the best alternatives through data envelopment analysis (DEA). Mavrotas et al. (2003) apply a two-step procedure. The first step consists in a multiple criteria decision aid (MCDA) that sorts the projects depending on several criteria. As a result, each alternative obtains a score, which is used to screen out the lowest performing alternatives. In the second step, the scores are used as coefficients in the objective function to be maximized via mixed-integer linear programming (MILP). The method uses weights to incorporate the decision maker's preferences. It is applied to a case study based on the evaluation of 113 potential projects in the wind sector. In another case study, Mavrotas et al. (2006) apply the same two-step method. However, they compare two types of MILP algorithms (knapsack formulation vs. a parametric formulation). Based on a case with 123 potential projects and 5 evaluation criteria, they conclude that the parametric formulation was faster and able to reach a near-optimal solution. Mavrotas et al. (2008) introduced a postprocessing algorithm that modifies the scores that come from the MCDA. In more recent works, Mavrotas et al. (2015) combine Monte Carlo simulation and multiobjective integer linear programming (ILP) to obtain the Pareto set of nondominated solutions and the robustness of each solution. The uncertainty about the relevant project parameters is modeled via probability distributions. This approach is applied to a use case with 108 potential projects and 2 evaluation criteria.

Khalili-Damghani et al. (2013) also propose a two-step approach, but with different algorithms and modeling the decision-maker aspiration levels as fuzzy numbers. First, they transform the multiobjective decision-making problem into a biobjective problem using an algorithm that is based on the so-called "technique for order preference by similarity to ideal solution" (TOPSIS). Then, the second algorithm is executed. This algorithm applies fuzzy goal programming in order to propose several solutions for final selection by the decision maker. In Khalili-Damghani and Sadi-Nezhad (2013), the authors add a postprocessing step to evaluate the degree of fitness for the portfolio proposals obtained through the previous methodology. Tavana et al. (2015) integrated DEA as the first decision step, where the projects are evaluated and the inefficient ones are filtered out. Then, a fuzzy TOPSIS follows in order to produce a ranked list of projects. The rank is translated into an augmented score that reflects the proportion of alignment to the organizational objectives. Finally, they apply ILP to maximize the overall augmented score under three constraints: budget limitation, classification constraint (at least one project per activity type), and a specific budgetary limitation associated with each project set. This is applied to an example that results in a set of 30 projects. Walczak and Rutkowska (2017) also apply TOPSIS with fuzzy criteria to a real case of a participatory budget in Poland. The example case involves citizens voting 100 potential candidate projects, from which only a range from 3 to 7 would finally be funded. In this case TOPSIS with fuzzy criteria was applied in order to rank the projects, which allows citizens to get familiar with potentially interesting projects. Karasakal and Aker (2017) combine DEA with the analytic hierarchy process (AHP) method, which is used only for determining priority weight intervals of the criteria. They implemented and compared several DEA-based models with another sorting approach called UTADIS (Utilités ADditives DIScriminantes). Their implementations include a threshold estimation model and an assignment model. More recently, Jafarzadeh et al. (2018) uses a fuzzy version of the quality function deployment method for determining the criteria priority. Then, they use DEA for proposing a maximal portfolio. To the best of our knowledge, this is the only paper in which the authors claim to get a maximal portfolio instead of a project ranking.

Rafiee and Kianfar (2011) propose to use the real-option valuation method (mentioned in several papers from Cluster I), but model uncertainty through probability distributions instead of possibilistic (fuzzy) distributions. Then, a scenario-tree approach is used to reduce scenarios and, finally, the optimal scenarios are chosen by means of linear programming. Barbati et al. (2018) propose a different approach to the multicriteria problem. They consider that there is a high risk of having an unbalanced portfolio if one only considers aggregated/averaged values instead of the ones associated with each individual project. An alternative approach is proposed to enable decision makers to control the distribution of evaluations on different criteria. They call it "interactive multiobjective optimization guided by rules generated with dominance-based rough set approach." The numerical problem is solved through linear programming.

There are two papers that differ significantly from the remaining papers in this set, and resemble more to the predominant approach in cluster number three. Xidonas et al. (2016) do not just rank the projects but they also focus on finding the Pareto-optimal set under stochastic uncertainty conditions. In this case they used an improvement of an iterative trichotomic approach (ITA). ITA was originally thought for integer programming, and separates iteratively the potential projects into three sets depending on their robustness respect to several runs of Monte Carlo simulation. The first set of projects includes the ones that always appear within the Pareto-optimal set during all simulation runs. The third set includes the ones that never appear within the Pareto-optimal set. The rest are in the second set, which is initially the most populated one. The next iterations concentrate only on the second set, but the simulations are run again under narrower uncertainty conditions in order to move more projects to a different set. The novelty in this proposal, with respect to previous ITA implementations, is that it is upgraded to achieve a biobjective optimization including NPV and an energy and environmental corporate responsibility score. The resulting Pareto-optimal set also includes a robustness degree, which helps the decision makers to identify the portfolios that are less likely to become suboptimal if there are deviations from the most likely scenario. Shafi et al. (2017) proposed to apply a multiobjective evolutionary optimization algorithm based on decomposition (MOEA/D), in order to find the Pareto-optimal set. First, an MOEA/D formulation is applied for a single period. For the following periods, the authors consider another formulation that combines the MOEA/D with a reinforced learning algorithm and Monte Carlo simulation. This allows to include the potential effects of changes in available resources or requirements.

