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ARTIFICIAL INTELLIGENCE APPLICATIONS IN PROJECT SCHEDULING: A SYSTEMATIC REVIEW, BIBLIOMETRIC ANALYSIS, AND PROSPECTS FOR FUTURE RESEARCH

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Abstract:
The availability of digital infrastructures and the fast-paced development of accompanying revolutionary technologies have triggered an unprecedented reliance on Artificial intelligence (AI) techniques both in theory and practice. Within the AI domain, Machine Learning (ML) techniques stand out as essential facilitator largely enabling machines to possess human-like cognitive and decision making capabilities. This paper provides a focused review of the literature addressing applications of emerging ML tools to solve various Project Scheduling Problems (PSPs). In particular, it employs bibliometric and network analysis tools along with a systematic literature review to analyze a pool of 104 papers published between 1985 and August 2021. The conducted analysis unveiled the top contributing authors, the most influential papers as well as the existing research tendencies and thematic research topics within this field of study. A noticeable growth in the number of relevant studies is seen recently with a steady increase as of the year 2018. Most of the studies adopted Artificial Neural Networks, Bayesian Network and Reinforcement Learning techniques to tackle PSPs under a stochastic environment, where these techniques are frequently hybridized with classical metaheuristics. The majority of works (57%) addressed basic Resource Constrained PSPs and only 15% are devoted to the project portfolio management problem. Furthermore, this study clearly indicates that the application of AI techniques to efficiently handle PSPs is still in its infancy stage bringing out the need for further research in this area. This work also identifies current research gaps and highlights a multitude of promising avenues for future research.

Key words: *Artificial intelligence, machine learning, project scheduling, bibliometric analysis, network analysis, review*

INTRODUCTION

Scheduling is the process of allocating scarce resources to activities over time in the most cost-effective manner. Project scheduling, in specific, stands out as a crucial step in the planning phase of a project which calls for establishing the sequence in which the tasks/activities comprising a project are to be carried out alongside ensuring the availability of required resources for their successful completion. A basic project schedule requires a list of project activities, an estimate of each activity's duration, consumable and renewable resources needed for each activity, and a precedence relationship among the activities. The objective usually is to complete the project as quickly as possible while adhering to budget and precedence constraints as well as quality standards. The Program Evaluation and Review Technique (PERT) and the Critical Path Method (CPM) are the two most frequently used techniques for basic project scheduling. They use polynomial time computation to define the time window for scheduling activities. However, besides overlooking limitations on resources availability [1], pointed out that classical CPM based techniques suffer from computational inefficiencies due to the sequential nature of their calculations, iterative enumeration of all paths in the project network, and inability to perform arbitrary node-to-node calculations. In the presence of inherent uncertainties, constrained resources availability and cash flow concerns, problems become more information-intensive and optimal or exact solutions become too expensive or impossible to produce, necessitating the development of strategies for efficiently obtaining near-optimal solutions.

Project scheduling problems are broadly classified into *Resource Constrained Project Scheduling Problem* (RCPSP) and *Time Constrained Project Scheduling Problem* (TCPSP). The RCPSP aims to determine the starting times for the project's activities in such a way that they satisfy precedence constraints and resource constraints while minimizing the total completion time of the whole project. The RCPSP has been studied since the 1960s and is known to be an NP-hard optimization problem (e.g. [2]), where several variants have emerged including multi-mode RCPSP, multi-skilled RCPSP and RCPSP with time windows. Given the difficulties associated with managing projects having erratic/irregular resources requirements over time, the TCPSP seeks to minimize the period-to-period variations in the resources usage profile, while meeting the agreed upon handover date of the project. This latter problem is commonly referred to in the literature as resource smoothing/leveling problem and it is also known to be NP-hard, even for the single resource case (see [3]). As such, to address real-life projects encompassing a large number of activities, researchers have devised a wide variety of approaches to attain good-quality solutions with reasonable computational time, including local search and populations based metaheuristics among many others. Depending on the problem, these metaheuristic approaches typically require excessive fine-tuning where they also may perform well in one instance but poorly in another. Recently, there has been success in the use of *Artificial intelligence* (AI) based approaches to efficiently handle this kind of problem, even for large instances.

In general, AI refers to the use of computers to reason, identify patterns, learn from experience, retain information, and generate various sorts of inferences towards solving problems especially when optimum or exact solutions are either prohibitively expensive or difficult to produce. *Machine Learning* (ML) is a main area of study within the AI domain and is described as a machine's or a computer's capacity to learn without being explicitly programmed [4]. Thus, the machine develops because of the pattern recognition algorithms identified by the computer when given data. The two most often used ML approaches are supervised and unsupervised learning. The computer is supplied with data that must be optimized or projected based on a known outcome in supervised learning. Unsupervised learning techniques do not describe the objective of the system [5]. Thus, the computer must deduce the meaning of the data and continue looking for a structure that could provide significant findings. Probabilistic modeling is a subset of ML models that may be used to anticipate the value of a desired attribute. In essence, ML is a key method for automating the process by which robots make meaningful use of data [6].

Over the past years, AI techniques have demonstrated proven efficiency for a wide-spectrum of applications, including cancer detection [7] smart city applications [8, 9], image classification [10], intensive care unit [11], maintenance [12], robotics [13] among many others. Aytug et al., [14] conducted a review of ML approaches adopted in project scheduling in specific and highlighted the importance of implementing AI-based techniques in complex scheduling problems. Other researchers, such as Adamu et al., [15], examined a specific ML heuristic for solving a multi-mode RCPSP, where the output of the ML heuristic proves to be an excellent starting point for the metaheuristic procedures used to solve the problem. While ML techniques can be applied to general scheduling problems, they can also be applied to more specific and direct scheduling problems, as discussed in [16]. They showed how combining ML and data streams from a construction site can improve project duration estimates during execution. Kartam and Tongthong [17] described three different classes of *Artificial Neural Networks* (ANNs) that can be applied to solve resource-leveling problems and suggested several approaches for mapping resource leveling problems to network architecture. Simeunovic et al., [18] demonstrated a decision support tool for workforce planning and scheduling. Their model uses ANN fitting techniques to predict demand and production, which is adequate for complex production systems with unpredictable and volatile demand. A more specific example from construction projects involves tunnel boring machines where ANNs have been efficiently used to predict the performance of the boring machines [19]. The aforementioned examples clearly exemplify how AI-based approaches have been successfully adopted to address various aspects of project scheduling problems.

This paper presents a systematic literature review coupled with a bibliometric analysis of works addressing AI approaches adaptation to project scheduling problems. At its core, bibliometric analysis represents a strong tool greatly facilitating the identification of existing and emerging research topics pertinent to a specific field of study. It can also help in identifying popular keywords to illustrate how different topics have evolved over time and their future outlook. The most influential countries and researchers are also recognized via this analysis which assists future researchers in capturing recent topics published in those countries and by those researchers. Reviews employing comparable bibliometric tools to those described in this paper exist in other areas of research. For instance, Mishra et al. [20] conducted an in-depth review of the relationship between big data and supply chain management by using various bibliometric tools. Another paper employed a similar approach for summarizing the review's findings in the more specific area of green supply chain management [21]. By examining various bibliometric based reviews across different disciplines and the tools utilized therein, the authors are able to conduct a thorough analysis of AI applications to project scheduling problems, identify emerging topics and thematic research clusters, highlight existing gaps as well as provide detailed directions for future research.

