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A Systematic Review of Project Scheduling Models under Renewable Resource Constraints and Uncertainty

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ABSTRACT

Objective: This study aims to develop a comprehensive resource-constrained project scheduling model (RCPSP) that accounts for uncertainty in activity durations and resource availability, thereby addressing the limitations of deterministic approaches.

Methodology: A mathematical formulation of the RCPSP is extended to an uncertain environment (URCPSP), considering renewable and semi-renewable resources under multiple constraints. The proposed framework integrates deterministic and stochastic components to better handle resource conflicts and project disruptions.

Results: Results indicate that classical RCPSP models fail to represent real-world project dynamics. Incorporating uncertainty and mixed resource types enhances scheduling flexibility and solution robustness while minimizing total project duration and resource fluctuation.

Conclusion: The proposed model provides a unified framework for project scheduling under uncertainty, supporting decision-making in complex environments. Future work may extend the model to multi-project contexts and advanced metaheuristic optimization techniques.

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Introduction

Large-scale projects are characterized by high complexity, multiple performance indicators, and substantial investment, creating significant management challenges. These challenges are further amplified by uncertainties throughout the project life cycle and often lead to delays, cost overruns, and reduced quality (Han et al., 2009; Jin, 2024). Traditional scheduling techniques such as CPM and PERT are inadequate in such environments because they assume unlimited resources and deterministic activity parameters, assumptions that rarely hold in practice (Chen et al., 2013; Balasubramanian & Grossmann, 2003). To explicitly account for limited resources under precedence constraints, the Resource-Constrained Project Scheduling Problem (RCPSP) has been widely studied, with the primary objective of minimizing project makespan (Nie et al., 2023). Classical RCPSP formulations, however, typically rely on deterministic assumptions regarding activity durations and resource availability, which restricts their applicability in dynamic and uncertain project environments. In real-world projects, uncertainty arises from multiple sources, including variability in activity durations, fluctuations in resource availability, and external disruptions. To cope with these challenges, uncertainty-aware extensions of RCPSP—commonly referred to as URCPSP—have been proposed using stochastic, reactive, and scenario-based scheduling approaches (RezaHoseini et al., 2021; Baharum et al., 2018; Ock & Han, 2010; Zhang et al., 2024).

These models aim to enhance schedule robustness by incorporating probabilistic information and adaptive decision-making mechanisms. Project resources are generally classified as renewable, non-renewable, or doubly constrained, and their efficient utilization is critical to avoiding conflicts and minimizing project delays (Nudtasomboon & Randhawa, 1997). Accordingly, several studies have combined proactive and reactive scheduling strategies with heuristic and scenario-based models to address uncertainty in resource-constrained environments (Zaman et al., 2020; Chakrabortty et al., 2016; Chand et al., 2019). Despite these efforts, most existing models focus on specific resource categories or isolated sources of uncertainty and do not provide an integrated treatment of heterogeneous resources under disruption. As a result, deterministic RCPSP and uncertainty-oriented URCPSP are still essentially treated as separate research streams, and a unified analytical structure that systematically connects them—particularly under disruption scenarios—remains absent. This limitation becomes increasingly critical in large-scale and dynamic projects, where disruptions simultaneously affect activity durations and heterogeneous resource behaviors.

Research Contribution and Identified Gap

Although an extensive body of literature has investigated RCPSP and its uncertainty-oriented extensions (URCPSP), existing studies predominantly address deterministic scheduling and uncertainty modeling independently. The interaction between renewable, non-renewable, and doubly-constrained resources under disruption and uncertainty has not yet been systematically integrated into a unified analytical framework, even though such interactions directly influence project feasibility, robustness, and completion time in practice. To address this methodological gap, the present study develops a unified multi-stage analytical framework that explicitly connects classical deterministic RCPSP structures with uncertainty-aware URCPSP mechanisms. Unlike prior works that focus on isolated uncertainty sources or specific resource types, the proposed framework captures the combined effects of resource-type heterogeneity and uncertainty within a single decision structure, thereby enabling both proactive planning and reactive scheduling adjustments.

Summary of the Paper's Contribution

The contribution of this study extends beyond a descriptive review by synthesizing and structurally organizing the literature into an integrative modeling perspective. While Song et al. (2022) emphasize project control under resource constraints, Rahman et al. (2021) focus on reactive scheduling under duration uncertainty, and Moradi et al. (2019) adopt scenario-based robust optimization, none of these approaches explicitly unify deterministic and uncertain scheduling environments while jointly considering renewable, non-renewable, and doubly-constrained resources. By bridging these fragmented research directions, the proposed framework offers a coherent methodological foundation that advances the current state of RCPSP and URCPSP research. Specifically, this study: (1) identifies the methodological gap between deterministic RCPSP and uncertainty-based URCPSP models; (2) introduces a unified analytical framework integrating both environments into a single multi-stage decision structure; (3) highlights the underexplored role of renewable, non-renewable, and doubly-constrained resource disruptions under uncertainty; and (4) provides structured theoretical and practical guidance for selecting appropriate scheduling models under diverse project conditions.

