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Review

Extensions of the resource-constrained project scheduling problem

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ABSTRACT

The resource-constrained project scheduling problem (RCPSP) aims to schedule a set of activities subject to resource and precedence constraints to minimize the project makespan. The construction schedule optimization is modeled and solved as the RCPSP, and research on the RCPSP has had a positive impact on construction projects. However, given the narrow assumptions of the standard RCPSP model, it fails to capture many practical engineering requirements. Consequently, various extended problems and more competitive solutions have been developed. However, few studies have discussed the extensions of the RCPSP and corresponding optimization algorithms. This paper reviews the literature on project scheduling over the last decade. First, the standard RCPSP is described, and extended models are summarized based on objectives, constraints, and activities. Then, the research progress of the algorithm and other variants of the RCPSP are investigated. Finally, based on statistics obtained previously, current limitations, challenges, and future research directions are discussed.

1. Introduction

Most activities worldwide are organized and executed in the form of projects. Project management (PM) applies knowledge, skills, tools, and technologies to project activities, and then it plans, organizes, coordinates, and controls them to achieve set objectives [1]. As a significant part of PM, project scheduling aims to allocate resources for activities under constraints and determine the time schedule for implementing project activities. Project activities follow predetermined precedence relationships and compete for scarce resources, ultimately arriving at the best schedule for achieving specific objectives. This situation was defined by Dike et al. [2] as the resource-constrained project scheduling problem (RCPSP), which has become a standard problem for project scheduling. The RCPSP has a strong application background and is widely present in engineering and construction, manufacturing, software development, and logistics management. In addition, the RCPSP has been proved to be an NP-hard problem [8].

The standard RCPSP can be summarized as follows. For a project with J activities that are labeled $j = 1, \ldots, J$, the processing time (i.e., duration) of activity j is denoted as d_j. Once it has begun, an activity cannot be interrupted until it has completed, that is, preemption is not allowed. Precedence relationships exist between some activities owing to technological requirements, which are shown by sets of immediate predecessors (P_j). This indicates that j cannot be started before each of its predecessors (w) has completed ($w \in P_j$).K types of renewable resources are required for each activity to be conducted. The per-period availability of each resource k is assumed to be a constant number given by R_k. Each activity j requires r_{jk} units of k in each period where the processing is carried out. Two additional dummy activities $j = 0$ and $j = J + 1$, are also considered, for which the durations and resource requests are zero, they represent the start and completion of the project, respectively. All information of the RCPSP is assumed to be known in advance and deterministic. The objective is to find the start time for each activity and a schedule that leads to the earliest completion time of the project, that is, the completion time of activity $J + 1$.

To date, there has been considerable research on the standard RCPSP model and solution methods. The books of Schwindt and Zimmermann (2015a, b) contain more than 60 papers covering many significant models and algorithms for project scheduling [3] [4]. The standard RCPSP knowledge base is powerful and extensive, but it is constrained by assumptions and objectives, and it cannot address many complicated scenarios that occur in practice. The research object is also mainly a single-mode project scheduling problem. Therefore, researchers have gradually turned their perspective to the expansion of the RCPSP under various conditions. Many more general project scheduling models and algorithms based on the standard RCPSP have been developed over time. A large number of articles have been published summarizing a certain RCPSP branch problem. For example, Behrouz et al. [5]

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conducted a literature review on models and methods for multi-skilled scheduling. Pellerin et al. [6] elaborated on the principles of hybrid meta-heuristic algorithms and compared the results of various combinations. In addition, Hartmann and Briskorn [8] provided an overview over variants and extensions of the RCPSP that have been proposed in the literature, but they focused on problem variants and models rather than on methods and algorithms. The overview of a particular extension problem of the RCPSP is extensive and complete, but there has been no systematic discussion covering various extensions and solutions to the RCPSP. Therefore, in this review, we provide a broad overview of the extended RCPSP models, algorithmic studies, applications of the RCPSP in other fields and other variant problems of the standard RCPSP based on the papers published in the field of project scheduling in the past decade. We summarize the latest research progress and identify the potential directions for future research to provide a reference for the in-depth study of the RCPSP and its application in actual construction projects.

The RCPSP model consists of three main elements: objective function (s), activities, and resources, the extensions are mainly conducted according to the above aspects. Based on this status, the structure of the remainder of this paper is as follows. We describe the statistical summary and reporting of relevant literature based on the systematic literature review (SLR) technology in Section 2. Sections 3, 4, and 5 provide an overview of the extensions of the three dimensions: alternative objectives, different constraints, and generalized activity characteristics. Section 6 deals with other variants of the RCPSP and explains its necessity in the construction field. Section 7 summarizes the research progress of the optimization algorithm. Current limitations and potential directions for the future are provided in Section 8. Finally, Section 9 provides our conclusion. (See Fig. 1)

2. Research methodology

This paper is based on the SLR. The SLR aims to study, evaluate, and report all relevant research in specific subject areas. In Kitchenham's [7] research, SLR was divided into the three phases: planning, implementation, and reporting, each of which consists of its own specific steps. The planning phase includes defining the research question, determining the scope of the search, and formulating the criteria for literature screening. The implementation phase focuses on searching, selecting, and synthesizing the literature. In the reporting stage, the research results are consolidated and systematically displayed. In this paper, the research steps related to the SLR are developed under the research background of the RCPSP. Fig. 2 shows the overall stage process based on SLR; the implementation and reporting stages are analyzed in detail.

2.1. Literature retrieval

To ensure that the selected literature was sufficiently advanced and referable, we limited our search to articles published in English from 2012 to 2022, Fig. 3 depicts the overall process of the literature search. First, *ScienceDirect*, *Web of Science*, *Scopus*, *Springer*, *Google Scholar*, *IEEE Explore* and *the Proceedings of Prestigious Conferences* were selected as the literature databases because of their extensive coverage of journals in computing science, operational research, management and construction engineering. The second step was to identify "project scheduling," "resource-constrained project scheduling," "RCPSP," "project

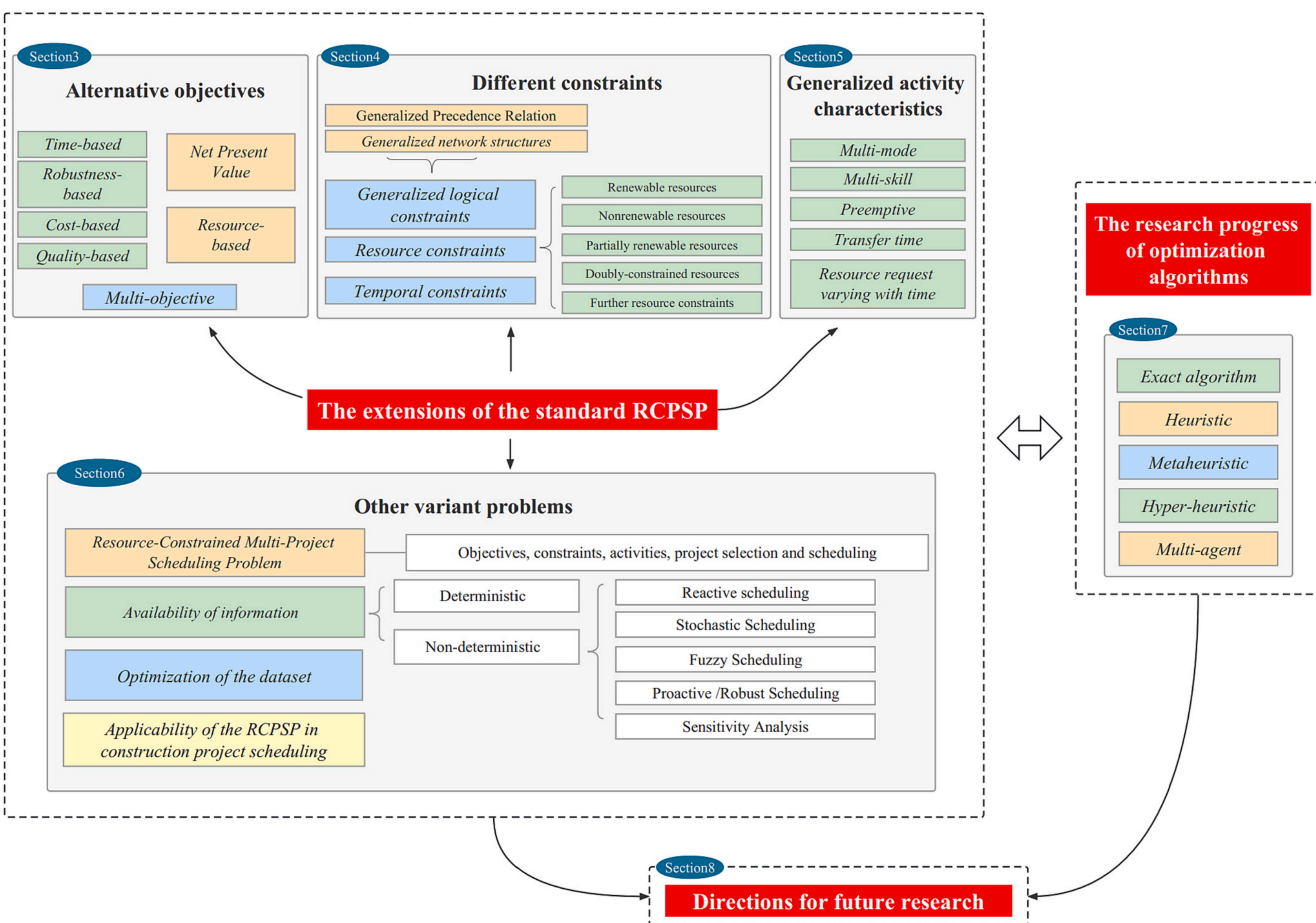

Fig. 1. General process for the review of the resource-constrained project scheduling problem.

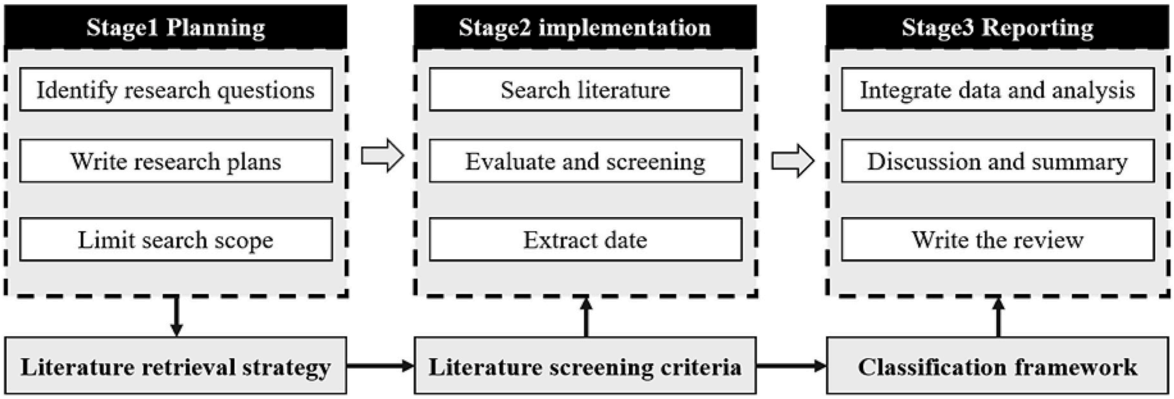

Fig. 2. Overall research design for the SLR.

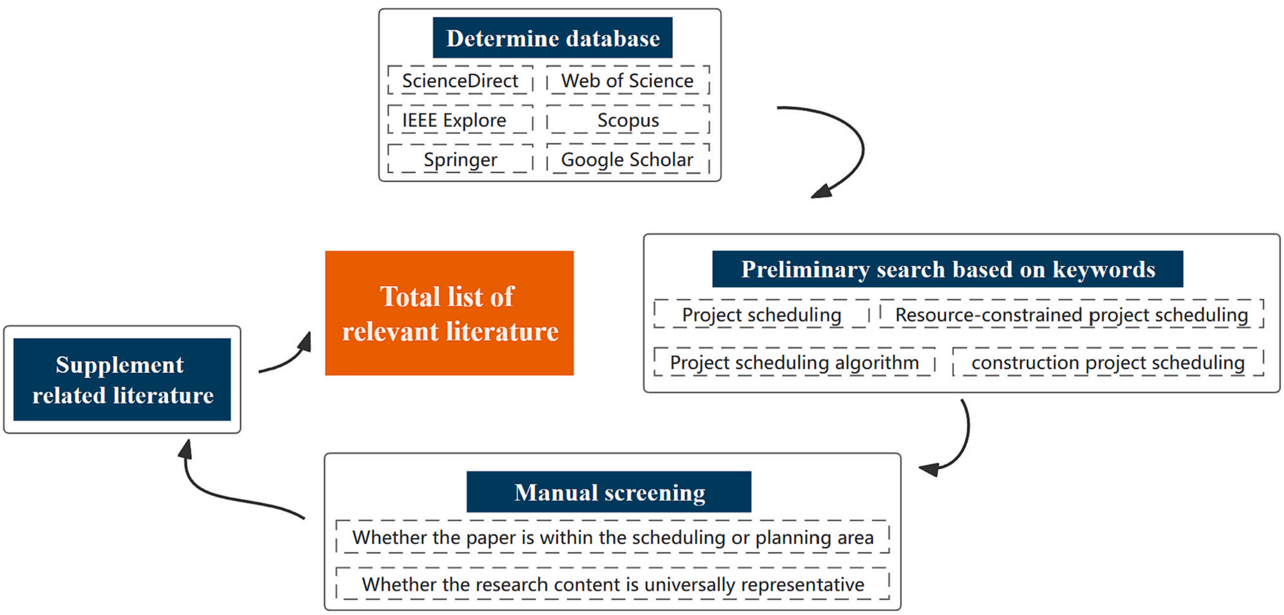

Fig. 3. Literature retrieval process.

scheduling algorithm," and "construction project scheduling" as keywords for the preliminary literature retrieval. To perfect our search, we checked the bibliographies of all the references and added the pertinent articles to the literature list. Then according to the preliminary screening results, we used manual screening to select literature that was most directly relevant to this review. One rule is that the papers had to be within the scope of the scheduling or planning area; for example, some articles focusing on project management or project decision-making and control had to be deleted. Another rule is that research on special activities conducted in the form of projects was not considered. These activities are often only aimed at practical problems and are not generally representative. Finally, additional searches were conducted based on the content of each chapter, such as using the keywords "multi-skilled," "multi-mode," and "multi-project" to select papers more accurately. To better illustrate the development history and background of the relevant issues, we also cited some publications beyond the scope of the last decade as supplementary material. Ultimately, 209 studies were retained and analyzed for this review.

2.2. Literature statistical summary

2.2.1. Location analysis

Fig. 4 shows the geographical distribution of relevant publications in the field. A total of 30 countries feature in this systematic review, and the top 10 countries in terms of the number of publications are as follows: China (55), Iran (29), Germany (22), Belgium (13), France (12), Australia (10), the United States (9), Turkey (6), Canada (6), and the United Kingdom (5). Fig. 5 shows the number of publications cited by countries.

2.2.2. Publication analysis

The 209 publications include 197 journal papers (94.26%), 11 conference papers (5.26%), and one monograph (0.48%). Elsevier is the leading publisher. Fig. 6 depicts the top 10 peer-reviewed journals covering publications on the RCPSP.

Among the published peer-reviewed journals, the top five are the *Computers & Industrial Engineering* (18%), *European Journal of Operational Research* (15%), *Automation in Construction* (11%), *Computers & Operations Research* (6%), and *Applied Soft Computing* (4%). Among journals in the field of operations research, *Computers & Industrial Engineering* is the most popular, and in terms of research on construction project scheduling, *Automation in Construction* ranks first.

2.2.3. Distribution of published works over the considered time horizon

The retrieved literature mainly involves extended models, optimized algorithms, and other variant problems (e.g., multi project scheduling).

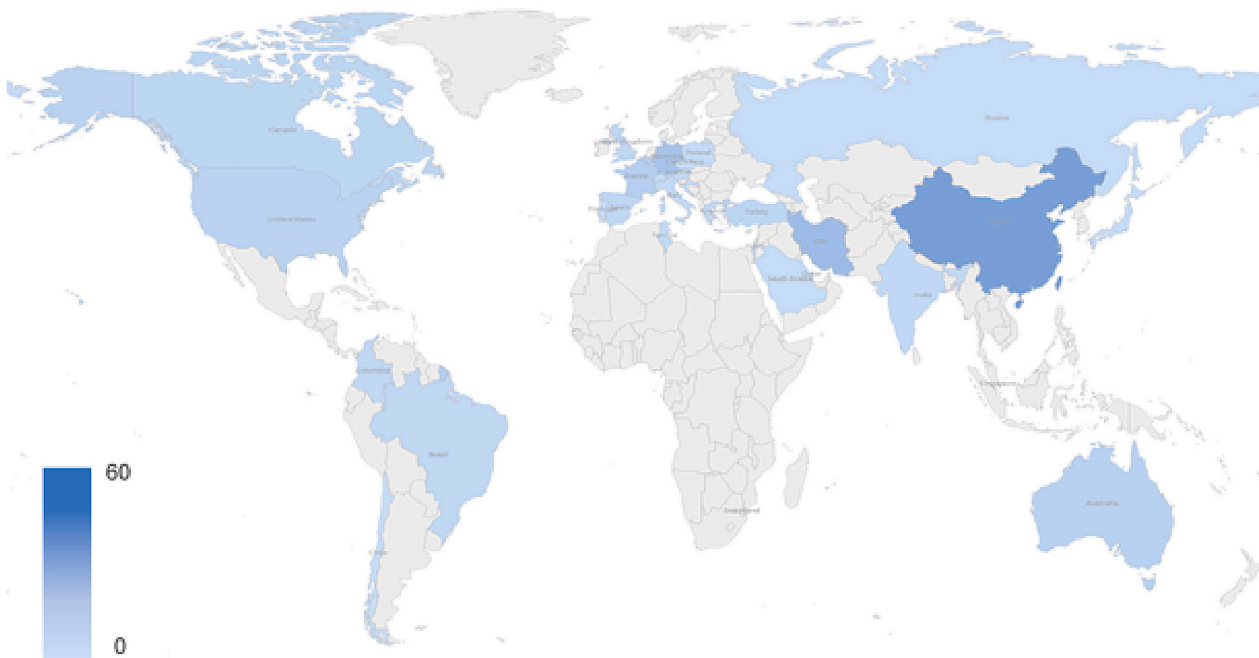

Fig. 4. Geographic distribution and quantity of publications.

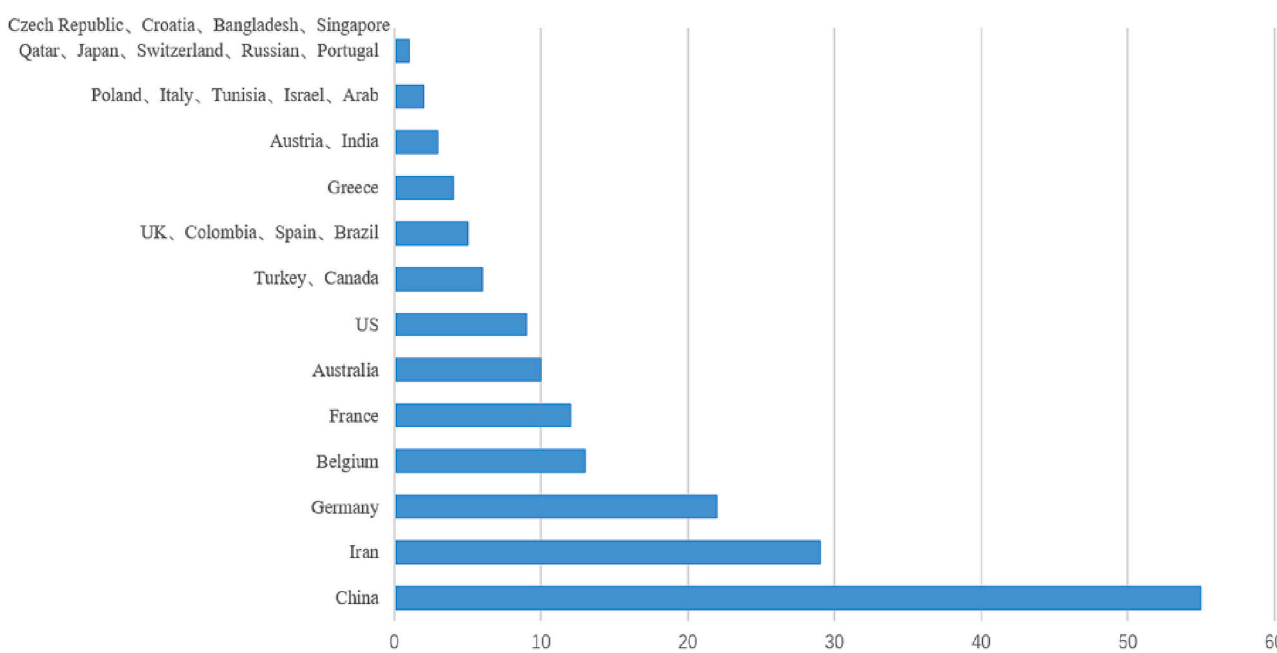

Fig. 5. Number of literature citations by countries.

The first two were divided into a class of extended problems because the model extensions were performed while the solution methods were adjusted accordingly. There were 146 papers involving extended models and algorithms, 39 papers involving other variant problems. An additional 24 papers were referenced to supplement the background of the problem (e.g., earlier reviews, as well as studies that originally posed a particular type of problem), and to make this review more integrated. Fig. 7 depicts the distribution of various types of problems over the considered time horizon.

2.3. Discussion and summary

As shown in Fig. 6, the *European Journal of Operational Research* and *Computer & Industrial Engineering* cover the vast majority of publications on the RCPSP, which indicates that researchers are particularly interested in theoretical research on the RCPSP model and algorithm extension. The number of publications in journals such as *Applied Soft Computing* and *Automation in Construction* shows the necessity of applying RCPSP theoretical research to the real world, especially in the field of construction projects.