While there is a recent and closely related review of AI applications in the Architecture, Engineering, and Construction industries, it has a broad scope and lacks focus on a particular aspect [22]. Another related review is that of Bilal et al., [23] which investigates the application of Big Data techniques in the construction industry, in specific, without focusing on a certain dimension while relying heavily on manual appraisals rather than quantitative tools such as those provided by the bibliometric approach. In this work, the use of bibliometric analysis is complemented with network analysis conducted via multiple computer packages, such as Gephi and VOSViewer, which helps with the creation of flexible visualizations of complex data. Since the work of Aytug et al., [14] and to the authors' best knowledge, this is the first focused and comprehensive review establishing the nexus between project scheduling and AI based techniques using bibliometric in conjunction with network analysis tools.

The remainder of this paper is organized as follows. Rather than summarizing each of the relevant works, Section 2 highlights the main contributions based on the ML technique employed and the scheduling problem/environment considered. Section 3 details the structured research methodology adopted and provides some statistical analysis. The bibliometric analysis results are reported in Section 4 followed by those of the network analysis in Section 5. A more elaborate discussion along with a categorization of the relevant works based on several dimensions as well as the identification of current research gaps is provided in Section 6. Lastly, Section 7 concludes the paper and summarizes the main findings while highlighting future research avenues based on the identified gaps.

LITERATURE REVIEW

A wide range of organizations across different industries have increasingly embraced AI based technologies to remain competitive in today's globalized markets given that they serve as the backbone for the creation of numerous intelligent ecosystems. Within the AI domain, ML techniques stand out as an essential facilitator largely enabling machines to possess human-like cognitive and decision-making capabilities. In essence, ML is defined as the ability of a machine or a computer to learn without being explicitly programmed [4]. ML distorts the traditional paradigm, which expects an output from raw data and an algorithm that explains how to use it. The underlying principle is that typically the data itself, once analyzed and mined for repeating patterns and hidden causal connections or correlations, offers the information necessary to generate new knowledge.

As noted earlier, ML algorithms are broadly classified into supervised, unsupervised, and reinforcement learning approaches. In the first category, an output variable is predicted from a set of input variables following a two-phase process: a training phase and a testing phase. These phases can be repeated with different labeled data sets until reaching a satisfying level of accuracy. If the output variable is continuous, regression algorithms such as Linear and Logistic Regression models are typically adopted. However, for discrete or nominal variables, classification algorithms such as Decision Trees, Deep Learning Models, and Random Forest, among others, are utilized. In the second category, the objective is to analyze unlabeled data through summarizing, segmenting and searching for hidden patterns. One can cite K-means algorithm and pattern recognition as examples of unsupervised learning approaches. While reinforcement/active learning methods do not rely on predefined data, they make use of an agent which interacts with the surrounding environment to learn via a trial-and-error method prior to performing the appropriate action. This section starts the categorization of the relevant literature with applications of knowledge-based approaches to solving project scheduling problems, followed by ANNs and BN, supervised ML techniques, and lastly reinforcement learning techniques.

Knowledge-based approaches

Prior to the emergence of modern ML algorithms, most of the approaches adopted to tackle project scheduling problems were mainly comprised of operational research techniques along with heuristics and metaheuristics solution approaches. Nevertheless, few works applied knowledge-based approaches to solve project scheduling problems in a variety of contexts. For instance, Rodrigues [24] devised a knowledge-based simulation system to investigate the relationship between modeling and knowledge representation in computer system simulations, namely discrete-event or network simulations. They considered both models with a finite lifespan, such as generalized activity networks with resources, and models with a restricted lifespan, such as queueing networks. In the same context, Chang and William Ibbs [25] developed a knowledge-based expert system that combines expertise and fuzzy logic reasoning. Indeed, when planning construction resources, it is critical to consider the effect of unforeseen events on the likes of weather conditions, resource availability, and raw material delivery delays. In another work, Nabrzyski and Weglarz [26] utilized a blackboard architecture to develop a knowledge-based multi-objective project scheduling system for a class of non-preemptive scheduling problems. The authors considered a mix of renewable and non-renewable, doubly constrained resources, multiple task performing modes, and multiple project performance measures. In the construction industry, Conlin and Retik [27] implemented a knowledge-based expert system to use information technology capabilities to improve various processes, including tracking and delay reduction strategies. Finally, Yannibelli and Amandi [28] developed a knowledge-based evolutionary approach for software project scheduling based on Genetic Algorithms (GA).

Artificial neural network and Bayesian network

As detailed in the next section, the adoption of modern ML approaches to address project scheduling problems has started gaining momentum recently, with a sharp steady increase just as of the year 2018. This subsection is devoted solely to presenting applications of *Artificial Neural Networks* (ANNs) and *Bayesian network* (BN) since those two techniques in specific could fall under the umbrella of either supervised or unsupervised ML depending on the type of data and extent of supervised training involved.

Artificial Neural Networks (ANNs) are a subset of ML techniques inspired by the functioning of human neurons, which are primarily used for classification and regression purposes [29]. They are typically composed of interconnected node layers where each node represents an artificial neuron, with weighted activation functions being used to activate the nodes. Using training data, these models learn and improve their accuracy over time. When an ANN comprises more than three layers, the term "deep neural networks" or "deep learning techniques" is used [30]. Recently, ANN techniques have been applied to efficiently solve project scheduling problems, where at times they would be combined with other metaheuristics for an enhanced performance. For instance, Colak et al., [31] combined the advantages of priority rule-based heuristics and neural network-based iterative learning towards solving the RCPSP. While tackling the same problem, Agarwal et al., [32] proposed a neurogenetic approach that is a combination of GA and neural network techniques. The search iterations are interleaved in a way that neural network can choose the best solution in the GA pool thus far and performs an intensification search in the solution's local neighborhood. Dimitrios et al., [33] used an initial set of solutions generated by GA as an input for a recurrent neural network model to solve a project portfolio scheduling problem. Then, using a Tabu search-based approach, the obtained results were improved. More recently, Roston and Kulejewsky [34] presented the potential benefits of combining metaheuristics and neural networks upon solving the multi-mode resource constrained project scheduling problem (MRCPSP). In the recent work of Alostad [35], ANNs are combined with GA to eliminate the trade-off between project duration and skill level for software scheduling projects.

Other relevant works include that of Huang and Gao [36] where a time-wave neural network approach was developed to optimally solve the time-dependent project scheduling problem within a reasonable amount of computational time. Liu and Hao [37] used backpropagation algorithm for training feedforward neural networks to come up with an approach for detecting scheduling problems and to forecast tasks successors and renewable resource characteristics. Pagani and Pfann [38] adopted ANNs based approach to develop reactive decision tools for RCPSP in specific, which seeks to determine priority values for "ready to begin" activities. Through mining data from previous construction projects, Ma and Wu [39] developed a construction plan that adheres to both quality and schedule constraints. They conducted a *Failure Mode and Effect Analysis* (FMEA) to assess construction quality, an *Earned Value Management* (EVM) technique to assess schedule control, and an ANN approach to correlate the evaluation results.