Originality and Unique Positioning of the Study

The originality of this study lies in bridging two previously disconnected research streams: classical deterministic RCPSP models and uncertainty-driven URCPSP approaches. The proposed framework demonstrates how deterministic scheduling logic can be systematically extended to uncertain environments through resource-type differentiation and staged decision-making. By explicitly linking prior literature to the structure of the integrated model, this study transforms fragmented insights into a coherent methodological contribution and positions the present work beyond existing review studies.

Paper Structure

The scope of this study is drawn from reputable industrial engineering journals, primarily published between 2000 and 2025, with greater emphasis on recent contributions. While foundational works are included where necessary, the focus remains on contemporary research. The paper is organized as follows. Section 2 reviews RCPSP literature and defines the standard RCPSP model considering constraints. Section 3 examines project scheduling under uncertainty (URCPSP). Section 4 introduces a comprehensive framework for project scheduling under deterministic and uncertain conditions. Finally, Section 5 discusses limitations, challenges, and future research directions.

Literature Background

Definition of the Resource-Constrained Project Scheduling Problem (RCPSP)

The Resource-Constrained Project Scheduling Problem (RCPSP) considers a finite set of activities with deterministic durations $d_i \in N$, which are scheduled in a non-preemptive manner, N = {0, ..., n}, meaning that once an activity starts, it must continue without interruption. Each renewable resource $k \in K$ has a limited capacity R_k, with resource usage $0 \leq r_{ik} \leq R_k$. Dummy activities 0 and nnn represent the project start and finish, respectively, both having zero duration and no resource consumption. A feasible schedule $s = (s_0, \dots, s_n)$ assigns integer start times that satisfy precedence constraints defined by a directed acyclic graph G(N, A), where activity 0 precedes and activity n succeeds all other activities (Kannimuthu et al., 2018). This structure guarantees a well-defined project timeline and enables formal feasibility analysis. In classical RCPSP formulations, Finish-to-Start (FS) precedence relations are typically assumed, implying that a successor activity may start only after its predecessor has finished. More general precedence relations, such as Start-to-Start (SS) **constraints (1)** $\mathbf{s_i \leq s_j}$**,** can also be incorporated when required by the project structure. Resource feasibility is ensured by defining the set of activities active at time t as A(s, t) = $\{i \in N : s_i \leq (t - 1) \wedge (s_i + d_i) \geq t\}$ representing activities active at time t. **A schedule is considered feasible** if and only if it. **Simultaneously** satisfies precedence constraints, resource capacity constraints, and integrality requirements **constraints** (2)–(4) is **feasible** (Pritsker et al., 1969).

$$Min \quad s_n \tag{1}$$

$$\mathrm{s_i} + \mathrm{d_i} \leq \mathrm{s_j} \qquad \forall (i,j) \tag{2}$$

$$\sum_{i \in A(s,t)}^{n} r_{ik} \leq R_k \qquad \forall t \epsilon N_0, \forall k \epsilon K \tag{3}$$

$$\mathrm{s_i} \epsilon N \qquad \forall i \epsilon N \tag{4}$$

This classical formulation provides the deterministic baseline upon which uncertainty-aware extensions are developed in later sections of this study.

Comparative Perspective: Deterministic RCPSP vs. Extended Approaches (Concise Version)

The classical RCPSP provides a deterministic baseline assuming fixed activity durations and stable resource availability (Pritsker et al., 1969). However, this assumption limits its applicability to dynamic, complex projects. Various modeling extensions have emerged to address these limitations. Exact methods (Branch-and-Bound, MIP, CP) guarantee optimality but scale poorly for large projects (Christofides, 1987; Hartmann & Briskorn, 2010).2. Heuristic and metaheuristic approaches, including priority-rule schemes, genetic algorithms, and hybrid methods, trade optimality for computational efficiency, suitable for large-scale projects (Van Eynde & Vanhoucke, 2022; Zhang et al., 2024; Martin et al., 2024; Geibinger et al., 2024). 3. Robust, stochastic, and fuzzy extensions explicitly model uncertainty in activity durations, resource availability, or external disruptions, improving resilience but increasing computational complexity (Moradi et al., 2019; Hu et al., 2024; Zhang et al., 2025; Ki et al., 2015; Barbalho et al., 2025). Most studies focus on renewable resources, while non-renewable and doubly-constrained resources remain underexplored, limiting practical applicability (Song et al., 2022; Ballesteros-Pérez et al., 2019). This gap motivates unified frameworks that integrate deterministic RCPSP logic with uncertainty-aware extensions across multiple resource types (Rahman et al., 2021; Barbalho et al., 2025; Zhang et al., 2025)