Fig. 7 shows that the extensions of the standard RCPSP and the optimization of algorithms account for the majority of published works, indicating that such issues have always been the key focus of scholars. The number of articles on other variants of the RCPSP gradually increases over the considered time horizon and exhibits an overall upward trend. It is evident that research on variants of the standard RCPSP, as

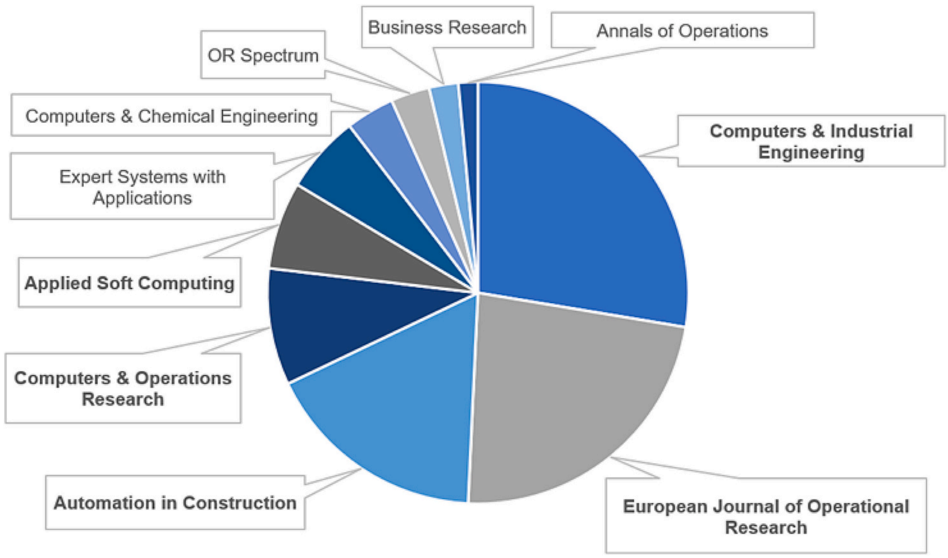

Fig. 6. Contribution of top 10 peer-reviewed journals on the RCPSP.

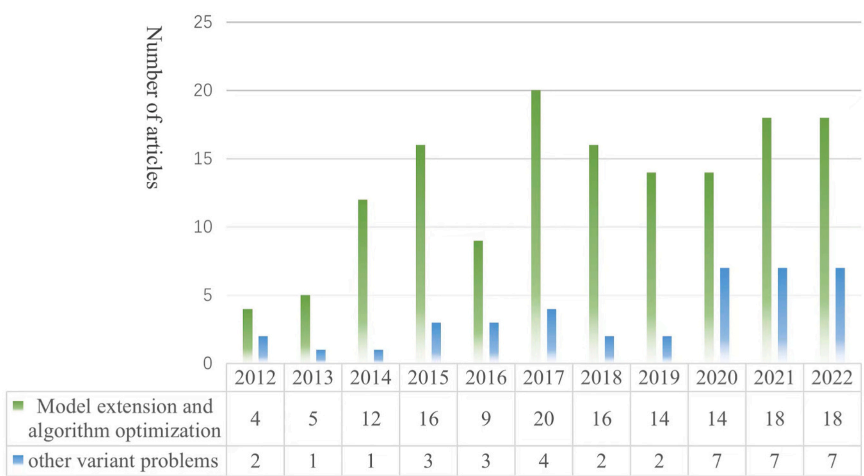

Fig. 7. Distribution of various types of problems over the considered time horizon.

represented by the multi-project scheduling issue, is becoming increasingly popular.

3. Alternative objectives

The objectives of the project scheduling problem are considered in two categories: regular and irregular. Regular performance objectives are a non-decreasing function of activity start time, among which the representative objectives include minimizing the makespan, project cost, and project delay time. This series of target values can be improved by advancing the start time or completion time of an activity. In contrast, changing the start time or completion time of an activity does not contribute to the target value, such as the maximization of the net present value and the resource leveling problem, which is regarded as irregular performance.

3.1. Regular objectives

3.1.1. Time-based objectives

The classical objectives of project scheduling problems are time-based, with the most common objective being to minimize the makespan. Kong et al. [9] constructed a mathematical model for the optimization of the makespan by considering all possible combinations of precedence relations and resource calendars. Considering the uncertainty of activity durations in the scheduling problem, Creemers et al. [10] proposed a model to minimize the expected makespan.

Several other time-based objectives have also been proposed to deal with the complex and flexible real-life situations. The shift mainly concerns earliness and tardiness. During project management, the start time and finish time of each activity are limited. Undoubtedly, the actual execution will deviate from the plan, and earliness and tardiness will occur. Wang et al. [11] and Gomes et al. [12] proposed an algorithm based on column generation for minimizing the total weighted tardiness of activities. Niño et al. [13] solved a bi-objective optimization problem by minimizing the makespan and total earliness of activities. Bagherinejad et al. [14] employed the objective to minimize tardiness and the earliness cost of activities with a meta-heuristic to determine a mode and start (or finish) time for each activity. While considering the earliness/tardiness of activities, the researchers also focused on the deviation of the project completion time from the deadline because the objective is to minimize the delay of the project with respect to a given due date. One of the objectives of Prata et al. [15] was to minimize total tardiness of the flowshop scheduling problem. Furthermore, Androutsopoulos et al. [16] aimed for a minimum total weighted earliness-tardiness using a hybrid heuristic algorithm.

3.1.2. Cost-based objectives

Costs are directly related to the benefits of the project, and the pursuit of maximizing project benefits should focus on both schedule-related and cost-based objectives. The classical cost-based objective aims to minimize the total project cost, but there are few papers on cost as a unique object. Most researchers regard it as one of the optimization objects in a multi-objective problem. In these papers, the equilibrium problem that explores the interaction of time and cost was in the majority, and the time-cost trade-off problem (TCTP) was formed.

Hariga et al. [17] developed an integrated model and addressed the issues of resource leveling and time-cost trade-off together that considers the minimization of the total costs within a multi-mode and preemptive activity model. Similarly, Rahman et al. [18] argued that the operators' human factors such as skill and learning effects result in a total project cost that consists of the tardiness cost and the total wage cost. Hence, the optimization goal is to minimize the total costs and the carbon footprints from energy consumption in the production process. Alcaraz et al. [19] proposed a method to find the exact solution to the TCTP, as well as to minimize the resource-related duration and the total cost.

3.1.3. Quality-based objectives

As a dimension of project scheduling objectives, quality optimization is more important for managers than shortening project duration, as confirmed in some studies. When considering quality-based objectives, we should first determine the indicators best suited to measuring the quality of scheduling results. However, it is difficult to effectively measure the solution quality. Moreover, there are few papers on quality-based objectives.

Considering that the completion quality of a project is measured by the quantity of rework and the corresponding additional costs, Tukel et al. [20] originally proposed minimizing rework as an optimization objective in 1997 to achieve the best quality of scheduling results. Since then, more research on the optimization of rework time has gradually been done. Wen et al. [21] aimed to minimize the rework time or costs of complex projects. Hossain et al. [22] searched for an optimal strategy of overlapping to reduce the amount of rework by quantifying the impact of design and activity execution on project completion and rework. The rework scenario is classified as an uncertainty problem when the project deviates from the original schedule owing to the rework disrupting schedule, and it has also been studied in the scenario of dealing with robust project scheduling problems (Section 3.2.3).

In some project organizations, the skill heterogeneity of the workforce can lead to different quality levels of project completion. A few published works suggest solutions for the distribution of workforces to meet quality-optimal objectives. Maghsoudlou et al. [23] argued that the reworking risk of each activity depends on the allocated level of multi-skilled workforces, and they established an optimization model to minimize the total costs and reworking risks. Qin et al. [24] developed a scheduling model for a multi-skilled workforce allocation based on the learning of knowledge and the requirements of project quality. Against the backdrop of the IT industry, Chen et al. [25] proposed a multi-objective optimization model for project portfolio scheduling and multi-skilled personnel assignment. Three objectives (i.e., staff skill enhancement, development cycle time, and product quality) were considered.

3.2. Irregular objectives

3.2.1. Resource-based objectives

Resources are generally mentioned in the constraints of project scheduling and are not negligible optimization objectives. The resource-based objectives are classified as the resource investment problem (RIP) (also known as the resource availability cost problem, or RACP), resource renting problem, and resource leveling problem.

1) Resource Availability Cost Problem

The RACP, also called the RIP, was first proposed by Möhring [26] in 1984. The aim of solving this problem is to minimize the total costs for resource capacities by determining the capacity of renewable resources and the start times of the activities within the deadline. The objective is as follows.

$$min\sum_{k} C_k R_k \tag{1}$$

In (1), C_k denotes the unit cost of resource k, and R_k denotes the resource capacities.

However, the standard RACP model deals with single-mode resource-constrained project scheduling problems and cannot be applied to complex practical situations. Coughlan et al. [27] considered a multi-mode extension of the RIP (MMRIP) and proposed the additional consideration of resource unavailability. Afshar-Nadjafi et al. [28] extended the multi-mode RIP more practically. Resources are no longer assigned to the project for the total project duration and the unit cost of resources depends on their availability durations. Moreover, the availability cost of resources is only incurred during the period when the resources are used. Fink et al. [29] extended the multi-mode resource investment problem to a multi-agent system, where each agent aims to minimize their individual investment resource costs associated with the project. Siamakmanesh et al. [30] paid more attention to the practical application scenarios. They considered the activities' daily resource demand levels as decision variables and applied the concept of work-content to tackle the RACP for the first time.

2) Resource Renting Problem

The fixed available cost of resources is easily acceptable for most renewable resource types (e.g., ordinary workers, small machines, and low-cost instruments), but not for heavy equipment such as cranes, trucks, and professional human resources. Nübel et al. [31] introduced the resource renting problem (RRP) with the objective of minimizing the total acquisition costs of purchasing resources and the renting cost of renting resources within the project deadline. Typically, the acquisition costs are independent of the length of use, and the renting costs are a function of the length of their use. The mathematical formulation for the cost of renting a unit of resource k over t periods is as follows.

$$min\ \mathrm{a}\cdot\left(\mathrm{C}_k^f + \mathrm{t}\cdot\mathrm{C}_k^v\right) \tag{2}$$

In (2), a denotes the unit resource volume of renting, C_k^f denotes the fixed costs per unit of renting resource k, and C_k^v is variable cost per unit. The RRP is transformed to the RIP if the variable costs are zero.

Nadjafi et al. [32] described the RRP with time lags with the objective of minimizing the total renting costs and the penalty costs for tardiness. Kerkhove et al. [33] proposed an extension of the RRP by including overtime, with the total costs divided into three parts in the RRP/overtime: the procurement costs of resources, the renting costs to use the resources during regular time, and the renting cost to use the resources during overtime. Vandenheede et al. [34] proposed extended resource renting problem (RRP/extended), and five different types of resource costs were newly defined.

3) Resource Leveling Problem

The scarcity and universality of renewable resources may lead to peaks or valleys in resource requirements, resulting in conflicts when activities are executed. The resource leveling problem refers to solving a schedule to assign resources evenly within the project deadline so that the resource consumption is as efficient as possible and the fluctuations in resource requirements are minimized. Different optimization objectives can be considered in the RLP. Set R_{kt} as the capacity of the resource k required in period t, and set C_k as the unit cost of resource k. When dealing with a single resource problem, the weight brought by the unit cost is ignored.

The most popular objective is to minimize the squared weighted sum of resource capacities (Eq. (3)), and introduce weight based on unit costs or resource-related factors.

$$min \sum_k C_k \sum_t R_{kt}^2 \tag{3}$$

Rieck et al. [35] proposed a new enumeration scheme for this objective. This has also been considered by Ponz-Tienda et al. [36] and Qiao et al. [38]. Li and Xiong et al. [39] investigated the RLP with additional minimal and maximal time lags. Li and Dong [40] also considered multi-mode scenarios based on previous studies.

In addition, the level of fluctuations in resource requirements can be measured by deviations from a given threshold. The objective is to minimize the squared deviation between the number of resources used in period t and the average resource request $\overline{R_k}$ (Eq. (4)).

$$min \sum_k C_k \sum_t \left(R_{kt} - \overline{R_k} \right)^2 \tag{4}$$

Qiao and Li [38] minimized the squared deviation from a given resource capacity while considering a minimal objective based on resource-based entropy theory.

When $\left(R_{kt} - \overline{R_k} \right)^+$ is used to represent the positive deviation from a given threshold, the objective shifts to minimize the penalty cost of total overload; that is, to minimize the resource capacities that exceed a given value. The mathematical formulation is as follows.

$$min \sum_k C_k \sum_t \left(R_{kt} - \overline{R_k} \right)^+ \tag{5}$$

Tarasov et al. [41] developed an RLP with flexible allocation of resources and aimed for a minimal total resource overload cost. Rieck et al. [35] studied the overloaded problem with a focus on positive deviations from the threshold rather than all deviations, and they attached the conditions for releasing and reemploying resources. Atan et al. [42] and Verbeeck et al. [43] also discussed the objective of minimizing the total overload cost.

When we consider the change in resource capacity within adjacent time periods, the objective is to minimize the squared changes of the resource requests from period to period (Eq. (6)) or minimize the absolute changes from period to period (Eq. (7)).

$$min \sum_k C_k \sum_t \left(R_{k,t+1} - R_{kt} \right)^2 \tag{6}$$

$$min \sum_k C_k \sum_t \left| R_{k,t+1} - R_{kt} \right| \tag{7}$$

Qiao and Li [38], Rieck et al. [35], and Ponz-Tienda et al. [36] have both studied these issues. In the construction industry, resource fluctuation can affect the efficiency of project completion and cause huge cost loss. The sequencing of construction activities needs to minimize the variability of resources while optimizing the project schedule sequence. Ponz-Tienda et al. [37] focused on the RLP in construction projects and proposed an improved adaptive harmony search algorithm to maximize the reduction of resource fluctuations, which was validated based on 71 examples of construction projects. Based on the adverse effects of peak demand and fluctuations of resources, Jaeho Son et al. [44] optimized an algorithms for resource leveling problem in construction engineering. In their research, a local optimizer based on the multiheuristic approach for the RLP was developed, and computational experiment showed that the approach can produce near-optimal solutions close to the global optimum. In addition, a hybrid model combining simulated annealing technology and local optimizer has been developed that can provide optimal solutions for complex scheduling networks.

3.2.2. Net present value

Cash outflows occur when resources are consumed during project execution, and cash inflows occur when specific portions of the project are completed. The net present value is the difference between cash inflows and outflows. Taking into account the time value of cash by discounting the cash flow value to a certain point in time, we can express this as mathematical expression as the discount rate (α). Since Russell first proposed a model for maximizing the net present value of a project without considering resource constraints (Max-NPV) in 1970 [45], the problem has been widely studied. Researchers have introduced NPV metrics into RCPSP, resulting in a resource-constrained project scheduling problem with discounted cash flows (RCPSPDC).

Different schedules can lead to cash flows being generated from activities executed at different points and affecting the overall project NPV. Asadujjaman et al. [46] discussed the RCPSPDC with material ordering problem and the cash outflows occur at the start time of the activities. Leyman et al. [47] discussed RCPSPDC with payments at activities' completion times and maximized the project NPV by delaying sets of activities with a negative NPV or advancing those with a positive NPV. Rezaei et al. [48] (2020) solved the stochastic project scheduling problem and proposed a conditional-value-at-risk (CVaR) model to measure the risk of the project's NPV. They also studied the trade-off between the risk and expected NPV. In the follow-up study [49] (2021), they assumed that the payments would occur at the activities' completion times to maximize the expected NPV and aimed to minimize the risk of the project's NPV by semi-variance risk measurement. The performance of 16 heuristic priority rules was evaluated in their research. Creemers et al. [50] studied the project NPV maximization for activities with stochastic durations. Additionally, Hartmann et al. [51] provided an overview of the problem of maximizing the net present value.

Tirkolaee et al. [52] considered maximizing the NPV in multi-mode RCPSP. Tabrizi et al. [53] reduced cash outflows from material procurement through supplier selection to maximize the net present value of the system. Bulavchuk et al. [54] proposed a genetic algorithm based on idempotent algebra to maximize the NPV. Asadujaman et al. [55] proposed a hybrid immune-genetic algorithm to solve the problem of maximizing NPV considering the supply capacity of multiple suppliers and the own inventory capacity.

3.2.3. Robustness-based objectives

RCPSPs often present uncertainties that interfere with the schedule. These uncertainties are associated with many potential sources, including difficulties in obtaining project parameters like activity durations, rework corrections, resource shortages, and personnel absenteeism. When a project is implemented, activities may take longer or cost more than estimated. The deviation of the project completion time from the deadline in Section 3.1.1 is regarded as quality robustness, while the time deviation of each activity's execution is the solution robustness.

To maximize the robustness of the schedule, Palacio et al. [56] maximized the sum of the slack times of all activities. Balouka et al. [57] suggested a robust optimization method for scheduling problems with uncertain activity durations and pursued a minimum project duration in the worst-case scenario. If the current schedule becomes infeasible owing to the delay of an activity or the shortage of a resource, it must be rescheduled. Chakrabortty et al. [58] discussed the rescheduled RCPSP with the objective of minimizing the expected makespan plus the weighted deviations from the previously scheduled start times. Elloumi et al. [59] rescheduled the multi-mode RCPSP with the objectives of minimizing the makespan and optimizing the schedule stability. In their study, the sum of start time variations, the largest start time variation, and resource requirement variations in the new schedule were taken as stability measures.

In other cases, the robustness-based objective exists as one of the optimization objectives of the multi-objective scheduling problem (Section 3.3). Several studies have maximized the robustness by different methods while minimizing the makespan. Liu et al. [60] evaluated the solution robustness by using six robustness measures depending on the free slack determined by the start time and renewable resource surplus per unit time. Tian et al. [61] introduced time-based robustness and capability-based robustness in terms of modeling to evaluate the robustness of scheduling schemes. Some studies have considered minimizing costs and performing robust optimization. Tabrizi et al. [62] considered the uncertainty problem in terms of both the corresponding costs and robustness, and a bi-objective mathematical model was proposed to maximize the weighted slack and minimize total costs. The makespan, cost, and robustness were also considered together in some studies. Zhou et al. [63] introduced the objective of a minimum robustness while minimizing the expected makespan and expected cost. Shen et al. [64] considered the minimization of the makespan and cost, as well as optimization of employee satisfaction and robustness to uncertainty in software project scheduling.

3.3. Multi-objective

Traditional project management usually considers the optimization of one dimension, but in an actual decision-making process, managers face requirements from different departments. Thus, single-objective optimization no longer meets practical requirements. Models for bi-objective or multi-objective combinatorial optimization have been gradually established.

Tian et al. [65] considered the extra operation time required and costs incurred when resources are switched for skills and developed a mixed-integer programming model to minimize the project completion time and total cost. Dridi et al. [66] conducted a multi-mode project scheduling model with uncertain activity durations to minimize makespan and cost. Tirkolaee et al. [52] also proposed a multi-objective model to maximize the NPV and minimize the makespan for multi-mode RCPSP. Nemati-Lafmejani et al. [67] discussed a bi-objective optimization model to minimize the project duration and total cost while also considering the selection of contractors. Maghsoudlou et al. [68] studied a tri-objective model to minimize makespan and the skill-costs and maximize the completion quality. Shahsavar et al. [69] considered the goals in RCPSP, RLP and RIP at the same time, and they proposed three adaptive evolutionary algorithms. Differences in priority between objectives should be considered when multiple objectives conflict. A common approach is to consider the weights of different objectives. For example, Laszczyk et al. [134] used a weighted sum method for criteria to calculate the objective.

During the implementation of the project, the working hours of the labor force should be controlled to meet the scheduled deadlines. Especially in construction projects, shift work is more efficient and less costly per hour. However, the accompanying activities of multiple shifts, such as additional power consumption, increase the total cost of construction. At the same time, there are potential safety hazards for the night shift labor force. The project decision-makers plan the schedule to meet the deadline and construction budget requirements can help the construction company gain a significant advantage over its competitors in the market. Cheng et al. [70] developed a multi-objective differential evolution algorithm to solve the trade-off of the time-cost-labor utilization problem. In some more flexible construction sites, the site restrictions, the parameters of mechanical equipment, and the application of automation equipment need to be considered when scheduling. Liu et al. [71] considered the requirements of processes for various pieces of equipment and established a multi-objective model that satisfies the processing time, total equipment load, and total energy consumption requirements based on the earthwork site construction site, which aimed to realize a unified and coordinated arrangement of the automated resources involved in the construction.

With the development of robust scheduling, the amount of research on the multi-objective problem of robustness has also increased (Section 3.2.3). Daryani et al. [72] proposed a new robustness index based on the preferential weights to solve the multi-objective portfolio optimization problem. A complex multi-project multi-objective resource constrained project scheduling is discussed in what follows for the scenario of multiple projects existing in parallel (Section 6.1.1).

4. Different constraints

4.1. Generalized logical constraints

4.1.1. Generalized precedence relation

An activity cannot start before its predecessor is completed that is required in the standard RCPSP. It is referred to as the finish-start type precedence relationship in the study of logical relationships between activities. The possible logical relationships between the activities are summarized in Table 1 (using Activity A-B as an example).

The different logical relationships between activities indicate the existence of time lags between them, and the extension of the RCPSP with minimum and maximum time lags is provided. The model is referred to as RCPSP with generalized precedence relations or as RCPSP/max. Bianco et al. [73] proposed a new branch and bound algorithm for RCPSP with generalized precedence relations. Tran et al. [74] considered a new model for hybrid flow Shop with time-varying resources and time-Lag Constraints. The mathematical formulation was revised and improved in the subsequent study. de Azevedo et al. [75] described a new exact method based on satisfiability and workload for the PCPSP/max problem. Bianco et al. [76] proposed a new method to overcome the failures and limitations of existing theories for non-preemptive project scheduling with generalized precedence relations under infinite resources.

Schnell et al. [77], Ballestín et al. [78], Bagherinejad et al. [14] and Quintanilla et al. [79] believed that time lag value depends on the execution mode of the activity, and employed minimal and maximal time lags in multi-mode RCPSP. The MRCPSP/max was developed (Section 5.1). Li et al. [40] embedded the resource leveling problem into MRCPSP/max. Tavana et al. [80] proposed a multi-objective multi-mode model for solving discrete time-cost-quality trade-off scheduling problems under preemption and generalized priority relations. Kreter et al. [81] considered RACP with generalized precedence relations and calendar constraints. In their study, activities can only be interrupted during the resource unavailability period specified in the calendar. Watermeyer et al. [82] introduced partially renewable resources into RCPSP/Max, which expanded the research scope. Activity overlapping allows a downstream activity to start based on some preliminary information and feedback before its upstream activity is completed, and Chu et al. [83] studied a RCPSP with multiple overlapping modes.

4.1.2. Generalized network structures

All activities must be carried out in the standard RCPSP. The generalized network structures in which some activities must be carried out while others can be performed selectively. Kellenbrink et al. [84] studied RCPSP with model-endogenous decision on the project structure (RCPSP-PS). The mandatory activities that must be performed and optional non-mandatory activities were distinguished in their works. Each set of optional activities is connected to a triggering activity. If the

Table 1
Logical relationships between activities.