In contrast to ANNs, a *Bayesian network* (BN) is a probabilistic graphical model in which each node represents a random variable, and the edges represent the variables' conditional dependencies [40]. BN based approaches have recently been used to account for uncertainty and risk factors in project scheduling problems, and help in real-time decision-making. BNs have been adopted in a variety of applications, including critical path method calculations [41] and the well-known PERT approach [42]. In the same context, Cheng et al., [43] developed a fuzzy Bayesian schedule risk network for offshore wind turbine installation taking into consideration uncertainties due to typhoons, high winds, etc. BNs were also applied to determine statistical dependence between subsets of activity durations [42]. In another work, Knudsen and Blackburn [44] developed a BN model to predict schedule performance and to address cost and scheduling delays in *Large-Scale Engineering Projects* (LSEP). The model is based on a set of quantitative and qualitative causal factors related to scheduling performance.

Supervised ML algorithms

Few researchers have hybridized *Support Vector Machine* (SVM) techniques with evolutionary methods to enhance their performance [45]. In essence, SVM uses nonlinear transformations to translate a collection of data into a much higher-dimensional space where regression and data fitting may be performed. This approach builds on statistical ML theory and it may be used for data categorization, pattern identification, and regression. Quite interestingly, the application of this method has barely been explored in a project scheduling context. Among the few existing works, Gersmann [46] applied SVM to improve iterative repair (local search) strategies of deterministic RCPSP. Yang et al., [47] developed an accelerated particle swarm optimization and a nonlinear SVM to form a framework for solving RCPSP.

Alternatively, “ensembles methods” is a ML technique that combines different models or approaches to improve the accuracy of the results. Đumić et al., [48] developed an approach based on producing ensembles of priority rules for the RCPSP and a voting algorithm to select the best one for a specific context. In their work, four different approaches were considered to combine priority rules, and the results showed that ensembles of priority rules achieve much better results as opposed to using a single priority rule. Adamu et al., [15, 49] also utilized a ML technique that relies on selecting the best priority rule from a set of rules depending on the problem input when solving MRCPSP.

It shall also be noted that few authors made use of decision trees based ML algorithm to tackle project scheduling problems. The recent work of Guo [50], for example, presented two decision trees classification techniques to categorize priority rules for RCPSP. The generated trees are then used to forecast the optimal priority rule based on the project indicators' known values. Awada et al., [16] also used random forest decision trees based predictive model to forecast the outcome of field submittals for building project scheduling. In particular, the authors showed how to make use of ML to forecast project delays, where they devised a random forest predictive model to forecast the probability of concrete pouring requests acceptance.

Reinforcement learning algorithms

Reinforcement Learning (RL) is another commonly used ML technique for solving problems related to project scheduling in a variety of contexts. At its core, RL utilizes agents to make decisions in a coordinated environment toward optimizing different performance criteria, such as the completion time, or to predict the behaviour of project activities. It is noted that the vast majority of research on RL has occurred in the past decade, and it currently represents one of the most promising AI strategies for project scheduling. Moreover, it is frequently used in conjunction with classical metaheuristic solution approaches. For instance, Jedrzejowicz [51] implemented a team of asynchronous agents (A-Team) to solve the RCPSP, and later extended this work to the MRCPSP case [52]. In both works, dynamic RL strategies are suggested to manage the interactions between the optimization agents. The proposed algorithms are based on several well-known metaheuristics, including simple local search, Tabu search, and path relinking, as well as crossover heuristics. Zheng and Wang [53] developed a multi-agent optimization algorithm based on swarm intelligence to optimize the RCPSP. Agent evolution is accomplished through the use of four primary components: social behavior, autonomy, self-learning, and environmental adjustment. Ratajczak-Ropel [54] developed a multi-agent approach to solve the MRCPSP, where each agent represents a metaheuristic or optimization approach, while RL based cooperation strategies between agents are applied. Recently, Sallam et al., [55] used a RL approach to switch between *Multi-Operator Differential Evolution* (MODE) and *Discrete Cuckoo Search* (DCS) algorithms in order to maximize the utility of both heuristics when solving the RCPSP.

A stand-alone adoption of RL techniques also exists in the project scheduling literature. Zhang et al., [56], for instance, presented a RL based strategy for resolving the scheduling difficulty associated with distributed projects. The approach optimizes the schedule by conducting scattered conversations between the order management and brokers who interact with each other through the agent negotiation mechanism. In two related works, Padberg and Weiss [57] [58] applied RL techniques to assign tasks to developers based on their past performance in software development projects. The developed models explicitly account for uncertainty and ripple effects where task completion times are stochastic. A *Reinforcement Learning-based Assigning Policy* (RLAP) approach was developed to obtain non-dominated solution sets for minimizing the makespan and logistical distance of multi-project scheduling problems in Cloud Manufacturing systems [59]. Lastly, Sung et al., [60] adopted RL to determine the best resource allocation policy in a Markov decision process for project management resource allocation.

The previous works have illustrated that the application of RL techniques to project scheduling generally yields an improvement in terms of solution convergence and computational time. However, some challenges are still arising to allow for a wider reliance on this technique. Sallam et al., [55] pointed out that dynamic resource availability or demand might affect the performance of the approach. In addition, Sung et al., [60] mentioned that more historical data is generally needed to efficiently implement RL by building a more comprehensive simulation environment. Cheng et al., [43] suggested that "forget rules" should be introduced in RL models to incite the agents to explore more solutions. The scalability of such techniques represents another prominent challenge, and more efficient approaches are still needed for large-scale projects.

RESEARCH METHODOLOGY AND DATA STATISTICS

To comprehensively explore the landscape of the general body of knowledge pertaining to AI applications in project scheduling, this paper embraces an integrated approach that combines rigorous bibliometric and network analysis tools along with systematic literature review. As pointed out by Borregan-Alvarado et al., [61], bibliometric analysis provides a mean to inspect, organize, analyze and quantify publications related to a particular field of research with the aim of assessing academic productivity, identifying research tendencies and detecting the impact of various research subtopics. A comprehensive network analysis, encompassing citation and co-citation analysis, aids in identifying the major research clusters and the most influential researchers within each cluster which serves the basis for establishing emergent study fields captured by those researchers. As for systematic literature reviews, they employ a rigorous and structured procedure for the search and screening of the relevant articles and their content leading to further insights into previously unexplored areas while establishing directions for future work. The bibliometric analysis approach presented herein is inspired by the methodology developed in Saunders et al., [62] and later adapted by Fahimnia et al., [21] and Mishra et al., [20]. The articles have been collected from Scopus as it is one of the largest multi-disciplinary abstract and citation database of peer-reviewed research works, and is known to be more comprehensive than Web-of-Science database [21]. Furthermore, it is a well-organized and indexed database that provides sufficient details about the publications with practical export features of metadata [63, 64].

