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Resource-constrained project scheduling problem: Review of recent developments

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A B S T R A C T

The Resource-Constrained Project Scheduling Problem (RCPSP) remains a critical area of study in project management, focusing on optimizing project schedules under constraints such as limited resources and task interdependencies. This review synthesizes advancements from 2016 to 2024, encompassing problem variants, optimization techniques, objectives, and real-world applications. Key developments include the evolution of hybrid metaheuristics, multi-objective optimization approaches, and the integration of stochastic models to enhance robustness against uncertainties. Furthermore, the application of machine learning and sustainability-driven models has expanded the practical scope of RCPSP in dynamic and complex environments. Challenges such as scalability, uncertainty management, and the need for practical implementations are addressed, with future directions emphasizing AI integration, decentralized scheduling, and real-time adaptive solutions. This study provides a comprehensive perspective on RCPSP, bridging theoretical research with practical implications for diverse industries.

1. Introduction

Efficient project scheduling is pivotal in ensuring the timely and cost-effective completion of projects across various industries. However, resource limitations and task interdependencies pose significant challenges, making the Resource-Constrained Project Scheduling Problem (RCPSP) a central focus in project management research. RCPSP seeks to optimize project schedules by minimizing the makespan (total project duration) while satisfying resource constraints and precedence relations among activities. Since its introduction, RCPSP has evolved into a versatile framework applicable to diverse fields, including construction, manufacturing, and software development (Ding et al., 2023).

RCPSP is widely regarded as an NP-hard problem due to its combinatorial nature. As the size of the project increases, the number of potential schedules grows exponentially, making exact methods like branch-and-bound computationally impractical for large-scale projects. Consequently, modern research has shifted towards heuristic and metaheuristic approaches such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). These techniques are popular for their scalability and flexibility in handling complex problem variants, such as multi-mode RCPSP, where activities have multiple execution modes depending on available resources (Vanhoucke & Coelho, 2024); (Hauder et al., 2020).

Recent advancements have introduced extensions to the RCPSP framework, enhancing its practical applicability. Multi-objective RCPSP is one such extension, where the focus expands beyond minimizing makespan to include objectives like cost reduction, resource leveling, and maximizing project quality. Researchers have adopted Pareto-based optimization techniques to generate trade-off solutions that allow decision-makers to balance competing objectives effectively. These models have shown considerable success in addressing real-world challenges in construction, manufacturing, and logistics (Van Peteghem & Vanhoucke, 2014).

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Another key development is the incorporation of stochastic models to account for uncertainties in activity durations and resource availability. Unlike deterministic models, stochastic RCPSP enables project managers to generate schedules that remain feasible under diverse scenarios, enhancing project resilience. This approach has found applications in dynamic environments where disruptions are frequent, such as construction sites and supply chain networks (Ding et al., 2023). The integration of hybrid optimization techniques marks a significant trend in RCPSP research. Hybrid approaches combine the strengths of metaheuristics with exact algorithms, such as Mixed-Integer Linear Programming (MILP), to improve solution accuracy and efficiency. For example, hybrid algorithms can leverage metaheuristics for global exploration while employing exact methods for local refinement, achieving superior results in multi-project scheduling environments (Hauder et al., 2020; Kim, 2020). The use of artificial intelligence (AI) and machine learning (ML) has further advanced RCPSP research. AI-driven systems can adapt dynamically to changes in project parameters, such as resource availability or task delays, enabling real-time decision-making. Additionally, ML techniques are being utilized to predict project metrics, optimize resource allocation, and fine-tune scheduling algorithms. Such innovations have paved the way for intelligent project management tools capable of handling complex, real-world challenges (Vanhoucke & Coelho, 2024). Despite significant progress, challenges persist in RCPSP research. Scalability remains a primary concern, particularly for large, multi-project environments with interdependent tasks and shared resources. There is also a growing need for robust scheduling algorithms that can adapt to uncertainties and disruptions. Finally, integrating RCPSP models with practical project management software is crucial for bridging the gap between theory and practice. Addressing these challenges requires a multidisciplinary approach, combining advancements in operations research, computational intelligence, and data-driven methodologies (Ding et al., 2023; Tian et al., 2020).

The following chart in Figure 1, illustrates the major developments and trends in the Resource-Constrained Project Scheduling Problem (RCPSP) research from 2016 to 2024. It categorizes advancements into four main areas: optimization techniques, problem variants, applications, and future directions. Under optimization techniques, it highlights the evolution of heuristics, hybrid approaches, and the integration of AI and machine learning for enhanced scheduling. Problem variants include multi-objective, stochastic, and dynamic RCPSP, showcasing efforts to tackle complex and uncertain environments. Applications span critical industries like construction, manufacturing, and software development. Future directions emphasize emerging areas such as AI integration, decentralized scheduling, and real-time adaptive solutions, pointing towards the next generation of intelligent project management tools. This comprehensive framework underscores the interdisciplinary nature of RCPSP research, bridging theoretical advancements with practical applications.

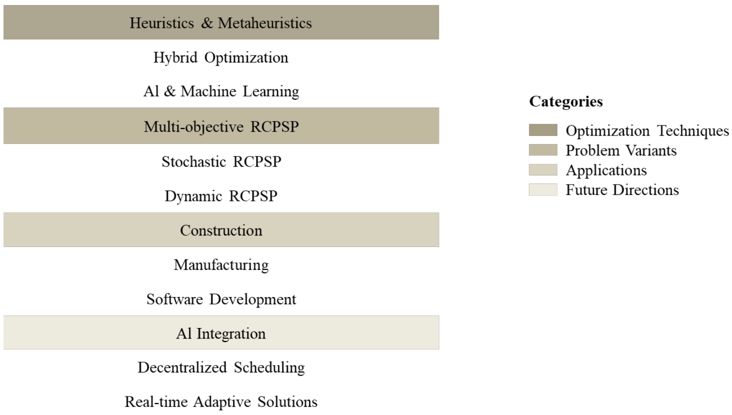

Fig. 1. Key Developments and Trends in RCPSP Research (2016-2024)

2. Literature Categorization and Review: Resource-Constrained Project Scheduling Problem (RCPSP)

The Resource-Constrained Project Scheduling Problem (RCPSP) is a well-studied topic in project management, addressing the challenge of optimizing schedules under limited resources and precedence constraints. Below is a categorized and detailed review of the literature from 2016 to 2024, exploring its problem variants, optimization techniques, objectives, and applications.

2.1 Problem Variants

RCPSP has evolved beyond its traditional single-mode framework, where activities are executed with fixed durations and resources. Multi-mode variants allow for different execution options with varying durations and resource needs, offering flexibility for real-world scenarios like construction and manufacturing (Ding et al., 2023). Multi-project RCPSP extends this by managing shared resources across interdependent projects, aiming for optimal portfolio performance (Hauder et al., 2020).

Uncertainty has led to stochastic RCPSP models that incorporate probabilistic elements for durations and resources, enhancing schedule robustness under dynamic conditions. Moreover, flexible RCPSP integrates decision-making freedom in activity selection and timing, making it highly adaptable for industries with variable operational demands (Tao & Dong, 2017). The integration of Lean Construction principles, as discussed by (Ballard & Tommelein, 2021), highlights an evolution in project scheduling from static planning towards adaptive, dynamic models. These approaches emphasize collaborative planning mechanisms like the Last Planner® System (LPS) to enhance workflow reliability and reduce variability in project execution. LPS extends beyond traditional RCPSP frameworks, addressing broader production control and incorporating learning loops for continuous improvement. The Last Planner System (LPS), as depicted in following Figure 2, serves as a practical framework for addressing key challenges in Problem Variants within the Resource-Constrained Project Scheduling Problem (RCPSP). Specifically, LPS aligns closely with stochastic and dynamic RCPSP due to its focus on adaptability and real-time disruption management. By incorporating structured processes like Lookahead Planning, Workable Backlog, and iterative feedback mechanisms such as Percent Plan Complete (PPC), LPS effectively mitigates risks related to resource constraints and activity interdependencies. This ensures critical tasks are prioritized and work is made ready, even in uncertain and rapidly changing environments. Moreover, LPS supports multi-objective RCPSP by balancing multiple goals, such as minimizing makespan, enhancing workflow reliability, and optimizing resource utilization. For example, the Lookahead Process and Commitment Plan dynamically sequence tasks while resolving constraints and aligning resources, reflecting a comprehensive and integrated approach to project scheduling. The system's iterative feedback loops, including Charting PPC and Act on Reasons, play a crucial role in improving project robustness. These mechanisms enable teams to identify and address root causes of delays, integrating lessons learned into the planning process. This adaptive feedback approach parallels hybrid optimization techniques, where real-time data informs adjustments to both global and local scheduling decisions. The Last Planner System exemplifies how advanced methodologies can bridge theoretical RCPSP advancements with real-world applications, offering resilience and efficiency in dynamic, resource-constrained project environments. Its structured yet adaptive workflow makes it a valuable tool for managing complex project scheduling problems.

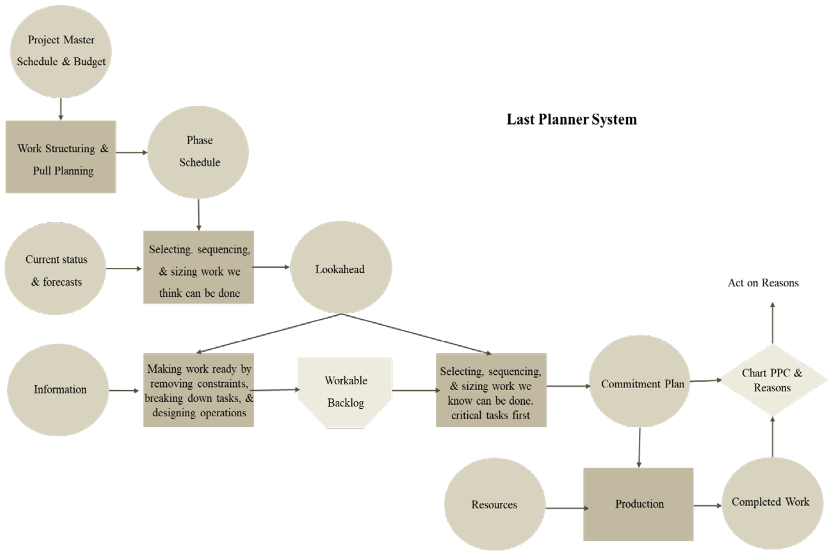

Fig. 2. Relationships between planning levels in the Last Planner System

The integration of multi-skill resource considerations into RCPSP introduces a significant evolution, as highlighted in the study by (Lin et al., 2020). The Multi-Skill RCPSP (MS-RCPSP) extends traditional RCPSP by accommodating resources with varying skill levels, enabling the modeling of real-world workforce dynamics. This expansion aligns tasks to resources based on skill requirements, which may differ across projects.