Types	Explanation
Finish-Start (FS)	Activity B cannot start before activity A is finished.
Finish-Finish (FF)	Activity B cannot be finished before activity A is finished.
Start-Start (SS)	Activity B cannot start before Activity A starts.
Start-Finish (SF)	Activity B cannot be finished before Activity A starts.

triggering activity is mandatory, optional activity in the related set is also mandatory and one optional activity must be carried out. However, if the triggering activity is optional, none of its associated optional activities will be implemented. In the RCPSP-PS, precedence constraints are defined in the same manner as the standard RCPSP but a precedence constraint is only implemented whenever the succeeding activities that are connected via this constraint are actually implemented. Kellenbrink also pointed out that multi-mode RCPSP can be used as a special case of their research. Tao et al. [85] proposed a resource-constrained project scheduling problem with alternative activity chains (RCPSP-AC). Activity chains include sets of activities connected by precedence relations. Each activity chain can be used as an alternative to other activity chains, and the most optimal utility for the objectives is selected for execution. Otherwise, they developed the AND-OR network to make the problem more intuitive. An AND node corresponds to an activity that all successors must be executed, whereas an OR node corresponds to an activity that only one successor must be executed. Tao et al. [86] optimized and supplemented the objective function and AND-OR network in subsequent articles.

4.2. Temporal constraints

The deadlines are given in the standard RCPSP to limit the total project duration, without considering the start and completion time limits for each activity. Due to different application, there might be a time-window for each activity. The time-window constraint describes the time interval where the activity can be scheduled in. It sets the start time and end time range allowed for each activity, and the minimum or maximum time lags between activities can be obtained. Therefore, the time-window constraint can be regarded as an extension of the precedence relation constraint in the previous section. The calculation of the time-window can be described as follows: determining the initial upper limit T of project duration, determine the earliest start time ES_j and earliest finish time EF_j for each activity using the forward recursive method, and then calculate the latest start time LS_j and latest finish time LF_j for each activity using the backward recursive method. The time-window of activity j starting is $\{ES_j, \ldots, LS_j\}$, and the time-window of finishing is $\{EF_j, \ldots, LF_j\}$.

Cheng et al. [87] set time-window rules for multi-mode RCPSP with non-preemptive activity splitting. Hua et al. [88] proposed a genetic algorithm based on time-windows decomposition to narrow the solution space and improve search efficiency, and showed the advantages of high success rate and small sample cost in solving the optimal solutions of two real construction cases. Hartmann [89] proposed three types of temporal constraints in project scheduling with resource capacities and requests varying with time, namely two activities cannot start at the same time, cannot finish at the same time, and cannot be in process at the same time (i.e., cannot overlap). These temporal constraints can also be achieved by modeling resource constraints.

In addition to the time-window constraint for activity, the availability of resources may be discontinuous thus creating a time-window constraint on resources, where resources can only be used within the available time. The time-window of resources has the characteristics of periodicity, calendar correlation and randomness. Periodicity indicates that resources have planned, periodic fixed arrangements. Calendar correlation means that resources are not scheduled for periods such as days off, vacation, etc. Randomness indicates that the availability of resources changes randomly over time. Furthermore, the resource time-windows also have different characteristics due to the particularity of device function and activity network. So far, there are few papers on RCPSP constrained by resource time-window, mainly for human resources with working time constraints, resources with planned maintenance attributes, and renting resources.

Wang et al. [90] developed a mathematical model to solve the scheduling problem of shared agricultural machinery with characteristics of clusters and time-windows. Benttaleb et al. [91] considered resource availability constraints caused by machine maintenance requirements, machine faults, etc. in job shop scheduling problems. Kreter et al. [81] introduced the resource calendar that described the unavailability of resources into the study of resource availability costs. Time-window constraints on resources are merged into resource constraints in some works.

4.3. Resource constraints

4.3.1. Renewable resources

Renewable resources refer to the supply of resources is periodically limited, but the number of resources will not be consumed with the completion of activities, such as human resources, venues and machinery. It is be considered in the standard RCPSP. In some studies [92], renewable resources are divided into two categories (type A and type B). Type A refers to extremely expensive resources that must be prepared or obtained from outside within a specified time frame, and Type B refers to resources are completely available for project organizations.

Renewable resources are also divided into constant and time-varying based on whether they are time-dependent. Considering the time-varying property, resource capacities varying with time (Section 5.5) and RCPSP with resource time-window constraints (Section 4.2) are introduced. Considering that renewable resources such as manpower and heavy machinery will be transferred between different sites in some scheduling environments, RCPSP with resource transfer time is introduced (Section 5.4). Considering the skill level of human resources, multi-skill RCPSP is introduced (Section 5.2).

4.3.2. Nonrenewable resources

Nonrenewable resources are expendable, and be assigned to the project in a certain amount. It will gradually decrease until run out as the project progresses, such as raw materials, project budget, etc. In the study of RCPSP/max, Chaleshtarti et al. [93] considered the non-renewability of project budget and consuming materials by pre-arranging the procurement. Since different execution modes correspond to different resource usages, Nonrenewable resources are common part of multi-mode RCPSP. Chakrabortty et al. [95], Elloumi et al. [59] have considered non-renewable resources in multi-mode RCPSP. Li et al. [94] proposed that the solution should be checked against the nonrenewable resource infeasibility and processed it by adjusting the mode-combination.

4.3.3. Partially renewable resources

Partially renewable resources can be seen as a promotion of renewable resources and nonrenewable resources. It means that resources are limited for a certain period of time, for example, there is periodically an upper limit of the labor working hours. Partially renewable resources summarize the time-varying capability of renewable and nonrenewable resources. Böttcher et al. [96] have shown that both renewable and nonrenewable resources can be described by partially renewable resources, and the RCPSP with partially renewable resources is called RCPSP/π. Okubo et al. [97] addressed multi-project scheduling problems with partially renewable resource by setting energy consumption constraints during machine operation. Watermeyer et al. [82] considered RCPSP/max and RCPSP/π synchronously. The concept of partially renewable resources can be oriented to a variety of practical applications, which can be studied in-depth later.

4.3.4. Doubly-constrained resources

Doubly-constrained resources have the properties of both renewable and non-renewable resources, which are limited both in each period and even throughout the total duration of the project, such as funds [98]. Talbot et al. [110] showed that a doubly constrained resource can be represented by a renewable and a nonrenewable resource, this category of resources is not considered separately. In the actual construction process, both renewable resources and non-renewable resources will be limited. Considering the resource constraints in the construction field, Li et al. [94] studied the multi-mode RCPSP with doubly resource constraints and proposed an improved ant colony optimization algorithm for solving.

4.3.5. Further resource constraints

1) Continuous resources

Only a constant number of resources can be assigned to activities from a given set in the standard RCPSP(Discrete). Actually, an arbitrary amount of resources is allowed to assign at a specified time interval in some cases(continuous), Such as public power sources, refueling terminals, etc. Różycki et al. [99] addressed a scheduling problem for power allocation. In this study, the amount of capacity assigned is variable and the processing speed of each activity depends on the amount of capacity assigned. Under this circumstance, the resource usage in each period and the duration of each activity needs to be simultaneously determined while scheduling activities. Naber et al. [100] considered this problem as the RCPSP with flexible resource profiles (FRCPSP), and optimized the quality and operation time of solution in subsequent study [101]. Tritschler et al. [102] proposed a hybrid meta-heuristic approach for FRCPSP.

2) Cumulative resources

Cumulative resources can be produced or consumed by activities. When the consumption of resources at the beginning of each activity is equal to the supply of resources at the end, it corresponds to the renewable resources in the standard RCPSP, when the consumption is greater than the supply, it corresponds to nonrenewable resources. The remaining cases occur only in some specific production industries. Koné et al. [103] defined this extension as the RCPSP with consumption and production of resources (RCPSP/CPR).

A special case of activities with processing time of zero is called events, e.g., the instant of start and completion of activities. Sahli et al. [104] generalized the event scheduling problem with cumulative resources into the Event Scheduling Problem with Consumption and Production of Resources (ESPCPR). The ESPCPR consists of events, nonrenewable resources and generalized precedence constraints between event pairs. Hanzalek et al. [105] considered the take-give resources needed from the beginning of an activity to the completion of another activity of the production process in a lacquer production scheduling problem.

3) Resource procurement and resource capacity to withstand hazardous environment

The procurement time of materials have been discussed in some papers. Fu et al. [106] integrated the multi-mode RCPSP and the material ordering for construction project to promote trade-off among several costs. Zoraghi et al. [107] proposed a mixed integer programming model combining project scheduling and material ordering, and developed a hybrid genetic algorithm and a hybrid simulated annealing algorithm. They improved the model with multiple models, while proposing a hybrid meta-heuristic algorithm that outperforms the previous two methods in the subsequent research. In construction project scheduling, prefabricated components and other construction materials can take up a large amount of storage space, but space on a construction site is limited, so it is necessary to integrate project scheduling with material ordering issues. Zhang et al. [108] also took into account the storage space constraints of materials when dealing with project scheduling and material procurement, and developed a bi-objective model for optimizing project duration and total cost.

Li et al. [109] argued that the availability of resources is limited by the accumulated amount of harm that the workers could sustain. They established a RCPSP model in the hazardous environment like a nuclear power plant, with the objective of keeping the cumulative hurt suffered by each worker under the given limit.

5. Generalized activity characteristics

5.1. Multi-mode

The basic RCPSP requires that each activity has only one execution mode while each activity can be associated with several modes in the actual processing process. Each mode corresponds to specific processing duration, resource and cost. In 1982, Talbot [110] proposed the mathematical model of multi-mode resource constrained project scheduling problem (MRCPSP). As a well-known generalization of the RCPSP, MRCPSP has been proved to be an NP-hard problem. Chakrabortty et al. [95], Fernandes Muritiba et al. [111], Gnägi et al. [112], and Schnell et al. [113] have studied the basic MRCPSP. Furthermore, the in-depth study of MRCPSP includes various extensions, is most commonly combined with other extensions of the RCPSP.

Several articles considered the MRCPSP with maximum and minimum time lags (MRCPSP/max). Schnell et al. [77] built multi-mode model with the constraints of renewable resources and generalized precedence relations. Bagherinejad et al. [14] employed the objective to minimize tardiness and earliness cost of activities in MRCPSP/max.

Elloumi et al. [114] combined multi-mode RCPSP with preemptive RCPSP and proposed a reactive heuristic to quickly repair the initial disrupted schedule. Afshar-Nadjafi et al. [115] investigated the preemptive multi-mode resource-constrained project scheduling problem (P-MRCPSP) with mode changeability to resumption. Cheng et al. [87] studied a MRCPSP with time-window constraints.

For another, some works focused on multi-objective multi-mode resource-constrained project scheduling (Section 3.3). Yuan et al. [116] proposed a hybrid cooperative co-evolution algorithm to obtain the better robustness of project scheduling and reduce the impact of the mode changing. Zoraghi et al. [117] tackled an MRCPSP with triple objective: minimizing the makespan of the project, maximizing the robustness of the project schedule, minimizing the total costs related to resources. Tirkolaee et al. [52] studied MRCPSP for maximum of net present value and minimum of makespan. Subulan et al. [118] added an additional objective of maximizing the utilization of renewable resources to the uncertain multi-objective multi-mode resource investment project scheduling problem.

Tao et al. [86] processed MRCPSP using an alternative network structure and implemented it based on AND-OR network. Bofill et al. [119] developed a mathematical formula based on satisfiability modulo theories (SMT) to solve the MRCPSP and RCPSP/t. Maghsoudlou et al. [68] tackled a multi-skill multi-mode resource-constrained project scheduling problem with tri-objective. Cui et al. [120] embedded multi-skill and multi-mode in multi-project scheduling.

The discrete time-cost trade-off problem (DTCTP) and the discrete time-resource trade-off problem (DTRTP) are special cases of the MRCPSP.

1) DTCTP

The discrete time-cost trade-off problem was first proposed by Hindelang et al. [121] in 1979, in which the activity duration is discrete and the resources are nonrenewable. The research on DTCTP mainly focuses on three aspects: deadline, project budget and time-cost curve. The deadline issue aims to minimize the total costs of the project subject to a given project deadline. The budget issue aims to minimize the makespan a given project budget. The time-cost curve problem attempts to describe a set of time-cost profiles within the duration of project.

Sonmez et al. [122] presented a hybrid evolutionary algorithm for DTCTP to minimize the sum of direct and indirect costs. Aminbakhsh et al. [123] developed a discrete particle swarm optimization algorithm for large DTCTP instances. Said et al. [124] also solved the robust DTCTP with random activity durations, the sum of the activities costs and tardiness penalty is minimized. Çakir et al. [125] integrated classical MRCPSP and DTCTP to a multi-mode resource-constrained discrete-time cost trade-off problem (MRC-DTCTP), which is able to solve more practical problems.In addition, constraints for time, cost and quality are given concurrently to form a discrete time-cost-quality trade-off problem (DTCQTP) in some studies [126]. The objective is to obtain the optimal scheduling schedule with the constraints for time, cost and quality.

Ghoddousi et al. [127] focused the application on construction projects with complex activity networks. Each activity has a variety of execution modes. Considering DTCTP and RLP, they established a multi-mode discrete time-cost-resource optimization multi-objective model, which is validated by real-world construction project cases. In addition, total project cost minimization is common in the construction management with limited resources, so it is necessary to study the time-cost trade-off problem to improve the benefits of the construction project.

2) DTRTP

The discrete time-resource trade-off problem (DTRTP) was proposed by De Reyck et al. [128] in 1998, which contains renewable resources constraints and the standard precedence constraints. Most of the existing research on DTRTP aims to develop algorithms for finding the best schedule, and with the deepening of research, uncertainty is also embedded in the problem. Tian et al. [128] tackled DTRTP under the stochastic environment with an uncertain amount of work content of each activity and aimed to find better scheduling strategies and better pattern combinations for the execution phase. Van Peteghem et al. [129] studied the influence of learning effects on execution efficiency and applied it to DTRTP. Eeckhout et al. [130] considered only one type of renewable resources, i.e., manpower, in the project scheduling problem. The objective is to minimize the total personnel costs required to carry out a project.

5.2. Multi-skill

Resource requirements in the execution of activities are reflected in the demand for skills in some flexible work scenarios, especially it comes to human resources or multi-purpose machines. Therefore, the multi-skill resource-constrained project scheduling problem (MSRCPSP) was first proposed by Hegazy et al. [131] in 2000. In the MSRCPSP, the resources have multiple skills required to carry out an activity, and each activity requires resources with specific skills. The objective is to allocate the appropriate resources and determine the start time for each activity to minimize makespan. Behrouz et al. [5] comprehensively analyzed and summarized the literature of MSRCPSP from the aspects of quantity and type of objective functions, mathematical formulations, solving methods and applications.

What's more, some papers focused on the variants of the MSRCPSP. The most extensive variant is the shift from single-objective to the study of multi-objective. Zhu et al. [132] developed a genetic programming hyper-heuristic algorithm for multi-objective MSRCPSP, aimed to minimize the makespan and the total cost. Wang et al. [133] addressed MSRCPSP with the objectives of minimizing the makespan and the total cost simultaneously. Laszczyk et al. [134] considered minimizing makespan and resource costs. Maghsoudlou et al. [135] added preemption to multi-skilled RCPSP and employed the objective to minimize the total costs of earliness/tardiness penalties and preemption.

For another, multi-skill resources should not only consider the amount of skills they master, but also the impact of skill level on activities, that is, an activity requires a given amount of each skill and has a fixed minimum level of mastering. Snauwaert (2021) et al. [136] measured the ideal skill level by the depth and breadth of skills of resources, and aimed to aiming to allocate the best staffing. Snauwaert (2022) et al. [137] introduced hierarchical levels of skills and studied the efficiency differences, cost differences and quality differences brought by different skill levels. Maghsoudlou et al. [23] also considered different skill levels. They believed that resources with higher levels of skills could reduce the risk of rework, and considered two objectives, namely the minimization of the rework risk and the minimization of resource costs.

Several researchers have proposed multi-skill problems with learning effects and believed that learning effects and experience accumulation can improve the skill efficiency of resources. Qin et al. [24] considered the minimum quality limit of tasks and improved the execution quality of multi-skilled labor through knowledge learning. Zabihi et al. [138] considered the influence of learning effects on improving resource efficiency.,and there is a direct relationship between efficiency of performing skill and the time that workforce is assigned to do it.

Tian et al. [61] developed a MSRCPSP with skill switches which may occur extra operation cost and duration. At this point, the problem can also be converted to an RCPSP with resource transfer time (Section 5.4). In the study of MSRCPSP, Chen et al. [139] considered that the efficiency of skills grows with the accumulation of experience and dealt with the multi-objective scheduling problem under the uncertainty of processing duration and material arrival time. Javanmard et al. [140] studied the integrated multi-skill and resource investment scheduling problem that preemption is allowed. The goal is to determine the best skill level of resources and find the optimal schedule with the least total resource investment.

5.3. Preemptive

One of assumptions related to the basic RCPSP is that each activity cannot be interrupted or discontinued until it is completed. Actually, due to resource constraints, interruptions are considered for the redeployment of resources between different activities. The Preemptible Resource-Constrained Project Scheduling Problem (PRCPSP) was introduced and studied in 1988. In PRCPSP, it is allowed to forcibly pause the ongoing activity, release the resources occupied by activity, and allocate the resources to higher priority activities to improve the utilization of resources.

There are two cases of activity interruptions: continuous and discrete. Discrete means that the activity can only be interrupted at an integer time instant, while continuous means that the activity can be interrupted at arbitrary time during execution. What's more, the frequency of interruption is also required for the PRCPSP. Based that the problem is divided into only one-time preemption and multiple preemption issues. Shou et al. [141] studied the preemptive RCPSP in which a maximum of one preemption per activity is allowed, and interruption occurs at an integer time instant. Multiple interruptions at integer points were permitted in the study of Vanhoucke et al. [142], and the set times when resuming from interruption are also taken into account. Moukrim et al. [143] addressed PRCPSP that activities can be interrupted at arbitrary rational dates.

If activity interruptions are allowed, in some cases, the restart cost, the setup time or the transfer time may need to be considered. Afshar-Nadjafi et al. [144] claimed that a fixed setup time is required to restart when a process is preempted. Kreter et al. [145] introduced the concept of calendar to allow a fraction of activities to be interrupted by days off. Creemers et al. [146] studied random preemptive RCPSP with uncertain durations. Afshar-Nadjafi et al. [115] also discussed preemptive scheduling in a multi-mode setting.

5.4. Transfer time

When resources need to be transferred from one activity to another or must be adjusted according to the activity content, a certain amount of time is consumed and the resources are not available while in the transfer period. Some of these include the operation of installing and setting up machinery. Research on such problems is summarized as the resource-constrained project scheduling problem with transfer time (RCPSPTT) [147].

It consumes both time and cost when projects are situated in different geographic locations on multi-project scheduling. Suresh et al. [148] presented a new genetic algorithm to solve the multi-project scheduling problem with resource transfer times, aimed for maximizing the NPV of all projects. Kadri et al. [149] assumed that preemption is not allowed and the durations and resource transfer times of activities are known and deterministic in RCPSPTT. Based on the resource transfer time between different stations in the aircraft moving assembly line, Ren et al. [150] also assumed that the resource transfer times are known and deterministic.

In addition to the study of RCPSPTT in deterministic environment, scholars have also paid attention to the impact of uncertainty. Wang et al. [151] considered the resource transfer time s in the robustness-based resource profiles problem. Ma et al. [152] investigated the RCPSPTT under uncertain environment, aiming to generate as stable as possible robust baseline scheduling. Zhang et al. [153] believed that the transfer time depends on the site where the project is located, and it does not take time to transfer resources locally. Laurent et al. [154] studied RCPSPTT in a multi-site environment, where resource transfer operations will affect the start time of an activity. Some Publications also considered the transfer time caused due to mode changes in multi-mode problems, and the mode selected determines the length of time (Section 5.1).

5.5. Resource requests varying with time

In the standard RCPSP, the capacity R_k of resource k is constant, that is, the resource requirement remains constant during the implementation process. However, in the actual processing process, the capacity of resources changes over time. This situation can be identified in the problems with time-window constraints of resources (Section 4.2) and continuous resource constraints (Section 4.3.5). We will not repeat it in this section.

6. Other variant problems

6.1. Resource-constrained multi-project scheduling problem

As an extension of the RCPSP, the resource-constrained multi-project scheduling problem (RCMPSP) was proposed in 1969 [155], where several projects must be executed simultaneously. Each project is limited by the internal logical relationships and the external shared resources. The goal is to schedule the start time of each task to minimize the makespan. The features studied in the standard RCPSP also exist in multi-project environments. Gómez Sánchez et al. [155] supplemented the objective functions, activity characteristics and constraints of the RCMPSP, but did not involve the project selection and scheduling problem.

6.1.1. Objectives for multi-project scheduling

The research on multi-project scheduling objective functions has mainly focused on time, resources, and multiple objectives.

1) Time-based objectives

Contrary to single project scheduling, the studies on multi-project scheduling completion time, the project completion time or makespan is the time when all jobs are fully executed. And the optimization objective is defined as the maximum makespan among all projects, such objectives were considered in the study of Satic et al. [160] In addition, the objective can also be defined based on weight coefficients to minimize the weighted completion time of all projects, such as Shu et al. [159].

When the project completion time is larger than the due date, tardiness-related goals become the main objective of discussion. Araujo et al. [156] studied the objective of minimizing the average project tardiness. This objective is of the same nature as minimizing the total tardiness of all projects, which is also the most common tardiness-related objective in multi-project scheduling problems. Van Eynde et al. [157] attempted to minimize the average percent project delay. Li et al. [158] believed that each project has different weights. The higher the weight, the greater the delay penalty. Therefore, the objective function aims to minimize the weighted project delay.

2) Resource-based objectives

Satic et al. [160] and Amirian et al. [161] considered the costs of resource usage, transfer, unavailability, renting, and maintenance, to achieve the goal of minimizing total project costs. Several scholars posited that profits can be obtained after investing resources to complete the project; so, Satic et al. [160] also aimed to maximize the total project profits. Some studies have also focused on the resource profiles' problem. In the scenario, when no tasks have that resource demand, Hauder et al. [162] aimed to minimize the total idle times of resources and the amount of empty resources.

3) Multiple objectives

Some studies have focused on the trade-offs between different goals, such as the study conducted by Hauder et al. [162]. In addition to the minimization of the makespan, research has also been done the maximization of the balanced duration of different activities and the maximization of balanced resource utilization. Amirian et al. [161] proposed a multi-objective grey project selection scheduling model and handled the uncertainty in forms of grey values. They aimed to maximize the total profit of completed projects and minimize the total cost and total unused resources of the selected projects.