Defining the appropriate keywords

One of the most crucial steps in data collection is identifying the most suitable search terms that are likely to capture all key publications most relevant to the topic at hand. As noted in Saunders et al., [62], structured literature reviews are typically accomplished through an iterative procedure of defining appropriate search keywords, searching the literature, and conducting the analysis. As for the refinement of the search query, the search was initially carried out using few terms in the search query which returned a small number of documents. For instance, using “Case-Based Reasoning” AND “Project Scheduling” yielded only 8 documents, leading to the decision of making use of a longer query. Accordingly, a list of keywords that cover a wide spectrum of AI techniques was created, including terms on the likes of "Machine Learning", "Deep Learning", "Reinforcement Learning", "Expert Systems", "Artificial Neural Networks", "Case-Based Reasoning", "Data Mining", "Knowledge-Based Systems", "Support Vector Machines" among others, where all these terms were combined using the “OR” conjunction. It shall be noted that terms only relevant to recent AI approaches were included, leaving out classical terms pertaining to operational research techniques and nature inspired metaheuristics-based approaches, such as “Genetic Algorithms”, “Particle Swarm Optimization” and “Ant Colony Optimization” to name a few. After several rounds of refining the search terms, the following search query was applied in Scopus database within the papers’ titles, abstracts and keywords sections:

"Artificial Intelligence" OR "Machine Intelligence" OR "Machine Learning" OR "Expert Systems" OR "Neural Networks" OR "Artificial Neural Networks" OR "Case-Based Reasoning" OR "Data Mining" OR "Knowledge-Based Systems" OR "Support Vector Machines" OR "Intelligent Systems" OR "Natural Language Processing" OR "Deep Learning" OR "Reinforcement Learning" OR "K-Means" OR "Learning Systems" OR "Intelligent Optimization" AND "Project Scheduling".

The AI related keywords were combined with the specific term of “Project scheduling” rather than a more general term such as “Project management” to ensure the scope is limited only to the scheduling phase of the project’s lifecycle. Note that no mention of a specific field or domain is present (e.g., construction, software development, turnaround maintenance, etc.) in order to capture applications spanning several industries.

Initial search results

The applied search query resulted in 411 documents, where the search was restricted to articles published in English language only during a 36-year period, between 1985 and August 2021. Given that the term AI was first coined in the year 1956 [22] and the slow realization for the advantages of applying AI techniques to solve project scheduling problems over several years to follow (see [14]), a midway value for the start of the search period was chosen. This would also allow identifying the publication trend over an extended period of time. For ease of further processing, the information obtained from Scopus for all returned articles were exported to a CSV file including title, authors, abstracts, keywords, references, source title, etc. The obtained articles include journal papers, conference papers, and book chapters. Those articles went through a multi-stage systematic filtering approach, where at first articles published in unrelated journals were omitted. Given that many combinations of keywords have been adopted during the search process, two articles appeared more than once as they satisfied more than one combination and therefore the duplicates were eliminated. Next, the pool of articles was examined based on the title and the abstract to assess their relevance and only those pertinent to the scope of this review were retained. Lastly, a more thorough examination of the remaining articles took place based on the content to ensure that only those relevant to the scope were included. This filtering process resulted in a reduction in the pool size from an initial number of 411 articles down to 104 relevant ones.

Initial data statistics

Figure 1 shows the evolution of the publication trend over the years since 1985 till August 2021, where the actual number might increase at the end of the year. It can clearly be seen that the number of publications is fluctuating, where it has been on the low end till the year 2010, followed by an intermittent growth in the realization of the significance of AI techniques as applied to project scheduling between 2011 and 2017, then a sharp increase as of 2018. This consistent growth in the last couple of years clearly illustrates the rising interest among researchers toward exploiting the benefits obtained from utilizing AI based techniques to efficiently solve project scheduling problems.

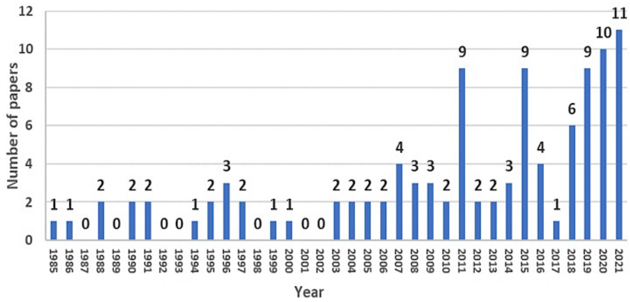

Fig. 1 Annual breakdown of the relevant articles

Given those publications appeared in a wide variety of journals and conference proceedings, Table 1 depicts the top 10 contributing journals in terms of number of publications. It can be noted that the top contributing source, *Expert Systems with Applications*, is more of an AI related journal than a specialized project management/scheduling journal.

Moreover, Table 2 presents a more detailed analysis of the top contributing journals, based on the number of publications per year. To make the analysis visually suitable, we show the top journals based on their publications over the past ten years. It can be seen that there are no new journals that have appeared in Table 2 as compared to Table 1. *Expert Systems with Applications* remains the top contributing source in both tables. The dominance of AI journals over scheduling journals, in general, is also evident in the last ten years.

Table 1
Top contributing journals based on publications

Journals	No. of articles
Expert Systems with Applications (ESA)	4
European Journal of Operational Research (EJOR)	3
Lecture Notes in Computer Science Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes In Bioinformatics (LNCS)	3
ACM International Conference Proceeding Series (ACM)	2
Annals of Operations Research (AOR)	2
Communications in Computer and Information Science (CCIS)	2
International Journal of Production Research (IJPR)	2
Journal of Intelligent Manufacturing (JIM)	2
Journal of Scheduling (JS)	2
Procedia Computer Science (PCS)	2
Total	**24**

Table 2
Top publishing journals in the last ten years

Journal	Publication Year											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
ESA	1				1						2	**4**
LNCS				1					1		1	**3**
ACM								1		1		**2**
CCIS	1		1									**2**
IJPR					1				1			**2**
PCS						1	1					**2**
Total	**2**	**0**	**1**	**1**	**2**	**1**	**1**	**1**	**2**	**1**	**3**	**15**

BIBLIOMETRIC ANALYSIS

Bibliometric analysis is a strong tool that helps in identifying existing and emerging research topics within a specific field where the most influential countries and researchers are also identified which would assist future researchers in capturing recent topics published in those countries and by those researchers. In addition, one can get a sense of the most important keywords in the AI field as applied to project scheduling via performing the analysis on keywords and title words. In general, bibliometric analysis can be conducted using various software packages including Perish [65], HistCite, and BibExcel [66]. In this study, BibExcel was chosen because of its high degree of flexibility in handling the data imported from Scopus database and its compatibility with several network analysis software such as Gephi and VOSViewer, both of which are used in subsequent analysis.

The pool of documents generated using Scopus was transformed to an RIS (Research Information Systems) format that contains all bibliographic information needed for the bibliometric analysis. Using BibExcel, the authors were able to convert the RIS file to many different files in order to extract the information needed for the analysis. The main focus is on information that relates to authors, journal, keywords, affiliations, and references. Interested readers may refer to the work of Persson et al., [67] for a more elaborate discussion on the BibExcel software. The following sub-sections provide statistics pertaining to author influence, affiliation and keywords as obtained from BibExcel and Scopus software.

Author influence

Upon extracting the authors' metadata, one can obtain the frequency of text occurrence towards analyzing the author's influence. Table 3 shows the top ten contributing authors with the corresponding number of published articles.

Table 3
Top contributing authors

Author	No. of papers
Ratajczak-Ropel, E.	6
Adamu, P.I.	3
Agarwal, A.	3
De Causmaecker, P.	3
Jedrzejowicz, P.	3
Verbeeck, K.	3
Wauters, T.	3
Bil, C.	2
Colak, S.	2
Gersmann, K.	2

It can be observed that Ratajczak-Ropel, E. is a leading researcher in this field with six articles, followed by Adamu, P.I., Agarwal, A., De Causmaecker, P., Jedrzejowicz, P., Verbeeck, K., and Wauters, T., with three publications each. The breadth of AI techniques adopted by those prolific scholars while tackling various project scheduling problems under different settings, as detailed later, exemplifies the proven efficiency and wide-spread applicability of AI related techniques to solve a multitude of such problems.