The proposed genetic programming hyper-heuristic (GP-HH) algorithm in the study addresses MS-RCPSP by efficiently generating feasible solutions through a combination of high-level genetic programming strategies and low-level heuristic rules. Key features include:

1. Single Task Sequence Encoding: This method encodes solutions in a compact form, enhancing computational efficiency.
2. Repair-Based Decoding: To ensure feasible schedules, tasks violating precedence constraints are dynamically repositioned.
3. Local Search Methods: Techniques like left-shift optimization maximize resource utilization by compacting task schedules.

The robust optimization approach for MRCPSP, as proposed by (Balouka & Cohen, 2021), represents a significant advancement in project scheduling. This method addresses the inherent uncertainty in activity durations by minimizing the worst-case project duration. The research focuses on incorporating polyhedral uncertainty sets and dynamic adjustments in mode selections and resource allocations.

Key contributions of the study include:

Integration of Mode Selection and Resource Allocation: The robust optimization framework combines tactical decisions (mode selection) with operational adjustments (resource allocation), reflecting real-world project complexities (Kosztyán & Szalkai, 2020).

Dynamic Uncertainty Sets: By employing dynamically changing polyhedral uncertainty sets, the approach allows for flexibility and robustness in adapting to evolving project conditions.

The work by (Sánchez et al., 2023) provides a comprehensive survey on the Resource-Constrained Multi-Project Scheduling Problem (RCMPSP), which extends the RCPSP to consider multiple projects executed simultaneously while competing for limited resources. The study categorizes the variants, features, and solution approaches for RCMPSP, offering a robust taxonomy and insights into its practical applications.

Key contributions include:

- Taxonomy Development: The study introduces a detailed classification of RCMPSP features, including job-based, resource-based, relationship-based, and project-based characteristics.
- Comprehensive Survey of Solution Methods: Algorithms ranging from exact methods (e.g., Mixed Integer Linear Programming) to heuristics and metaheuristics are analyzed for their applicability to RCMPSP.

The Resource-Constrained Project Scheduling Problem (RCPSP) has several variants, which differ based on the number of objectives, constraints, and specific conditions that must be satisfied. The classical RCPSP focuses on minimizing project completion time (makespan) while respecting resource constraints. However, more recent studies have introduced bi-objective versions of RCPSP, where the goal is to minimize both makespan and resource costs. Additionally, other variants consider factors like time-dependent resource costs, precedence constraints, or stochastic durations for project activities. For example, the bi-objective RCPSP with time-dependent resource costs introduced in the literature requires scheduling activities while minimizing both makespan and the cost associated with resource usage, which is influenced by the time it is utilized (Tian et al., 2023; Xie et al., 2024). The Resource-Constrained Multi-Project Scheduling Problem (RCMPSP) is an extension of the classic Resource-Constrained Project Scheduling Problem (RCPSP) that involves scheduling multiple projects simultaneously while managing shared resources. In its standard form, RCMPSP considers the allocation of limited resources (e.g., labor, equipment) across several projects with the goal of optimizing overall project completion time and resource utilization. Variants of the problem address different complexities, such as differing project priorities, multi-objective optimization involving time and cost, and stochastic elements where activity durations are uncertain. Additionally, time-dependent resource constraints, where the availability or cost of resources changes over time, can add further layers of difficulty (Sánchez et al., 2023).

The Dynamic and Stochastic Resource-Constrained Multi-Project Scheduling Problem (RCMPSP) extends traditional multi-project scheduling by incorporating uncertainty in both task durations and project arrival times. Unlike deterministic problems, this variant accounts for the dynamic nature of resource availability and the stochastic behavior of project tasks. In this variant, projects arrive randomly, and their durations are not fixed but probabilistic, meaning that the scheduling decisions must adapt over time as new information becomes available. Other variations of RCMPSP consider multiple types of resources, where different projects consume varying amounts of these resources, and tasks may require specific resource types that are available in limited quantities (Satic et al., 2024).

The Resource-Constrained Project Scheduling Problem (RCPSP) has undergone significant evolution, with various problem variants emerging to tackle increasingly complex real-world scheduling scenarios. These variants include single-project and multi-project scheduling problems, each with different degrees of resource constraint and complexity. In multi-project scenarios, resources such as labor, equipment, and materials are shared among projects, requiring efficient allocation strategies. Another key variant involves the introduction of renewable versus non-renewable resources, where renewable resources (e.g., machines) can be reused, while non-renewable resources (e.g., funds) are consumed entirely upon use. Further complexity arises with the introduction of time-dependent resource constraints, where the availability of resources fluctuates over time, adding another layer of scheduling challenge (Habibi et al., 2018; Zaman et al., 2020). The Resource-Constrained Project Scheduling Problem (RCPSP) has evolved significantly, addressing various real-world scheduling challenges across industries such as construction, manufacturing, and software development. One of the common variants involves considering projects with multiple tasks that are interdependent, where precedence relations and resource constraints must be managed simultaneously. In construction management, for example, projects are characterized by numerous activities with complex precedence relations and high resource consumption. Another variant is the introduction of dynamic constraints or multi-resource scheduling, where multiple types of resources (e.g., labor, machinery, materials) are involved, each with its own constraints and availability periods. The RCPSP may also include stochastic elements, where task durations or resource availability are uncertain (Liu et al., 2020).

The Multi-Skilled Resource-Constrained Project Scheduling Problem (MS-RCPSP) is an advanced extension of the traditional Resource-Constrained Project Scheduling Problem (RCPSP). It incorporates the added complexity of multi-skilled resources, where each resource (e.g., worker, equipment) can perform multiple tasks or require various skill sets to execute different activities within a project. In addition to the standard constraints of resource availability and precedence relations, the MS-RCPSP considers the skill requirements of tasks, which can vary across activities. These variants introduce even more complexity, as the availability of multi-skilled workers or equipment must be dynamically allocated to tasks that require specific skills. The problem variants can also differ in terms of the objective functions, such as minimizing project duration, total cost, or a combination of several criteria (Bahroun et al., 2024). The Multi-Skilled Resource-Constrained Project Scheduling Problem with Hierarchical Skills (MS-RCPSP-HS) is an extension of the classic Resource-Constrained Project Scheduling Problem (RCPSP), incorporating hierarchical skill sets assigned to resources. In contrast to standard RCPSP, where resources can be allocated without detailed consideration of their skills, MS-RCPSP-HS introduces the challenge of managing multi-skilled resources with varying levels of expertise. This hierarchical structure further complicates the scheduling process, as tasks require specific skill levels that must be matched to available resources. MS-RCPSP-HS is thus a more complex variant that involves both resource constraints and skill matching, making it particularly relevant in industries such as construction, manufacturing, and software development, where tasks depend on specialized skills (Jedrzejowicz & Ratajczak-Ropel, 2023). In the context of Software Engineering (SE) and Information Technology (IT), scheduling problems are diverse and can be categorized into multiple variants based on the specific challenges of each domain. One key variant is task scheduling, where the goal is to allocate resources to tasks within a project, considering various constraints such as deadlines and resource availability. Another variant is resource-constrained scheduling, where the allocation of limited resources (e.g., developers, servers) must be managed efficiently to minimize project delays and maximize resource utilization. Additionally, the concept of time-based scheduling is crucial, where the scheduling decisions need to account for the dynamic nature of task durations and shifting priorities over time (Ciupe et al., 2016).

The paper focuses on the multi-mode resource-constrained project scheduling problem (MMRCPSP) applied to flexible job shop scheduling (FJSSP). In MMRCPSP, multiple modes for each activity can be considered, meaning that different resources or approaches can be used for the same task, influencing the duration and resource consumption. This flexibility is beneficial in the job shop scheduling context, where multiple machines and various processing routes are available for tasks.

1. Flexible Job Shop Scheduling Problem (FJSSP): A variant where the goal is to schedule jobs on machines, with the flexibility to choose different machines for different operations.
2. Multi-Mode: Each task in the scheduling problem can be performed in multiple modes, each mode requiring different amounts of resources and having varying durations (Yuraszeck et al., 2023).

The paper (Snauwaert & Vanhoucke, 2023) addresses the Multi-Skilled Resource-Constrained Project Scheduling Problem (MSRCPSP), a variant of the classical RCPSP, where tasks require multi-skilled resources, i.e., workers or machines capable of performing multiple types of activities. The key aspects of the problem include:

Multi-Skilled Resources: Resources can perform various tasks, each requiring different skill sets, which adds complexity to the scheduling process.

Resource Constraints: The scheduling is constrained by the availability of these multi-skilled resources, as well as other project resources (e.g., equipment, materials).

Complex Task Dependencies: The tasks in the project have precedence constraints, meaning certain tasks must be completed before others can begin, adding another layer of complexity to the scheduling process.

The paper (Asadujjaman et al., 2021) focuses on the Net Present Value (NPV)-Based Resource-Constrained Project Scheduling Problem (RCPSP), which is a critical problem in industries such as construction, software development, and manufacturing. The objective of the NPV-based RCPSP is to schedule project tasks such that the net present value is maximized, considering both the time and resources available. The problem variants in this context include:

1. Single-Objective RCPSP: Where the goal is to minimize the makespan or total cost.

2. NPV-Based RCPSP: Focuses on maximizing the net present value of the project, taking into account the costs and revenues associated with task completion and resource utilization.
3. Multi-Objective RCPSP: Where multiple conflicting objectives, such as cost and time, are optimized simultaneously.

The paper (van der Beek et al., 2024)focuses on the Resource-Constrained Project Scheduling Problem (RCPSP) with a flexible project structure, incorporating both resource consumption and production factors. This extension of the traditional RCPSP considers:

Flexible Project Structure: Tasks and resources can be linked in non-linear ways, and tasks may depend on variable resources, which makes scheduling more complex.

Resource Consumption and Production: Tasks not only consume resources but may also produce them, creating dynamic shifts in resource availability during the project timeline.

Researchers also investigates how the Hybrid Differential Evolution (HDE) Algorithm can be applied to solve this variant, offering improvements in solution quality and computational efficiency.