Note that this is one of the clusters with a higher number of methodologies and models including DEA, MILP, fuzzy goal programming, Monte Carlo simulation, AHP, interactive multiobjective approach, TOPSIS ranking, UTADIS sorting, etc. In most cases, however, they promote the active interaction with decision makers. Regarding the size of the tested instances—which is about 10 projects on the average, although there are some exceptions in which the authors analyze instances with up to 120 projects. The most employed constraints are based on budget and resources capacities. Many papers in this cluster use Monte Carlo simulation, in combination with other techniques, in order to deal with the uncertainty that arises in most real-life applications. This can be seen as an effective alternative to the use of fuzzy modeling, especially whenever historical data exist, and it can be modeled by means of probability distributions. Hybridization of methodologies seem a necessary step whenever real-life project portfolio problems need to be solved, which explains that this cluster contains so many and methodologically diverse papers.

3.3. Cluster III: efficient frontier, Pareto optimality, and metaheuristics

The most predominant topic in this cluster is the use of metaheuristic algorithms. In addition, many of the papers mention the use of metaheuristics in generating the efficient frontier of portfolios. This *efficient frontier*, also known as nondominated or Pareto-optimal, comprises all the feasible sets of projects that cannot yield higher benefits or consume less resources in at least one objective without showing a worse behavior in some other objective (Stummer and Heidenberger, 2003). The identification of such efficient frontier of portfolios is a critical part of the project portfolio optimization problem. Thus, in one of the first publications from this cluster, Fernandez and Navarro (2002) model the multicriteria decision problem via an additive value function, which has to be maximized. They include potential redundancies among projects and also decision-maker preferences with respect to potential projects. There is an overall budget constraint, as well as a constraint per project category. They consider a fuzzy modeling of the membership degree associated with each project. Based on this model, a near-optimal solution is obtained via an evolutionary algorithm. The proposed method is compared to a heuristic solution in a benchmark including 40 projects, achieving a 18% of improvement in the target function.

Ringuest and Graves (1990) proposed to substitute the classical optimization criteria through the NPV maximization by a multiobjective optimization problem that considers cash flows separately for each period. For solving this problem they propose the use of linear programming, which yields a set of different Pareto-optimal solutions (one of which is always the classical NPV one). This has the advantage of allowing decision makers to choose among different optimal solutions. Stummer and Heidenberger (2003) extended the multicriteria concept to all relevant and resource categories. In their example, there were 6 criteria, 5 periods (resulting in a total of 30 objectives), and 10 projects. They succeed in identifying the Pareto frontier using an ILP method, but also concluded that most multiobjective problems would require the use of metaheuristics when the number of projects is higher. Doerner et al. (2001) proposed the use of an ant colony optimization (ACO) metaheuristic, and compared its performance with the Monte Carlo simulation method and a two-phase heuristic. The test conditions for the comparison were 20 candidate projects, 5 planning periods, 3 benefit categories, and 12 restrictions. After 500 iterations, the ACO algorithm could identify 128 of the 138 efficient portfolios, while Monte Carlo simulation identified only 11 and the heuristic 124. The same authors made a comparison between the Pareto-ACO (P-ACO) and two other metaheuristics: a Pareto-simulated annealing (PSA) and a nondominated sorting genetic algorithm (NSGA) (Doerner et al., 2004). They tested 18 randomly generated instances as well as instances based on real-life data. In their tests, P-ACO outperformed PSA and NSGA. In Doerner et al. (2006), the authors improved the algorithm by means of an initialization procedure based on ILP. The ILP preprocessing raised the amount of efficient portfolios identified in the first two minutes of run time.

Gabriel et al. (2006) integrate multiobjective optimization, Monte Carlo simulation, and the AHP methodology to test a real-life case comprising 84 projects. The cost distribution is modeled through beta or triangular distributions, depending on the project type. Then, several simulation runs are executed using Monte Carlo simulation. The algorithm is designed to optimize four objectives simultaneously: (i) maximization of the AHP-based rank; (ii) minimization of the total number of required project managers; (iii) project manager overallocations; and (iv) overall deviation in the total budget with respect to the predicted one. Following the proposed portfolio with their methodology, all 84 projects are completed in 14 years instead of the actual 17 years in the real case. Gutjahr and Reiter (2010) apply an adaptive Pareto sampling, combined with the evolved NSGA-II as an auxiliary procedure. There are two objective functions: (i) weighted average of economic and strategic gains; and (ii) a risk measure expressed as the expected total overtime cost. The problem incorporates nonlinearity, stochasticity, and mixed-integer decision variables. The method is tested in a real-world case consisting of 12 candidate projects (with 1–3 tasks per project), 20 employees, 20 competencies, and a planning horizon of 24 periods. Medaglia et al. (2007) also apply an algorithm based on the NSGA-II to a project selection problem with partially funded projects, multiple uncertain objectives, project interdependencies, and linearly constrained resources. They compare it to a stochastic parameter space investigation (PSI) method presented in Ringuest et al. (2000), which belongs to cluster V of this study. According to their numerical experiments, the NSGA-II shows to be a fast and robust algorithm, which is able to provide higher quality nondominated solutions.