Affiliation statistics

In a similar fashion, we identified the top 11 contributing countries in terms of number of published papers based on the authors' affiliation data. Needless to say, papers with authors from different geographic regions are assigned to multiple countries. From Table 4, it can clearly be seen that the US dominates the list with 17% of the papers published.

Table 4
Top contributing countries

Country	No. of papers
United States	20
China	15
Poland	9
Germany	8
India	8
Iran	5
Australia	4
Belgium	4
Taiwan	4
Nigeria	3
United Kingdom	3

Note that the top 3 contributing countries lead the publications in their respective continents, US in North America, China in Asia, and Poland in Europe. It should be noted that 11 countries were chosen as the number of publications drops to 2 after the United Kingdom. Generally speaking, the wide-spread geographical dispersion of the top contributing countries illustrates how the research topic at hand has triggered the interest of researchers and academic institutions from around the globe.

Keyword statistics

In this sub-section, an attempt to identify the most commonly used words/phrases in the paper title and the authors' keyword sections is conducted. This information is relevant as it may be used to expand the keyword selection of the topic at hand to include words beyond those chosen in the search string of this study. Table 5 displays the most frequently used author keywords in the selected pool of 104 papers, while Table 6 shows the words appearing most frequently in the titles of those articles.

Table 5
Top author keywords

Keyword	Frequency
Scheduling	82
Project Scheduling	69
Optimization	31
Reinforcement learning	25
Project management	25
Resource-constrained project scheduling problem	22
Artificial intelligence	20
Machine learning	19
Problem solving	19
Learning systems	17

Table 6
Top title keywords

Title word	Frequency
Scheduling	66
Project	62
Learning	25
Approach	18
Problem	18
Resource-Constrained	17
Resource	14

The commonalities between the two tables are apparent where words such as "Scheduling", "project", and "Resource-Constrained" for example, are among the top words in both tables. This indicates the dominance of keywords that relate to project scheduling, where the class of "resource constrained" project scheduling problems, in specific, is seemingly tackled using AI techniques to a larger extent as compared to its "time constrained" counterpart. Other top words on the likes of "learning" and "reinforcement" show areas of AI that seem to be the most frequently used in the context of project scheduling. It shall be noted that most keywords shown in Table 5 coincide with the search query used to gather the final pool of papers.

NETWORK ANALYSIS

To conduct a network analysis, different software such as Pajek, HistCite, VOSviewer [68], and Gephi [69] can be used. As Pajek works only with files in". Net" format and HistCite is compatible only with Web-of-Science output file [21], this work adopts both Gephi and VOSviewer towards a better visualization of the bibliographic data. Gephi is a powerful tool that is capable of creating flexible visualizations of complex data through several built-in toolboxes for network analysis. Although Gephi has the ability to work with input files of different formats, it is not compatible with the RIS file that is directly generated from Scopus, but rather uses a network file obtained using BibExcel. VOSviewer, on the other hand, is a more simplified software that has limited capabilities when dealing with bibliographic data yet has the advantage of being readily compatible with Scopus's RIS file which saves the pre-processing step of the data. The following sub-sections present the details of the Citation analysis, PageRank analysis, Co-authorship and Co-word Analysis, Co-citation analysis as well as Data clustering.

Citation analysis

In citation analysis, the relevant papers are evaluated and ranked based on their citation frequency, where this ranking helps in identifying the most significant papers in a specific field of research [70]. It is also an indication of the researcher's impact [71, 72]. It shall be noted that this method is not the only measure of papers impact in a research area as other indicators will also be discussed later. Within the preset timeframe, the authors were able to identify the most influential papers addressing AI applications in Project Scheduling. Table 7 depicts the top 10 most influential works based on their local and global citations. Local citations represent the number of times this paper was cited by other papers from within the pool of 104 papers under study, while global citations denote the number of citations a paper has received from works across different areas of research as obtained from Scopus. The notable difference in the number of local and global citations clearly illustrates that these works have also received attention from researchers in other disciplines. As seen in Table 7, Agarwal [73] is the top cited paper following both criteria, wherein the authors explored a hybrid neurogenetic approach for the RCPSP based on GA and neural networks approaches.

Table 7
Top articles based on citation analysis

Paper	Global Citations	Local Citations
Agarwal [73]	110	5
Wauters [74]	26	5
Schirmer [75]	52	4
Jedrzejowicz [51]	17	3
Gersmann [46]	14	3
Adamu [15]	1	2
Jędrzejowicz [52]	15	2
Jedrzejowicz [76]	7	2
Guo [50]	2	1
Van Dorp [42]	7	1

The second most cited paper [74] tackles the use of multi-agent RL for building high-quality solutions for the multi-mode RCPSP.

PageRank analysis

Generally, the most common approach of assessing the importance of a publication is via the use of citation analysis [77], as presented in the previous section. However, another way a certain publication's importance can be assessed is by the times it has been cited by highly cited papers [78]. This method was introduced by Brin and Page [79] and is called PageRank analysis. In essence, it considers both popularity and prestige, and makes sure that they are correlated in the analysis as briefly explained next.

Given that paper A has been cited by T_1,… T_n papers, parameter d is defined as the damping factor and is set to have a value between 0 and 1. The damping factor represents the fraction of random walks that continue to propagate along the citations [21]. Then, $C(T_i)$ is defined as the number of times paper T_i has cited other papers. Thus, the PageRank of paper A, which is denoted by $PR(A)$, in a network of N papers is calculated by:

$$PR(A) = \frac{(1-d)}{N} + d\left(\frac{PR(T_1)}{C(T_1)} + \cdots .. + \frac{PR(T_n)}{C(T_n)}\right) \quad (1)$$

It should be noted that in case $C(T_i) = 0$, then $PR(T_i)$ will be divided by the number of papers instead of $C(T_i)$. In addition, the damping factor d usually assumes a value of 0.5 in citation networks [80]. However, other scholars have suggested different values such as 0.85 [79].

Using Gephi, the authors were able to identify the top 10 papers based on their PageRank as seen in Table 8. However, before finding the PageRank, the self-loops had to be removed so that the PageRank of all papers sums up to one. Comparing Tables 7 and 8, one can note that all papers appear again in Table 8 except for the last two papers. Schirmer [75] appears to be the most important paper as it has the highest PageRank but lower global and local citations. The author developed a case-based reasoning and improved adaptive search for Project Scheduling. Agarwal [73] and Wauters [74] are still in the top 3 papers with a significant PageRank score. It should be noted that more recent papers have a lower chance of being cited by highly cited papers given the high citation score builds gradually over time.