The Resource-Constrained Project Scheduling Problem (RCPSP) is typically addressed through various variants, depending on the nature of the resources, objectives, and constraints considered. In the study provided, the problem is extended to a multi-objective and multi-mode setting, where each activity in the project can be executed through different modes, which might affect resource consumption and completion times. Additionally, the paper introduces renewable and non-renewable resources, further complicating the scheduling process. The goal is to balance two primary objectives: maximizing the Net Present Value (NPV) and minimizing the project completion time. These variants make the problem more applicable to real-world project management scenarios, where resource limitations and payment planning must be accounted for simultaneously (Isah & Kim, 2021; Tirkolaee et al., 2019).

The RCPSP has several well-established variants that consider different aspects of resource and time management in projects. In this article, the authors discuss the summary measures used to evaluate the effectiveness of RCPSP formulations. While the focus is on correcting previous **versions** of the models, the underlying problem variants involve the allocation of limited resources across multiple project activities, often with precedence constraints (e.g., finish-to-start). These variants are crucial for representing real-world scheduling scenarios, where resources and time are finite and must be optimized (Eynde et al., 2024).

The paper discusses the Problem Management Plus (PM+) intervention, **a** transdiagnostic psychological treatment designed to address a variety of mental health issues across different populations. This approach is particularly suited for regions affected by conflict and natural disasters. Unlike traditional interventions that are tailored to specific disorders, PM+ targets a broad range of mental health conditions, such as anxiety, depression, and stress-related disorders. The pilot trial in Pakistan demonstrates how this transdiagnostic model can be applied in settings where traditional, specialized mental health services are not available. The document emphasizes the flexibility of the PM+ model, which can be adapted to address different psychological issues, making it a promising solution in resource-constrained environments (Rahman et al., 2016).

The Resource-Constrained Project Scheduling Problem (RCPSP) is a widely studied problem in operations research and project management. In the paper by Etminaniesfahani, Gu, and Salehipour, the authors focus on a variant of RCPSP that considers a relax-and-solve algorithm to address the challenges of scheduling tasks under resource constraints. The problem itself involves scheduling a set of tasks or activities with precedence constraints, where each task requires certain resources (e.g., manpower, machinery) for its execution.

The variant explored in this paper highlights the relaxation of the problem by decoupling the scheduling decisions from the resource allocation decisions. This approach allows for the solution of the problem in phases, where an initial solution is derived using relaxed constraints, and then refined to incorporate the full set of resource constraints. By applying this strategy, the authors aim to improve the computational efficiency and solution quality, especially for large-scale problems. Other variants of RCPSP typically consider factors like multi-mode (where each task can be performed in different ways with varying resource requirements) and multi-objective optimization (optimizing multiple conflicting goals, such as time and cost) (Etminaniesfahani et al., 2022).

Figure 3 below, presents a detailed classification of Resource-Constrained Multi-Project Scheduling Problem (RCMPSP) variants, categorized into five key dimensions: jobs, relationships, resources, projects, and their interdependencies. It highlights critical attributes such as job flexibility, resource renewability, economic factors, and mobility while addressing complex constraints like concurrency, exclusiveness, and uncertainties. This classification framework provides a comprehensive understanding of the diverse elements influencing RCMPSP solutions in real-world scenarios.

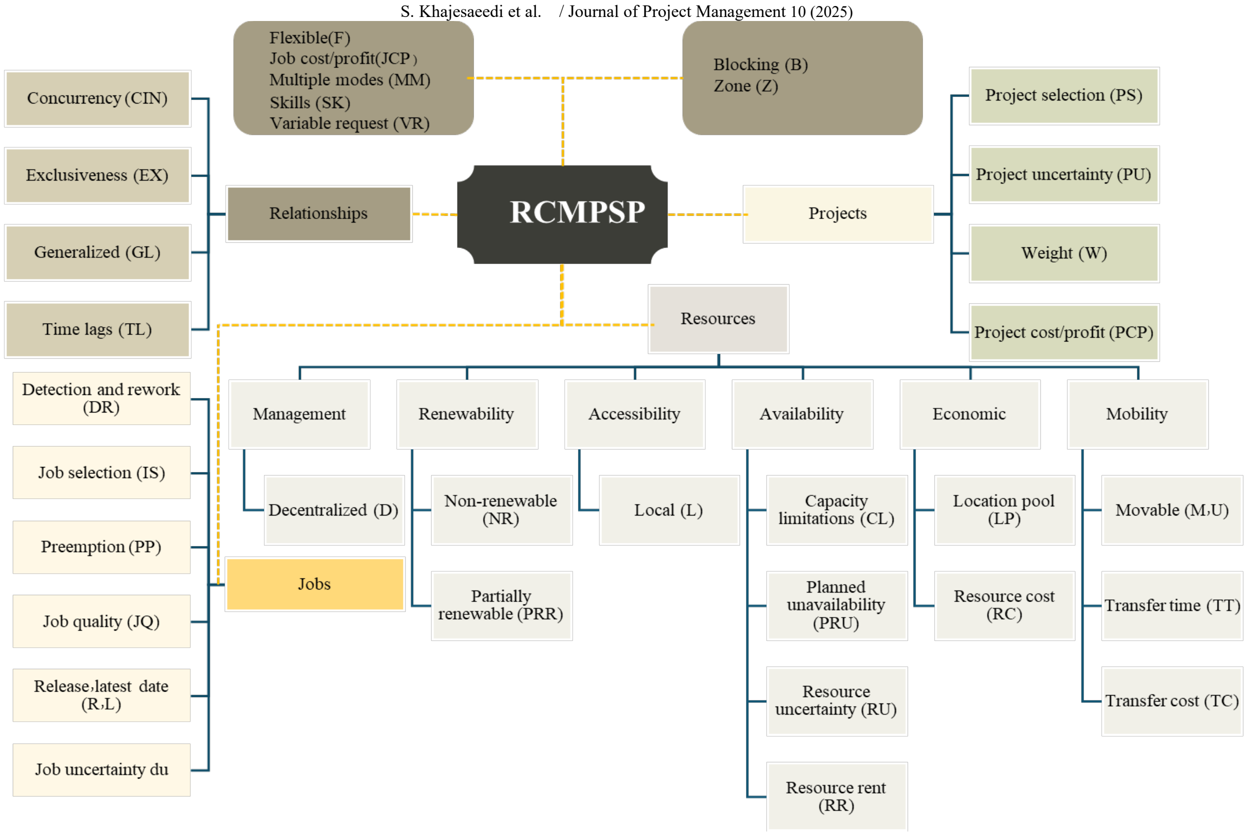

Fig. 3. Classification of the RCMPSP variants

2.2 Optimization Techniques

Metaheuristic algorithms, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Simulated Annealing (SA), dominate the field for their efficiency in solving large-scale RCPSP problems. Recent advances include hybrid approaches that combine metaheuristics with exact methods like Mixed Integer Linear Programming (MILP), leveraging the exploratory capabilities of heuristics and the precision of exact solutions (Gehring et al., 2022; Peykani et al., 2023).

MILP formulations, while computationally intensive, have been refined to handle more complex problem instances. These methods are particularly useful for generating optimal solutions in smaller cases, often serving as benchmarks for metaheuristic performance (Liu & Huang).

The LPS methodology enhances metaheuristic and hybrid techniques by introducing structured communication and decision-making processes. Techniques like Pull Planning, described in detail by (Ballard & Tommelein, 2021), align project objectives with on-the-ground realities by iteratively adjusting task dependencies and constraints. This aligns well with stochastic models for managing uncertainty, providing a robust framework for handling variability in resource-constrained environments.

Hyper-Heuristic Framework (Lin et al., 2020) emphasized hyper-heuristics as a robust approach for managing complex RCPSP variants. In GP-HH, genetic programming operates as the high-level strategy to combine and manage low-level heuristics dynamically. The framework leverages:

- Diverse Heuristics: Including task-swap, task-forward-insert, and task-segment-exchange methods.
- Flexible Decision-Making: The adaptive nature of hyper-heuristics allows tailoring solutions to varied project scenarios.

The comparative analysis against state-of-the-art algorithms like Hybrid Ant Colony Optimization (HACO) and Differential Evolution (DE) demonstrated the GP-HH's superiority in computing feasible solutions with minimal makespan deviations.

The application of SI and EA emphasizes hybrid and ensemble methods for enhanced performance:

- Encoding Strategies: Encoding solutions into vectors representing resource allocations and task sequences is crucial for algorithm efficiency. Strategies include binary encoding, machine-based assignment, and unified encoding methods, which simplify the transition from problem representation to actionable schedules.
- Improvement Strategies: Local search operators, such as insertion, swap, and critical path-based modifications, are integral to improving the quality of solutions. These operators enhance exploration within the algorithm's framework, targeting better convergence and reduced makespan (Gao et al., 2019).

Balouka and Cohen's use of Benders decomposition for solving MRCPSP introduces specialized optimality cuts that converge the solution iteratively. The decomposition separates the problem into:

A master problem to determine mode selections and resource allocations using nominal durations.

A subproblem to compute the worst-case project duration within the defined uncertainty set.

The methodology ensures feasible and optimal solutions for both deterministic and stochastic instances of MRCPSP (Balouka & Cohen, 2021).

The robust optimization framework is particularly suited for industries facing high uncertainty in project execution, such as:

- Manufacturing: Optimizing schedules where production variability impacts resource allocation.
- Construction: Managing uncertainties in material availability and labor schedules.
- Technology Development: Balancing time and cost in dynamic innovation projects.

The study highlights the practical implications of robust scheduling:

- Price of Robustness: While robust policies may extend project duration slightly compared to deterministic schedules, they significantly enhance reliability and feasibility under uncertain conditions.
- Adaptability: Dynamic mode selection ensures that project schedules remain viable despite deviations in activity durations (Balouka & Cohen, 2021).

The comprehensive review by (Pellerin et al., 2020) emphasizes the evolution of hybrid metaheuristics in solving RCPSP. Hybrid metaheuristics combine the strengths of various optimization methods to address the limitations of standalone algorithms, enabling them to explore solution spaces more effectively while maintaining computational efficiency.

Hybrid metaheuristics are classified based on their structure:

Integrative Hybrids: These combine population-based methods like Genetic Algorithms (GA) with local search strategies (e.g., Simulated Annealing or Tabu Search). For instance, GAs can be enhanced with local improvement steps to refine solutions iteratively.

Collaborative Hybrids: These employ multiple algorithms sequentially or in parallel. Sequential hybrids often use one algorithm to preprocess or enhance initial solutions for another, while parallel hybrids simultaneously explore different areas of the solution space and share information.