Carazo et al. (2010) propose a simultaneous combination of project portfolio selection and scheduling, with the aim to optimize several attributes (cash flow, sales, risk, etc.). These authors also consider that there can be potential synergies among projects, as well as time, precedence, and resource constraints. The metaheuristic approach that is applied consist in a combination of tabu search with scatter search. The method, named scatter search for project portfolio selection is compared to another metaheuristic called SPEA2 (Zitzler et al., 2001). Rabbani et al. (2010) also compare their metaheuristic proposal, a multiobjective particle swarm optimization (PSO), to SPEA2. They conclude that their PSO is superior to SPEA2 in different metrics, such as the number of nondominated solutions, quality of solutions, and diversity of solutions. The main goal was to maximize total benefits while keeping total risk and cost as low as possible. Shou and Huang (2010) also proposed a method to solve simultaneously the project portfolio selection and scheduling problems. The problem is formulated as a binary integer programming combined with an iterative multiunit combinatorial auction process. They compared their method to the one by Chen and Askin (2009). Later, Shou et al. (2014) proposed the application of a multiagent evolutionary algorithm (MAEA) to solve scheduling and portfolio selection problems. The MAEA works at two levels. In the upper level, agents in a lattice search for feasible portfolios automatically. Two operators (neighborhood competition and self-learning) are integrated to accelerate the evolution of agents. In the lower level, each agent adopts a priority rule-based heuristic to conduct multiproject scheduling to better utilize the scarce resources. Litvinchev et al. (2010) obtained the Pareto frontier through an MILP formulation that maximizes two objectives: portfolio quality and the number of supported projects. They include a fuzzy modeling for the degree of membership to the set of sufficiently funded projects, in the same way as Fernandez and Navarro (2002). Their algorithm does not include synergies, or resource constraints, making it capable of supporting an instance with up to 25,000 projects in just a few seconds. Also, Litvinchev et al. (2011) included project interdependencies and synergies at activity and project level. Due to these inclusions, the problem becomes significantly more difficult than the one from the previous study, with typically longer computational times.

Fernandez et al. (2013) use a variant of the NSGA-II to work with nonstrictly outranked individuals, instead of with nondominated ones. The method also includes multicriteria preferences that are modeled through a binary fuzzy outranking relation, which express the true value of the predicate "portfolio X is at least as good as portfolio Y." Using the previous outranking model, Cruz-Reyes et al. (2014) upgrade a nonoutranked ACO (NO-ACO) approach. Gutjahr and Froeschl (2013) propose a variable neighborhood search metaheuristic that uses numerical optimization. This numerical step corresponds to the scheduling-and-staffing subproblem. They also integrate Monte Carlo sampling, which is performed every time an objective function evaluation is necessary. Their approach is tested in a real-life case. With the goal of maximizing the NPV under several constraints, such as project preassignments, a minimum and maximum range of supported projects, a maximum level of risk, and a limited budget, Gutjahr and Froeschl (2013) and Panadero et al. (2020) combine Monte Carlo simulation with a VNS (variable neighborhood search) metaheuristic. Their studies conclude that the constraints generated nonlinearities in the relation between the expected NPV and the level of risk, and that the deterministic method yield suboptimal results with respect to the stochastic one. Cruz-Reyes et al. (2017) also confirmed that the incorporation of the decision maker preferences would facilitate the selection process. Their approach is composed of two phases. The first phase uses an NO-ACO algorithm to obtain an approximated Pareto frontier. This set of nondominated solutions is then sorted by decision makers in order to reflect their preferences. The second phase consist in a combination of the NSGA-II algorithm and the THESEUS method. They apply this hybrid approach to several real-world cases, ranging from 4 to 16 objectives. From the previous analysis, one can note that many authors use metaheuristics when they need to deal with multiobjective project portfolio optimization. This is especially the case considering realistic constraints (which make the problem *NP-hard*) and large-scale projects including many stages. Metaheuristics are employed in these cases due to their modeling flexibility as well as to their capacity to solve large-scale and realistic project portfolio problems in short computing times.

3.4. Cluster IV: from analytical hierarchy to analytical network process

The common ground for this cluster is the proposal of the analytical network process (ANP) methodology as an enhancement of the well-known analytical hierarchy process (AHP). This enhancement consists in including the relationships between each pair of decision criteria (Wey and Wu, 2007; Yang et al., 2016a). The pairwise criteria comparison, which is typical both in AHP and ANP, has two inconveniences: (i) potential inconsistencies in the priorities set and (ii) the fact that it is considered unsuitable for cases with a high amount of alternatives to be evaluated (Iniestra and Gutiérrez, 2009). The latter is mainly due to the geometrical increase in pairwise comparisons with respect to the number of alternatives. There are several strategies that may help mitigate the potential inconsistencies. For example, Aragonés-Beltrán et al. (2014) include a consistency check aided through an eigenvalue-based ratio. In García-Melón et al. (2015), the criteria are taken from the corporate strategic objectives stated on the balanced scorecard of the firm. Awasthi and Omrani (2019) proposes to model the decision-maker criteria via the fuzzy Delphi method, which was also proposed by Hong and Ali (2009). This approach is considered as advantageous by the authors due to the possibility of using linguistic terms to support the expert's assessment.

Another common characteristic of the papers in this cluster is the limited number of projects assessed. Only Iniestra and Gutiérrez (2009) evaluate a large amount of projects, up to 74. They are also the only work in this cluster using a ranking methodology in order to prioritize portfolio alternatives instead of individual projects. Likewise, they also discard AHP/ANP for the ranking process, and choose another methodology (ELECTRE-III) that does not have the limitation related to pairwise comparisons. The portfolio proposals are obtained in earlier stages via a genetic algorithm. Then, they are refined through a knee-identification algorithm before the ranking step.

3.5. Cluster V: uncertainty, fuzzy parameters, and integrative selection models

Analyzing the work in this cluster of articles, one common point is that most papers consider the uncertainty caused by (i) fuzzy parameters such as risk and (ii) variables such as cost, benefit, profits, or NPV—since these values cannot be known until the projects are completed. For this reason, these papers use selection models such as mixed-integer programming, multiknapsack models, stochastic dynamic programming, etc. (Basso and Peccati, 2001; Dickinson et al., 2001; Wang and Hwang, 2007).

In addition, most of these papers also share the difficulty that represents the selection of projects. Generally, this selection must be considered from more than one dimension or variable. This is why it is common to observe more integrative models for project selection, where simultaneous variables and flexible parameters are considered. This is the case, for example, of multicriteria decision-making approaches, which allow to take into account both qualitative and quantitative criteria during the project selection stage (Kester et al., 2011). These selection models consider the correlations among projects, their interaction, interdependence, and synergies, thus allowing to improve the decision-making process (Beaujon et al., 2001; Hall et al., 2015).