6.1.2. Constraints for multi-project scheduling

1) Precedence relation constraints

The basic relationship between tasks in the RCMPSP is finish-start, meaning that a task can be started only after all its predecessors have been fully completed. In the study conducted by Gholizadeh-Tayyar et al. [163], four types of generalized precedence relation constraints were considered. Joo et al. [164] considered the problem of time lags.

2) Resource constraints

Local and global resources: Global resources can be used to execute all projects and must be shared by all projects, while local resources are those that should be used only for the project. In a scheduling problem, resources can only have one characteristic; they cannot be both global and local. For example, Fu et al. [168] defined local resources as fixed facilities and unprofessional workers, and they defined global resources as specialized equipment and personnel with professional skills. Adhau et al. [165] considered transfer times when transporting global resources between projects, thus increasing the objective for transfer costs. Geiger et al. [166] assumed that local resources are nonrenewable and that global resources are renewable.

Resource management mode: In the RCMPSP, resource management can be centralized or decentralized. Under centralization, assuming that multiple projects are uniformly scheduled by only one general decision-maker who manages the projects, each project has to compete for shared resources among projects in addition to local resource constraints. In the other case, each project is scheduled by the decision- makers of each project, and the shared global resources are coordinated through global decisions by a general decision-maker.

Resource availability: Resources are limited by available and unavailable time. Hu et al. [167] considered resource availability in uncertain environments and described this as the uncertainty of resource effectiveness in their research. In addition, Fu et al. [168] and Eeckhout et al. [169] considered the impact of resource transfer time on scheduling in multi-project scheduling problems.

6.1.3. Activity characteristics for multi-project scheduling

Multi-mode and multi-skill characteristics are still popular extensions in multi-project scheduling problems. Araujo et al. [156] and Chen et al. [174] studied the multi-mode problem in multi-project scheduling. Moreover, Cui et al. [120] considered the resource profile problem with multiple skills in multi-project scheduling. In addition, Joo et al. [164] considered preemptive scheduling under multiple projects. Satic et al. [160] discussed uncertain multi-project scheduling.

6.1.4. Project selection and scheduling

In the basic RCMPSP, it is assumed that there is no preference for multiple projects executed simultaneously; that is, only the number of existing projects and the deadline are known. It is necessary to schedule according to the priority of the project in some special situations. The project selection and scheduling problem has been developed. Kannimuthu et al. [170] assigned different delay penalties to each project and selected projects by comparing the priority levels or delay impacts between projects. Tian et al. [171] dealt with the resource conflict between two sub-projects by the priority; the project with a lower priority of resource usage is required to wait for the project with a higher priority to finish. Zorluoğlu et al. [172] designed an interactive process that integrates selection and scheduling into project management to select projects based on the project scores given in belief degrees. Shafahi et al. [173] integrated project selection and scheduling. Then, they considered the actual construction scenario in which the selected project is divided into multiple stages, and they proposed a mixed integer programming (MIP) formulation for small-scale problems and a two-step heuristic algorithm for larger-scale problems.

Owing to the insertion of a new project, Satic et al. [160] updated the schedule when each new project arrived and used a rule-based algorithm that prioritizes the processing of activities with the highest processing durations. Chen et al. [174] considered the initial planned project set and the set of projects to be inserted. At any period *t*, if the number of projects being executed is less than the maximum number allowed, a project is randomly selected from the new insert collection to start.

6.2. Availability of information

The accuracy of scheduling depends on the information provided before the start of project. All information is known and determined in the standard RCPSP, but this assumption is not accurate in practice. The uncertainty of information has triggered a research boom. These uncertainties can be related to the following sources: uncertain duration of the activities, unavailability of resources or materials when needed, the start time or deadline of the activities being affected by some factors, and environmental interference. As a consequence, various strategies have been evaluated in studies on project scheduling in uncertain environments, and they are described as the following five methods.

1) Reactive scheduling

Reactive scheduling is driven by a perturbation event, after which an unexecuted activity is scheduled by a strategy or algorithm. This method can react immediately to unexpected events, but it requires a lot of processing time along with a variety of successive calculations. One of the traditional response strategies is repair scheduling, which uses a right-shift rule to move the affected activities to the right along the timeline. Another strategy is rescheduling, which rearranges activities that have not been performed. Chakrabortty et al. [175] performed rescheduling with the objective of minimizing the makespan time plus the weighted deviations of all activities' completion times in the revised schedule. Peng et al. [176] designed a proactive–reactive scheduling algorithm that applies the critical chain method to actively generate the baseline schedule before the start of the project. The Markov decision process model and dynamic scheduling program were applied to adjust the schedule reactively during project execution. Chakrabortty et al. [58] formulated an event-based reactive model to address disruptions during project execution. Wang et al. [177] proposed an adaptive selection method of priority rules based on reinforcement learning in dynamic environments to obtain better rescheduling performance.

2) Stochastic scheduling

The stochastic RCPSP (SRCPSP) has the same assumptions as the standard RCPSP, except that the duration of activities is uncertain and is considered a random variable. The result of random scheduling is no longer an explicit schedule, but a policy that determines how to dynamically schedule activities in each possible scenario. Creemers et al. [10] used stochastic dynamic programming to solve the SRCPSP with exponential and PH-distributed activity durations. Zhou et al. [178] solved an SRCPSP with time varying weather conditions based on an improved estimation of the distribution algorithm. Ning et al. [179] proposed a scheduling model for multi-mode cash flow balance based on the stochastic activity duration to balance the cash outflows and cash inflows of contractors in large-scale construction projects, and they chose different activity execution modes to adjust the cash flows.

3) Fuzzy scheduling

The probability distribution for the duration of activities cannot be determined when historical data are lacking. In this case, the duration of activities is estimated by experts under the unique conditions of the project and its non-repeatability. It is more important to deal with ambiguity than with uncertainty. Liu et al. [180] established a credibility-based chance-constrained model for MRCPSP under fuzzy uncertainty, and also introduced a credibility distribution function and its inverse function to deal with fuzziness. Zhao et al. [181] developed three types of fuzzy models for project scheduling under fuzziness; the α-cost minimization, credibility maximization, and time-cost trade-off models. Ghamginzadeh et al. [182] proposed an optimization algorithm based on imperialist competition to solve the multi-objective multi-skill fuzzy scheduling problem. Fathallahi et al. [183] addressed the problem of maximizing the project NPV in fuzzy RCPSP.

4) Proactive/Robust scheduling

Unlike the concept of reactive scheduling, proactive scheduling aims to prevent events that cause project tardiness by creating robust baseline schedules. The main objective considered in proactive scheduling is to maximize robustness (Section 3.2.3). In general, two strategies have been used to create robust schedule in research: add buffers (time buffering, resource buffering) and consider resource flow networks. Ma et al. [152] studied the proactive RCPSP with resource transfer times under an uncertain environment, and aimed for a robust baseline schedule by inserting a time buffer. Nabipoor et al. [184] applied robust optimization methods to the multi-project scheduling problem under an uncertain environment, proposed a two-stage model and applied a scenario-relaxation algorithm. Li et al. [185] considered the actual construction application, set the appropriate buffer for the project to ensure the timely completion of the project, and proposed a data-driven buffer size prediction model based on the machine learning algorithm to flexibly deal with the impact of the uncertainty of the activity duration.

5) Sensitivity analysis

Another way to deal with uncertainty is sensitivity analysis. Most studies on the sensitivity analysis of scheduling problems have focused on the sensitivity of production factors like machinery in workshop scheduling. Such problems have not been discussed in the field of project scheduling; so, they can serve as an interesting research topic in the future.

6.3. Optimization of the dataset

To test and compare the performance of different algorithms or verify the effectiveness of the algorithm on RCPSP, we produced two sets of standard datasets commonly used internationally: Patterson and PSPLIB. The Patterson library has 110 single-mode project scheduling problems, each containing 7–50 activities and involving 1–3 renewable resources. The Patterson library was widely used in the early days. Obviously, these 110 questions do not represent the various possibilities of project scheduling. Kolisch et al. [186] formed a standard problem library PSPLIB by designing the software ProGen, which generates scheduling problems with different objectives that meet the parameter requirements. It includes 480 scheduling problems, each containing 30 activities and involving four renewable resources. Schwindt [75] designed ProGen/max based on the ProGen to expand the scope of application.

In recent years, extension problems and optimization algorithms have been proposed continuously, which makes the existing benchmark datasets unable to compare the advantages and disadvantages of algorithms and models fairly. Therefore, some scholars have proposed new benchmark datasets while solving the problems. Verbeeck et al. [43] proposed a meta-heuristic for multi-mode RCPSP. Furthermore, to achieve accurate testing and comparison, researchers have generated new benchmark datasets based on the RanGen project scheduling instance generator developed by Vanhoucke et al. [187]. Snauwaert et al. [188] proposed a new data generation program for multi-skilled RCPSP, and introduced multiple artificial datasets for different research purposes. The new datasets were generated based on multi-skill resource parameters and were also compared with the existing benchmark datasets in the literature.

6.4. Applicability of the RCPSP in construction project scheduling

In addition to the above-mentioned applications of the RCPSP extended model in construction projects, there has been a lot of research dedicated to linking it to more real-world complexities. Some construction processes distinguish construction components rather than areas. Each component has a fixed installation location and sequential requirements. The detailed scheduling down to the component level has not been focused on, but individual researchers have discussed it. To respond to the requirements of green construction and reduce labor cost, researchers have proposed the construction structure of hybrid concrete (HC). The HC structure consists of different components, and few studies on the RCPSP have taken the construction sequence of components into consideration; thus, Ma et al. [189] established a component-level RCPSP model and proposed a multi-objective discrete symbiotic organisms search algorithm. It solved the sequential conflict problem occurring during the component-level construction and improved the efficiency of resource utilization. This is a more practical extension model of the RCPSP applied to construction projects. Liu et al. [190] adjusted the construction sequences based on the standard RCPSP problem, and generated the RCPSP simulation model by correlating building information modeling (BIM) with resource information. Moreover, a particle swarm optimization algorithm was proposed. Wang et al. [191] improved on the transmission of data flow. The BIM manages the data information within the life cycle of the construction project, but it cannot meet the information requirements of the RCPSP model. Therefore, they proposed an integrated information model based on the work package to enable fluent data flow from the information model to the RCPSP model.

Repetitive activities run during the implementation of construction projects. García-Nieves et al. [192] proposed a flexible scheduling model, specially designed to handle repetitive activities in construction projects. It has been proved that the schedule generated by the proposed mathematical model is robust and suitable for real construction projects such as highways and high-rise buildings. Birjandi et al. [193] proposed a real-world scenario different from the multi-mode scenario and defined it as the RCPSP with multiple routes for flexible activities. A project network can have multiple flexible activities and each flexible activity has multiple execution routes. In their research, they also developed a new method to deal with RCPSP-MR in an uncertain environment, which is useful for project managers dealing with construction projects. Taghaddos et al. [194] proposed a hybrid simulation and optimization method for large and complex industrial projects to deal with uncertainty and realize continuous planning based on dynamic data.

The competition in the construction industry is increasingly fierce, and large and complex projects are common. The additional constraints to be considered vary with specific projects. The ability to deal with various real situations and provide more efficient solutions determines the competitive position of construction companies. Many real situations in the process of construction are related to the RCPSP and its extension. Therefore, it is meaningful to focus on the research on various models of the RCPSP and transfer them to the construction field.

Similar to the application of project scheduling theory in the field of construction projects, the application of project scheduling theory in other fields has also confirmed the importance of RCPSP expansion research. Some researchers have also tackled problems in other fields by using project scheduling concepts. Mezouari et al. [195] proposed a random heuristic based on the health priority of patients to plan the operation time in a medical setting. The availability of resources and uncertain interference have also been considered. Androtsopoulos et al. [16] solved the airport slot scheduling problem based on the RCPSP theory and then proposed a bi-objective optimization model with partially renewable resources. Rahman et al. [196] studied a green RCPSP embedded with the objectives of minimizing the makespan and green project indicators, aimed for minimal energy consumption and noise pollution. Although these problem settings are not strictly related to the project, they have a positive impact on the study of project scheduling.

7. Algorithm research

At present, three main solutions exist for the RCPSP and its extended models: the exact algorithm, heuristic algorithm and meta-heuristic algorithm (also known as intelligent optimization algorithm).

1) Exact algorithm

The exact algorithm solves the scheduling model by the mathematical programming method. As long as there is enough time, the global optimal solution can be obtained. Such methods are represented by branch and bound (B&B), dynamic programming, and integer programming. Among them, B&B has the best solution effect and the most extensive research on it. When exact algorithms deal with complex larger problems, the computational complexity increases, and the solution time increases exponentially. Researchers have embedded the column generation (CG) method into problem solving. Thomas et al. [197] developed an iterative scheme based on a customized column generation. Liu et al. [198] proposed a distributed scheduling algorithm based on CG to solve multi-mode RCPSP.

To simultaneously satisfy the time consumption and global optimal solution requirements, branch-and-price (B&P) was proposed. It is a combination of the B&B algorithm and the CG method. Moukrim et al. [143] proposed a B&P algorithm for the preemptive RCPSP, but it is mainly effective for small instances. Although the CG approach embedded within a B&P procedure has been presented, there have been fewer related studies for the RCPSP. The development of algorithms for which the time consumption and global optimal solution requirements are satisfied simultaneously remains a research priority.

Over time, heuristics and meta-heuristics have become the dominant algorithms for solving large-scale complex scheduling problems.

2) Heuristic algorithm

The heuristic algorithm searches for the best solution within the acceptable range through a series of heuristic rules, but it usually obtains the relatively ideal solution which deviates from the global optimal solution. Owing to its short time consumption, the heuristic algorithm has received a great amount of attention since it was proposed. The most widely used heuristic for project scheduling problems is the priority rule-based heuristic, which adopts the schedule generation scheme (SGS) and priority rule to construct the feasible schedule of the project.

SGS can be classified as the serial schedule generation scheme (SSGS), with activity as the phase variable, and the parallel schedule generation scheme (PSGS) with time as the phase variable. Under the serial method, the activities are arranged in the order of priority. The parallel approach aims to determine the set of feasible activities within the time interval, and to select multiple activities from the set according to the priority rules. The start time of these activities is determined, and then, the remaining number of resources and the set of feasible activities for the next phase are updated in time.

The priority rules are based on different task duration, network, and resource requirements, and they are gradually diversified according to practical problems. In the RCPSP, the study of heuristic algorithms has also focused on testing and comparing different priorities. Preference rules that can be applied with various types of instances have not been set; so, many studies have combined heuristic rules. Zhu et al. [199] adopted three priority rules commonly used in the RCPSP (i.e., the greatest cumulative resource requirement, rank positional weight, minimum activity slack) to generate initial activity lists of the RACP by combining rules. Chakrabortty et al. [200] integrated six priority rules with the proposed heuristic to identify the best rule.

To help decide which heuristics are better for solving problems or combining them, researchers have proposed ***hyper-heuristic*** algorithms. Chand et al. [201] introduced a genetic programming based hyper-heuristic for generating efficient priority rules targeting the RCPSP. Đumić et al. [202] conducted a similar study, and demonstrated the use of genetic programming based hyper-heuristic to evolve appropriate scheduling heuristics for the RCPSP. Koulinas et al. [203] proposed a hyper-heuristic algorithm based on Tabu search to solve the RLP in construction projects.

3) Meta-heuristic (Intelligent optimization algorithm)

The meta-heuristic algorithm is an improvement on the heuristic algorithm. It usually draws on the concepts of different disciplines and abstracts them to form a general algorithm. It no longer depends on the specific problem organization structure and algorithm framework. The heuristic can be used to generate the initial solution required by the meta-heuristic algorithm. Commonly used meta-heuristic algorithms in the RCPSP are shown in Table 2 [6].

To improve the performance of the meta-heuristic algorithm, rather than purely following the concept of a single meta-heuristic, more effective methods combine various meta-heuristics or other optimization techniques. Pellerin et al. [6] summarized various hybrid meta-heuristics that have emerged over the past 20 years to address the RCPSP. Two main hybrid techniques were mentioned in their study. The first technique combines several different meta-heuristic concepts. For example, the local search algorithm is embedded in the population-based algorithm, such as in Koulinas et al. [204] (PSO + LS), Tritschler et al. (GA + VNS). Another category includes the combination of meta-heuristics with other operations research techniques such as mathematical programming with meta-heuristics. Zamani et al. [205] proposed a genetic algorithm based on a tree search. Cheng et al. [206] integrated the fuzzy-clustering algorithm and chaos algorithm into the DE to improve the performance of the original DE, and used two real world construction project examples to verify its accuracy and efficiency. Rahman et al. [207] proposed a more competitive modal algorithm based on GA to solve the construction project scheduling problem with higher complexity. There is a growing interest in developing reasonable hybrid meta-heuristic algorithms to solve the RCPSP, and the hybrid method has steadily improved in terms of accuracy and speed. The introduction of adaptive adjustment and control technology into the hybrid meta-heuristic algorithm is also worthy of further research.

Table 2
Main meta-heuristics exploited in the RCPSP.

Types	Algorithms
Local search meta-heuristics	Adaptive large neighborhood search (ALNS) Harmony search (HS) Filter and fan (FAF) Greedy randomized adaptive search procedure (GRASP) Large neighborhood search (LNS) Local search (LS) Nested partitions (NP) Simulated annealing (SA) Tabu search (TS) Variable neighborhood search (VNS)
Population-based meta-heuristics	Estimation of distribution algorithm (EDA) Ant colony optimization (ACO) Artificial immune (AI) Bee colony optimization (BCO) Artificial bee colony (ABC) Differential evolution algorithm (DEA) Electromagnetism (EM) Estimation of distribution (EOD) Bat algorithm (BA) Firefly algorithm (FFA) Evolutionary programming (EP) Genetic programming (GP) Genetic algorithm (GA) Memetic algorithm (MA) Particle swarm optimization (PSO) Shuffle frog-leaping (SFL) Wolf search (WS) Scatter search (SS) Termite colony optimization (TCO)
Learning meta-heuristics	Neural network (NN) Artificial neural network (ANN)

Researchers have proposed various decision-aid methods, such as simulation, multi-criteria decision-making, and automation techniques, to solve scheduling problems during construction. However, these methods cannot respond and make changes in real time when faced with an uncertain environment, nor can they cope with coordinated decision-making for multiple construction projects. With the rapid development of artificial intelligence, methods such as multi-agent technology and reinforcement learning have been gradually applied to project scheduling. Based on local rewards and exploration, RL agents continuously train and learn to carry out better actions, which can be well used for complex and dynamic construction environments. Kedir et al. [208] proposed a hybrid reinforcement learning-graph embedding network model to deal with construction scheduling in an uncertain environment based on multi-agent technology. However, the study was limited to the demonstration of model principles and there were many differences with the actual construction process. Soman et al. [209] used reinforcement learning to assist data-driven forward-looking scheduling so as to improve the decision-making of construction projects. The application of AI technology in project scheduling can be regarded as meaningful research content and can enrich the decision-making knowledge system in the field of construction projects.

8. Directions for future research

Some research on the RCPSP in the last decade is summarized in Table 3 to present existing achievements and indicate potential directions for future research in this area.

Based on statistical tables we could obtain the frequency percentage of each of the extended items which are shown in Figs. 8 to 12.

8.1. Selection and portfolio of objectives in the multi-objective RCPSP

It is clear from Fig. 8 that the vast majority of studies employ objectives based on practical problems and then gradually develop general models. In the extensions of the single-objective model, 46% of the articles employ time-based objectives, followed by cost- and resource-based objectives. More specifically, minimizing the makespan, total weighted tardiness of activities, and total project costs are the most popular objectives. With the development of the research scope and the overall consideration of the decision-makers, the multi-objective model is being widely used. Research on trade-offs is also presented.

Future multi-objective portfolios can be oriented to more single goals, such as nonrenewable resource-based, economy-based or society-based goals. 1) It is promising to consider the time-dependent costs of resources. The heavy investment and excessive holding of resources can optimize the makespan to a certain extent, but can also incur significant costs (e.g., overtime payroll). A trade-off model of resource input time and cost can be established in future studies, and can be employed in combination with the completion time objective. 2) It is meaningful to consider green performance indicators such as energy efficiency, ecology and the environment, and sustainable development. Specifically, in construction projects, green scheduling can be considered.

8.2. Consideration of nonrenewable resource constraints

It can be seen from Fig. 9 that the renewable resource constraints are used in most of the studies (about 50%). There is less consideration for nonrenewable resources and doubly-constrained resources, which can be extended in future studies. It is useful to pay attention to the challenges that the total project budget constraints pose to problem solving. For construction projects, the total project budget is an important constraint that cannot be ignored.

8.3. Learning and forgetting effects of multi-skill resources

According to Fig. 10, activity characteristics such as multi-mode (about 30%), multi-skill (about 11%) have the most significant results in theory and practice. In the study of the multi-skill RCPSP, the capability level of resources is assumed to be stable by default. However, the resource skill levels tend to be dynamic; they it can grow with the accumulation of experience and learning. The efficiencies of workers are also affected by the learning and forgetting effect.

It can be a promising addition to the MSRCPSP to establish the response mechanism of a variable skill depth that is affected by learning or forgetting. Future research on this problem can develop a hierarchical assessment system of skill levels and a standard of the completed activities. The corresponding training costs and time associated with learning and forgetting effects are also issues to be considered.

Construction projects involve many types of work, so there is a greater demand for multi-skilled labor. Moreover, the actual construction of some projects is carried out by the outsourcing engineering team. The project manager or engineering team leader needs to coordinate the skill resources provided by the contractor to improve the completion efficiency. Whether outsourcing engineering problems can be abstracted into distributed multi-projects and effective skill allocation based on multi-agent technology can be further considered in future research.

8.4. Decentralized multi-project scheduling problem and the multi-agent system

With the in-depth study of complex problems, more attention has been paid to multi-project scheduling according to Figs. 7 and 11. Although the multi-project scheduling problem has been discussed since the 1960s, the research remains relatively immature, especially for the decentralized multi-project scheduling problem. In the decentralized scheduling of multiple projects, each project is scheduled by an independent project leader. Different projects share resources, but the information is asymmetric.

Opaque information between projects will have a greater impact on the overall scheduling, project decision-makers will be competing for more resources, which may lead to lying. Therefore, future study of an integrity policy and lying penalty mechanism is of particular significance. Another point of view can also require a single project in the project group's appropriate disclosure of information to speed up the algorithm, and it is also necessary to propose certain indicators or thresholds to measure whether the published information meets the demand.