Key Features

Schedule Representation: Hybrid methods often utilize activity lists or priority rule-based representations to encode solutions. This enables algorithms to maintain precedence and resource feasibility constraints effectively.

Diversity vs. Intensification: Successful hybrids balance exploration (diversity) with exploitation (intensification) by combining randomized search strategies with deterministic refinement processes.

Model Optimization

(Han et al., 2016) employ advanced model optimization techniques, including matrix factorization, pruning, and architectural changes, to significantly reduce memory and computational demands:

Matrix Factorization: Reduces storage and processing overhead while maintaining high accuracy.

Pruning: Sparse representations are utilized to cut down resource use without substantial loss in model performance.

Architectural Modifications: Adjustments in layer configurations result in optimized models tailored for resource-constrained environments.

Heuristic Scheduling

The AMS problem is addressed with heuristic algorithms that allocate resources based on real-time usage patterns. This approach prioritizes frequently accessed models, allowing them to utilize higher accuracy variants while adhering to resource constraints.

The work by (Alluhaidan & Prabu, 2023) introduces a novel approach to lightweight cryptography specifically designed for resource-constrained environments, including IoT devices. Their proposed encryption methodology focuses on balancing computational efficiency with robust security, making it a promising addition to RCPSP solutions.

Key contributions include:

1. Symmetric Key Encryption: A lightweight cryptographic model based on a modified Feistel architecture, leveraging linear and non-linear transformations to optimize both security and computational overhead.
2. Integration of Genetic Algorithm Principles: Sub-key generation techniques enhance the randomness and complexity of the encryption process, crucial for maintaining data integrity in environments with limited resources.

The methodology emphasizes a dual focus on efficiency and security:

Key Scheduling: A dynamic process using substitution-permutation (SP) operations and bitwise transformations to minimize computational cycles while maintaining encryption strength.

Adaptive Resource Allocation: By tailoring encryption complexity based on available resources, the approach aligns well with RCPSP objectives of optimizing limited resource use.

The work by (Dai et al., 2019) explores the integration of energy efficiency into flexible job shop scheduling problems (EFJSP) with transportation constraints, representing a critical advancement in energy-aware scheduling. The study focuses on minimizing both makespan and energy consumption by considering production and transportation activities holistically. This approach addresses a significant gap in the literature where transportation energy consumption has often been overlooked.

Key contributions include:

1. Multi-Objective Optimization Model: The study proposes a model that incorporates energy consumption from machine setups, operations, idle states, transportation, and auxiliary processes, ensuring comprehensive energy optimization.
2. Enhanced Genetic Algorithm (EGA): A novel hybrid algorithm combining genetic algorithm (GA), particle swarm optimization (PSO), and simulated annealing (SA) is developed to solve the complex NP-hard EFJSP problem effectively.

Energy Modules and Transportation Constraints

The optimization model breaks down energy consumption into:

- Setup Energy (SE): Energy for machine preparation, such as tool changes and part loading.
- Processing Energy (PE): Energy directly consumed during operations.
- Idle Energy (IE): Energy used when machines are waiting between tasks.
- Transportation Energy (TE): Energy for moving jobs between machines using automated guided vehicles (AGVs).
- Auxiliary Energy (AE): Energy for maintaining environmental conditions (e.g., lighting, heating).

By integrating transportation constraints, the model accounts for dynamic interactions between machine and transportation operations, improving schedule efficiency and reducing total energy use.

Hybrid Algorithm

The EGA enhances traditional GA with:

1. PSO-Inspired Crossover: Guided learning mechanisms improve solution diversity and accelerate convergence.
2. SA-Based Mutation: An adaptive annealing mechanism prevents premature convergence and explores better solutions in the solution space.

Decentralized and Centralized Resource Management

The paper work by (Sánchez et al., 2023) identifies two key strategies for managing resources in multi-project environments:

- Centralized Management: A global decision-maker assigns resources based on an overarching objective, ensuring optimal resource utilization across projects.
- Decentralized Management: Individual project managers allocate resources to jobs within their projects, often prioritizing local objectives over global efficiency.

Solution Approaches

- Exact Methods: Used for small-scale problems, leveraging MILP formulations to guarantee optimality.
- Heuristics and Metaheuristics: Techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are employed for larger, more complex problems. These methods often incorporate hybrid strategies to improve convergence and solution quality.

To solve the various RCPSP variants, a variety of optimization techniques have been developed. Exact methods such as branch-and-bound and dynamic programming are used for small problem instances where exact solutions are feasible. However, for larger and more complex instances, metaheuristic approaches have become dominant due to their ability to explore large solution spaces efficiently. Popular metaheuristics include Genetic Algorithms (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). These techniques are particularly useful in multi-objective optimization, where both makespan and resource costs need to be minimized simultaneously. In the case of time-dependent costs, specialized metaheuristic modifications are often required to handle the dynamic nature of resource cost changes over time (Tian et al., 2023).

Various optimization techniques have been applied to solve the RCMPSP and its variants. These techniques can be categorized into exact methods and heuristic/metaheuristic methods. Exact algorithms such as branch-and-bound and mixed-integer linear programming (MILP) are employed for smaller instances of the problem, where optimal solutions can be found in a reasonable time. For larger and more complex problem instances, metaheuristics like Genetic Algorithms (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Tabu Search have been widely used. These methods are particularly effective in exploring the large solution space and handling the multi-objective nature of RCMPSP. For multi-project scheduling, hybrid approaches that combine multiple metaheuristics or incorporate problem-specific knowledge have shown promising results (Osz & Hegyhati, 2018; Sánchez et al., 2023).

The solution to dynamic and stochastic RCMPSP requires optimization techniques that can handle both the uncertainty in project durations and the dynamic resource allocation. Traditional exact methods like mixed-integer programming are often inadequate due to the complexity and uncertainty. Instead, approximation and heuristic methods are favored. The article introduces an Approximate Dynamic Programming (ADP) approach, which uses a linear approximation model to address the problem efficiently. This method is particularly useful in online decision-making environments, where decisions need to be adjusted in real time as new projects are introduced, and resource availability fluctuates. Markov Decision Processes (MDPs) are also employed to model the problem, where the objective is to maximize long-term profit while minimizing tardiness costs (Satic et al., 2024).

Over the years, various optimization techniques have been proposed to solve the RCPSP, ranging from exact methods to heuristic and metaheuristic approaches. Exact methods such as branch-and-bound and dynamic programming are commonly used for small to medium-sized instances of the problem. However, due to the NP-hard nature of RCPSP, heuristic and metaheuristic methods such as Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search, and Particle Swarm Optimization (PSO) have been extensively employed for large-scale problems. Recent research has also explored hybrid approaches that combine these metaheuristics with exact methods to improve solution quality and computational efficiency, particularly for multi-project scheduling problems where complexity is significantly higher (Habibi et al., 2018).

Various optimization techniques have been applied to solve the RCPSP, and among the most popular are metaheuristics like Genetic Algorithms (GA). This particular article proposes an enhanced GA for solving RCPSP, introducing modifications to the typical genetic algorithm framework. These include a new selection operator for parent selection, a modified two-point crossover operator with specific crossover order, and a linearly decreasing mutation probability. The effectiveness of this modified GA is demonstrated through benchmark problems from the Project Scheduling Problem Library (PSPLIB), where it is compared against other state-of-the-art metaheuristics. The results suggest that this algorithm is competitive and suitable for solving RCPSP, particularly for large-scale problems (Liu et al., 2020).

Solving the MS-RCPSP requires efficient optimization techniques due to its NP-hard nature and the complexity of managing multi-skilled resources. Several techniques have been applied to solve MS-RCPSP, including exact methods like mixed-integer programming (MIP), as well as heuristic and metaheuristic methods. Metaheuristics such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO) are particularly popular for handling the complexity of the problem. These methods are useful for exploring large solution spaces and finding near-optimal solutions in a reasonable time frame. Recently, hybrid approaches that combine different metaheuristics with exact methods have also gained traction, aiming to balance solution quality and computational efficiency (Bahroun et al., 2024; Vanhoucke & Coelho, 2021).

To solve the MS-RCPSP-HS, the article proposes a Parallelized Population-Based Multi-Heuristic System controlled by Reinforcement Learning (RL). This method involves evolving a population of solutions using multiple heuristics, which are selected and controlled by a reinforcement learning strategy. This approach allows for the exploration of a wide solution space, offering flexibility in handling the complexity of hierarchical skills in resource allocation. The system is implemented on the Apache Spark platform, leveraging parallel computing to accelerate the search for optimal solutions. The combination of multi-heuristics with RL and parallelization makes the approach highly efficient for solving large-scale MS-RCPSP-HS instances. Experimental results demonstrate that this method often outperforms existing algorithms, making it a promising solution for real-world scheduling problems (Jedrzejowicz & Ratajczak-Ropel, 2023).

In SE and IT, optimization techniques for scheduling problems often draw from a wide range of approaches, including exact methods, heuristics, and metaheuristics. Exact methods such as branch-and-bound and dynamic programming are typically used for smaller instances of scheduling problems where optimal solutions are feasible. However, for larger, more complex instances, metaheuristics like Genetic Algorithms (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO) are employed. These methods are particularly effective in tackling the computational complexity of large-scale scheduling problems. The document references Systematic Literature Reviews (SLRs) and their application in reviewing various optimization techniques, emphasizing the importance of using these techniques effectively to manage resource allocation in software projects (Ciupe et al., 2016).

A wide range of methods have been applied to solve RCPSP, often categorized into:

1. Exact Methods: Include branch-and-bound and constraint programming, suitable for small-scale problems due to computational limitations.
2. Heuristics and Metaheuristics: Genetic algorithms (GA), particle swarm optimization (PSO), and simulated annealing have been widely used for large-scale problems. Recent innovations include multi-heuristic systems controlled by reinforcement learning for solving MS-RCPSP.
3. Hybrid Approaches: Combine exact and heuristic techniques to balance computational efficiency and solution quality.
4. Approximate Dynamic Programming (ADP): Specifically for DS-RCPSP, ADP uses a linear approximation model for real-time decision-making (Pimapunsri et al., 2022).

The paper introduces a novel approach using Genetic Programming (GP) for designing priority rules. GP has proven effective due to its generalization ability and performance in designing rules that dictate the scheduling order of tasks. However, one of the main challenges in applying GP is its high computational cost during the fitness evaluation process.