In some papers of this cluster, it is also possible to identify a trend based on the combination of fuzzy and robust models. Thus, for example, Liu and Liu (2017) converted the credibilistic programming model into its equivalent deterministic programming model. The latter could then be solved using nonlinear mixed-integer programming. This approach was successfully applied to a numerical experiment featuring 16 candidate projects and human resource restrictions related to competences and availability.

3.6. Cluster VI: expanding multicriteria decision making

The common pattern in this cluster is that most authors propose AHP as a tool for multicriteria decision making (Taylan et al., 2014; Leśniak et al., 2018). This is somewhat original, since AHP has usually been employed only in hierarchical decision models. For difficult decision-making challenges, ANP is also suggested as an effective alternative (Cheng and Li, 2004).

The problem lies in choosing the best solution from the point of view of many criteria, and the multicriteria decision making requires the use of methods supporting fuzzy logic (Gajzler and Zima, 2017). Examples of such methods are the fuzzy AHP, the fuzzy TOPSIS (Taylan et al., 2018), the EDAS (Keshavarz-Ghorabaee et al., 2018), the MAUT, or the PROMETHEE (Semaan and Salem, 2017). Branch-and-bound approaches (Ip et al., 2004) and multiple linear regression models (Doloi, 2009) are also used, in the construction and engineering industry, whenever technical attributes need to be evaluated.

In the multicriteria decision-making models presented in this cluster, there exists an intention to incorporate vital qualitative attributes on the selection criteria, thus transforming qualitative data into the equivalent quantitative measures. Selection criteria based on interrelated parameters—such as time, cost, and quality—consider both qualitative and quantitative data including safety, environment sustainability, inefficiency, past performance, commitment and dedication, organizational capability, etc.

3.7. Cluster VII: the resource-constrained project scheduling problem

Most papers in this cluster investigate different alternatives to deal with the resource-constrained project scheduling problem (RCPSP) (Tao and Dong, 2017). Also, some of them analyze how to integrate the RCPSP with the project selection problem (Huang and Zhao, 2014; Tofighian and Naderi, 2015; Shariatmadari et al., 2017). In an effort to combine the RCPSP and the project selection problem, Tofighian and Naderi (2015) propose a P-ACO metaheuristic that uses a colonial procedure, an update of the Pareto front, and a pheromone updating mechanism. Likewise, Huang and Zhao (2014) propose a genetic algorithm where different generations of portfolios are evolved and scheduled through iterative steps of selection, crossover, and mutation. It also includes the consideration of portfolio cost overrun risk due to the uncertainty of the assumed net incomes and investment costs. Shariatmadari et al. (2017) define a specific index to study the problem called integrated resource management, which considers simultaneous project selection and scheduling. All in all, authors of this cluster agree to consider both simultaneous selection and scheduling, as projects have a variety of interdependencies between them (Kumar et al., 2018). In their paper, Coelho and Vanhoucke (2011) define an approach that executes two steps (mode assignment and a single-mode project scheduling) in one run. This approach relies on a single priority list. Tao et al. (2018) introduce a stochastic chance constraint to formulate the RCPSP, and define a metaheuristic framework called SAA/DAAA (where SAA is sampling average approximation and DAAA is discrete artificial algae algorithm) through integrating the SAA with a population-based evolutionary algorithm. Servranckx and Vanhoucke (2019) propose an alternative subgraph in which one alternative execution mode must be selected for each work package. Then, the selected activities in the project structure are scheduled.

3.8. Cluster VIII: hybrid multicriteria decision analysis into robust portfolio modeling

This cluster proposes robust portfolio modeling (RPM) in the presence of multiple evaluation criteria and incomplete information. In the selection of the projects portfolio, multiple evaluation criteria, project interdependencies, and uncertainties about project performance need to be considered. Also, financial and other relevant constraints have to be considered as well (Mild et al., 2015).

Greiner et al. (2003) propose a methodology that allows the decision maker to incorporate qualitative and intangible criteria into the decision-making process. Linkov et al. (2004) include risk assessment and stakeholder participation as crucial concern in their analysis. In the most cited paper from this cluster, Liesiö et al. (2007) develop an RPM methodology based on the principles of preference programming, extending its concepts and algorithms to the portfolio context. It includes a project-specific measure, the core index, which is based on the share of those nondominated portfolios containing a given project. This index separates core projects (fully recommendable to be part of the selected portfolio) from exterior projects (fully recommendable to be discarded from the selected portfolio). This simplifies the task of the decision maker who can then focus on the borderline projects—that is, those not categorized as core or exterior. Liesiö et al. (2008) extend the RPM in order to lead a multiobjective integer (binary) linear programming model with interval-valued objective function coefficients, for which all nondominated solutions are determined by a tailored algorithm. Guo et al. (2008) consider four categories of project interdependencies: outcome, resources, technical, and risk interdependence. Yang et al. (2015) propose a stochastic multiattribute acceptability analysis to solve the multiattribute project portfolio optimization problem. Fliedner and Liesiö (2016) consider a linear-additive portfolio value function with uncertain parameters. This allows to reduce the set of possible realizations by limiting the number of project scores that may simultaneously deviate from their most likely value.

All in all, most papers in this cluster agree in that decision makers can choose better with a hybrid multievaluation criteria method, where quantitative parameters (cost, benefit–cost analysis, etc.) can be combined with qualitative parameters (uncertainty, safety, stakeholders participation, environment impact, ethical and moral principles, sociopolitical and economic impact, etc.).