Furthermore, projects share global resources and are distributed in different locations in the decentralized multi-project scheduling. Obviously, transfer time and costs are required when resources are transferred to various destinations, and another meaningful extension is conducted. It has been generally assumed in previous research that global resources are homogeneous. However, in many practical situations, the global resources will be different in terms of prices or locations if global resources are provided by different suppliers. The heterogeneous resources and the choice of suppliers can be considered in future research.

The mainstream algorithms for the allocation (or competition) of shared resources among projects in decentralized scheduling are currently based on combinatorial auctions and negotiation mechanisms. However, the algorithm research is not in-depth and lacks a unified set of negotiation rules and framework. Designing more effective game methods, developing more complex meta-heuristic algorithms, and studying multi-agent systems can better improve computational efficiency, which are all worth exploring in the future. The distributed project scheduling is more consistent with the real situation of the construction project, and its in-depth study will help optimize the multi-project portfolio in the construction field.

8.5. Project scheduling under uncertainty

In the field of RCPSP, 83% of the problems are carried out under deterministic conditions (Fig. 11). The research on uncertainty has also increased significantly in the past decade and has focused on the uncertainty of activity duration. More types of uncertainties will arise during project execution; so, how to mend disrupted schedules should be studied. How to build models and algorithms in different dynamic environments also needs to be considered in future research. Other important future research topics include considering additional uncertainties, such as the arrival of new projects.

8.6. Combinatorial problems of extended models

Some studies have combined extended models for discussion, such as the multi-objective model in multi-mode RCPSP. In future research, it is also possible to incorporate multi-mode, multi-objective, or multi-skill in multiple projects. When studying project scheduling in the construction field, considering characteristics such as large quantities, a long duration, high investment, complex construction conditions, we can tap into practical constraints or needs that have not yet been

Table 3
Summary of published works on the RCPSP in the last decade.

Article	Constraint	Characteristics	Objective	Information	Number	Method
[73] Bianco et al. (2012)	GPR/RR	DRD	Cmax	DS	S	Branch and bound
[79] Quintanilla et al. (2012)	GPR/RR	MM/P	Cmax	DS	S	GA
[98] Kyriakidis et al. (2012)	RR/NRR	MM	Cmax	DS	S	MILP
[122] Sonmez et al. (2012)	RR	MM	MO	DS	S	GA + SA + QSA
[159] Ghoddousi et al. (2012)	RR	MM	MO	DS	S	NSGA-II
[165] Adhau et al. (2012)	OC	DRCMPSP/TT	CBO	DS	M	Auctions based negotiation
[78] Ballestín et al. (2013)	RR/NRR	MM	Cmax	DS	S	SA
[89] Hartmann et al. (2013)	RR	RV	Cmax	DS	S	Heuristic
[94] Li et al. (2013)	RR/NRR	MM	Cmax	DS	S	ACO
[103] Koné et al. (2013)	NRR	ESPCPR	Cmax	DS	S	MILP
[127] Ghoddousi et al. (2013)						
[203] Koulinas et al. (2013)	RR	DRD	RLP	DS	S	Hyper-heuristic+TS
[12] Gomes et al. (2014)	RR	DRD	MO	DS	S	GRASP +VNS + PILS
[14] Bagherinejad et al. (2014)	GPR/RR	MM	CBO	DS	S	GA
[22] Hossain et al. (2014)	GPR/RR	MM	CBO	DS	S	OSM + GA
[28] Afshar-Nadjafi et al. (2014a)	RR	MM	RACP	DS	S	SA
[66] Dridi et al. (2014)	RR	DRD	MO	DS	S	Hybrid ACO
[80] Tavana et al. (2014)	RR	P/MM	MO	DS	S	NSGA-II
[99] Różycki et al. (2014)	DCR	P	Cmax	DS	S	NIP
[100] Naber et al. (2014)	OC	DRD	Cmax	DS	S	MILP
[106] Fu et al. (2014)	RR	MM	CBO	DS	S	MIP
[144] Afshar-Nadjafi et al. (2014)	RR	P/TT	Cmax	DS	S	GA
[197] Thomas et al. (2014)	NRR	DRD	CBO	DS	S	Column generation
[204] Koulinas et al. (2014)	OC	DRD	Cmax	DS	S	PSO + LS(hyper-heuristic)
[206] Cheng et al. (2014)	RR	DRD	Cmax	DS	S	Fuzzy Clustering Chaotic-based DE
[10] Creemers et al. (2015)	RR	DRD	Cmax	SS	S	Column generation
[70] Cheng et al. (2015)	RR	DRD	MO	DS	S	DEA
[27] Coughlan et al. (2015)	RR	MM	RLP	DS	S	Branch-price-and-cut
[35] Rieck et al. (2015)	RR	DRD	RLP	DS	S	Tree-based Branch-and-bound
[47] Leyman et al. (2015)	RR	DRD	NPV	DS	S	GA
[69] Shahsavar et al. (2015)	RR	DRD	MO	DS	S	Self-adaptive+GA
[84] Kellenbrink et al. (2015)	GNS/RR/ NRR	DRD	Cmax	DS	S	GA
[87] Cheng et al. (2015)	RR/NRR	P/MM/RV	TBO	DS	S	Tree-based branch-and-bound
[97] Okubo et al. (2015)	PRR/OC	DRD	Cmax	DS	S	IP + CP
[124] Said et al. (2015)	RR/NRR	MM	MO	SS	S	Heuristic
[126] Damghani et al. (2015)	GPR	MM	MO	DS	S	Improved PSO
[129] Van Peteghem et al. (2015)	RR	MM	MO	DS	S	GA
[141] Shou et al. (2015)	RR	P	Cmax	DS	S	Hybrid PSO
[143] Schwindt et al. (2015)	GPR/OC	P	Cmax	DS	S	Column generation+MILP
[144] Moukrim et al. (2015)	RR	P	Cmax	DS	S	Branch-and-price
[148] Suresh et al. (2015)	RR	TT	NPV	DS	M	GA
[167] Hu et al. (2015)	RR/OC	DRD	Cmax	FS	M	Outer–inner fuzzy cellular automata algorithm
[174] Chen et al. (2015)	OC	DRD	Cmax	DS	M	Comparative analysis of methods
[190] Liu et al. (2015)	RR	DRD	Cmax	DS	S	PSO
[13] Niño et al. (2016)	RR	DRD	MO	DS	S	LS
[62] Tabrizi et al. (2016)	NRR	DRD	RBO	PS	S	NSGA-II
[24] Qin et al. (2016)	RR	MS	TBO	DS	S	MLP
[34] Vandenheede et al. (2016)	RR	DRD	TBO	DS	S	Scatter search
[68] Maghsoudlou et al. (2016)	RR	MM/MS	MO	DS	S	Invasive weeds optimization algorithm
[77] Schnell et al. (2016)	RR/NRR/ GPR	MM	Cmax	DS	S	/
[104] Sahli et al. (2016)	RR/NRR	ESPCPR	Cmax	DS	S	MILP
[123] Aminbakhsh et al. (2016)	RR/NRR	MM	MO	DS	S	DPSO
[145] Kreter et al. (2016)	RR	DRD	Cmax	DS	S	BLMF+SS
[163] Gholizadeh-Tayyar et al. (2016)	NRR/OC	DRD	Cmax	DS	M	MIP
[175] Chakrabortty et al. (2016)	RR/NRR/OC	MM	Cmax	RS	S	MILP
[183] Fathallahi et al. (2016)	RR	DRD	NPV	FS	S	Hybrid genetic algorithm
[56] Palacio et al. (2017)	RR	DRD	MO	PS	S	MILP
[59] Elloumi et al. (2017)	RR	MM	MO	RS	S	EA
[23] Maghsoudlou et al. (2017)	RR	MS	MO	DS	S	FSCS
[32] Afshar-Nadjafi et al. (2017)	OC	DRD	RRP	DS	S	ACO + GA
[33] Kerkhove et al. (2017)	RR	DRD	CBO	DS	S	SS
[36] Ponz-Tienda et al. (2017)	OC	DRD	RLP	DS	S	IAHS
[37] Ponz-Tienda et al. (2017)	OC	DRD	RLP	DS	S	Branch and Bound
[43] Verbeeck et al. (2017)	OC	DRD	MO	DS	S	AI
[85] Tao et al. (2017)	GNS/RR/ NRR	DRD	Cmax	DS	S	SA
[101] Naber et al. (2017)	RR	FRCPSP	Cmax	DS	S	MIP
[102] Tritschler et al. (2017)	RR	FRCPSP	Cmax	DS	S	GA + VNS
[105] Hanzalek et al. (2017)	GPR	DRD	Cmax	DS	S	Parallel heuristic
[107] Zoraghi et al. (2017)	RR/NRR	MM	CBO	DS	S	PSO-GA/GA-GA/SA-GA

(continued on next page)

Table 3 (*continued*)

Article	Constraint	Characteristics	Objective	Information	Number	Method
[113] Schnell et al. (2017)	NRR	MM	Cmax	DS	S	Exact CP-SAT
[117] Zoraghi et al. (2017)	RR/NRR	MM	MO	DS	S	EA
[128] Tian et al. (2017)	RR	MM	MO	RS	S	/
[140] Javanmard et al. (2017)	RR	MS/P	Cmax	DS	S	GA + PSO
[154] Laurent et al. (2017)	RR	TT	Cmax	DS	S	LS + SA
[161] Amirian et al. (2017)	OC	DRD	MO	DS	M	SFLA
[164] Joo et al. (2017)	OC	MM	Cmax	DS	M	SA
[166] Geiger et al. (2017)	RR/OC	MM	Cmax	DS	M	LS + VNS
[179] Ning et al. (2017)	NRR	MM	NPV	DS	S	SA + TS
[199] Zhu et al. (2017)	RR	DRD	RACP	DS	S	MSIS
[205] Zamani et al. (2017)	OC	DRD	TBO	DS	S	IEM + GA
[38] Qiao et al. (2018)	RR	DRD	RLP	DS	S	Discrete particle swarm optimization
[39] Li et al. (2018)	GPR/RR	DRD	RLP	DS	S	GA
[40] Li et al. (2018)	GPR/RR	MM	RLP	DS	S	EDA
[42] Atan et al. (2018)	GPR/RR	DRD	RLP	DS	S	Greedy heuristic
[50] Creemers et al. (2018)	OC	P	NPV	SS	S	SDP
[52] Tirkolaee et al. (2018)	RR/NRR	MM	MO	DS	S	NSGA II + SA
[81] Kreter et al. (2018)	GPR/RR	DRD	RACP	DS	S	MILP+CP
[86] Tao et al. (2018)	GNS/RR/NRR	MM	MO	DS	S	TS + NSGA II
[109] Li et al. (2018)	RR/OC	DRD	Cmax	DS	S	PSO
[111] Fernandes Muritiba et al. (2018)	NRR	MM	Cmax	DS	S	PR
[115] Afshar-Nadjafi et al. (2018)	RR/NRR/OC	MM/P	Cmax	DS	S	SA
[149] Kadri et al. (2018)	RR	TT	Cmax	DS	S	GA
[133] Wang et al. (2018)	RR	MS	MO	DS	S	LS
[159] Shu et al. (2018)	OC	DRD	Cmax	DS	M	GA
[173] Shafahi et al. (2018)	RR/NRR	DRD	Cmax	DS	S	Genetic programming based hyper-heuristic
[198] Liu et al. (2018)	OC	MM	CBO	DS	S	Column generation
[201] Chand et al. (2018)	RR	DRD	Cmax	DS	S	Hyper-heuristic
[202] Đumić et al. (2018)	RR	DRD	Cmax	DS	S	Hyper-heuristic
[11] Wang et al. (2019)	OC	DRD	TBO	DS	S	Column generation+GA
[61] Tian et al. (2019)	RR	MM	MO	PS	S	GA + EDA
[17] Hariga et al. (2019)	RR/OC	P	MO	DS	S	MILP
[53] Tabrizi et al. (2019)	NRR	DRD	NPV	DS	S	GA
[67] Nemati-Lafmejani et al. (2019)	RR/NRR	MM	MO	DS	S	NSGA II + MO-PSO
[83] Chu et al. (2019)	RR/OC	MM	Cmax	DS	S	Heuristic
[91] Benttaleb et al. (2019)	RR	DRD	Cmax	DS	S	Branch and Bound
[112] Gnägi et al. (2019)	RR/NRR/OC	MM	Cmax	DS	S	MILP
[130] Eeckhout et al. (2019)	RR	MM	MO	DS	S	Heuristic
[134] Laszczyk et al. (2019)	RR	MS	MO	DS	S	NSGA II
[135] Maghsoudlou et al. (2019)	RR	MS/P	CBO	DS	S	ACO
[138] Zabihi et al. (2019)	RR	MS	MO	DS	S	Teaching-learning based optimization
[142] Vanhoucke et al. (2019)	RR	MS	MO	DS	S	NSGA II + MOTLBO
[146] Creemers et al. (2019)	RR	P	Cmax	SS	S	Exact
[192] García-Nieves et al. (2019)	OC	MM	MO	DS	S	Exact LP binary formulation
[193] Birjandi et al. (2019)	RR/NRR	MM	CBO	FS	S	PSO + GA
[9] Kong et al. (2020)	GPR/OC	DRD	Cmax	DS	S	GA
[16] Androutsopoulos et al. (2020)	PRR	DRD	MO	DS	M	Hybrid heuristic
[64] Shen et al. (2020)	RR	DRD	MO	PS	S	Cooperative coevolution
[25] Chen et al. (2020)	RR	MS	MO	DS	M	GA + ACO
[48] Rezaei et al. (2020)	RR	MS	Cmax	DS	S	MP + CP
[72] Daryani et al. (2020)	RR	MS	MO	PS	M	NSGA III
[82] Watermeyer et al. (2020)	PRR/GPR	DRD	Cmax	DS	S	Branch-and-bound
[93] Chaleshtarti et al. (2020)	NRR/RR	DRD	Cmax	DS	S	GA + LR
[95] Chakrabortty et al. (2020)	RR	MM	Cmax	DS	S	VNS
[118] Subulan et al. (2020)	RR/NRR	MM	MO	SS	S	MIP
[119] Bofill et al. (2020)	RR/NRR/OC	MM/RV	Cmax	DS	S	Satisfiability Modulo Theories
[150] Ren et al. (2020)	RR	TT	Cmax	DS	S	Branch-and-bound+GA
[156] Araujo et al. (2020)	RR/NRR/OC	MM	TBO	DS	S/M	MILP
[157] Van Eynde et al. (2020)	OC	MM	MO	DS	M	GA
[162] Hauder et al. (2020)	RR	MM	MO	DS	M	New MIP + CP
[170] Kannimuthu et al. (2020)	RR	MM	MO	DS	M	/
[171] Tian et al. (2020)	RR	DRD	TBO	PS	M	Improvement of the CCM
[160] Satic et al. (2020)	RR	DRD	CBO	RS	M	GA
[184] Nabipoor Afruzi et al. (2020)	RR	DRD	MO	PS	M	Scenario-relaxation algorithm
[191] Wang et al. (2020)	OC	MM	MO	DS	S	An integrated approach
[200] Chakrabortty et al. (2020)	OC	RV	MO	SS	S	VNS + LS + PR
[207] Rahman et al. (2020)	RR	DRD	Cmax	DS	S	MA
[46] Asadujjaman et al. (2021)	RR	DRD	NPV	DS	S	Hybrid immune GA
[57] Balouka et al. (2021)	OC	MM	Cmax	PS	S	Benders decomposition approach
[58] Chakrabortty et al. (2021)	RR	ESPCPR	Cmax	RS	S	Enhanced iterated greedy
[60] Liu et al. (2021)	RR	MM	MO	DS	S	VGA + VSA
[21] Wen et al. (2021)	OC	DRD	TBO	DS	S	Design structure matrix
[29] Fink et al. (2021)	RR/NRR	MM	RACP	DS	S	Distributed decision making

(*continued on next page*)

Table 3 (*continued*)

Article	Constraint	Characteristics	Objective	Information	Number	Method
[41] Tarasov et al. (2021)	RR	FRCPSP	RLP	DS	S	Benders decomposition
[49] Rezaei et al. (2021)	RR	DRD	NPV	SS	S	Heuristic priority rules
[55] Asadujaman et al. (2021)	RR	DRD	NPV	DS	S	GA + IA
[75] de Azevedo et al. (2021)	GPR	DRD	Cmax	DS	S	Satisfiability(SAT)
[108] Zhang et al. (2021)	NRR	DRD	MO	DS	S	NSGA-II
[116] Yuan et al. (2021)	RR/NRR	MM	MO	FS	S	Hybrid cooperative EA
[114] Elloumi et al. (2021)	RR/NRR	MM/P	Cmax	RS	S	Reactive heuristics
[120] Cui et al. (2021)	RR	MM/MS	Cmax	DS	M	VNS + Heuristic AC
[132] Zhu et al. (2021)	RR	MS	MO	DS	S	Hyper-heuristic
[136] Snauwaert et al. (2021)	RR	MS	Cmax	DS	S	GA
[151] Wang et al. (2021)	RR	TT	MO	DS	S	NSGA II + SA
[158] Li et al. (2021)	NRR	DRD	MO	DS	M	Multi-agent-based cooperative
[168] Fu et al. (2021)	RR/OC	DRD	CBO	DS	M	Heuristic-based+argumentation
[169] Eeckhout et al. (2021)	RR	TT	CBO	DS	M	Diving heuristic
[178] Zhou et al. (2021)	RR	DRD	MO	SS	S	Ranking and selection+EDA
[182] Ghamginzadeh et al. (2021)	RR/OC	MS	MO	FS	S	Imperialist Competitive Algorithm
[189] Ma et al. (2021)	OC	DRD	MO	DS	S	Discrete symbiotic organisms search
[194] Taghaddos et al. (2021)	RR/OC	MM	Cmax	FS	S	Hybrid simulation and optimization
[15] Prata et al.(2022)	RR/OC	DRD	MO	DS	S	MILP
[63] Zhou et al. (2022)	RR/NRR	MM	MO	FS	S	Improved PSO
[18] Rahman et al. (2022)	RR/NRR	DRD	MO	DS	S	Memetic algorithm
[19] Alcaraz et al. (2022)	RR	RV	MO	DS	S	Meta-heuristic based on NSGA-II
[71] Liu et al. (2022)	RR/OC	DRD	MO	DS	S	NSGA-III
[30] Siamakmanesh et al. (2022)	RR	DRD	RACP	DS	S	GA
[65] Tian et al. (2022)	RR	MS/TT	MO	DS	S	Evolution Strategy
[74] Tran et al. (2022)	RR/NRR	RV	Cmax	DS	S	Discrete Continuous formulation
[76] Bianco et al. (2022)	GPR	DRD	Cmax	DS	S	CPM
[88] Hua et al. (2022)	OC	DRD	Cmax	DS	S	Improved GA
[90] Wang et al. (2022)	RR	RV/TT	CBO	DS	S	A novel two-step dispatching
[125] Çakir et al. (2022)	RR	MM/P	MO	DS	S	CP/GA
[139] Chen et al. (2022)	RR/OC	MS	CBO	SS	M	GA with a heuristic workforce assignment
[137] Snauwaert et al. (2022)	RR/OC	MS	Cmax	DS	S	MILP
[152] Ma et al. (2022)	RR/OC	TT	RBO	PS	S	Improved GA
[153] Zhang et al. (2022)	RR/OC	TT	TBO	DS	M	GA
[172] Zorluoğlu et al. (2022)	OC	DRD	MO	DS	M	Interactive decision support
[176] Peng et al. (2022)	RR	DRD	MO	RS/PS	S	CPM
[177] Wang et al. (2022)	NRR	DRD	Cmax	RS	S	Dynamic Selection of Priority Rules Based on Deep Reinforcement
[180] Liu et al. (2022)	RR/NRR	MM/RV	MO	FS	S	PSO + GA
[181] Zhao et al. (2022)	OC	DRD	MO	FS	S	Operational law
[185] Li et al. (2022)	OC	DRD	Cmax	PS	S	Data-driven project buffer sizing approach
[195] Mezouari et al. (2022)	RR/OC	DRD	CBO	FS	S	Heuristic
[196] Rahman et al. (2022)	NRR/OC	DRD	MO	DS	S	Memetic algorithm
[208]Kedir et al. (2022)	RR/NRR	DRD	Cmax	DS	S	Reinforcement learning + agent
[209]Soman et al. (2022)	OC	DRD	Cmax	DS	S	Look-ahead Schedule

Constraints (RR: Renewable Resource | NRR: Non-renewable Resource | DCR: Doubly Constrained Resource | PRR:Partially renewable resources | CPR: Generalized Precedence Relation | GNS: Generalized network structures | OC: Other constraints).
Activity characteristics (MM: Multi-mode | MS: Multi-skill | RV: Resource Variation | P: Preemptive | TT: Transfer time | DRD: Disregarded).
Objectives (Cmax: Minimize the makespan | RBO: Robustness-based objectives | TBO: Time-based Objectives (except Cmax) | NPV: Net Present Value | CBO: Cost-based Objectives | RRP: Resource Renting Problem | RACP: Resource Availability Cost Problem | RLP: Resource Leveling Problem | MO: Multi-objective).
Information (DS: Deterministic Scheduling | RS: Reactive Scheduling | SS: Stochastic Scheduling | FS: Fuzzy Scheduling | PS: Proactive Scheduling).

considered so as to construct new models, which means that the problem size is increasing and that the algorithms need to be optimized simultaneously.

8.7. More competitive solutions

Fig. 12 shows the progress of algorithm research on the RCPSP. In addition to the improvement of exact, heuristic, meta-heuristic or hyper-heuristic models, hybrid methods have also been discussed. A hybrid method that can perform well in most situations can also be proposed. Some algorithms proposed in the literature are only for specific problems, and the scope of their application can be extended in future research. Some scholars have focused on optimizing mathematical formulas to improve the quality of solutions. The improvement of heuristic methods based on mathematics is also a promising future direction.

There is a growing interest in developing a reasonable hybrid meta-heuristic to solve the RCPSP, and the existing hybrid methods have been steadily improved in terms of accuracy and speed. The introduction of adaptive adjustment and control technology in the hybrid meta-heuristic algorithm also merits further study.

8.8. The impact of adjacent links in project management on project scheduling

As a part of project management, the results of other aspects (plan or control) will also affect the quality of project scheduling to a certain extent. Project planning and project scheduling have been considered simultaneously in several studies. In future research, the project planning process can be optimized to make the scheduling input more accurate, and the scheduling results can be monitored and controlled to reduce the uncertainty occurring in the scheduling process.