To address this issue, the paper proposes surrogate models to assist in evaluating the fitness of the solutions without requiring as much computational power. These surrogate models aim to approximate the original model, significantly reducing runtime while still achieving similar or better performance. The effectiveness of these surrogate models is verified through experiments, showing that they can provide solutions with improved efficiency compared to the original GP model (Luo et al., 2023).

The paper (Snauwaert & Vanhoucke, 2023) proposes a new classification scheme for MSRCPSP, which builds upon existing classification frameworks for project scheduling problems. The classification helps researchers categorize different types of multi-skilled scheduling problems, which can guide the development of solution methods. The classification scheme is based on various criteria, including the type of resources (multi-skilled vs. single-skilled), the number of tasks and resources, and the types of constraints (e.g., precedence constraints, resource constraints).

To optimize the scheduling process, different metaheuristics and exact methods can be applied. However, the paper emphasizes the importance of classifying the problem first to select the most appropriate optimization technique for each variant.

Rosłon (2017) explores various algorithms and methodologies used for solving MRCPSP, particularly focusing on those applied in construction-related projects. Common optimization techniques include:

1. Exact Methods: Such as branch-and-bound algorithms and dynamic programming, which provide exact solutions but are computationally expensive for large-scale problems.
2. Heuristic Methods: Techniques like priority-based rules and greedy algorithms, which are faster but provide approximate solutions.
3. Metaheuristics: Advanced techniques such as Genetic Algorithms (GA), Simulated Annealing (SA), and Tabu Search, which are widely used to find good solutions for large, complex scheduling problems.

The paper emphasizes the need for algorithms that balance computational efficiency and solution quality, particularly in the context of construction management where scheduling decisions directly impact project timelines and costs.

While the paper (Elmezain et al., 2021) does not delve directly into computational optimization techniques (such as those used for scheduling or resource allocation), it indirectly touches on optimization through its exploration of human resource management and project leadership as a key determinant of project success. The optimization here is conceptual, focusing on how the right combination of managerial skills can optimize project outcomes. It suggests that enhancing the skills of project managers may lead to more efficient and successful project execution, which can be considered a soft optimization of the project management process.

The optimization techniques discussed in this paper revolve around two main approaches**:** time-indexed linear programming models and the Bianco-Caramia formulation. While time-indexed models are often used to represent the scheduling of activities over time, the Bianco-Caramia approach offers a more flexible and computationally efficient solution. The study provides a theoretical comparison to explain why Bianco and Caramia's formulation performs better in certain cases, especially when the activities involve complex precedence constraints and limited resource availability. This comparison is crucial for understanding which model provides better performance under different scheduling conditions (Bianco & Caramia, 2017).

To address the NP-hard nature of RCPSP, various optimization techniques have been proposed. The paper likely focuses on the effectiveness of metaheuristic methods, such as Genetic Algorithms (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO), which have been adapted for solving RCPSP. These algorithms are commonly used to find near-optimal solutions in a reasonable amount of time, given the computational complexity of RCPSP. The paper emphasizes the importance of selecting the right optimization technique based on the specific project scenario and the resources available (Peng et al., 2023).

In this paper, (Naderi et al., 2022) propose a multi-objective optimization approach for solving the RCPSP with a reliability function. The optimization technique aims to minimize the overall project completion time while considering the impact of resource failures. The model is formulated as a mathematical programming problem and solved using optimization algorithms that take into account both resource availability and reliability.

To handle the complexity of the problem, the authors suggest using exact methods, such as branch-and-bound or mixed-integer linear programming (MILP), for small instances of the problem. For larger instances, metaheuristic algorithms such as Genetic Algorithms (GA) and Simulated Annealing (SA) can be used to find near-optimal solutions in a reasonable amount of time. The paper provides a comparison between these methods, showing how incorporating the reliability function into the RCPSP can lead to more realistic scheduling solutions, particularly in situations where resource failures are likely.

The paper (Dai et al., 2023) proposes a Tabu Search algorithm to solve the RCPSP with step deterioration. Tabu Search (TS) is a well-established metaheuristic algorithm that is particularly effective for solving combinatorial optimization problems like RCPSP. In the proposed approach, the authors focus on solution-based Tabu Search, where the algorithm iteratively explores the solution space, maintaining a set of tabu moves to avoid revisiting previously explored solutions.

The algorithm incorporates various features, such as:

- Step deterioration model: The algorithm adjusts the scheduling process by considering the deterioration of resources over time.

- Memory structures: The Tabu Search uses memory to store previously visited solutions, preventing the search from cycling back to suboptimal solutions.
- Diversification and intensification: The method employs mechanisms to explore new areas of the solution space (diversification) while intensifying the search in regions with promising solutions (intensification).

The authors compare their solution-based Tabu Search approach with other traditional optimization methods, showing that the proposed algorithm outperforms other methods in terms of computational efficiency and solution quality. The results demonstrate that the Tabu Search approach is effective in solving large-scale instances of the RCPSP with step deterioration.

2.3 Objectives and Constraints

Minimizing project duration remains a key focus, but recent research has integrated cost and quality considerations. Cost-based models aim to balance time and financial efficiency, addressing issues like resource expenses and penalties for delays. Robustness against uncertainties, such as resource unavailability or fluctuating durations, has also become a central theme, with models ensuring reliable schedules under dynamic conditions (Tao & Dong, 2017).

Ballard and Tommelein's framework underlines the importance of aligning objectives at multiple levels from milestone planning to daily task execution. Their work emphasizes risk assessment and mitigation through real-time feedback and visual management tools, improving both resource utilization and schedule adherence (Ballard & Tommelein, 2021).

From the study by (Alluhaidan & Prabu, 2023), the objectives and constraints of lightweight cryptography align with the goals of addressing limited resources in project scheduling environments, such as IoT and other embedded systems:

Objectives

- Minimizing Computational Overhead: The primary aim is to reduce the number of computational cycles required for encryption and decryption, ensuring compatibility with resource-constrained devices like IoT sensors and embedded systems.
- Enhancing Security: Despite resource limitations, the model strives to maintain robust data security by employing advanced cryptographic techniques such as non-linear bit transformations and genetic algorithm principles.
- Energy Efficiency: Achieving lower power consumption to extend the battery life of devices while ensuring high data confidentiality and integrity.
- Adaptability: The cryptographic model is designed to adjust its complexity based on the device's available resources, striking a balance between performance and security.

Constraints

1. Limited Resources: Devices have strict limitations on memory (RAM/ROM), processing power, and energy capacity, requiring the algorithm to function effectively within these bounds.
2. Real-Time Requirements: Encryption and decryption processes must operate swiftly to ensure real-time communication and processing.
3. Scalability: The cryptographic system must accommodate a range of devices with varying resource capacities, from high-end IoT gateways to low-power sensors.
4. Interoperability: The system should integrate seamlessly with existing IoT frameworks, protocols, and devices without requiring significant modifications or upgrades

These objectives and constraints reflect the critical balance required in lightweight cryptographic systems for resource-constrained environments, contributing valuable insights to RCPSP research and applications (Akbar et al., 2022; LOPES & ULLAH).

From the study by (Dai et al., 2019), the objectives and constraints of energy-efficient flexible job shop scheduling focus on achieving a balance between production efficiency and energy consumption within resource-constrained environments.

Objectives

- Minimizing Makespan: The primary goal is to reduce the total time required to complete all jobs, ensuring efficient utilization of machines and transportation resources.
- Reducing Energy Consumption: A key focus is to minimize the total energy consumed during machine setup, processing, idle states, transportation, and auxiliary operations.

- Optimizing Transportation Activities: By integrating transportation energy into the scheduling model, the framework seeks to streamline job movements between machines using automated guided vehicles (AGVs) to minimize delays and energy costs.
- Balancing Multiple Objectives: The study adopts a Pareto-based approach to balance competing objectives of time efficiency and energy conservation.

Constraints

Precedence and Routing Constraints:

1. Jobs must follow predefined processing sequences.
2. Machines and AGVs must adhere to specific routing paths without conflicts.

Resource Availability:

1. Limited availability of machines and AGVs requires careful scheduling to avoid resource contention.
2. Energy and time budgets impose additional constraints on feasible schedules.

Capacity Constraints:

Each machine has a finite capacity for processing jobs, and each AGV has a maximum load capacity for transportation.

Dynamic Interactions:

Synchronization between machine operations and transportation activities is critical to prevent bottlenecks and idle times.

Energy Constraints:

Each machine and AGV has defined energy profiles, limiting the total energy available for operations.

This comprehensive objective and constraint framework ensures that EFJSP solutions address both operational efficiency and sustainability in energy-constrained environments. The methodology demonstrates significant potential for application in modern, energy-conscious manufacturing systems.

The primary objectives in RCPSP typically focus on minimizing the makespan, which is the total time required to complete a project, and minimizing the total cost of resource usage. In bi-objective problems, both these goals are pursued simultaneously, often resulting in a trade-off between the two. For instance, minimizing the makespan may require using more resources in parallel, which could increase the total cost, while minimizing costs may involve delaying certain activities, which extends the makespan. The constraints in RCPSP include resource constraints (such as the availability of limited resources) and precedence constraints (which dictate the order in which activities must be performed). In some variants, additional constraints like time-dependent resource costs or resource renewal limitations further complicate the problem (Tian et al., 2023).

The primary objectives in RCMPSP typically include minimizing the makespan (i.e., the total time required to complete all projects) and minimizing the total cost of resource usage. These objectives often conflict with each other, meaning that improving one objective may worsen the other. Constraints in the RCMPSP include resource constraints (limited availability of resources), precedence constraints (activities must follow a specific order), and sometimes, more complex constraints such as time-dependent costs or renewable resources. Additionally, the problem may include constraints on project-specific deadlines or resource usage limits that must be respected while scheduling (Sánchez et al., 2023).

The primary objective of dynamic and stochastic RCMPSP is to maximize the expected long-term profit while considering the cost of tardiness for delayed projects. This contrasts with traditional static scheduling problems, where the objective is typically limited to minimizing the makespan or resource usage. The constraints in this problem include resource availability (with stochastic fluctuations), task precedence relationships, and the requirement to adapt to the random arrival of new projects. Furthermore, projects may have varying resource demands over time, adding an additional layer of complexity to the scheduling process. The stochastic nature of the problem also means that the scheduler must continuously adapt to uncertainty, making robust decision-making techniques essential (Satic et al., 2024).