3.9. Cluster IX: multicriteria decision making in portfolio optimization

More than half of the authors in this cluster use techniques similar to the techniques employed in Cluster IV. However, they aim at optimizing the portfolio just by improving one single process (mainly supplier selection) via AHP or a similar multicriteria decision-making technique. These topics are considered less relevant for this survey, as we focus on project selection. Still, three papers are relevant for project selection. In Read et al. (2017), a hierarchical tree of decision criteria is used to obtain a project ranking, which is then double-checked through a sensitivity analysis based on Monte Carlo simulation. In Cristóbal (2011), a combination of the AHP and VIKOR methods is used to obtain a renewable energy project ranking, which includes a consistency index calculation similar to the one provided in Aragonés-Beltrán et al. (2014). Also, in Yazdani-Chamzini et al. (2013) the same projects described in Cristóbal (2011) are ranked based on a combination of AHP with COPRAS (complex proportional assessment).

3.10. Cluster X: heuristics, metaheuristics optimization, stochastic models, and simulation

Subramanian et al. (2003) model the portfolio problem taking into account the tasks needed for each project as well as the precedence, resource, and demand constraints. They apply two loops of optimization. The first loop is called *sim-opt*, and it consists in a simulation-based optimization framework that uses MILP and a discrete-event system simulation module. The second loop consists of three heuristic steps that combine all the possible timelines (5000 in the example) in order to simulate the NPV probability distribution. Bardhan et al. (2006) propose a portfolio optimization algorithm combined with a nested options model. They also take into account project interdependencies, but only at a high level. Monte Carlo simulation is also applied in order to model the portfolio volatility. Solak et al. (2010) define a multistage stochastic integer model with endogenous uncertainty.

Another interesting item in this cluster is the scheduling problem. Hartmann (2001) applies a genetic algorithm based on a precedence feasible list of activities and a mode assignment, combined with a local search extension, which is used to improve the schedules found by the basic genetic algorithm. Li and Zhang (2013) apply an ACO algorithm for solving the problem. Based on some keywords (e.g., uncertainty, metaheuristics, simulation, etc.), one can see connections between this cluster and the first three ones, as well as with Cluster XII, which will be discussed later.

3.11. Cluster XI: modeling interactions among criteria

This cluster contains three highly cited publications. Meade and Presley (2002) present an ANP-based method that allows for considering important interactions among decision levels and criteria. Lee and Kim (2000) combine ANP with binary goal programming, so that there is a minimum amount of unused resources. Lin and Wu (2008) propose a fuzzy DEMATEL (decision-making trial and evaluation laboratory) method. Their goal is to transform complex interactions among criteria into a visible structural model, thus providing support to decision makers.

3.12. Cluster XII: combining metaheuristics with simulation

The most mentioned topic in this cluster is the combination of metaheuristic algorithms with simulation techniques. Some authors refer to this combination as “simheuristics” (Juan et al., 2018; Chica et al., 2020). In the most cited article from this cluster, April et al. (2003) propose a combination between a metaheuristic optimizer and a Monte Carlo simulation model, enhanced by filtering out potentially bad solutions via the use of a neural network metamodel. This methodology, which is embedded inside the OptFolio commercial software, is further tested and discussed in April et al. (2004) and Better and Glover (2006).

3.13. Special cluster: trending topic articles

As explained before, our clustering approach is based on the number of direct citations received by a paper. Hence, it becomes more difficult for new articles to be included in the previous analysis, despite some of them receiving citations already. To partially avoid this methodological limitation, we have created an *ad hoc* cluster containing those “trending-topic” papers published on or after

2018 that accumulate a relatively high number of citations in such a short period. For instance, Wu et al. (2018) consider both uncertainty and interactions among projects when managing project portfolios in large-scale photovoltaic installations. With the goal of maximizing enterprise's benefits and total installed capacity, they propose a hybrid methodology combining fuzzy multiobjective programming and the NSGA-II metaheuristic algorithm. Ghasemi et al. (2018) perform a risk analysis of project portfolios considering interdependencies among projects as well as cause–effect relationships between risks. For this, a Bayesian network is employed to estimate the probability of portfolio risk. A case study referring a construction company in Iran is employed to illustrate their approach. Also with the goal of dealing with realistic scenarios characterized by uncertainty conditions as well as by interdependencies among projects (e.g., synergies, incompatibilities, and precedence constraints), Pérez et al. (2018) introduce a mathematical model with fuzzy parameters. Their model has been tested in a case study concerning project portfolio selection and planning in a Spanish university. Danesh et al. (2018) offer a recent survey on multicriteria decision-making methods for PPM. In this study, they identify some critical challenges in PPM, which include interdependencies among projects, project monitoring, integration of quantitative and qualitative data, and uncertainty. As these authors conclude: "…the most suitable methodologies for developing a portfolio for one program might not be the best for another. Therefore, finding the most suitable […] technique(s) is a challenging task which requires further investigation." Li et al. (2019) take into account project divisibility and uncertainty conditions in their analysis. To deal with these complexities, they propose a mean–variance mixed-integer model. Their approach also allows to dynamically consider existing projects during the project portfolio selection. In the context of selecting project portfolios for distributed energy generation, Wu et al. (2019) recognize uncertainty in some environmental conditions as the most challenging factor. They present a multicriteria fuzzy model to select project portfolios under several strategic scenarios, which consider both uncertainty and interactions among projects. The NSGA-II metaheuristic is employed to solve the associated optimization problem. Tavana et al. (2019) also acknowledge the challenges introduced by uncertainty conditions, as well as the existence of both quantitative and qualitative criteria. In order to deal with those challenges in IT-related project portfolio selection, they propose a hybrid mathematical programming model which integrates fuzzy methods. The authors illustrate these concepts using a case study from the cyber-security industry. Ma et al. (2020) emphasize the need for considering sustainability concepts in project portfolio selection, among many other objectives. These authors propose a fuzzy logic model to deal with a realistic and multiobjective project portfolio selection under an uncertainty scenario. Also dealing with uncertainty, Panadero et al. (2020) propose a simheuristic algorithm to deal with complex project portfolio selection under uncertainty. These authors combine Monte Carlo simulation with a variable neighborhood search metaheuristic in order to search for the project portfolio configuration that minimizes the expected net present value in a multiperiod horizon. Hoffmann et al. (2020) raise the need for "agile" decision making in IT-related PPM. Based on a case study from the financial services sector, and using an active theory approach, these authors are able to provide a series of recommendations to efficiently manage IT project portfolios with agility. Considering a project portfolio selection and scheduling problem, Dixit and Tiwari (2020) aim at minimizing the risk of achieving low returns. These authors propose a model based on the conditional value at risk measure, which allows to maximize the lowest return in the worst-case scenario.