Table 8
Top articles based on PageRank

Paper	PageRank	Global Citations	Local Citations
Schirmer [75]	0.08912	52	4
Agarwal [73]	0.065184	110	5
Wauters [74]	0.056709	26	5
Jedrzejowicz [51]	0.040873	17	3
Adamu [15]	0.036786	1	2
Jedrzejowicz [76]	0.034748	7	2
Gersmann [46]	0.03127	14	3
Guo [50]	0.029432	2	1
Ma and Wu [39]	0.029432	6	1
Pathak et al. [81]	0.029432	15	1

Co-authorship analysis

Upon analyzing the pool of 104 documents, it turns out that the list of contributors amounts to a total of 228 different authors. This work adopts VOSviewer software to visualize the co-authorship pattern as seen in Figure 2. A node represents an author and an edge links two authors if they have co-authored the same paper. The authors in the network formed 13 clusters that are colored based on the publication year as seen in Figure 2, where a cluster can be viewed as a group of authors with similar research interests. The size of each node is proportional to the number of edges connecting other authors. The maximum number of edges between two authors is equal to 6 indicating they have co-authored six different papers. Only 25 authors have co-authored at least one paper. From the analysis, it can clearly be seen that the co-authorship in the selected pool of papers is weak as each cluster is small and not connected with other clusters. This might indicate the existence of a variety of studied topics with no authors being clearly dominant.

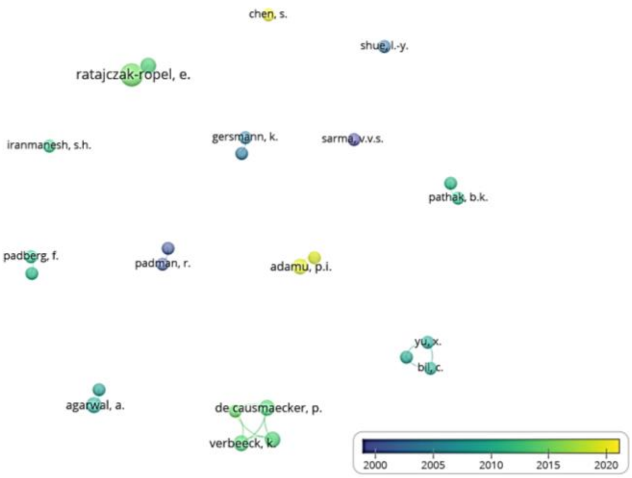

Fig 2 Network visualization for co-authorship analysis

Co-word Analysis

An alternative mean of analyzing the pool of papers at hand is using co-word analysis. This approach considers the authors keywords used in the papers in order to find existent relationships between them and map them out. Via the use of co-occurrence relationships to build the network, the analysis helps identify the most important keywords and their relatedness to different areas of research. From the pool of 104 papers, a total of 844 keywords were identified. A minimum threshold value of 5 is set for the keyword occurrences in order to be included in the network. A node represents a keyword and an edge links two keyword in the same paper. This results in a network of 48 keywords with 4 different clusters. The co-word analysis network presented in Figure 3 was generated using VOSviewer, which features 48 nodes with 597 edges.

The size of a specific node represents the number of occurrences it has with other nodes. The 4 clusters are color coded where the red cluster has 17 keywords with 24 occurrences for the main keywords being "optimization" and "resource constrained project".

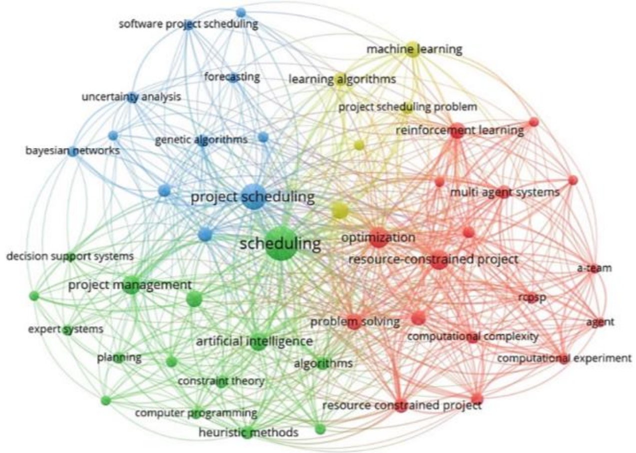

Fig. 3 Co-word analysis network

The second cluster is green and has 15 keywords with the main keyword being "scheduling" appearing 74 times. The third cluster is blue and has 11 keywords where the main keyword is "project scheduling" with 43 occurrences. The final yellow cluster has 5 keywords with the main keyword being "learning systems" having 17 occurrences.

Co-citation analysis and data clustering

Co-citation analysis is an approach that explains the existing relationships between authors, topics, journals or keywords and how each group interacts with one another [82, 83]. Therefore, once applied on authors, it will reveal the structural social relationships between authors, while if co-citation analysis is applied on publications, it will help identify the intellectual structure of the field of study [84]. In addition, it can be used to analyze the resultant clusters and their evolution over time [85]. The co-citation network that is created following the analysis consists of nodes that represent the articles and edges that show the co-occurrence of said nodes in their reference list of articles [86]. It is important to note that the co-citation analysis is based on the cited papers in the reference list of the pool of 104 papers. It is said that articles A and B are co-cited if both articles are cited by article C. It has been shown in the literature that articles which are cited together more frequently tend to be related in their research area [87].

To start the co-citation analysis, the network file that was generated using Bibexcel is used to create a network map on Gephi. Gephi has identified 172 articles that were co-cited by other papers within the sample. Although the initial map that Gephi generates is random and has no patterns to analyze, it offers numerous algorithms that can be used to create different layouts. Force Atlas is a force-driven algorithm that is one of the most recommended algorithms by Gephi developers in terms of readability and ease of understanding [21]. This algorithm creates a network where linked edges attract, and linked nodes repulse each other. Gephi allows for adjustments of repulsion speed, strength, gravity, node size and other characteristics [69]. In addition, the algorithm also makes nodes that are most connected move to the center while the less connected are farther away. Figure 4 shows the layout generated using Force Atlas of 172 nodes.

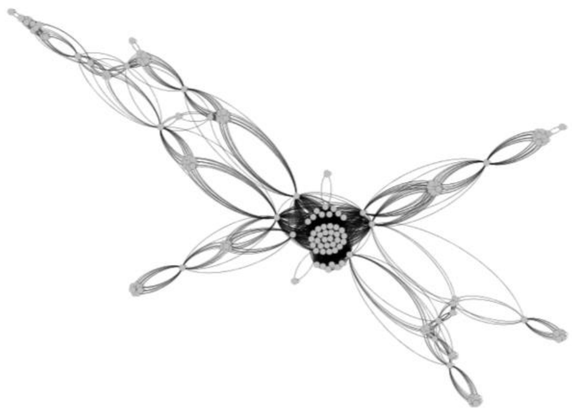

Fig. 4 The Force Atlas layout of the 172-node network

In data clustering, the aim is to group articles that have similar characteristics and relate to the same area of research [88]. To create clusters of similar articles, nodes are set such that the links between nodes from a cluster are denser compared to other clusters [88, 89, 90]. Clustering allows for network analysis to identify thematic topics, interrelations, and any common patterns between clusters. The concept of modularity is used to measure the density of the links within cluster nodes [91]. The default modularity tool used in Gephi is based on Louvain algorithm which is explained in Equation (2). The tool is used to find the modularity index of a partition, which is a scalar value between -1 and +1. This value measures the density of links inside a cluster and compares it to other clusters. Blondel et al. [91] defined the modularity index as:

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i, c_j) \quad (2)$$

where:

A_{ij} represents the weight of the edge between nodes *i* and *j*,

k_i is the sum of the weights of the edges attached to node *i* ($k_i = \sum_j A_{ij}$),

c_i is the community to which vertex *i* is assigned,

$\delta(u, v)$ is equal to 1 if $u = v$ and 0 otherwise, and finally $m = \frac{1}{2}\sum_{ij} A_{ij}$.