Positioning of the Proposed Framework Relative to Recent Studies

Recent research has addressed RCPSP and URCPSP from multiple perspectives:

- **Project control under renewable resources:** Song et al. (2022)
- **Reactive scheduling under duration uncertainty:** Rahman et al. (2021)
- **Buffer-based control under dynamic disruptions:** Nie et al. (2023)

- **Advanced heuristics for uncertainty-aware RCPSP:** Hu et al. (2024); Zhang et al. (2025)

These studies often treat deterministic and uncertainty-aware methods separately and focus on specific resource types or single uncertainty sources. In contrast, the proposed framework integrates deterministic RCPSP and URCPSP within a unified analytical structure, jointly considering renewable, non-renewable, and doubly-constrained resources, bridging previously fragmented research streams. The Research Gaps in RCPSP and URCPSP are displayed in Table 1. Accordingly, Table 1 provides a structured synthesis of recent RCPSP and URCPSP studies (2022–2025) by systematically extracting and comparing key features, including resource types, uncertainty modeling approaches, and solution methodologies. The systematic review (Table 1) highlights the fragmentation between deterministic RCPSP and uncertainty-aware URCPSP studies across different resource types and uncertainty sources. Motivated by these findings and the comparative insights summarized in Table 5, the proposed model unifies deterministic and uncertainty-aware scheduling within a single analytical framework.

Table 1. Research Gaps in RCPSP and URCPSP

Recent Advances 2024–2026	Key Gap	Uncertainty Considered	Resource Type	Methodology	Research Focus
• Qiu et al. (2025) • Wang et al. (2025)	Ignores uncertainty; limited resource scope	None	Renewable	Exact, Heuristic	Classical RCPSP
• Chao et al. (2026) • Martin et al. (2024)	Limited robustness; no multi-resource integration	Limited	Renewable	Priority rules, GA, Hybrid	Heuristic / Metaheuristic
• Sadeghloo et al. (2024) • Salvadori et al. (2025)	Not unified with deterministic baseline; single resource focus	Duration & resource uncertainty	Renewable, Non-renewable	Scenario-based, RO, Chance-Constrained	Robust / Stochastic
• Geibinger et al. (2024) • Aghileh et al. (2025)	Partial integration; real-world multi-mode disruptions underexplored	Multi-source uncertainty	Renewable, Non-renewable, Doubly-constrained	Reactive / Proactive	URCPSP Extensions
• Barbalho et al. (2025) • Martin et al. (2024) • Zhang et al. (2025)	Emerging methods are not fully validated in integrated frameworks	Duration uncertainty, industrial disruptions	Renewable & Multi-skill	DRL, Preemptions, Robust Scheduling	Advanced Recent Approaches

Systematic Review Protocol and Study Selection

To ensure methodological rigor and compliance with systematic review standards, this study follows a formal systematic literature review protocol. Relevant studies were identified through structured searches in major scientific databases using predefined keywords and Boolean combinations. Explicit inclusion and exclusion criteria were applied, and a multi-stage screening process was conducted, including duplicate removal, title and abstract screening, and full-text eligibility assessment. Figure 1 presents the PRISMA flow diagram summarizing the study selection process and the number of articles retained at each stage. Ultimately, 128 peer-reviewed studies were included in the final qualitative and quantitative synthesis, ensuring transparency, reproducibility, and adherence to established systematic review guidelines.

Selection Methodology and Quality Control

To strengthen the rigor of the study selection process, a structured and multi-stage selection methodology was applied. After duplicate removal, studies were screened based on predefined inclusion and exclusion criteria. Eligible full-text articles were then assessed using methodological quality indicators, including relevance to RCPSP/URCPSP modeling, clarity of problem formulation, and analytical contribution. Each retained study was subsequently coded according to resource type, uncertainty modeling approach, and solution methodology. A standardized data extraction protocol was used to ensure consistency and reproducibility across the final set of 128 studies included in the qualitative and quantitative synthesis.