4. Critical review of the clusters

From the previous cluster analysis, it is possible to identify the following approaches:

1. *Possibilistic approaches based on fuzzy numbers and fuzzy logic:* These approaches appear due to vagueness of certain parameters, such as the future cash flows, the restrictions, or even the decision-maker criteria. They model and handle such indefinition with the help of the fuzzy set theory (Yager and Zadeh, 2012).
2. *Approaches conceived to interact with decision makers:* In these approaches, it is more likely to find interactions with the decision makers. A sound interaction is prioritized over identifying the whole Pareto set of optimal solutions.
3. *Metaheuristic approaches:* These approaches appear due to the limitations of linear programming methods (which use is generalized among the previous approaches). Linear programming methods work well on some problems, but they cannot deal efficiently with more realistic scenarios with a large number of projects, constraints, and nonsmooth objective criteria. Metaheuristics-related papers are likely to provide good results in terms of computational efficiency and solution quality. They aim to identify the efficient frontier of portfolios in conditions that are as closely as possible to the real-life ones.
4. *Multicriteria project ranking methods:* These approaches aim to obtain a project ranking that reflects, as closely as possible, the decision-maker criteria. The most predominant techniques present here are the AHP and the ANP.

The first approach is found to be quite common in Clusters I and V, despite its presence in most of the other clusters as well. The second approach is quite frequent in Clusters II and XI. The third approach is predominant in Clusters III, VII, X, and XII. Finally, the fourth approach appears quite often in Clusters IV, VI, VIII, IX, and XI. The first approach is more present than one would expect in advance. We consider this is due to the fact that there is less historical or quantitative data than in other optimization areas—for example, vehicle routing problems or production scheduling problems. To the best of our knowledge, this approach has not been applied to cases with a large number of projects, which makes us think that it might be more suitable for cases with a reduced amount of candidate projects. The second approach is more focused on the interaction with decision makers. It is also the most likely to include elements from other approaches. However, as it is oriented to decision makers, it has two risks clearly involved: (i) the risk of ignoring several possible optimal portfolios from the Pareto frontier that may be counterintuitive but interesting; and (ii) the risk of ignoring other criteria that may be important for stakeholders other than the decision makers. However, since it takes into account human interactions, it might constitute a good source for ideas on how to better align the interests of all stakeholders.

The third approach is the "go-to" approach when there are many candidate projects involved (more than 100), as well as realistic constraints such as shared resources and scheduling interactions among the projects. This is where we have seen clear advances during the last years and also a notable trend to combine metaheuristics with simulation while considering a larger number of criteria. Finally, the fourth approach has been mainly used in projects where there are no shared resources and topics such as organizational learning are not relevant. From a computing perspective,

Table 1
Highlights of Clusters I to XII

No. of clusters	No. of papers	Predominant approach	Predominant models and solving algorithms	Levels in constraints	Size of instances (no. of projects)
I	24	Fuzzy modeling	Linear programming, mixed-integer linear programming	Portfolio level only (budget, total manpower)	From 4 to 20
II	23	Decision aids	Data envelopment analysis, linear programming, goal programming, and ranking/sorting methods	Portfolio level only (budget, total manpower)	10 (sometimes 120)
III	22	Metaheuristics	Metaheuristics alone or combined with linear programming and/or Monte Carlo simulation	Portfolio and project (activities, skills) level	Up to 500
IV	21	Project ranking	Ranking through analytic network process and analytic hierarchy process	Portfolio level only	10 (sometimes 70)
V	20	Fuzzy modeling	Mathematical programming: mixed-integer programming, linear programming, nonlinear programming	Portfolio level only	10
VI	20	Project ranking	Ranking through analytic network process (ANP) and analytic hierarchy process (AHP)	Portfolio level only	Typically 10 until 30
VII	16	Metaheuristics	Metaheuristics alone or combined with Monte Carlo simulation	Portfolio and project level	100 or more
VIII	14	Project ranking	Improvement of project ranking via preference programming and robust portfolio modeling	Portfolio level only	From 10 to 60
IX	14	Project ranking	Ranking through AHP, VIKOR, and COPRAS	Portfolio level only	10
X	13	Metaheuristics	Metaheuristics alone or combined with linear programming	Portfolio and project level	10 (sometimes 40)
XI	12	Project ranking	Ranking through ANP and fuzzy DEMATEL	Portfolio level only	10
XII	11	Metaheuristics	Metaheuristics combined with Monte Carlo simulation	Portfolio and project level	From 5 to 60

it is a less demanding approach. Here, we have observed a trend toward postprocessing algorithms that modify the ranking in order to minimize potential underusage of budget or resources.