In this study, the algorithm was applied to the 172-node network resulting in 6 major clusters. In fact, those 6 were chosen out of 51 clusters as they appeared to be the strongest clusters in terms of number of nodes. The positioning of such clusters and their interaction can be seen in Figure 5.

The modularity index for the network in Figure 5 is 0.429 which indicates the existence of a relatively moderate interrelationships between clusters. Even with the moderate clusters-interrelationships, one can still analyze the existing relationships within each cluster.

Furthermore, the top 10 papers for each cluster based on their co-citation PageRank score are identified and are summarized in Table 9.

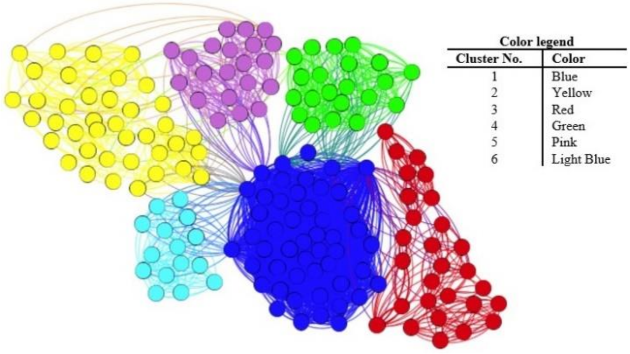

Fig 5 Network of 6 clusters

Table 9
Top 10 papers of each cluster as per co-citation PageRank measure

Cluster 1	Cluster 2	Cluster 3
Kolisch and Hartmann [92]	Kurtulus and Davis [93]	Kolisch and Drexl [94]
Kolisch and Drexl [95]	Confessore et al. [96]	Korf [97]
Kolisch and Padman [98]	Kaelbling et al. [99]	Talbot and Patterson [100]
Debels and Vanhoucke [101]	Nareyek [102]	Lee and Kim [103]
Brucker et al. [104]	Cohoon et al. [105]	Liu and Sycara [106]
Valls et al. [107]	Kolisch [108]	Ndumu [109]
Drexl [110]	Agarwal [73]	Özdamar and Ulusoy [111]
Agarwal et al. [112]	Blazewicz et al. [2]	Parunak [113]
Alcaraz et al. [114]	Kolisch and Sprecher [115]	Pulk [116]
Bouleimen and Lecocq [117]	Lenstra and Kan [118]	Rostami et al. [119]
Cluster 4	**Cluster 5**	**Cluster 6**
Wooldridge and Jennings [120]	Davis and Patterson [121]	Kirkpatrick et al. [122]
Hegazy [123]	Browning and Yassine [124]	Liu et al. [125]
Leu et al. [126]	Gonçalves et al. [127]	Ng and Zhang [128]
Li and Love [129]	Cooper [130]	Bhupendra [131]
Neligwa [132]	Laili et al. [133]	Kumar et al. [134]
Nilsson [135]	Lee and Katz [136]	Pathak and Srivastava [137]
Parunak [113]	Li [138]	Pathak and Srivastava [139]
Peña-Mora and Wang [140]	Naber and Kolisch [141]	Pathak et al. [81]
Que Bryan [142]	Oh et al. [143]	Raj et al. [144]
Ramos [145]	Pritsker et al. [146]	Lin and Kernighan [147]

After that, a thorough assessment of the content and the area of research of those top papers enables the determination of key thematic research topics/areas mainly characterizing each cluster, as reported in Table 10.
Closely examining the top papers in Cluster 1 reveals significant attention towards the application of different nature inspired metaheuristic approaches to solve the RCPSP in specific, such as GA and simulated annealing among others. It also includes several review works addressing the same problem and its many variants.

Table 10
Cluster classification and details

Cluster	No. of Papers	Area of Research
1	49	RCPSP metaheuristic solution approaches and surveys
2	38	Application of emerging AI techniques to solve project scheduling problems (e.g. multi-agent systems and reinforcement learning techniques)
3	28	Search procedures and reviews for RCPSP
4	21	Genetic Algorithms applications in project scheduling
5	21	Portfolio scheduling problem and various priority rules
6	15	Solving time-cost trade-off problems in construction industry

Only one publication introduced a relatively modern AI approach based on Augmented Neural Network [112]. As mentioned earlier, papers appearing in Table 1 are all cited by the pool of 104 papers under study, and most of them were published in the late 1990s where the authors tend to rely more on classic metaheuristic approaches to solve optimization problems such as the RCPSP. As for Cluster 2, it mainly presents different approaches to solve and categorize general project scheduling problems. While many classic metaheuristics were suggested, one may note the dominance of adopting multi-agent systems along with RL approaches. In the third cluster, the top papers lack a particular common focus as they address a multitude of topics ranging from search procedures to systematic reviews where, similar to Cluster 1, most of the papers address the RCPSP.
Cluster 4 is almost exclusively focusing on the application of GA based approaches toward solving different project scheduling problems. Similar to Cluster 2, this indicates that many of the works from the pool of selected papers have cited papers adopting GA which was among the widely adopted approaches in the late 1990s. The fifth cluster focuses on different project scheduling problems such as the multi-project scheduling problem or resources allocation problem in conjunction with the development of different priority rules and heuristics. Finally, the last cluster is largely dedicated to scheduling problems in the construction industry in particular, and more specifically the Time-Cost Trade-Off problem. Overall, these clusters indicate that in the 1990s and 2000s, most of the works focused on the RCPSP and developed different metaheuristics to solve the problem, with GA being clearly the dominating one across the different papers.

DISCUSSIONS AND RESULTS

The term "project scheduling problem" (PSP) refers to any problem that involves optimizing the (expected) duration/cost of a project and the allocation of scarce resources to the various activities comprising the project, among other things. To accomplish these fundamental objectives, PSP seeks to establish a sequence of activities organized around a decision criterion that results in a suitable solution to the problem at hand. Depending on the nature of the problem, the PSP has at least the following variants: the Basic PSP, TCPSP, RCPSP, MRCPSP, the Multi-Objective RCPSP, Time-Dependent Project Scheduling Problems (TPSP), Software PSP (SPSP), and Time RCPSP (TRCPSP). Unfortunately, the majority of them are known to be NP-hard combinatorial problems, which renders the attainment of optimum solutions prohibitively costly or impossible. Classically, Operations Research inspired approaches (e.g. mathematical modeling and simulation) coupled with the use of metaheuristics were widely adopted to obtain near-optimal solutions in a reasonable computational time. Recently, however, the employment of AI based approaches for solving, predicting, and optimizing project scheduling problems has seen an unprecedented surge. In particular, from the pool of papers under consideration, over 57% have solved the basic RCPSP using AI based techniques, followed by 13% for SPSP, and around 10% for MRCPSP. Although preset deadlines is a common practice in reality, less than 7% of the literature has examined the application of AI based techniques for solving TCPSP. This clearly indicates the necessity for additional research that seeks to validate the efficiency, accuracy and robustness of AI approaches in solving such class of problems.