The primary objectives of RCPSP typically focus on minimizing the makespan, i.e., the total time required to complete all activities within a project. In more complex variants, multi-objective optimization is employed, where the objectives could include minimizing resource usage and maximizing resource utilization efficiency. Constraints in RCPSP are divided into resource constraints, precedence constraints (activities must follow a specific order), and sometimes time-dependent constraints, where resource availability or project priorities may change over time. Additionally, in multi-project environments, inter-project constraints may arise, where the completion of one project may impact the start or progress of others, adding further layers of complexity to the scheduling process (Habibi et al., 2018; Kong & Dou, 2021).

The primary objective of RCPSP is usually to minimize the makespan, i.e., the total time required to complete all tasks. However, in practical applications, the RCPSP often involves multiple objectives such as minimizing the total resource usage and cost, while simultaneously adhering to various constraints. These constraints include limited resource availability (e.g., machines, labor) and precedence constraints, which dictate the order in which tasks must be executed. Furthermore, in some cases, RCPSP problems may also involve time-dependent constraints, such as fluctuating resource costs or availability, adding an additional layer of complexity to scheduling decisions. In construction, for instance, managing both time and resource usage effectively can significantly reduce delays and costs (Liu et al., 2020).

The main objectives of the MS-RCPSP typically focus on minimizing project duration (makespan) and cost while ensuring that all activities are completed within the constraints of limited resources. These objectives may conflict, as reducing the project duration may lead to increased costs due to the need for additional or more expensive resources. The constraints include resource availability (labor, machines, materials), precedence constraints (activities must be performed in a specific order), and the skill sets required for each task. In the MS-RCPSP, the resources are multi-skilled, meaning that workers or machines may need to be assigned based on specific skill requirements, adding a layer of complexity in scheduling (Bahroun et al., 2024).

The objectives of this problem generally include minimizing the overall project duration (makespan) while considering resource constraints. The constraints include:

1. Resource Constraints: Limited availability of multi-skilled staff and other resources across multiple projects.
2. Stochastic Activity Durations: The uncertainty in how long activities will take due to unforeseen delays or rework.
3. Distributed Decision-Making: The coordination between local schedules for each project to ensure a global optimal solution (Yu et al., 2023).

The primary objective in this variant of the RCPSP is to maximize the Net Present Value (NPV) of the project. This involves:

Maximizing the revenue generated by completing tasks on time while minimizing the cost associated with using resources (e.g., labor, equipment).

Resource Constraints: Limited availability of resources (both renewable and non-renewable) must be managed efficiently to ensure that tasks are completed within the specified time.

Precedence Constraints: Certain tasks must be completed before others can begin, dictating the scheduling order (Asadujjaman et al., 2021).

The primary objective of this research is to determine the relationship between project managers' skills and project success. The study seeks to answer two research questions:

1. Are technical, conceptual, political, and human skills significantly related to project success?
2. Does the project manager's age have an impact on project success?

Constraints in this context include:

1. Project Complexity: Projects with varying levels of complexity may require different skill sets from the project manager.
2. Stakeholder Expectations: Different stakeholders may have different expectations, making it harder to measure "success" in a standardized way.

Thus, the research emphasizes not just the skill set but also the age-related experience and how these elements play a role in project outcomes (Elmezain et al., 2021).

The primary objectives in this study (Ramos et al., 2023) are to:

- Minimize the Makespan: The total time required to complete all tasks in the project, which is a key performance indicator in project management.

- Optimize Resource Utilization: Ensuring that resources are used as efficiently as possible, given their multi-skilled nature.

The constraints in the problem include:

- Resource Constraints: Resources are limited and must be allocated effectively to various tasks.
- Uncertainty Constraints: Resource availability can change due to breakdowns or other unpredictable factors.
- Precedence Constraints: Tasks must be scheduled in a specific order, based on their dependencies (Song et al., 2021).

The main objectives in the RCPSP revolve around minimizing project completion time while optimizing the use of available resources. The constraints include resource limitations (both renewable and non-renewable), precedence relationships between activities (such as finish-to-start relationships), and project deadlines. The thesis emphasizes the challenges of modeling these constraints, especially in real-world scenarios where resource availability is dynamic, and uncertainty may play a significant role. The work explores how different formulations of RCPSP address these constraints and objectives, particularly in scenarios where projects must be completed within tight schedules and with limited resources (Golab, 2023).

The objective of the RC-MPSP is to maximize the expected discounted long-run profit by completing projects while minimizing the tardiness **costs** associated with late project completions. This objective is influenced by several constraints, including:

- Resource constraints: There are multiple types of resources available, such as manpower, equipment, and materials, and each project consumes different amounts of these resources during its execution.
- Tardiness costs: If a project is completed late, there are associated penalties that reduce the overall profitability.
- Stochastic factors: Task durations and project arrival times are uncertain, which introduces variability into the scheduling process and requires adaptive decision-making to optimize outcomes.

The ADP algorithm models these constraints in a way that allows for dynamic adjustments to resource allocation as new projects arrive and task durations evolve (Satic et al., 2024).

The primary objective in the proposed variant of the RCPSP is to minimize project makespan while considering the reliability of resources. The addition of the reliability function introduces a trade-off between optimizing project completion time and accounting for the possibility of resource failures, which could lead to delays.

The main constraints in the problem are:

- Resource constraints: Each task requires specific resources, and the total available resources must not exceed the capacity at any time during the project.
- Reliability constraints: Each resource has a reliability factor, which introduces the possibility that resources may fail or not perform as expected. The reliability function models this risk, and the scheduling process must account for it by adjusting the allocation of resources.
- Precedence constraints: Certain tasks must be completed before others can start, creating a dependency structure between tasks.

(Johnson et al., 2023) show how these constraints can be modeled within the optimization framework, allowing decision-makers to account for both uncertainty and resource availability in their scheduling decisions.

The primary objectives of the MOMRCPSP are:

1. Maximizing Net Present Value (NPV): This objective aims to optimize the financial return of the project, considering the timing of payments and the cost of resources over time.
2. Minimizing Completion Time: The second objective focuses on reducing the project duration, which is critical for improving overall project efficiency and meeting deadlines.

The constraints of the problem include:

- Resource Constraints: Both renewable (e.g., labor, machinery) and non-renewable (e.g., budget, consumables) resources are limited, and their usage must be optimized across the scheduling process.

- Precedence Constraints: Certain activities must be completed before others can begin, which restricts the scheduling flexibility.
- Mode Selection Constraints: Each activity can be performed using different modes, each with its own resource consumption and duration. The challenge is to choose the optimal mode for each task, balancing project duration and resource usage.

By combining these objectives and constraints, the paper provides a comprehensive framework for solving the scheduling problem in a way that is both efficient and realistic .

2.4 Applications

RCPSP has wide-ranging applications, particularly in construction, where it optimizes resource allocation and minimizes delays in large infrastructure projects. In manufacturing, it is used to schedule tasks in flexible production systems, managing shared resources dynamically for industries like steel and glass. The software development sector applies RCPSP principles in agile environments to optimize iterative task allocation and ensure timely delivery (Pellerin et al., 2020).

The Last Planner® System, as articulated in this benchmark, demonstrates significant applications in construction projects, showcasing its adaptability to diverse industries. The emphasis on collaborative workflows and commitment-based task allocation bridges theoretical advancements in RCPSP with practical implementations in manufacturing, healthcare, and large-scale infrastructure (Ballard & Tommelein, 2021).

The MS-RCPSP finds critical applications in industries requiring skill-based resource allocation:

- Manufacturing: Aligning workforce competencies with production demands, particularly in multi-project environments.
- IT and Software Development: Optimizing task allocations in cross-functional teams where skills vary widely.
- Construction: Effective scheduling of skilled labor across large-scale infrastructure projects.

The benchmarking on the iMOPSE dataset, which includes 36 instances, highlighted the adaptability of the GP-HH algorithm in both small and large-scale projects (Lin et al., 2020).

The flexibility and adaptability of SI and EA methods make them applicable across a wide range of industries:

- Construction: Optimizing labor and resource utilization.
- Manufacturing: Scheduling in multi-project environments with shared resources.
- IT and Software Development: Allocating tasks dynamically in agile workflows (Gao et al., 2019).

Pellerin et al. (2020) benchmarked hybrid methods using the PSPLIB dataset, which contains standardized project scheduling instances. They identified that integrative approaches, especially those combining GAs with local search techniques, consistently achieved lower average deviations from optimal solutions compared to standalone methods. Notably:

1. Population Learning Algorithms: These iterative frameworks combine metaheuristics with adaptive learning strategies to improve solution quality dynamically.
2. Decomposition-Based Hybrids: By dividing the problem into smaller sub-problems, these hybrids focus on optimizing individual components before integrating the results.

Hybrid metaheuristics are particularly effective in industries with complex scheduling requirements:

Construction: Sequential hybrids optimize large-scale resource allocation problems by balancing labor and equipment usage dynamically.

Manufacturing: Integrative methods are used to schedule tasks in multi-product manufacturing environments, optimizing production times and resource utilization.

Technology Development: Collaborative hybrids assist in task prioritization and resource allocation in agile software development frameworks.

The approximation-based methods presented in this study have broad implications for RCPSP, particularly in domains with fluctuating resource availability:

- Mobile Computing: Efficiently managing computation on resource-constrained devices like smartphones or wearables.
- Cloud-Integrated Systems: Dynamic offloading of tasks between local devices and cloud platforms to optimize energy and cost efficiency.
- Video and Audio Streaming: Real-time processing of high-frequency data streams with minimal latency and energy consumption (Han et al., 2016).

This lightweight cryptographic approach is particularly applicable in environments where resources are constrained:

IoT Systems: Ensures secure communication between devices with minimal energy and memory overhead.

Industrial Control Systems: Protects sensitive operational data in automated processes without compromising system efficiency.

Healthcare IoT: Enhances security in remote patient monitoring systems, balancing data protection with real-time processing needs.

The integration of lightweight encryption models into RCPSP demonstrates their potential to secure data flows within resource-constrained projects, adding an essential layer of reliability (Alluhaidan & Prabu, 2023).

The EFJSP framework proposed by (Dai et al., 2019) has widespread applicability in industries aiming to optimize energy use:

- Manufacturing: Reducing operational and transportation energy costs in production lines.
- Warehousing: Optimizing the allocation of automated vehicles for material handling.
- Smart Factories: Implementing energy-efficient scheduling strategies in Industry 4.0 settings.

RCMPSP is widely applicable in environments where resource sharing and prioritization are critical:

- Construction: Scheduling overlapping construction projects with shared labor and equipment.
- Manufacturing: Managing production lines for multiple product categories within shared facilities.
- IT Project Management: Allocating resources across concurrent software development projects with competing deadlines (Sánchez et al., 2023).