Table 1 provides a summary of the predominant approaches, models, constraints, and instance sizes, Similarly, Fig. 3 shows a radar plot comparing the four predominant approaches. In terms of papers published from Clusters I to XII, Project ranking, Metaheuristics, Fuzzy modeling and decision aids have 81, 62, 44, and 23, respectively. Hence, ratings of high (Hi.), mid-high (MHi.),

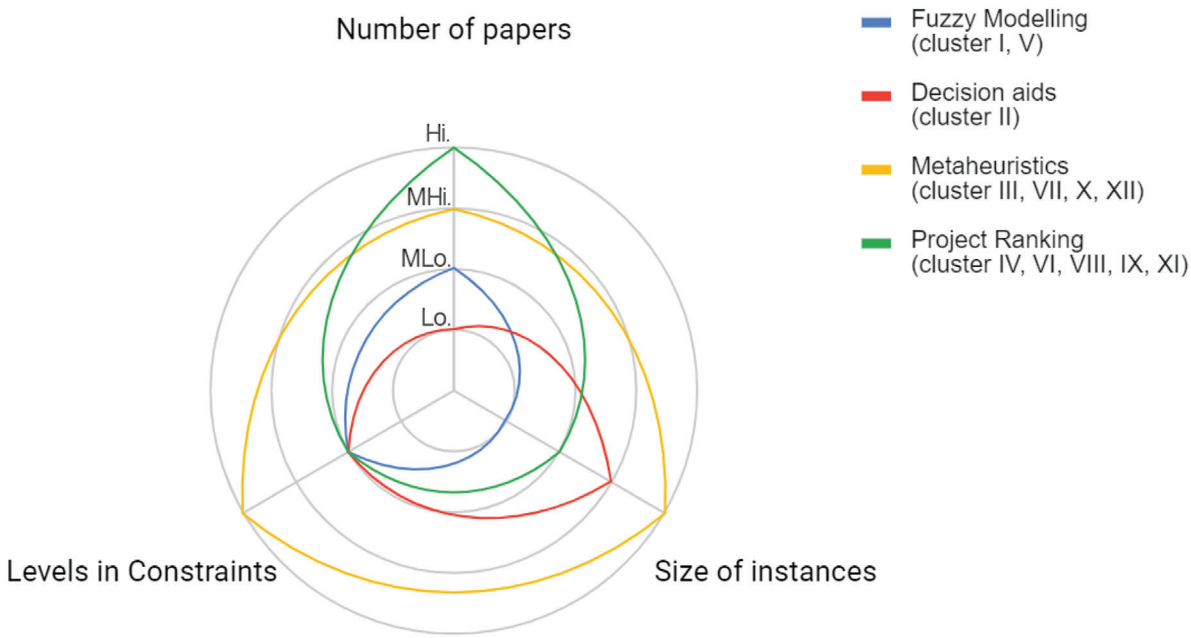

Fig. 3. Characteristics of the four predominant approaches.

mid-low (MLo.), and low (Lo.) levels have been assigned according to these figures. Regarding the size of the instances, Metaheuristics are clearly on top (with instances of size 500 assets or more). The Decision aids approach has tackled instances with up to 120 assets (hence, it has been rated as mid-high), while Ranking covers instances with up to 70 assets (hence, it has been rated as mid-low). Finally, Fuzzy modeling, with less than 20 assets per instance, has been rated as low. Similarly, regarding levels of constraints, Metaheuristics is the only one that considers two levels (portfolio and project), therefore the rating is high. The remaining approaches have been qualified as mid-low.

A reasonable question is whether the citations are due to the topic relevance or the journal selection. In order to check this, we have counted how many papers come from each specific journal inside each cluster. The result on the 12 most frequent journals for Clusters I until XII is depicted in Fig. 4. This analysis illustrates a certain degree of uniformity in the distribution of clusters across journals, although some clusters seem to be predominant in most journals. We have also run a K-means function, based on the Euclidean distance, applying the algorithm proposed in Elkan (2003). Thus, a text-based clustering analysis on all the abstracts is performed. First, we have requested the algorithm to propose the top four clusters in order to check whether the result matches our previously obtained classification (Fig. 5). Taking into consideration the exclusive words (highlighted in green), we can also see some trends that are quite similar to the ones previously obtained using the original clustering method. In particular, (i) the new Cluster 0 matches with our previous Cluster III "Metaheuristic approach"—this is not only due to the "genetic" and "algorithm" keywords but also due to the fact that this approach is typically related to scenarios where personnel, human resource planning, and cost are considered; (ii) the new Cluster I has only two exclusive words,

Journal \ Cluster	1	2	3	4	5	6	7	8	9	10	11	12	Subtotal
European Journal of Operational Research		3	4	1	3		3	6		1			25
Expert Systems with Applications	2	3	1	1		2					2		12
Applied Soft Computing		1	1	3	2	1							8
Computers & Industrial Engineering	1	1					5					1	8
Journal of Civil Engineering and Management						2			4		2		8
Annals of Operations Research		3	2							1		1	7
IEEE Transactions on Engineering Management	1				3			1			1		6
Information Sciences	1	2		1			1						5
Lecture Notes in Computer Science	1		1	1						1			5
Decision Support Systems	1			1			1	1					4
Omega		2			2								4
The International Journal of Advanced Manufacturing Technology	2	1					1						4

Fig. 4. Most frequent journals at Clusters I until XII.

Cluster 0:	Cluster 1:	Cluster 2:	Cluster 3:
algorithm ●	project ◆	portfolio ➤	fuzzy ●
team ●	selection ▲	projects ◆	decision ▲
problem ▲	model ▲	model ▲	selection ▲
cost ●	decision ▲	project ◆	criteria ➤
genetic ●	portfolio ➤	optimization ●	project ◆
human ●	projects ◆	problem ▲	method ●
project ◆	process ●	decision ▲	construction ●
instances ●	criteria ➤	portfolios ➤	proposed ●
personnel ●	problem ▲	selection ▲	projects ◆
resource ●	anp ●	risk ●	model ▲

◆ Words repeated in four clusters
▲ Words repeated in three clusters
➤ Words repeated in two clusters
● Words exclusive of one cluster

Fig. 5. Four clusters from text-clustering analysis.