8.9. Real-time schedule

Traditional project scheduling research has mainly used optimization methods as tools. Forecasting, reinforcement learning, machine

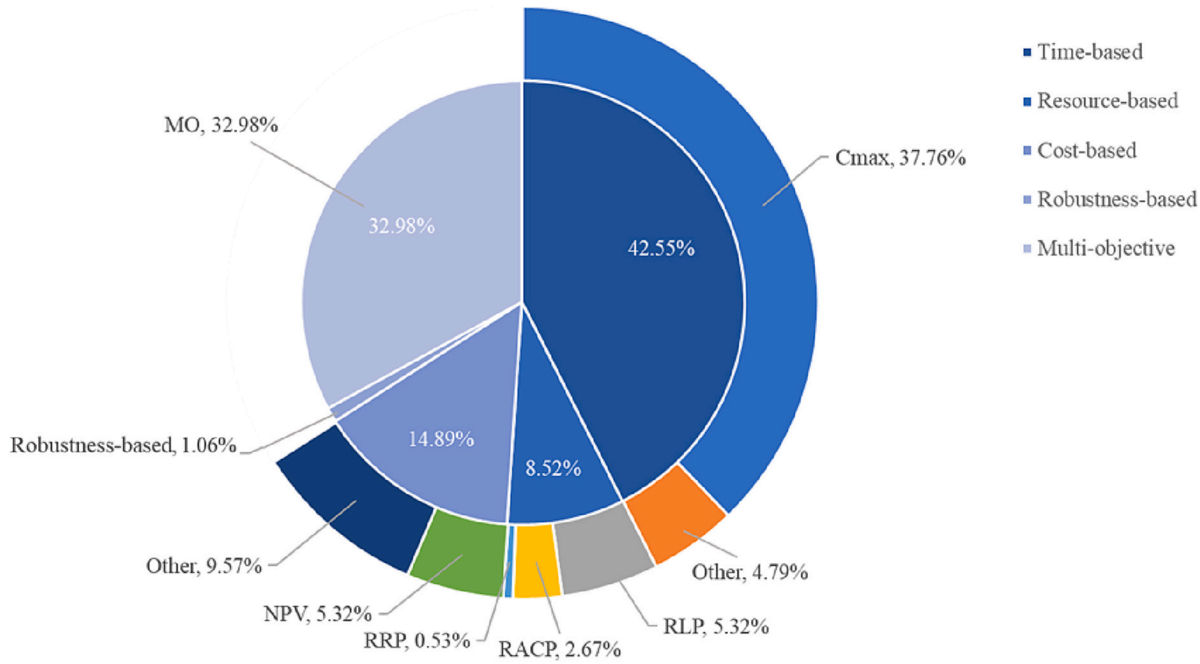

Fig. 8. Frequency percentage of objectives.

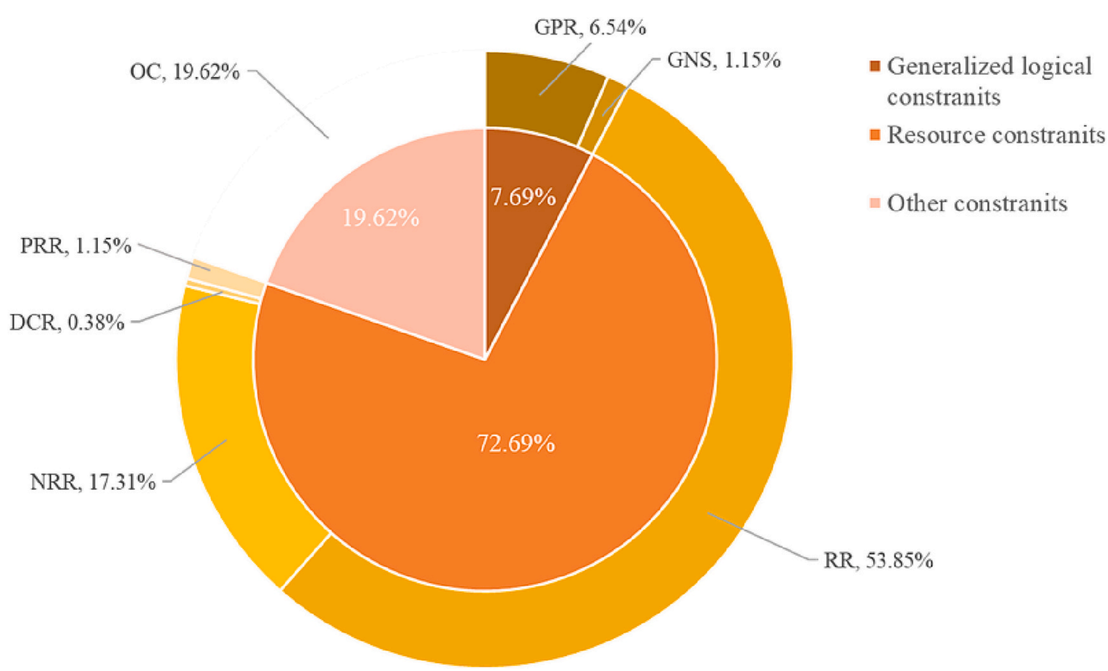

Fig. 9. Percentage of different constraints.

learning and other methods in artificial intelligence can be applied to projects in the future to develop new online real-time project scheduling methods. For example, for the construction project, we can use artificial intelligence methods to predict the construction duration of activities from historical data, and combine them with the BIM with artificial neural networks for data mining.

8.10. Proximity between scheduling theory and practical applications

Over the past decade, researchers have developed many complex project scheduling problems, and these models are often too detailed to become standard problems. However, they do capture many requirements in practice. Therefore, it is valuable to form generalizable standard models by extracting or simplifying features of complex problems, or to motivate other real-world-based models by discussing the connection between these complex models and real-world problems.

However, more comprehensive datasets should be designed and developed so that they can be made available for various problems. In this way, different papers can test and compare their developed methods or scheduling results, and more extended models and algorithms of the RCPSP can be explored.

For construction projects, in addition to focusing on the new RCPSP models and methods, we should also focus on the data collection time and model solving efficiency in the application of complex RCPSP.

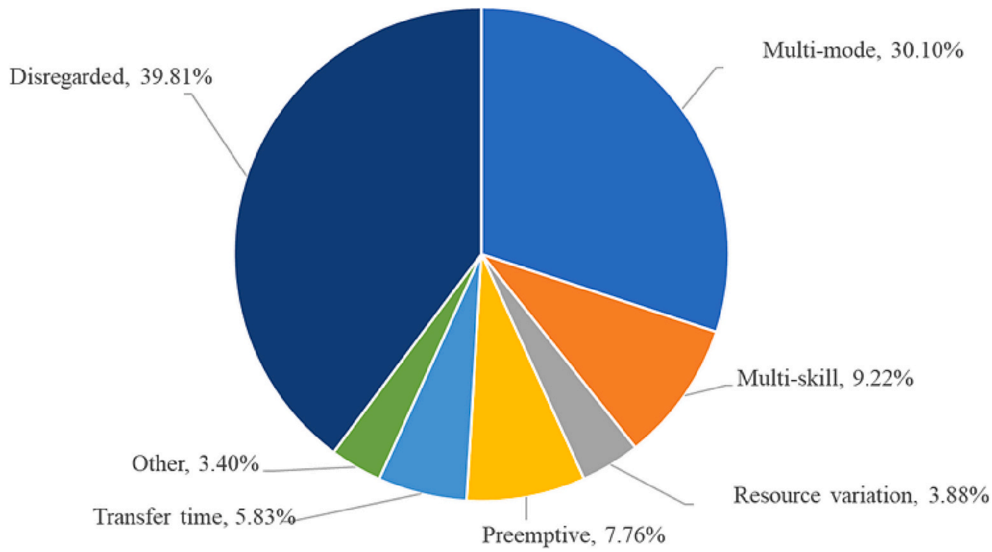

Fig. 10. Frequency percentage of activity characteristics.

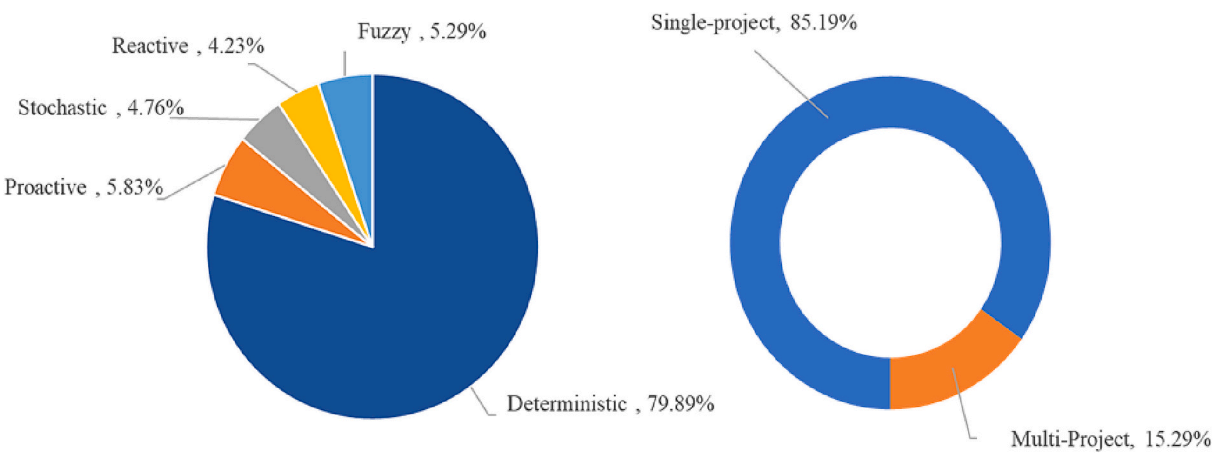

Fig. 11. Frequency percentage of other extended items.

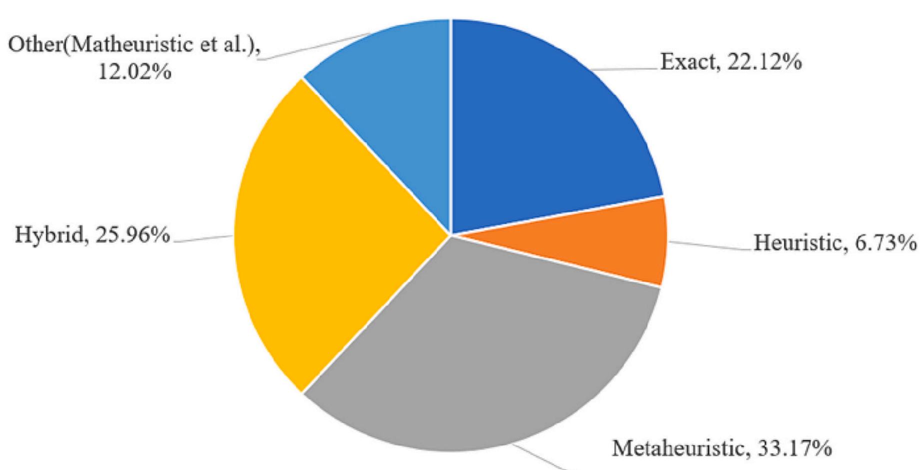

Fig. 12. Frequency percentage of different solution methodologies.

Considering the combined use of automation technology and simulation technology, we can explore the automatic generation method of models, which is conducive to the practice of complex RCPSP models in the real world.

9. Conclusion

The RCPSP has received unabated attention since it was proposed. It affects the effectiveness of project management and is regarded as one of the most interesting optimization problems. Significant achievements have been made in research on the variants and extensions of the RCPSP and algorithm optimization. The various extensions of the RCPSP have gradually become the research priority and have developed into classical models over time, such as multi-mode (MRCPSP), multi-skill (MSRCPSP), and generalized precedence relation (RCPSP/max) models. The variants of the RCPSP and more competitive solutions are still salient topics. This paper reviewed the literature in the field of project scheduling over the last decade. The development of the RCPSP was introduced in terms of the extended models around the three basic elements of objectives, constraints, activities, as well as the multi-project scheduling problem, the information availability, and the progress of algorithm research. We also analyzed the statistics obtained from previous papers and made suggestions for future research. The theory of the RCPSP can be applied to numerous practical problems, and has extraordinary significance for the development of combinatorial optimization problems. This review can also provide a reference for further research.

Code availability

Not applicable.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee or comparable ethical standards.

Consent to participate

Informed consent is obtained from all individual participants included in the study.

Consent to publication

The participants provided informed consent for publication of their statements.

Declaration of Competing Interest

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

Data availability

All data generated or analyzed during this study are included in this published article [and its supplementary information files].

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References

[1] Project Management Institute, A Guide to the Project Management Body of Knowledge, Project Management Institute, In C, 2021, 978-1628256642.
[2] S.H. Dike, Project scheduling with resource constraints, IEEE Trans. Eng. Manag. 1 (14) (1964) 155–157, https://doi.org/10.1109/TEM.1964.6446423.
[3] C. Schwindt, J. Zimmermann, Handbook on project management and scheduling, in: International Handbooks on Information Systems vol. 1, Springer, 2015, https://doi.org/10.1007/978-3-319-05443-8, 978-3-319-05443-8.
[4] C. Schwindt, J. Zimmermann, Handbook on project management and scheduling, in: International Handbooks on Information Systems vol. 2, Springer, 2015, https://doi.org/10.1007/978-3-319-05915-0, 978-3-319-05915-0.
[5] A.N. Behrouz, Multi-skilling in scheduling problems: a review on models, methods and applications, Comput. Ind. Eng. 151 (2021), 107004, https://doi.org/10.1016/j.cie.2020.107004.
[6] R. Pellerin, N. Perrier, F. Berthaut, A survey of hybrid meta-heuristics for the resource-constrained project scheduling problem, Eur. J. Oper. Res. 280 (2) (2020) 395–416, https://doi.org/10.1016/j.ejor.2019.01.063.
[7] B. Kitchenham, O.P. Brereton, D. Budgen, M. Turner, J. Bailey, S. Linkman, Systematic literature reviews in software engineering - a systematic literature review, Inf. Softw. Technol. 51 (1) (2009) 7–15, https://doi.org/10.1016/j.infsof.2008.09.009.
[8] S. Hartmann, D. Briskorn, An updated survey of variants and extensions of the resource-constrained project scheduling problem, Eur. J. Oper. Res. 297 (1) (2022) 1–14, https://doi.org/10.1016/j.ejor.2021.05.004.
[9] F. Kong, D. Dou, RCPSP with combined precedence relations and resource calendars, J. Constr. Eng. Manag. ASCE. 146 (12) (2020), 04020133, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001929.
[10] S. Creemers, Minimizing the expected makespan of a project with stochastic activity durations under resource constraints, J. Sched. 18 (3) (2015) 263–273, https://doi.org/10.1007/s10951-015-0421-5.
[11] Q. Wang, C. Liu, Z. Li, A column-generation-based algorithm for a resource-constrained project scheduling problem with a fractional shared resource, Eng. Optim. 125 (52) (2019) 798–816, https://doi.org/10.1080/0305215X.2019.1610946.
[12] H.C. Gomes, F.D. Neves, M.J. Souza, Multi-objective meta-heuristic algorithms for the resource-constrained project scheduling problem with precedence relations, Comput. Oper. Res. 44 (2014) 92–104, https://doi.org/10.1016/j.cor.2013.11.002.
[13] K. Niño, G. Mejía, L. Amodeo, A multi-objective dedicated local search for project scheduling problem, IFAC-Papers OnLine. 49 (12) (2016) 875–880, https://doi.org/10.1016/j.ifacol.2016.07.885.
[14] J. Bagherinejad, Z. Majd, Solving the MRCPSP/max with the objective of minimizing tardiness/earliness cost of activities with double genetic algorithms, Int. J. Adv. Manuf. Technol. 70 (2014) 573–582, https://doi.org/10.1007/S00170-013-5303-4.
[15] B.D. Prata, V. Fernandez-Viagas, J.M. Framiñan, C.D. Rodrigues, Matheuristics for the flowshop scheduling problem with controllable processing times and limited resource consumption to minimize total tardiness, Comput. Oper. Res. 145 (2022), 105880, https://doi.org/10.1016/j.cor.2022.105880.
[16] K.N. Androutsopoulos, E.G. Manousakis, M.A. Madas, Modeling and solving a bi-objective airport slot scheduling problem, Eur. J. Oper. Res. 284 (1) (2020) 135–151, https://doi.org/10.1016/j.ejor.2019.12.008.
[17] M. Hariga, A. Shamayleh, F. Ei-Wehedi, Integrated time-cost tradeoff and resources leveling problems with allowed activity splitting, Int. Trans. Oper. Res. 26 (1) (2019) 80–99, https://doi.org/10.1111/itor.12329.
[18] H.F. Rahman, T. Servranckx, R.K. Chakrabortty, M. Vanhoucke, S. Sawah Ei, Manufacturing project scheduling considering human factors to minimize total cost and carbon footprints, Appl. Soft Comput. (2022), 109764, https://doi.org/10.1016/j.asoc.2022.109764.
[19] J. Alcaraz, L. Anton-Sanchez, F. Saldanha-da-Gama, Bi-objective resource-constrained project scheduling problem with time-dependent resource costs, J. Manuf. Syst. 63 (2022) 506–523, https://doi.org/10.1016/j.jmsy.2022.05.002.
[20] O. Icmeli-Tukel, W.O. Rom, Ensuring quality in resource constrained project scheduling, Eur. J. Oper. Res. 103 (3) (1997) 483–496, https://doi.org/10.1016/S0377-2217(96)00305-0.
[21] M. Wen, J. Lin, Y. Qian, W. Huang, Scheduling interrelated activities in complex projects under high-order rework: a DSM-based approach, Comput. Oper. Res. 130 (2021), 105246, https://doi.org/10.1016/j.cor.2021.105246.
[22] M.D. Hossain, D.K. Chua, Overlapping design and construction activities and an optimization approach to minimize rework, Int. J. Proj. Manag. 32 (6) (2014) 983–994, https://doi.org/10.1016/j.ijproman.2013.10.019.
[23] H. Maghsoudlou, B. Afshar-Nadjafi, S.T. Niaki, Multi-skilled project scheduling with level-dependent rework risk; three multi-objective mechanisms based on cuckoo search, Appl. Soft Comput. 54 (2017) 46–61, https://doi.org/10.1016/j.asoc.2017.01.024.
[24] S. Qin, S. Liu, H. Kuang, Piecewise linear model for multiskilled workforce scheduling problems considering learning effect and project quality, Math. Probl. Eng. (2016) 1–11, https://doi.org/10.1155/2016/3728934.
[25] R. Chen, C. Liang, D. Gu, H. Zhao, A competence-time-quality scheduling model of multi-skilled staff for IT project portfolio, Comput. Ind. Eng. 139 (2020), 106183, https://doi.org/10.1016/j.cie.2019.106183.
[26] R.H. Möhring, Minimizing costs of resource requirements in project net-works subject to a fixed completion time, Oper. Res. 32 (1) (1984) 89–120, https://doi.org/10.1287/opre.32.1.89.
[27] E.T. Coughlan, M.E. Lübbecke, J. Schulz, A branch-price-and-cut algorithm for multi-mode resource leveling, Eur. J. Oper. Res. 245 (1) (2015) 70–80, https://doi.org/10.1016/j.ejor.2015.02.043.
[28] B. Afshar-Nadjafi, Multi-mode resource availability cost problem with recruitment and release dates for resources, Appl. Math. Model. 38 (21) (2014) 5347–5355, https://doi.org/10.1016/j.apm.2014.04.009.