It is particularly important for today's project-oriented companies to devise a well-thought-out strategy for the concurrent execution of multiple projects that share common resources, such as workforce, equipment and materials. Closely examining the pool of papers at hand indicates that the vast majority of them focused on a single project, overlooking the potential benefits associated with implementing those techniques to solve multi-project problems in what is commonly referred to in the literature as "project portfolio management" problem. As a matter of fact, 85% of the articles examined project scheduling in a single project context, while only 15% examined the multi-project case. In future research, AI-based approaches ought to be extended to address this latter case. From a practical perspective and depending on the industry, managing multiple projects at once brings rise to a multitude of challenging combinatorial optimization problems that foster further potential applications of AI techniques. Examples include the multi-project multi-resource leveling problem and the hybrid supplier selection, vehicle routing and project scheduling problems, among many others, where the latter is drawn from the multi-site construction industry.

From a scheduling environment perspective, existing models for PSP are often considered to be deterministic in nature despite the inherent complexities of the problem. Nevertheless, in reality, some models need information that is either unavailable or insufficient to predict certain project characteristics. Typically, uncertainties in parameters estimation associated with PSPs are believed to be of a stochastic nature. While probabilistic techniques are often used to address some of these issues, it is possible that project characteristics may not be correctly predicted from a statistical standpoint. In such cases, fuzzy set theory is well-suited for assessing the impact of linguistic-based activity and project duration as well as the direct and indirect costs. It is worthy to point out that 41% of the surveyed works tackled PSPs from a stochastic viewpoint, whereas 49% approached them from the more simplistic deterministic perspective. However, the literature does not sufficiently handle PSPs in a fuzzy context, with only 10% of studies examining the application of AI to project scheduling problems in a fuzzy environment.

Furthermore, it is important to note that the most commonly adopted ML techniques for solving PSPs are ANN, BN and RL. Towards improving the performance of such techniques, they have been hybridized via the use of several nature inspired metaheuristics, mainly GA and particle swarm optimization. In particular, this study reveals that 60% of the publications focused their efforts on hybridized algorithms, compared to 40% for stand-alone solution approaches. Moreover, classical combinatorial optimization was enhanced using knowledge extraction methods in order to improve outcomes via the extraction and use of information throughout the optimization stage. While the results are very promising, most of the conducted studies are very recent, and more research is needed to confirm and improve the efficacy of these approaches.

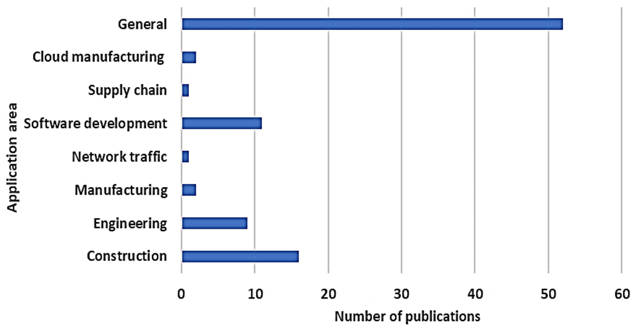

Fig. 6 Classification of relevant works by application area

As PSPs are frequently encountered in a wide range of application areas/industries, Figure 6 depicts the classification of the surveyed publications in terms of application area. The vast majority of these studies (52 of them) have tackled PSPs in a general context without relating it to a specific industry. While still deemed as significant contributions, it is also important to establish the practical relevance of a certain technique to a certain industry. This is attributed to the fact that different industries might pose distinguishing characteristics and peculiarities that set them apart from others rendering the applicability and/or efficiency of certain AI based approaches a questionable matter. Along these lines, Figure 6 also shows that 16 publications have adopted AI techniques to solve PSPs encountered in the construction industry, 11 studies in software development, 9 studies in the general engineering discipline, and only 2 studies addressing the manufacturing sector.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Given the emergence of AI based technologies and their wide-spread applicability across different disciplines, this paper has investigated the existing nexus between project scheduling problems and the AI domain. Following bibliometric and network analysis approach, this study identified the major contributing authors, journals, countries along with the most influential papers. Furthermore, five major clusters are obtained from the networking algorithm which illustrates current and past research trends allowing researchers to investigate how each is likely to evolve in the future. The network analysis showed that the building block for the recent application of AI techniques in project scheduling problems is largely the Operations Research (OR) based techniques that were developed in the 1990s and 2000s. In particular, it showed that nature inspired metaheuristics, such as GA, were the most used approaches to solve the RCPSP.

This study also adopted a systematic literature review approach which revealed a noticeable growth in the number of papers published lately, with a steady increase as of the year 2018. AI techniques were recently used to solve, predict and optimize project scheduling problems, where mostly supervised ML algorithms were considered. The vast majority of works are related to the application of ANN, BN, and RL algorithms. It is worthy to note that AI techniques were frequently hybridized with metaheuristics for an enhanced performance. In the same context, combinatorial optimization techniques were enriched via the use of knowledge extraction techniques.

Having thoroughly analyzed the pool of 104 papers via a systematic literature review and using bibliometric and network analysis tools, several existing research gaps have been identified which brings rise to the following future research directions:

- Generally, Artificial Neural networks assist in generating probabilistic scheduling solutions in a reasonable amount of computational time, while taking into consideration different risks and uncertainties. In the surveyed literature, they are often combined with other well-known metaheuristics such as GA or Tabu search to improve the obtained results. Despite being the most commonly used ML techniques, relatively few papers so far have dealt with ANNs in the context of project scheduling in the presence of uncertainty and limited data availability. As such, further exploration is needed to confirm how effective and accurate these techniques are for such settings.
- Despite the fact that the adopted Bayesian Network approaches have illustrated very promising results, only few and very recent papers investigated their use in the context of project scheduling. Their efficiency and accuracy is yet to be confirmed in future works where tackling uncertainty and risks in project scheduling continues to pose an important challenge.
- The conducted in-depth analysis revealed that the basic RCPSPs account for 57% of the problems tackled using AI based techniques, followed by software project scheduling problems (13%). Furthermore, only 7% of the addressed problems belong to the class of TCP-SPs which clearly illustrates that there is still much needed adaptation of AI tools towards efficiently solving this sort of problems.
- An important future research direction stems from the fact that only 15% have addressed the "project portfolio management" problem, wherein the scheduling problem involves activities comprising different project being carried out concurrently. This clearly points out the need for adapting AI tools to handle the multi-project case especially for large scale realistic projects.
- Considering uncertainty in the duration of the tasks, this review showed that AI techniques and knowledge-based approaches can definitely help with the development of dynamic optimization approaches in reasonable computational times. However, there are still many challenges that PSPs are facing and are mostly related to the complexity of large scale projects under a stochastic environment suggesting another promising avenue for future research.

Overall, the surveyed works indicate the added benefits and the cutting advantages that AI based approaches provides when it comes to solving PSPs as compared to purely OR based techniques. However, it is still in its infancy stage and further studies are needed to confirm the efficacy and accuracy of these approaches to handle various classes of PSPs across different industries. Despite some limitations of the current study concerning the adopted search queries and the selection of Scopus database only to retrieve the relevant works, it provides future researchers with the existing research trends within this field of study along with future research directions they could pursue. Promising areas of AI have proven their worth of being implemented into the practices of project scheduling. Both project scheduling problems and AI approaches are still growing and keep evolving over time suggesting an anticipated growth in the use of AI tools in the next years to assess project managers with their decision making. Getting to understand and implement practical techniques of AI would lead to an improved overall execution of the project and reflect positively on the company's reputation through timely handover of the projects at reduced costs.

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