"ANP" and "process," which match with our previous cluster IV "Multicriteria project ranking methods"—in the latter, the most predominant techniques are ANP and AHP; and (iii) the new Cluster III also matches with our previously identified Cluster I "Possibilistic approaches based on fuzzy numbers and fuzzy logic"—the connection is clear by means of the keyword "fuzzy."

5. Conclusions and open research challenges

Methodologies based on project ranking (such as AHP, ANP, ELECTRE, VIKOR, etc.) seem to be good enough for mutually exclusive projects that do not share resources. Such approaches tend to rank projects based on a consolidation of the decision criteria into one parameter—such as contribution to value, alignment to strategy, or deviation from the ideal situation. The most typical application fields are in the energy industry or in infrastructure projects. Cases where other factors become critical, such as possible shared resources within the same company, tend to (i) obtain the Pareto set of nondominated portfolios and (ii) rank the portfolios instead of the projects. From a computational perspective, this is a more challenging approach, but it offers several advantages. First, these approaches allow to include more realistic restrictions, such as potential resource conflicts, synergies between different projects, and inclusion of resource skill matrices. They are also more likely to be used in combination with Monte Carlo simulation. Another important advantage is the availability of several near-optimal solutions, which enrich the review interactions with the decision makers. This is especially interesting in cases where preferences among different criteria can change quickly due to the modification of the working conditions.

The fact that the vast majority of authors are looking for methodologies that integrate several decision-making criteria shows that, despite its importance, NPV is not rich enough to capture all the factors that need to be considered. The inclusion of other concepts, like ROV, is also supporting this statement. Hence, authors address the decision-making process according to different approaches, which depend on the type of industry, the specific context of each project, the type of organization, and the restrictions on the use of its resources. The selection of projects should be considered from more than one dimension or variable, in order to be able to make an effective decision making. The use of methodologies, tools, or models for project selection is required from an integrative conception, in which both qualitative and quantitative variables can be considered to measure the long-term impact of the decisions. A hybrid multievaluation criteria approach is required. In this approach, a sustainability dimension—which allows and guarantees an efficient use of resources in the long term—could be analyzed and included during the decision-making process.

Focusing on PPM, this paper provides a clustering-based review of the existing literature. The study has identified a total of three main clusters plus another nine secondary clusters, which are conveniently analyzed. The main frameworks, authors, and algorithms have been highlighted. The review shows how some authors focus in improving the interaction with decision makers, while others concentrate on providing better solutions in reduced computing times by employing metaheuristic algorithms. We have also discussed the need for considering uncertainty, as well as the need for built robust models. The tendency then is to consider richer and more realistic models, which are able to integrate aspects such as realistic constraints at both portfolio and project levels, multiple objectives, shorter computing times, robustness, combination of constraints with different degrees of uncertainty, as well as flawless interactions with decision makers and other stakeholders. The paper also shows the usefulness of being able to (i) list all those qualitative parameters that need to be considered in the selection processes (such as trust, security, social impact, environmental impact, etc.); (ii) group the aforementioned parameters as required by the type of industry or market; and (iii) define a measurement system for these parameters in order to transform them into reliable numerical data by reducing their fuzzy value.

The rising interest on project portfolio tools shows that organizations are becoming increasingly aware about the need for having better models that can accurately reflect the duration of project tasks, as well as other constraints. Hence, the combination of simulation techniques or fuzzy sets with metaheuristic algorithms is becoming a growing trend in the related literature. Actually, we have analyzed how project-level scheduling is approached, identifying proposals such as the ones made by Yang et al. (2016b) and Nikoofal Sahl Abadi et al. (2018), in which metaheuristic algorithms and simulation play a critical role. These hybrid approaches are advantageous both at portfolio and at project levels. Therefore, it seems reasonable to continue exploring these techniques for the simultaneous optimization of the project portfolio, their scheduling, reliability/availability levels (Faulin et al., 2008), and resource leveling.

According to Urli and Terrien (2010), most practitioners consider that the project portfolio selection problem is still not fully solved, at least from a practical perspective. In other words, there is still a gap between research methods and the needs of different industrial and business sectors. Several open challenges have been identified from this study. First, there are several *ad hoc* comparisons of different techniques, but there is just a limited number of comparisons regarding the commercial products available for decision makers. Likewise, there is a need for more standard comparisons among the different approaches proposed in the literature. Second, there is still work to do in terms of identifying the best approaches for real-life cases requiring many constraints. This is especially the case for projects where there is a relevant pool of shared resources, and there are key factors like skill availability and development. Third, there are many experiences related to the application of fuzzy modeling, but not so many yet combining simulation and metaheuristics. However, it seems clear that several commercial solvers prefer to use the latter better than the former. In other words, the combination of metaheuristics with simulation seems to fit better the needs of most enterprises. For this reason, one interesting research line would be the development of simheuristic algorithms that consider: the combination of internal and outsourced resources, the scheduling of all projects, the skills available inside the organization, the learning effects through the projects, the stochastic uncertainty on different variables as well as on the future benefits of the projects (not only cash flow), as well as the possibility of forcing some projects to be mandatory—allowing only for a limited budget shortage with others, which could be completely canceled. Some interesting efforts in these lines are those found in Stummer et al. (2009), Litvinchev et al. (2011), and Gutjahr and Froeschl (2013).

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