RCPSP and its variants have a wide range of applications in industries where project scheduling is critical. Examples include construction projects, software development, research and development tasks, and manufacturing systems. In construction, managing time and costs while respecting the availability of resources such as labor and equipment is essential. In manufacturing, RCPSP is used to schedule production activities under resource constraints, ensuring minimal delays and optimal cost management. The bi-objective variant with time-dependent costs has been particularly useful in scenarios where the cost of resources fluctuates based on their usage over time, such as electricity or raw materials in production systems (Tian et al., 2023).

RCMPSP has widespread applications in industries where multiple projects need to be managed concurrently under resource constraints. Notable examples include manufacturing, construction, and service industries where effective scheduling can significantly impact project delivery times and costs. In manufacturing, the RCMPSP can be used to schedule production activities across multiple product lines with limited machinery and workforce. In construction, managing multiple building projects concurrently while optimizing the use of construction equipment and labor is a key application. RCMPSP also finds applications in research and development, where the scheduling of various projects (such as product development, testing, and marketing) needs to be optimized in terms of time and cost (Sánchez et al., 2023).

This variant of the resource-constrained multi-project scheduling problem has direct applications in industries where multiple projects are managed concurrently, and uncertainties in task durations or project arrivals exist. For instance, in manufacturing environments, the production of multiple products (each requiring different resources) must be scheduled while accounting for variability in production times and resource availability. In project management, especially in construction or R&D sectors, unforeseen delays and the arrival of new projects must be accommodated within the existing resource constraints. The dynamic scheduling approach is also applicable in logistics and supply chain management, where the timing of tasks and resource allocation are subject to change (Satic et al., 2024).

RCPSP and its variants are widely applicable in industries such as construction, manufacturing, research and development, and software engineering, where scheduling multiple tasks and managing resources are crucial for project success. In construction, for example, scheduling tasks like building construction or renovation involves managing various shared resources such as cranes and workers. In software development, managing the concurrent scheduling of multiple software modules while allocating developers and computational resources is critical to meeting deadlines. The ability to effectively manage resources while considering time-dependent constraints in industries such as these can significantly improve project outcomes by reducing delays and minimizing costs (Habibi et al., 2018).

The RCPSP is particularly relevant to industries where projects involve multiple activities and limited resources. In construction management, for example, scheduling tasks such as building construction, equipment operation, and labor allocation requires effective management of both time and resources to avoid project delays. The enhanced genetic algorithm proposed in this study has practical applications in these contexts, especially for large-scale construction projects with complex resource and time constraints. Similarly, the GA approach can be applied to manufacturing, where it is used to schedule production tasks under varying resource constraints, or in IT projects where multiple teams and resources are involved in delivering software or hardware systems (Liu et al., 2020).

Scheduling problems are crucial in various domains of SE and IT. In software development, effective scheduling ensures that different phases of a project (e.g., coding, testing, and deployment) are completed on time, while also managing the allocation of developers and other resources. In IT infrastructure management, scheduling plays a key role in ensuring that tasks like system updates, backups, and resource allocation are performed efficiently. Furthermore, scheduling is essential in agile software development, where teams must continually adjust their plans based on changing priorities and resource availability. The document highlights systematic reviews in software engineering that analyze the application of scheduling techniques in these real-world contexts (Ciupe et al., 2016).

The MMRCPSP model is applicable to industries with flexible job shop environments, such as:

1. Manufacturing: Where tasks require various machines, and the optimal allocation of resources and scheduling decisions can significantly affect production efficiency.
2. Project Management: In industries such as construction, where multiple tasks with dependencies need to be scheduled while optimizing resource utilization and minimizing project duration (Yuraszeck et al., 2023).

The approach discussed in the paper is widely applicable in industries where resource-constrained scheduling is critical:

1. Construction Projects: Efficient scheduling is essential to ensure that projects are completed on time while adhering to limited resource availability.
2. Manufacturing: Optimizing production schedules with multiple resources, ensuring tasks are completed with minimal delay and cost.
3. IT Projects and Research: Scheduling tasks within research and development or software development environments, where task dependencies and resource constraints are key considerations (Luo et al., 2023).

The NPV-based RCPSP is highly applicable in industries where project success is often determined by the combination of efficient scheduling and financial returns:

Construction: In large construction projects, scheduling tasks such as procurement, labor allocation, and project completion while maximizing profitability is critical.

Software Development: Managing resources across multiple software development tasks while maximizing the financial returns from project completion.

Manufacturing: Optimizing production schedules to ensure that resources are used efficiently and that production meets financial targets (Asadujjaman et al., 2021).

The approach presented in the paper (van der Beek et al., 2024) is applicable in various industries where project scheduling is critical, particularly in environments that involve complex resource allocation and flexible project structures. Specific applications include:

1. Construction Projects: Where multiple tasks require various resources, and project schedules must be adapted dynamically to resource availability.
2. Manufacturing: In production lines where tasks may need to be rescheduled based on resource consumption and production.
3. Software Development: Managing software projects with interdependent tasks and varying resource demands over time.

The hybrid DE algorithm can be used to optimize scheduling in these industries by improving efficiency and reducing the makespan.

The proposed multi-objective, multi-mode, resource-constrained scheduling model is highly relevant for real-world projects in industries such as construction, manufacturing, and energy sectors, where resource management and project timing are critical. By accounting for both renewable and non-renewable resources, the model is applicable to projects with complex scheduling and budget constraints. For example, in construction, machinery, manpower, and consumables are all resources that must be carefully planned and utilized to optimize the project's financial and temporal outcomes. The model could also be applied to large-scale infrastructure projects, R&D projects, and even software development initiatives where multiple resources and objectives need to be balanced (Tirkolaee et al., 2019).

Though this article (Eynde et al., 2024) serves primarily as a correction, it is relevant to industries applying RCPSP, such as construction, manufacturing, and software development. The correction updates prior findings, ensuring that the methods used to evaluate RCPSP formulations are aligned with real-world project scheduling challenges. The adjustments made will help practitioners better assess the performance of scheduling models, ultimately improving their ability to manage resource allocation and timing in complex projects.

The MS-RCPSP is particularly relevant to industries where projects involve complex resource management, such as construction, manufacturing, and software development. In these fields, multi-skilled workers are often required to handle different types of tasks, and the challenge lies in assigning these tasks efficiently to available resources while respecting project timelines. The optimization techniques proposed in the paper can be applied to real-world scenarios, such as scheduling tasks in construction projects, where skilled labor (e.g., electricians, carpenters, etc.) must be allocated to various tasks. Similarly, in manufacturing and shipbuilding, where tasks often require specific technical skills, the proposed method could enhance the overall efficiency of project execution and resource utilization (Hu et al., 2023).

The MS-RCPSP is highly relevant to industries where projects involve multiple resources with varied skill sets. Construction, manufacturing, and energy production are key areas where this problem arises. For example, in construction projects, different activities such as bricklaying, electrical work, and plumbing require workers with specific skill sets. Similarly, in manufacturing, tasks might require specialized machines or technicians with specific expertise.

The hybrid PSO algorithm proposed in this paper can be applied to these industries to optimize the scheduling process, ensuring that resources are utilized efficiently and projects are completed on time. The algorithm is particularly useful in large-scale projects where managing multi-skilled resources is critical to minimizing delays and reducing costs.

In software development, this method could be applied to schedule tasks that require developers with varying expertise (e.g., front-end development, back-end programming, database management) and optimize the allocation of personnel and tools. The flexibility of the proposed algorithm makes it applicable to any industry where tasks are interdependent and resources have specialized skills (Dang Quoc et al., 2022).

The Multi-objective Multi-mode Resource-Constrained Project Scheduling Problem (MOMRCPSP) has broad applications in industries where resource allocation is a critical factor, such as:

- Construction: Scheduling tasks like excavation, foundation work, and structural construction, where equipment and labor have different skill sets and usage modes, and project timelines must be balanced with cost considerations.
- Manufacturing: Optimizing the scheduling of production tasks across multiple production lines or machines with different capacities and operation modes, ensuring efficient resource usage and minimal delays.
- Energy Projects: Scheduling maintenance and construction activities in power plants, where the use of different resource types and project execution modes can significantly impact both cost and time.
- Research and Development (R&D): Managing the scheduling of activities in product development or innovation projects, where the available budget and resources (e.g., labs, technical expertise) must be optimized for efficient project execution.

The algorithms proposed in the paper can be directly applied to these industries to optimize project schedules, balancing both financial returns and the time required to complete the project (ARATOVSKYI & LIUBCHENKO, 2024; Tirkolaee et al., 2019).

2.5 Conclusion

The collected data across multiple sources highlights significant advancements in the field of the Resource-Constrained Project Scheduling Problem (RCPSP), showcasing a transition from classical deterministic models to complex, multi-objective, and stochastic frameworks. Recent studies emphasize the integration of resource reliability, step deterioration, and multi-skilled resource management, which better reflect real-world challenges in diverse industries like construction, manufacturing, and energy. Optimization techniques such as Tabu Search, Genetic Algorithms, and Non-Dominated Sorting

Genetic Algorithm II (NSGA-II) have proven effective in tackling the NP-hard nature of these problems, providing robust solutions for time-cost trade-offs. Collectively, this literature underscores the evolution of RCPSP methodologies towards more adaptive, dynamic, and scalable approaches, enabling better project performance in resource-constrained environments.

Following Table 1, demonstrate the background of researchers' work on RCPSP.