[29] A. Fink, P. Gerhards, Negotiation mechanisms for the multi-agent multi-mode resource investment problem, Eur. J. Oper. Res. 295 (1) (2021) 261–274, https://doi.org/10.1016/j.ejor.2021.02.023.
[30] N. Siamakmanesh, A.A. Najafi, F. Azimi, A work-content based resource availability cost problem: mathematical modeling and solving procedure, Econ. Comp. Econom. Cybern. Stud. Res. 56 (1) (2022) 75–90, https://doi.org/10.24818/18423264/56.1.22.05.
[31] H. Nübel, The resource renting problem subject to temporal constraints, OR Spectr. 23 (2001) 359–381, https://doi.org/10.1007/PL00013357.
[32] B. Afshar-Nadjafi, M. Basati, H. Maghsoudlou, Project scheduling for minimizing temporary availability cost of rental resources and tardiness penalty of activities, Appl. Soft Comput. 61 (2017) 536–548, https://doi.org/10.1016/j.asoc.2017.08.033.
[33] L.P. Kerkhove, M. Vanhoucke, B. Maenhout, On the resource renting problem with overtime, Comput. Ind. Eng. 111 (2017) 303–319, https://doi.org/10.1016/j.cie.2017.07.024.
[34] L. Vandenheede, M. Vanhoucke, B. Maenhout, A scatter search for the extended resource renting problem, Int. J. Prod. Res. 54 (16) (2016) 4723–4743, https://doi.org/10.1080/00207543.2015.1064177.
[35] J. Rieck, J. Zimmermann, Exact methods for resource leveling problems, in: C. Schwindt, J. Zimmermann (Eds.), Handbook on Project Management and Scheduling vol. 1, International Handbooks on Information Systems. Springer, 2015, pp. 361–387, https://doi.org/10.1007/978-3-319-05443-8_17, 978-3-319-05443-8.
[36] J.L. Ponz-Tienda, A. Salcedo-Bernal, E. Pellicer, J. Benlloch-Marco, Improved adaptive harmony search algorithm for the resource leveling problemwith minimal lags, Autom. Constr. 77 (2017) 82–92, https://doi.org/10.1016/j.autcon.2017.01.018.
[37] J.L. Ponz-Tienda, A. Salcedo-Bernal, E. Pellicer, A parallel branch and bound algorithm for the resource leveling problem with minimal lags, Comp. Aid. Civ. Infrastruct. Eng. 32 (6) (2017) 474–498, https://doi.org/10.1111/mice.12233.
[38] J. Qiao, Y. Li, Resource leveling using normalized entropy and relative entropy, Autom. Constr. 87 (2018) 263–272, https://doi.org/10.1016/j.autcon.2017.12.022.
[39] H. Li, L. Xiong, Y. Liu, H. Li, An effective genetic algorithm for the resource levelling problem with generalised precedence relations, Int. J. Prod. Res. 56 (5) (2018) 2054–2075, https://doi.org/10.1080/00207543.2017.1355120.
[40] H. Li, X. Dong, Multi-mode resource leveling in projects with mode-dependent generalized precedence relations, Expert Syst. Appl. 97 (2018) 193–204, https://doi.org/10.1016/j.eswa.2017.12.030.
[41] I.A. Tarasov, A. Haït, O. Battaïa, Benders decomposition for a period-aggregated resource leveling problem with variable job duration, Comput. Oper. Res. 132 (2021), 105258, https://doi.org/10.1016/j.cor.2021.105258.
[42] T. Atan, E. Eren, Optimal project duration for resource leveling, Eur. J. Oper. Res. 266 (2) (2018) 508–520, https://doi.org/10.1016/j.ejor.2017.10.022.
[43] C. Verbeeck, V. Van Peteghem, M. Vanhoucke, A meta-heuristic solution approach for the time-constrained project scheduling problem, OR Spectr. 39 (2017) 353–371, https://doi.org/10.1007/s00291-016-0458-7.
[44] J. Son, M.J. Skibniewski, Multiheuristic approach for resource leveling problem in construction engineering: hybrid approach, J. Constr. Eng. Manag. 125 (1) (1999) 23–31, https://doi.org/10.1061/(ASCE)0733-9364(1999)125:1(23).
[45] A.H. Russell, Cash flows in networks, Manag. Sci. 16 (5) (1970) 357–373, https://doi.org/10.1287/mnsc.16.5.357.
[46] M. Asadujjaman, H.F. Rahman, R.K. Chakrabortty, M.J. Ryan, Resource constrained project scheduling and material ordering problem with discounted cash flows, Comput. Ind. Eng. 158 (2021), 107427, https://doi.org/10.1016/j.cie.2021.107427.
[47] P. Leyman, M. Vanhoucke, A new scheduling technique for the resource–constrained project scheduling problem with discounted cash flows, Int. J. Prod. Res. 53 (9) (2015) 2771–2786, https://doi.org/10.1080/00207543.2014.980463.
[48] F. Rezaei, A.A. Najafi, R. Ramezanian, Mean-conditional value at risk model for the stochastic project scheduling problem, Comput. Ind. Eng. 142 (2020), 106356, https://doi.org/10.1016/j.cie.2020.106356.
[49] F. Rezaei, A.A. Najafi, R. Ramezanian, E. Demeulemeester, Simulation-based priority rules for the stochastic resource-constrained net present value and risk problem, Comput. Ind. Eng. 160 (2021), 107607, https://doi.org/10.1016/j.cie.2021.107607.
[50] S. Creemers, Maximizing the expected net present value of a project with phase-type distributed activity durations: an efficient globally optimal solution procedure, Eur. J. Oper. Res. 267 (1) (2018) 16–22, https://doi.org/10.1016/j.ejor.2017.11.027.
[51] S. Hartmann, D. Briskorn, A survey of variants and extensions of the resource-constrained project scheduling problem, Eur. J. Oper. Res. 207 (1) (2010) 1–14, https://doi.org/10.1016/j.ejor.2009.11.005.
[52] E.B. Tirkolaee, A. Goli, M. Hematian, A.K. Sangaiah, T. Han, Multi-objective multi-mode resource-constrained project scheduling problem using Pareto-based algorithms, Computing. 101 (6) (2018) 547–570, https://doi.org/10.1007/s00607-018-00693-1.
[53] B.H. Tabrizi, S.F. Ghaderi, S. Haji-Yakhchali, Net present value maximisation of integrated project scheduling and material procurement planning, Int. J. Operat. Res. 34 (2) (2019) 285–300, https://doi.org/10.1504/IJOR.2019.097581.
[54] A.M. Bulavchuk, D.V. Semenova, Genetic algorithm based on idempotent algebra methods for RCPSP, in: 2021 IEEE 15th International Conference on Application of Information and Communication Technologies (AICT), 2021, pp. 1–4, https://doi.org/10.1109/AICT52784.2021.9620510.
[55] M. Asadujaman, H.F. Rahman, R.K. Chakraborty, M.J. Ryan, Resource constrained project scheduling andmaterial ordering problem with discounted cash flows, Comput. Ind. Eng. 158 (2021), 107427, https://doi.org/10.1016/j.cie.2021.107427.
[56] J.D. Palacio, O.L. Larrea, A lexicographic approach to the robust resource-constrained project scheduling problem, Int. Trans. Oper. Res. 24 (1–2) (2017) 143–157, https://doi.org/10.1111/itor.12301.
[57] N. Balouka, I. Cohen, A robust optimization approach for the multi-mode resource-constrained project scheduling problem, Eur. J. Oper. Res. 291 (2) (2021) 457–470, https://doi.org/10.1016/j.ejor.2019.09.052.
[58] R.K. Chakrabortty, H.F. Rahman, K.M. Haque, S.K. Paul, M.J. Ryan, An event-based reactive scheduling approach for the resource constrained project scheduling problem with unreliable resources, Comput. Ind. Eng. 151 (2021), 106981, https://doi.org/10.1016/j.cie.2020.106981.
[59] S. Elloumi, P. Fortemps, T. Loukil, Multi-objective algorithms to multi-mode resource-constrained projects under mode change disruption, Comput. Ind. Eng. 106 (2017) 161–173, https://doi.org/10.1016/j.cie.2017.01.029.
[60] H. Liu, S. Qu, R. Li, H. Razaa, Bi-objective robust project scheduling with resource constraints and flexible activity execution lists, Comput. Ind. Eng. 156 (2021), 107288, https://doi.org/10.1016/j.cie.2021.107288.
[61] J. Tian, X. Hao, M. Gen, A hybrid multi-objective EDA for robust resource constraint project scheduling with uncertainty, Comput. Ind. Eng. 130 (2019) 317–326, https://doi.org/10.1016/j.cie.2019.02.039.
[62] B.H. Tabrizi, S.F. Ghaderi, A robust bi-objective model for concurrent planning of project scheduling and material procurement, Comput. Ind. Eng. 98 (2016) 11–29, https://doi.org/10.1016/j.cie.2016.05.017.
[63] T. Zhou, Q. Long, K.M. Law, C. Wu, Multi-objective stochastic project scheduling with alternative execution methods: an improved quantum-behaved particle swarm optimization approach, Expert Syst. Appl. 203 (2022), 117029, https://doi.org/10.1016/j.eswa.2022.117029.
[64] X. Shen, Y. Guo, A. Li, Cooperative coevolution with an improved resource allocation for large-scale multi-objective software project scheduling, Appl. Soft Comput. 88 (2020), 106059, https://doi.org/10.1016/j.asoc.2019.106059.
[65] Y. Tian, T. Xiong, Z. Liu, Y. Mei, L. Wan, Multi-objective multi-skill resource-constrained project scheduling problem with skill switches: model and evolutionary approaches, Comput. Ind. Eng. 167 (2022), 107897, https://doi.org/10.1016/j.cie.2021.107897.
[66] O. Dridi, S. Krichen, A. Guitouni, A multi-objective hybrid ant colony optimization approach applied to the assignment and scheduling problem, Int. Trans. Oper. Res. 21 (6) (2014) 935–953, https://doi.org/10.1111/itor.12071.
[67] R. Nemati-Lafmejani, H. Davari-Ardakani, H. Najafzad, Multi-mode resource constrained project scheduling and contractor selection: mathematical formulation and meta-heuristic algorithms, Appl. Soft Comput. 81 (2019), 105533, https://doi.org/10.1016/j.asoc.2019.105533.
[68] H. Maghsoudlou, B. Afshar-Nadjafi, S.T. Niaki, A multi-objective invasive weeds optimization algorithm for solving multi-skill multi-mode resource constrained project scheduling problem, Comput. Chem. Eng. 88 (2016) 157–169, https://doi.org/10.1016/j.compchemeng.2016.02.018.
[69] A. Shahsavar, A.A. Najafi, S.T.A. Niaki, Three self-adaptive multi-objective evolutionary algorithms for a triple-objective project scheduling problem, Comput. Ind. Eng. 87 (2015) 4–15, https://doi.org/10.1016/j.cie.2015.04.027.
[70] M.Y. Cheng, D.H. Tran, Opposition-based multiple objective differential evolution (OMODE) for optimizing work shift schedules, Autom. Constr. 55 (2015) 1–14, https://doi.org/10.1016/j.autcon.2015.03.021.
[71] Y. Liu, K. You, Y.T. Jiang, Z.G. Wu, Z.Y. Liu, G. Peng, C. Zhou, Multi-objective optimal scheduling of automated construction equipment using non-dominated sorting genetic algorithm (NSGA-III), Autom. Constr. 143 (2022), 104587, https://doi.org/10.1016/j.autcon.2022.104587.
[72] A.M. Daryani, M.M. Omran, A. Makui, A novel heuristic, based on a new robustness concept, for multi-objective project portfolio optimization, Comput. Ind. Eng. 139 (2020), 106187, https://doi.org/10.1016/j.cie.2019.106187.
[73] L. Bianco, M. Caramia, An exact algorithm to minimize the makespan in project scheduling with scarce resources and generalized precedence relations, Eur. J. Oper. Res. 219 (2012) 73–85, https://doi.org/10.1016/j.ejor.2011.12.019.
[74] Q.N.H. Tran, N.Q. Nguyen, F. Yalaoui, L. Amodeo, H. Chehade, Improved formulations and new valid inequalities for a hybrid flow shop problem with time-varying resources and chaining time-lag, Comput. Oper. Res. 149 (2022), 106018, https://doi.org/10.1016/j.cor.2022.106018.
[75] G.H.L. de Azevedo, A.A. Pessoa, A. Subramanian, A satisfiability and workload-based exact method for the resource constrained project scheduling problem with generalized precedence constraints, Eur. J. Oper. Res. 289 (3) (2021) 809–824, https://doi.org/10.1016/j.ejor.2019.07.056.
[76] L. Bianco, M. Caramia, S. Giordani, Project scheduling with generalized precedence relations: a new method to analyze criticalities and flexibilities, Eur. J. Oper. Res. 298 (2) (2022) 451–462, https://doi.org/10.1016/j.ejor.2021.07.022.
[77] A. Schnell, R.F. Hartl, On the efficient modeling and solution of the multi-mode resource-constrained project scheduling problem with generalized precedence relations, OR Spectr. 38 (2016) 283–303, https://doi.org/10.1007/s00291-015-0419-6.
[78] F. Ballestín, A. Barrios, V. Valls, Looking for the best modes helps solving the MRCPSP/max, Int. J. Prod. Res. 51 (3) (2013) 813–827, https://doi.org/10.1080/00207543.2012.674651.
[79] S. Quintanilla, Á. Pérez, P. Lino, V. Valls, Time and work generalised precedence relationships in project scheduling with preemption: an application to the

management of service centres, Eur. J. Oper. Res. 219 (1) (2012) 59–72, https://doi.org/10.1016/j.ejor.2011.12.018.
[80] M. Tavana, A.R. Abtahi, K. Khalili-Damghani, A new multi-objective multi-mode model for solving preemptive time-cost-quality trade-off project scheduling problems, Expert Syst. Appl. 41 (4) (2014) 1830–1846, https://doi.org/10.1016/j.eswa.2013.08.081.
[81] S. Kreter, A. Schutt, P.J. Stuckey, J. Zimmermann, Mixed-integer linear programming and constraint programming formulations for solving resource availability cost problems, Eur. J. Oper. Res. 266 (2) (2018) 472–486, https://doi.org/10.1016/j.ejor.2017.10.014.
[82] K. Watermeyer, J. Zimmermann, A branch-and-bound procedure for the resource-constrained project scheduling problem with partially renewable resources and general temporal constraints, OR Spectr. 42 (2020) 427–460, https://doi.org/10.1007/s00291-020-00583-z.
[83] Z. Chu, Z. Xu, H. Li, New heuristics for the rcpsp with multiple overlapping modes, Comput. Ind. Eng. 131 (2019) 146–156, https://doi.org/10.1016/j.cie.2019.03.044.
[84] C. Kellenbrink, S. Helber, Scheduling resource-constrained projects with a flexible project structure, Eur. J. Oper. Res. 246 (2) (2015) 379–391, https://doi.org/10.1016/j.ejor.2015.05.003.
[85] S. Tao, Z.S. Dong, Scheduling resource-constrained project problem with alternative activity chains, Comput. Ind. Eng. 114 (2017) 288–296, https://doi.org/10.1016/j.cie.2017.10.027.
[86] S. Tao, Z.S. Dong, Multi-mode resource-constrained project scheduling problem with alternative project structures, Comput. Ind. Eng. 125 (2018) 333–347, https://doi.org/10.1016/j.cie.2018.08.027.
[87] J. Cheng, J. Fowler, K. Kempf, S. Mason, Multi-mode resource-constrained project scheduling problems with non-preemptive activity splitting, Comput. Oper. Res. 53 (2015) 275–287, https://doi.org/10.1016/j.cor.2014.04.018.
[88] Z. Hua, Z. Liu, L. Yang, L. Yang, Improved genetic algorithm based on time windows decomposition for solving resource-constrained project scheduling problem, Autom. Constr. 142 (2022), 104503, https://doi.org/10.1016/j.autcon.2022.104503.
[89] S. Hartmann, Project scheduling with resource capacities and requests varying with time: a case study, Flex. Serv. Manuf. J. 25 (1) (2013) 74–93, https://doi.org/10.1007/s10696-012-9141-8.
[90] Y. Wang, G.Q. Huang, A two-step framework for dispatching shared agricultural machinery with time windows, Comput. Electron. Agric. 192 (2022), 106607, https://doi.org/10.1016/j.compag.2021.106607.
[91] M. Benttaleb, F. Hnaien, F. Yalaoui, Minimising the makespan in the two-machine job shop problem under availability constraints, Int. J. Prod. Res. 57 (2019) 1427–1457, https://doi.org/10.1080/00207543.2018.1489160.
[92] D. Golenko-Ginzburg, A. Gonik, A. Baron, Resource constrained project scheduling models under random disturbances, in: J. Józefowska, J. Weglarz (Eds.), Perspectives in Modern Project Scheduling. International Series in Operations Research & Management Science vol. 92, Springer, Boston, MA, 2006, pp. 53–78, https://doi.org/10.1007/978-0-387-33768-5_3, 978-0-387-33768-5.
[93] A.S. Chaleshtarti, S. Shadrokh, M. Khakifirooz, M. Fathi, P.M. Pardalos, A hybrid genetic and Lagrangian relaxation algorithm for resource-constrained project scheduling under nonrenewable resources, Appl. Soft Comput. 94 (2020), 106482, https://doi.org/10.1016/j.asoc.2020.106482.
[94] H. Li, H. Zhang, Ant colony optimization-based multi-mode scheduling under renewable and nonrenewable resource constraints, Autom. Constr. 35 (2013) 431–438, https://doi.org/10.1016/j.autcon.2013.05.030.
[95] R.K. Chakrabortty, A. Abbasi, M.J. Ryan, Multi-mode resource-constrained project scheduling using modified variable neighborhood search heuristic, Int. Trans. Oper. Res. 27 (2020) 138–167, https://doi.org/10.1111/itor.12644.
[96] J. Böttcher, A. Drexl, R. Kolisch, F. Salewski, Project scheduling under partially renewable resource constraints, Manag. Sci. 45 (4) (1999) 543–559, https://doi.org/10.1287/mnsc.45.4.543.
[97] H. Okubo, T. Miyamoto, S. Yoshida, K. Mori, S. Kitamura, Y. Izui, Project scheduling under partially renewable resources and resource consumption during setup operations, Comput. Ind. Eng. 83 (2015) 91–99, https://doi.org/10.1016/j.cie.2015.02.006.
[98] T.S. Kyriakidis, G.M. Kopanos, M.C. Georgiadis, MILP formulations for single-and multi-mode resource-constrained project scheduling problems, Comput. Chem. Eng. 36 (2012) 369–385, https://doi.org/10.1016/j.compchemeng.2011.06.007.
[99] R. Różycki, J. Weglarz, Power-aware scheduling of preemptable jobs on identical parallel processors to minimize makespan, Ann. Oper. Res. 213 (1) (2014) 235–252, https://doi.org/10.1016/j.ejor.2011.10.017.
[100] A. Naber, R. Kolisch, MIP models for resource-constrained project scheduling with flexible resource profiles, Eur. J. Oper. Res. 239 (2) (2014) 335–348, https://doi.org/10.1016/j.ejor.2014.05.036.
[101] A. Naber, Resource-constrained project scheduling with flexible resource profiles in continuous time, Comput. Oper. Res. 84 (2017) 33–45, https://doi.org/10.1016/j.cor.2017.02.018.
[102] M. Tritschler, A. Naber, R. Kolisch, A hybrid meta-heuristic for resource-constrained project scheduling with flexible resource profiles, Eur. J. Oper. Res. 262 (1) (2017) 262–273, https://doi.org/10.1016/j.ejor.2017.03.006.
[103] O. Koné, C. Artigues, P. Lopez, M. Mongeau, Comparison of mixed integer linear programming models for the resource-constrained project scheduling problem with consumption and production of resources, Flex. Serv. Manuf. J. 25 (2013) 25–47, https://doi.org/10.1007/s10696-012-9152-5.
[104] A. Sahli, J. Carlier, A. Moukrim, Comparison of mixed integer linear programming models for the event scheduling problem with consumption and production of resources, IFAC-Papers OnLine. 49 (12) (2016) 1044–1049, https://doi.org/10.1016/j.ifacol.2016.07.580.
[105] Z. Hanzalek, P. Sucha, Time symmetry of resource constrained project scheduling with general temporal constraints and take-give resources, Ann. Oper. Res. 248 (2017) 209–237, https://doi.org/10.1007/s10479-016-2184-6.
[106] F. Fu, Integrated scheduling and batch ordering for construction project, Appl. Math. Model. 38 (2) (2014) 784–797, https://doi.org/10.1016/j.apm.2013.07.017.
[107] N. Zoraghi, A. Shahsavar, B. Abbasi, V. Van Peteghem, Multi-mode resource-constrained project scheduling problem with material ordering under bonus-penalty policies, TOP. 25 (2017) 49–79, https://doi.org/10.1007/s11750-016-0415-2.
[108] Y. Zhang, N.F. Cui, Project scheduling and material ordering problem with storage space constraints, Autom. Constr. 129 (2021), 103796, https://doi.org/10.1016/j.autcon.2021.103796.
[109] S. Li, Z. Zhang, X. Yan, K. Hu, S. Zhao, Research on a resource- constrained project scheduling problem in a hazardous environment and its staffing strategies based on PSO algorithm, Syst. Sci. Control Eng. 6 (1) (2018) 304–318, https://doi.org/10.1080/21642583.2018.1494638.
[110] F.B. Talbot, Resource-constrained project scheduling with time-resource tradeoffs: the nonpreemptive case, Manag. Sci. 28 (10) (1982) 1197–1210, https://doi.org/10.1287/mnsc.28.10.1197.
[111] A.E. Fernandes Muritiba, C.D. Rodrigues, F.A. da Costa, A path-relinking algorithm for the multi-mode resource-constrained project scheduling problem, Comput. Oper. Res. 92 (2018) 145–154, https://doi.org/10.1016/j.cor.2018.01.001.
[112] M. Gnägi, T. Rihm, A. Zimmermann, N. Trautmann, Two continuous-time assignment-based models for the multi-mode resource-constrained project scheduling problem, Comput. Ind. Eng. 129 (2019) 346–353, https://doi.org/10.1016/j.cie.2019.01.033.
[113] A. Schnell, R.F. Hartl, On the generalization of constraint programming and boolean satisfiability solving techniques to schedule a resource-constrained project consisting of multi-mode jobs, Operat. Res. Perspect. 4 (2017) 1–11, https://doi.org/10.1016/j.orp.2017.01.002.
[114] S. Elloumi, T. Loukil, P. Fortemps, Reactive heuristics for disrupted multi-mode resource-constrained project scheduling problem, Expert Syst. Appl. 167 (2021), 114132, https://doi.org/10.1016/j.eswa.2020.114132.
[115] B. Afshar-Nadjafi, A solution procedure for preemptive multi-mode project scheduling problem with mode changeability to resumption, Appl. Comp. Inform. 14 (2) (2018) 192–201, https://doi.org/10.1016/j.aci.2014.02.003.
[116] Y. Yuan, S. Ye, L. Lin, M. Gen, Multi-objective multi-mode resource-constrained project scheduling with fuzzy activity durations in prefabricated building construction, Comput. Ind. Eng. 158 (2021), 107316, https://doi.org/10.1016/j.cie.2021.107316.
[117] N. Zoraghi, A. Shahsavar, S. Niaki, A hybrid project scheduling and material ordering problem: Modeling and solution algorithms, Appl. Soft Comput. 58 (2017) 700–713, https://doi.org/10.1016/j.asoc.2017.05.030.
[118] K. Subulan, An interval-stochastic programming based approach for a fully uncertain multi-objective and multi-mode resource investment project scheduling problem with an application to ERP project implementation, Expert Syst. Appl. 149 (2020), 113189, https://doi.org/10.1016/j.eswa.2020.113189.
[119] M. Bofill, J. Coll, J. Suy, M. Villaret, SMT encodings for resource-constrained project scheduling problems, Comput. Ind. Eng. 149 (2020), 106777, https://doi.org/10.1016/j.cie.2020.106777.
[120] L. Cui, X. Liu, S. Lu, Z. Jia, A variable neighborhood search approach for the resource-constrained multi-project collaborative scheduling problem, Appl. Soft Comput. 107 (2021), 107480, https://doi.org/10.1016/j.asoc.2021.107480.
[121] T.J. Hindelang, J.F. Muth, A dynamic programming algorithm for decision CPM networks, Oper. Res. 27 (2) (1979) 225–241, https://doi.org/10.1287/opre.27.2.225.
[122] R. Sonmez, Ö.H. Bettemir, A hybrid genetic algorithm for the discrete time–cost trade-off problem, Expert Syst. Appl. 39 (13) (2012) 11428–11434, https://doi.org/10.1016/j.eswa.2012.04.019.
[123] S. Aminbakhsh, R. Sonmez, Discrete particle swarm optimization method for the large-scale discrete time–cost trade-off problem, Expert Syst. Appl. 51 (2016) 177–185, https://doi.org/10.1016/j.eswa.2015.12.041.
[124] S.S. Said, M. Haouari, A hybrid simulation-optimization approach for the robust discrete time/cost trade-off problem, Appl. Math. Comput. 259 (2015) 628–636, https://doi.org/10.1016/j.amc.2015.02.092.
[125] G. Çakir, K. Subulan, S.T. Yildiz, A. Hamzadayi, C. Asılkefeli, A comparative study of modeling and solution approaches for the multi-mode resource-constrained discrete time-cost trade-off problem: case study of an ERP implementation project, Comput. Ind. Eng. 169 (2022), 108201, https://doi.org/10.1016/j.cie.2022.108201.
[126] K.K. Damghani, M. Tavana, A. Abtahi, F.J. Santos-Arteaga, Solving multi-mode time–cost–quality trade-off problems under generalized precedence relations, Optimiz. Methods Softw. 30 (5) (2015) 965–1001, https://doi.org/10.1080/10556788.2015.1005838.
[127] P. Ghoddousi, E. Eshtehardian, S. Jooybanpour, A. Javanmardi, Multi-mode resource-constrained discrete time–cost-resource optimization in project scheduling using non-dominated sorting genetic algorithm, Autom. Constr. 30 (2013) 216–227, https://doi.org/10.1016/j.autcon.2012.11.014.
[128] W. Tian, J. Xu, Z. Fu, On the choice of baseline schedules for the discrete time/resource trade-off problem under stochastic environment, J. Difference Equat. Appl. 23 (1–2) (2017) 55–65, https://doi.org/10.1080/10236198.2016.1155566.