Table 1
Summary of published works on the RCPSP in 2016-2024

Article	Constraint	Characteristics	Objective	Information	Method
Tao & Dong, 2017	RR, NRR, OC	MM, P, TT, DRD	CMAX, MO	DS, FS	SA, GA, LA
Ding et al., 2023	RR	Multi-mode, Single-project	Minimize makespan, optimize resource usage	Real-world applications (construction, manufactur-	Genetic Algorithm (GA)
Hauder et al., 2020	NRR	Multi-project, shared resources	Optimize portfolio performance	Multi-project, shared resource allocation	MILP, Metaheuristics
Tao & Dong, 2017	RR, NRR	Stochastic, flexible decision-making	Maximize robustness, minimize delays	Dynamic scheduling with decision freedom	Simulated Annealing (SA)
Ballard & Tommelein, 2021	OC	Lean construction, collaborative planning	Enhance workflow reliability, reduce variability	Lean Construction principles, Last Planner® System	LPS, Collaborative planning
Lin et al., 2020	RR	MS-RCPSP, Workforce scheduling	Minimize project time, cost	Workforce dynamics in real-world scheduling	Genetic Programming Hyper-Heuristic (GP-HH)
Balouka & Cohen, 2021	RR	Robust optimization, dynamic mode selection	Minimize worst-case duration	Polyhedral uncertainty sets, dynamic resource allocation	Hybrid metaheuristics
Sánchez et al., 2023	NRR	Multi-project, resource sharing	Minimize project time, optimize resource usage	Multi-project, shared resources	MILP, Metaheuristics
Gehring et al., 2022	NRR	Metaheuristics, hybrid	Minimize makespan, optimize resources	Large-scale problems, benchmark studies	Hybrid algorithms
Gao et al., 2019	RR	SI, EA, hybrid strategies	Maximize resource utilization, minimize delays	Project scheduling in real-world applications	PSO, GA, Simulated Annealing
Pellerin et al., 2020	OC	Hybrid metaheuristics	Minimize makespan and cost	Industry applications (construction, manufacturing)	Hybrid algorithms, Benders Decomposition
Snauwaert & Vanhoucke, 2023	RR	MS-RCPSP, multi-skilled resources	Maximize scheduling efficiency	Task dependency, resource allocation	Genetic Algorithms (GA), Tabu Search
Asadujjaman et al., 2021	NRR	NPV-based RCPSP, resource allocation	Maximize NPV, minimize makespan	Software, construction, and manufacturing industries	GA, MILP
van der Beek et al., 2024	OC	Flexible project structure, resource consumption	Minimize makespan, optimize resource usage	Dynamic scheduling in large projects	Hybrid Differential Evolution (HDE)
Tirkolaee et al., 2019	NRR	Multi-mode, multi-objective	Maximize NPV, minimize completion time	Construction, manufacturing, energy sectors	PSO, GA
Satic et al., 2024	OC	Stochastic, dynamic scheduling	Maximize long-term profit, minimize tardiness	Uncertainty in task durations, project arrivals	Approximate Dynamic Programming (ADP)
Liu et al., 2020	RR	Multi-resource, stochastic	Minimize makespan, maximize resource utilization	Construction, software development	Hybrid GA
Habibi et al., 2018	NRR	Multi-project, resource scheduling	Minimize project completion time	Multi-project, shared resources	GA
Sánchez et al., 2023	OC	Multi-project, resource sharing	Minimize project time, optimize resource usage	Resource allocation across projects	MILP, Metaheuristics
Yu et al., 2023	RR	MS-RCPSP-HS, hierarchical skills	Minimize makespan, maximize resource allocation	Multi-skilled resources	Reinforcement Learning (RL)
Bahroun et al., 2024	RR	MS-RCPSP, multi-skilled resources	Minimize makespan, reduce cost	Workforce dynamics, resource allocation	GA, PSO, ACO
Dai et al., 2019	RR	Energy-efficient scheduling, FJSSP	Minimize makespan, energy consumption	Manufacturing, energy consumption	Enhanced Genetic Algorithm (EGA)
Johnson et al., 2023	RR	Resource reliability, reliability function	Minimize makespan, account for resource failures	Reliability-based scheduling	MILP, GA, PSO
Aratovskyi & Liubchenko, 2024	NRR	Multi-project, software environment	Minimize makespan, maximize resource utilization	Multi-stage hybrid methods, machine learning	Heuristics, Genetic Algorithms (GA), Hybrid techniques
Ősz & Hegyháti, 2018	NRR	Multi-mode, time-varying resource capacities	Minimize makespan	S-graph framework with resource capacity variations	S-graph-based model, MRIS, Branch-and-Bound
Akbar et al., 2022	RR	Multi-skills, personality traits, software projects	Minimize makespan	Considers hard and soft skills, resource proficiency levels	Genetic Algorithm, Heuristic, Parallel Scheduling
Zaman et al., 2023	RR	Dynamic, disruption recovery, multi-resource	Minimize makespan, recover disruptions	Handling dynamic disruptions, maintaining resource balance	Heuristics, Hybrid Algorithms
Lopes & Ullah, 2022	RR	Multi-skills, personality traits, dynamic scheduling	Minimize makespan, optimize resource allocation	Incorporates technical and soft skills for task assignments	Genetic Algorithm, Heuristic, Parallel Scheduling

3. Survey methodology

This section outlines the systematic methodology employed to collect, categorize, and analyze the literature on the Resource-Constrained Project Scheduling Problem (RCPSP) and its variants. The process was designed to ensure comprehensive coverage and robust analysis, focusing on problem features, solution methods, benchmarks, and connections to practical applications.

3.1. Literature Collection and Scope

Data Sources: The survey incorporated manuscripts indexed in major academic databases, including Scopus, Web of Science (WoS), IEEE Xplore, ScienceDirect (Elsevier), Wiley, and SpringerLink. These platforms were chosen for their extensive repository of peer-reviewed journals and conference papers.

3.2. Data Processing

- Initial Screening: Full texts of retrieved manuscripts were reviewed to ensure relevance. Only papers explicitly addressing RCPSP, its variants, or related methodologies were included.
- Feature Identification:

1. Problem Features: 34 distinct problem features were identified, including aspects like resource renewability, project prioritization, and job preemption.
2. Objective Functions: 20 objective functions were recognized, encompassing project completion time, resource efficiency, and cost-effectiveness.

3.3. Taxonomy Formation

The survey categorized RCPSP variants based on four primary dimensions:

Jobs: Characteristics like job execution modes, cost/profit, and quality levels.

Projects: Aspects including project selection, uncertainty, and interdependencies.

Relationships: Dependencies among jobs and projects, such as precedence and concurrency.

Resources: Types, availability, mobility, and economic considerations.

3.4. Analytical Framework

Statistical Insights: The collected data were analyzed to identify trends and gaps in the literature. Metrics such as the frequency of studied features, distribution of solution methods, and application domains were evaluated.

Solution Methods:

- Techniques were classified into exact, heuristic, and metaheuristic methods, with emphasis on hybrid approaches combining these techniques.
- Benchmarks and datasets, such as the PSPLIB and iMOPSE datasets, were reviewed for their role in validating proposed methods.

3.5. Practical Relevance

- Connection to Real-World Applications: The survey highlighted how RCPSP methodologies are applied in industries such as construction, manufacturing, and software development.
- Emerging Trends: Recent advancements, including stochastic modeling and AI-driven scheduling, were examined for their impact on bridging theoretical models with practical challenges.

3.6. Limitations and Future Directions

- Coverage Gaps: While the study aimed for comprehensive coverage, certain niche RCPSP variants may have been underrepresented due to database limitations.
- Dynamic Features: The evolving nature of RCPSP applications necessitates periodic updates to incorporate emerging methodologies and technologies.

This structured approach ensures that the survey provides a thorough understanding of the RCPSP field, enabling future research to build upon a well-defined foundation.

4. Challenges and Future Directions

4.1. Challenges

Scalability and Complexity: The inherent NP-hard nature of RCPSP and its variants, such as Multi-Skilled RCPSP (MS-RCPSP), leads to exponential growth in solution space as problem size increases. Effective scalability solutions remain limited, necessitating further research in efficient optimization algorithms to handle real-world, large-scale projects.

Dynamic and Real-Time Scheduling: Dynamic environments, particularly in industries like construction and manufacturing, require adaptive solutions. Current models often fail to account for unforeseen disruptions such as resource unavailability or task delays, which are common in real-time project management.

Integration with Practical Tools: Bridging the gap between theoretical advancements in RCPSP and practical implementation tools remains challenging. Tools that combine AI-driven adaptability with user-friendly interfaces for project managers are sparse (Bahroun et al., 2024).

Uncertainty Management: Handling uncertainties in resource availability, task durations, and project priorities is a significant challenge. Stochastic models address some aspects, but their computational overhead often limits their practical applicability (Zahra & Ullah).

Multi-Objective Optimization: Balancing trade-offs between competing objectives such as minimizing cost, duration, and resource usage complicates decision-making. Multi-objective optimization techniques often yield Pareto-optimal solutions but lack clarity for stakeholders to make actionable decisions (Bahroun et al., 2024).

Data Scarcity and Model Training: AI and machine learning models require substantial datasets for training and validation. However, access to standardized, domain-specific project scheduling data remains limited, hampering progress in predictive and prescriptive analytics (Bahroun et al., 2024).

Environmental and Sustainability Concerns: Incorporating sustainability goals, such as minimizing carbon footprints or optimizing energy use, adds layers of complexity to RCPSP models. Current research often overlooks these critical objectives (Zahra & Ullah).

4.2. Future Directions

AI and Machine Learning Integration: Leveraging machine learning for predictive analytics and real-time decision-making in RCPSP can significantly enhance scheduling flexibility and accuracy. Reinforcement learning shows promise for dynamic optimization in stochastic environments (Zahra & Ullah).

Hybrid Algorithm Development: Combining metaheuristics with exact methods like Mixed Integer Linear Programming (MILP) can offer the precision of deterministic approaches and the scalability of heuristics. This hybridization is essential for solving multi-project scheduling problems effectively.

Decentralized and Collaborative Scheduling: Enabling decentralized management systems that allow stakeholders across multi-project environments to collaborate dynamically can improve resource allocation and project efficiency (Manousakis et al., 2024).

Sustainability-Focused Models: Integrating environmental objectives, such as reducing energy consumption and emissions, into RCPSP models will align with global sustainability goals and support industries transitioning toward green practices.

Real-Time Data Integration: Incorporating IoT and Industry 4.0 technologies to collect real-time data on resource usage, task progress, and environmental conditions can significantly improve the robustness of scheduling models.

Simulation and Scenario Analysis: Advanced simulation tools to test RCPSP solutions under varied scenarios and disruptions will help in developing more resilient schedules, particularly for industries prone to high variability (Zahra & Ullah).

Enhanced User Interfaces and Decision Support: Developing intuitive user interfaces and decision support tools that translate complex RCPSP solutions into actionable insights for project managers will bridge the gap between research and practice.

Benchmarking and Open Datasets: Creating standardized datasets and benchmarking metrics for RCPSP will facilitate more effective comparisons between different methodologies and algorithms.

Cross-Domain Applications: Expanding the application of RCPSP techniques to domains such as healthcare, IT, and urban planning can unlock new opportunities and refine the models further through diverse challenges.

Policy and Organizational Alignment: Research should focus on aligning RCPSP methodologies with organizational policies and industry standards to ensure seamless adoption and improved effectiveness in practical settings (Manousakis et al., 2024).

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