[129] V. Van Peteghem, M. Vanhoucke, Influence of learning in resource-constrained project scheduling, Comput. Ind. Eng. 87 (2015) 569–579, https://doi.org/10.1016/j.cie.2015.06.007.
[130] M.V. Eeckhout, B. Maenhout, M. Vanhoucke, A heuristic procedure to solve the project staffing problem with discrete time/resource trade-offs and personnel scheduling constraints, Comput. Oper. Res. 101 (2019) 144–161, https://doi.org/10.1016/j.cor.2018.09.008.
[131] T. Hegazy, A.K. Shabeeb, E. Elbeltagi, T.S. Cheema, Algorithm for scheduling with multiskilled constrained resources, J. Constr. Eng. Manag. 126 (6) (2000) 414–421, https://doi.org/10.1061/(ASCE)0733-9364(2000)126:6(414).
[132] L. Zhu, J. Lin, Y. Li, Z. Zhou, A decomposition-based multi-objective genetic programming hyper-heuristic approach for the multi-skill resource constrained project scheduling problem, Knowl.-Based Syst. 225 (2021), 107099, https://doi.org/10.1016/j.knosys.2021.107099.
[133] L. Wang, X. Zheng, A knowledge-guided multi-objective fruit fly optimization algorithm for the multi-skill resource constrained project scheduling problem, Swarm Evolution. Comp. 38 (2018) 54–63, https://doi.org/10.1016/j.swevo.2017.06.001.
[134] M. Laszczyk, P.B. Myszkowski, Improved selection in evolutionary multi-objective optimization of multi-skill resource-constrained project scheduling problem, Inf. Sci. 481 (2019) 412–431, https://doi.org/10.1016/j.ins.2019.01.002.
[135] H. Maghsoudlou, B. Afshar-Nadjafi, S.T. Niaki, Preemptive multi-skilled resource constrained project scheduling problem with hard/soft interval due dates, RAIRO-Operat. Res. 53 (5) (2019) 1877–1898, https://doi.org/10.1051/ro/2018103.
[136] J. Snauwaert, M. Vanhoucke, A new algorithm for resource-constrained project scheduling with breadth and depth of skills, Eur. J. Oper. Res. 292 (1) (2021) 43–59, https://doi.org/10.1016/j.ejor.2020.10.032.
[137] J. Snauwaert, M. Vanhoucke, Mathematical formulations for project scheduling problems with categorical and hierarchical skills, Comput. Ind. Eng. 169 (2022), 108147, https://doi.org/10.1016/j.cie.2022.108147.
[138] S. Zabihi, M.R. Kahag, H. Maghsoudlou, B. Afshar-Nadjafi, Multi-objective teaching-learning-based meta-heuristic algorithms to solve multi-skilled project scheduling problem, Comput. Ind. Eng. 136 (2019) 195–211, https://doi.org/10.1016/j.cie.2019.07.032.
[139] J.C. Chen, Y. Chen, T. Chen, Y. Lin, Multi-project scheduling with multi-skilled workforce assignment considering uncertainty and learning effect for large-scale equipment manufacturer, Comput. Ind. Eng. 169 (2022), 108240, https://doi.org/10.1016/j.cie.2022.108240.
[140] S. Javanmard, B. Afshar-Nadjafi, S.T. Niaki, Preemptive multi-skilled resource investment project scheduling problem: mathematical modelling and solution approaches, Comput. Chem. Eng. 96 (2017) 55–68, https://doi.org/10.1016/j.compchemeng.2016.11.001.
[141] Y. Shou, Y. Li, C. Lai, Hybrid particle swarm optimization for preemptive resource-constrained project scheduling, Neurocomputing. 148 (2015) 122–128, https://doi.org/10.1016/j.neucom.2012.07.059.
[142] M. Vanhoucke, J. Coelho, Resource-constrained project scheduling with activity splitting and setup times, Comput. Oper. Res. 109 (2019) 230–249, https://doi.org/10.1016/j.cor.2019.05.004.
[143] A. Moukrim, A. Quilliot, H. Toussaint, An effective branch-and-price algorithm for the Preemptive resource constrained project scheduling problem based on minimal interval order enumeration, Eur. J. Oper. Res. 244 (2) (2015) 360–368, https://doi.org/10.1016/j.ejor.2014.12.037.
[144] B. Afshar-Nadjafi, M. Majlesi, Resource constrained project scheduling problem with setup times after preemptive processes, Comput. Chem. Eng. 69 (2014) 16–25, https://doi.org/10.1016/j.compchemeng.2014.06.012.
[145] S. Kreter, J. Rieck, J. Zimmermann, Models and solution procedures for the resource-constrained project scheduling problem with general temporal constraints and calendars, Eur. J. Oper. Res. 251 (2) (2016) 387–403, https://doi.org/10.1016/j.ejor.2015.11.021.
[146] S. Creemers, The preemptive stochastic resource-constrained project scheduling problem, Eur. J. Oper. Res. 277 (1) (2019) 238–247, https://doi.org/10.1016/j.ejor.2019.02.030.
[147] D. Krüger, A. Scholl, A heuristic solution framework for the resource constrained (multi-)project scheduling problem with sequence-dependent transfer times, Eur. J. Oper. Res. 197 (2009) 492–508, https://doi.org/10.1016/j.ejor.2008.07.036.
[148] M. Suresh, P. Dutta, K. Jain, Resource constrained multi-project scheduling problem with resource transfer times, Asia-Pacific J. Operat. Res. 32 (6) (2015) 1550048, https://doi.org/10.1142/S0217595915500487.
[149] R.L. Kadri, F.F. Boctor, An efficient genetic algorithm to solve the resource-constrained project scheduling problem with transfer times: the single mode case, Eur. J. Oper. Res. 265 (2018) 454–462, https://doi.org/10.1016/j.ejor.2017.07.027.
[150] Y. Ren, Z. Lu, X. Liu, A branch-and-bound embedded genetic algorithm for resource-constrained project scheduling problem with resource transfer time of aircraft moving assembly line, Optim. Lett. 14 (2020) 2161–2195, https://doi.org/10.1007/s11590-020-01542-x.
[151] J. Wang, X. Hu, E. Demeulemeester, Y. Zhao, A bi-objective robust resource allocation model for the RCPSP considering resource transfer costs, Int. J. Prod. Res. 59 (2) (2021) 367–387, https://doi.org/10.1080/00207543.2019.1695168.
[152] Z. Ma, W. Zheng, Z. He, N. Wang, X. Hu, A genetic algorithm for proactive project scheduling with resource transfer times, Comput. Ind. Eng. 174 (2022), 108754, https://doi.org/10.1016/j.cie.2022.108754.
[153] J. Zhang, W. Liu, W. Liu, An efficient genetic algorithm for decentralized multi-project scheduling with resource transfers, J. Industr. Manag. Optimiz. 18 (1) (2022) 1–24, https://doi.org/10.3934/jimo.2020140.
[154] A. Laurent, L. Deroussi, N. Grangeon, S. Norre, A new extension of the RCPSP in a multi-site context: mathematical model and meta-heuristics. Mathematical model and meta-heuristics, Comput. Ind. Eng. 112 (2017) 634–644, https://doi.org/10.1016/j.cie.2017.07.028.
[155] M.C. Gómez Sánchez, E. Lalla-Ruiz, A. Fernández Gil, C. Castro, S. Voß, Resource-constrained multi-project scheduling problem: a survey, Eur. J. Oper. Res. (2022), https://doi.org/10.1016/j.ejor.2022.09.033.
[156] J.A. Araujo, H.G. Santos, B. Gendron, S.D. Jena, S.S. Brito, D.S. Souza, Strong bounds for resource constrained project scheduling: Preprocessing and cutting planes, Comput. Oper. Res. 113 (2020), 104782, https://doi.org/10.1016/j.cor.2019.104782.
[157] R. Van Eynde, M. Vanhoucke, Resource-constrained multi-project scheduling: benchmark datasets and decoupled scheduling, J. Sched. 23 (3) (2020) 301–325, https://doi.org/10.1007/s10951-020-00651-w.
[158] F. Li, Z. Xu, H. Li, A multi-agent based cooperative approach to decentralized multi-project scheduling and resource allocation, Comput. Ind. Eng. 151 (2021), 106961, https://doi.org/10.1016/j.cie.2020.106961.
[159] X. Shu, Q. Su, Q. Wang, Q. Wang, Optimization of resource-constrained multi-project scheduling problem based on the genetic algorithm, in: 2018 15th International Conference on Service Systems and Service Management (ICSSSM), 2018, pp. 1–6, https://doi.org/10.1109/ICSSSM.2018.8465086.
[160] U. Satic, P. Jacko, C. Kirkbride, Performance evaluation of scheduling policies for the dynamic and stochastic resource-constrained multi-project scheduling problem, Int. J. Prod. Res. 60 (4) (2020) 1411–1423, https://doi.org/10.1080/00207543.2020.1857450.
[161] H. Amirian, R. Sahraeian, Solving a grey project selection scheduling using a simulated shuffled frog leaping algorithm, Comput. Ind. Eng. 107 (2017) 141–149, https://doi.org/10.1016/j.cie.2017.03.018.
[162] V.A. Hauder, A. Beham, S. Raggl, S.N. Parragh, M. Affenzeller, Resource-constrained multi-project scheduling with activity and time flexibility, Comput. Ind. Eng. 150 (2020), 106857, https://doi.org/10.1016/j.cie.2020.106857.
[163] S. Gholizadeh-Tayyar, L. Dupont, J. Lamothe, M. Falcon, Modeling a generalized resource constrained multi project scheduling problem integrated with a forward-backward supply chain planning, IFAC-Papers OnLine. 49 (12) (2016) 1283–1288, https://doi.org/10.1016/j.ifacol.2016.07.700.
[164] B. Joo, P. Chua, Multi-mode resource-constrained multi-project scheduling with ad hoc activity splitting, in: 2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 2017, pp. 2261–2265, https://doi.org/10.1109/IEEM.2017.8290294.
[165] S. Adhau, M.L. Mittal, A. Mittal, A multi-agent system for distributed multi-project scheduling: an auction-based negotiation approach, Eng. Appl. Artif. Intell. 25 (8) (2012) 1738–1751, https://doi.org/10.1016/j.engappai.2011.12.003.
[166] M.J. Geiger, A multi-threaded local search algorithm and computer implementation for the multi-mode, resource-constrained multi-project scheduling problem, Eur. J. Oper. Res. 256 (3) (2017) 729–741, https://doi.org/10.1016/j.ejor.2016.07.024.
[167] W. Hu, H. Wang, C. Peng, H. Wang, H. Liang, B. Du, An outer-inner fuzzy cellular automata algorithm for dynamic uncertainty multi-project scheduling problem, Soft. Comput. 19 (8) (2015) 2111–2132, https://doi.org/10.1007/s00500-014-1395-5.
[168] F. Fu, H. Zhou, A combined multi-agent system for distributed multi-project scheduling problems, Appl. Soft Comput. 107 (2021), 107402, https://doi.org/10.1016/j.asoc.2021.107402.
[169] M.V. Eeckhout, M. Vanhoucke, B. Maenhout, A column generation-based diving heuristic to solve the multi-project personnel staffing problem with calendar constraints and resource sharing, Comput. Oper. Res. 128 (2021), 105163, https://doi.org/10.1016/j.cor.2020.105163.
[170] M. Kannimuthu, B. Raphael, P. Ekambaram, A. Kuppuswamy, Comparing optimization modeling approaches for the multi-mode resource-constrained multi-project scheduling problem, Eng. Constr. Archit. Manag. 27 (4) (2020) 893–916, https://doi.org/10.1108/ECAM-03-2019-0156.
[171] M. Tian, R.J. Liu, G.J. Zhang, Solving the resource-constrained multi-project scheduling problem with an improved critical chain method, J. Oper. Res. Soc. 71 (8) (2020) 1243–1258, https://doi.org/10.1080/01605682.2019.1609883.
[172] Ö.S. Zorluoğlu, Ö. Kabak, An interactive multi-objective programming approach for project portfolio selection and scheduling, Comput. Ind. Eng. 169 (2022), 108191, https://doi.org/10.1016/j.cie.2022.108191.
[173] A. Shafahi, A. Haghani, Project selection and scheduling for phase-able projects with interdependencies among phases, Autom. Constr. 93 (2018) 47–62, https://doi.org/10.1016/j.autcon.2018.05.008.
[174] T. Chen, C. Ju, Comparative analysis of swarm intelligence and heuristic priority rules for solving multi-project scheduling problem, Int. J. Comput. Sci. Math. 6 (6) (2015) 581–599, https://doi.org/10.1504/IJCSM.2015.073597.
[175] R.K. Chakrabortty, R.A. Sarker, D.L. Essam, Multi-mode resource constrained project scheduling under resource disruptions, Comput. Chem. Eng. 88 (2016) 13–29, https://doi.org/10.1016/j.compchemeng.2016.01.004.
[176] W. Peng, X. Lin, H. Li, Critical chain based proactive-reactive scheduling for resource-constrained project scheduling under uncertainty, Expert Syst. Appl. 214 (15) (2022), 119188, https://doi.org/10.1016/j.eswa.2022.119188.
[177] T. Wang, W. Cheng, Y. Zhang, X. Hu, Dynamic selection of priority rules based on deep reinforcement learning for rescheduling of RCPSP, IFAC-Papers OnLine. 55 (10) (2022) 2144–2149, https://doi.org/10.1016/j.ifacol.2022.10.025.
[178] Y. Zhou, J. Miao, B. Yan, Z. Zhang, Stochastic resource-constrained project scheduling problem with time varying weather conditions and an improved

estimation of distribution algorithm, Comput. Ind. Eng. 157 (2021), 107322, https://doi.org/10.1016/j.cie.2021.107322.
[179] M. Ning, Z. He, T. Jia, N. Wang, Meta-heuristics for multi-mode cash flow balanced project scheduling with stochastic duration of activities, Autom. Constr. 81 (2017) 224–233, https://doi.org/10.1016/j.autcon.2017.06.011.
[180] H. Liu, Z. Fang, R. Li, Credibility-based chance-constrained multimode resource-constrained project scheduling problem under fuzzy uncertainty, Comput. Ind. Eng. 171 (2022), 108402, https://doi.org/10.1016/j.cie.2022.108402.
[181] M. Zhao, J. Zhou, K. Wang, A.A. Pantelous, Project scheduling problem with fuzzy activity durations: a novel operational law based solution framework, Eur. J. Oper. Res. 306 (2) (2022) 519–534, https://doi.org/10.1016/j.ejor.2022.07.047.
[182] A. Ghamginzadeh, A.A. Najafi, M. Khalilzadeh, Multi-objective multi-skill resource-constrained project scheduling problem under time uncertainty, Int. J. Fuzzy Syst. 23 (2) (2021) 518–534, https://doi.org/10.1007/s40815-020-00984-w.
[183] F. Fathallahi, A.A. Najafi, A hybrid genetic algorithm to maximize net present value of project cash flows in resource-constrained project scheduling problem with fuzzy parameters, Scientia Iranica. 23 (4) (2016) 1893–1903, https://doi.org/10.24200/SCI.2016.3935.
[184] A.E. Nabipoor, A. Aghaie, A.A. Najafi, Robust optimization for the resource constrained multi-project scheduling problem with uncertain activity durations, Scientia Iranica. 27 (2020) 361–376, https://doi.org/10.24200/sci.2018.20801.
[185] H. Li, Y. Cao, Q. Lin, H. Zhu, Data-driven project buffer sizing in critical chains, Autom. Constr. 135 (2022), 104134, https://doi.org/10.1016/j.autcon.2022.104134.
[186] R. Kolisch, A. Sprecher, PSPLIB-A project scheduling problem library OR software-ORSEP operations research software exchange program, Eur. J. Oper. Res. 96 (1) (1997) 205–216, https://doi.org/10.1016/S0377-2217(96)00170-1.
[187] E. Demeulemeester, M. Vanhoucke, W. Herroelen, RanGen: a random network generator for activity-on-the-node networks, J. Sched. 6 (2003) 17–38, https://doi.org/10.1023/A:1022283403119.
[188] J. Snauwaert, M. Vanhoucke, A classification and new benchmark instances for the multi-skilled resource-constrained project scheduling problem, Eur. J. Oper. Res. 307 (1) (2022) 1–19, https://doi.org/10.1016/j.ejor.2022.05.049.
[189] Z. Ma, S. Li, Y. Wang, Z. Yang, Component-level construction schedule optimization for hybrid concrete structures, Autom. Constr. 125 (2021), 103607, https://doi.org/10.1016/j.autcon.2021.103607.
[190] H. Liu, M. Al-Hussein, M. Lu, BIM-based integrated approach for detailed construction scheduling under resource constraints, Autom. Constr. 53 (2015) 29–43, https://doi.org/10.1016/j.autcon.2015.03.008.
[191] H. Wang, J. Lin, J. Zhang, Work package-based information modeling for resource-constrained scheduling of construction projects, Autom. Constr. 109 (2020), 102958, https://doi.org/10.1016/j.autcon.2019.102958.
[192] J.D. García-Nieves, J.L. Ponz-Tienda, A.M. Ospina-Alvarado, M. Bonilla-Palacios, Multipurpose linear programming optimization model for repetitive activities scheduling in construction projects, Autom. Constr. 105 (2019), 102799, https://doi.org/10.1016/j.autcon.2019.03.020.
[193] A. Birjandi, S.M. Mousavi, Fuzzy resource-constrained project scheduling with multiple routes: a heuristic solution, Autom. Constr. 100 (2019) 84–102, https://doi.org/10.1016/j.autcon.2018.11.029.
[194] M. Taghaddos, H. Taghaddos, U. Hermann, Y. Mohamed, S. Abourizk, Hybrid multi-mode simulation and optimization for subarea scheduling in heavy industrial construction, Autom. Constr. 125 (2021), 103616, https://doi.org/10.1016/j.autcon.2021.103616.
[195] L. Mezouari, J.P. Boufflet, A. Moukrim, Surgery planning for elective patients: a dedicated heuristic and an effective ALNS, Eng. Appl. Artif. Intell. 115 (2022), 105220, https://doi.org/10.1016/j.engappai.2022.105220.
[196] H.F. Rahman, R.K. Chakrabortty, S. Elsawah, M.J. Ryan, Energy-efficient project scheduling with supplier selection in manufacturing projects, Expert Syst. Appl. 193 (2022), 116446, https://doi.org/10.1016/j.eswa.2021.116446.
[197] A. Thomas, J. Venkateswaran, G. Singh, M. Krishnamoorthy, A resource constrained scheduling problem with multiple independent producers and a single linking constraint: a coal supply chain example, Eur. J. Oper. Res. 236 (3) (2014) 946–956, https://doi.org/10.1016/j.ejor.2013.10.006.
[198] C. Liu, X. Xiang, C. Zhang, Q. Wang, L. Zheng, A column generation based distributed scheduling algorithm for multi-mode resource constrained project scheduling problem, Comput. Ind. Eng. 125 (2018) 258–278, https://doi.org/10.1016/j.cie.2018.08.036.
[199] X. Zhu, R. Ruiz, S. Li, X. Li, An effective heuristic for project scheduling with resource availability cost, Eur. J. Oper. Res. 257 (3) (2017) 746–762, https://doi.org/10.1016/j.ejor.2016.08.049.
[200] R.K. Chakrabortty, H.F. Rahman, M.J. Ryan, Efficient priority rules for project scheduling under dynamic environments: a heuristic approach, Comput. Ind. Eng. 140 (2020), 106287, https://doi.org/10.1016/j.cie.2020.106287.
[201] S. Chand, Q.N. Huynh, H.K. Singh, T. Ray, M. Wagner, On the use of genetic programming to evolve priority rules for resource constrained project scheduling problems, Inf. Sci. 432 (2018) 146–163, https://doi.org/10.1016/j.ins.2017.12.013.
[202] M. Đumić, D. Sisejkovic, R. Coric, D. Jakobovic, Evolving priority rules for resource constrained project scheduling problem with genetic programming, Futur. Gener. Comput. Syst. 86 (2018) 211–221, https://doi.org/10.1016/j.future.2018.04.029.
[203] G.K. Koulinas, K.P. Anagnostopoulos, A new tabu search-based hyper-heuristic algorithm for solving construction leveling problems with limited resource availabilities, Autom. Constr. 31 (2013) 169–175, https://doi.org/10.1016/j.autcon.2012.11.002.
[204] G. Koulinas, L. Kotsikas, K. Anagnostopoulos, A particle swarm optimization based hyper-heuristic algorithm for the classic resource constrained project scheduling problem, Inf. Sci. 277 (2014) 680–693, https://doi.org/10.1016/j.ins.2014.02.155.
[205] R. Zamani, An evolutionary implicit enumeration procedure for solving the resource-constrained project scheduling problem, Int. Trans. Oper. Res. 24 (2017) 1525–1547, https://doi.org/10.1111/itor.12196.
[206] M. Cheng, D. Tran, Y. Wu, Using a fuzzy clustering chaotic-based differential evolution with serial method to solve resource-constrained project scheduling problems, Autom. Constr. 37 (2014) 88–97, https://doi.org/10.1016/j.autcon.2013.10.002.
[207] H.F. Rahman, R.K. Chakrabortty, J.R. Michael, Memetic algorithm for solving resource constrained project scheduling problems, Autom. Constr. 111 (2020), 103052, https://doi.org/10.1016/j.autcon.2019.103052.
[208] N.S. Kedir, S. Somi, A.R. Fayek, P.H. Nguyen, Hybridization of reinforcement learning and agent-based modeling to optimize construction planning and scheduling, Autom. Constr. 142 (2022), 104498, https://doi.org/10.1016/j.autcon.2022.104498.
[209] R.K. Soman, M. Molina-Solana, Automating look-ahead schedule generation for construction using linked-data based constraint checking and reinforcement learning, Autom. Constr. 134 (2022), 104069, https://doi.org/10.1016/j.autcon.2021.104069.