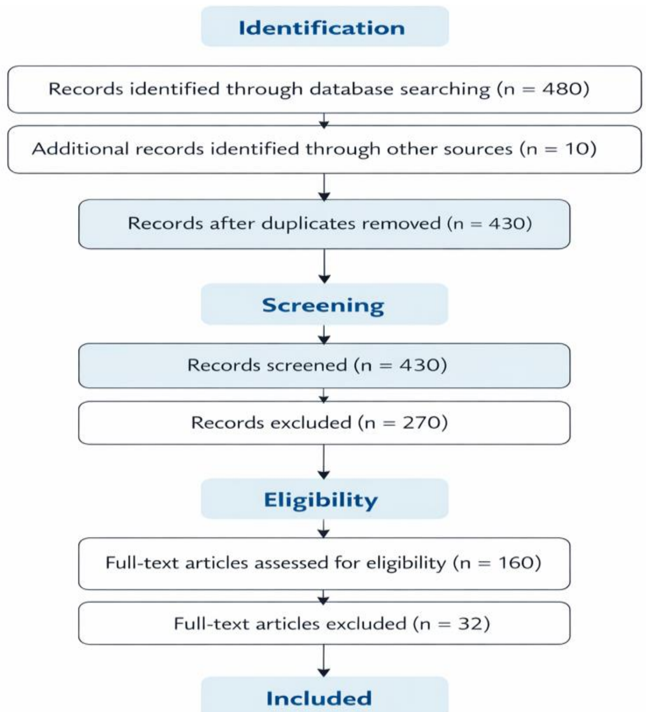

Figure 1. PRISMA flow diagram of the systematic literature review process

Conditions of the Project Scheduling Model with Resource Constraints (RCPSP) Considering Renewable and Non-Renewable Resources

Resources play a central role in project scheduling and may be classified as local (project-specific) or global (shared among multiple projects). From a modeling perspective, resources are further categorized into renewable, non-renewable, and doubly-constrained types, each of which directly influences the structure of the RCPSP. Per-period capacity constraints limit renewable resources, whereas non-renewable resources are constrained over the entire planning horizon, reflecting cumulative consumption effects. For renewable resources, the total consumption of preemptive and non-preemptive activities in each period t must not exceed the available capacity, as enforced by Constraint (5). Non-renewable resource limits are controlled through aggregate constraints over the planning horizon, as shown in Constraint (6). To stabilize renewable resource utilization over time, Constraint (7) minimizes fluctuations between consecutive per&y introducing positive and negative deviation variables, subscriptvariables $u^{-}_{\widehat{kt}}$, $u^{+}_{\widehat{kt}}$ representing downward and upward deviations, respectively. An earliest-start scheduling strategy is employed to evaluate and update resource allocations when conflicts arise. In such cases, deviations from a desired utilization rate D* are minimized using a strengthening-and-backtracking mechanism, as specified by constraints

(8) and (9), which iteratively adjusts the schedule to reduce inter-period fluctuations in resource usage (Nudtasomboon & Randhawa, 1997). This mechanism improves utilization stability while maintaining feasibility under dynamic resource conditions. For multi-mode activities, each job $j' \in J$ must be executed in exactly one mode. $m_j \in M_{j'}$ .For each mode, the processing time, required resource set $\mathrm{R}_{\mathrm{m_j}} = R^{re}_{m_{j'}} \cup R^{re}_{m_j}$, and corresponding resource demands are predetermined, allowing flexible modeling of alternative execution strategies under varying resource requirements. This formulation allows flexible modeling of alternative execution strategies under varying resource requirements. Regarding immediate precedence relations, if activityj_1 executed in mode M_{j_1} precedes activityj_2 executed in mode M_{j_2} and both require a common renewable resource, then Constraint (10) applies, ensuring that activity j_2 cannot start before j_1 is completed ($s_{j_2} \geq C_j = p_{m_j} + s_{j_1}$) (Nonobe & Ibaraki, 2002).

$$\sum_{i=1}^{I}\sum_{\forall j}\sum_{m=1}^{M_j}\sum_{q=t}^{t+d_{ijm}-1} r_{ijmk} * X_{ijmq} + \sum_{i=1}^{I}\sum_{\forall j'}\sum_{m=1}^{M_{j'}} r_{ij'mk} * X_{ij'mt} \leq R_{kt} \tag{5}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{N_i}\sum_{m=1}^{M_j}\sum_{q=t_1}^{t_2} W_{ijmq} * X_{ijmq} + d_{\bar{p}} = Wp(t_1,t_2)\,, \quad \text{for all p} \tag{6}$$

$$\sum_{i=1}^{I}\sum_{\forall j}\sum_{m=1}^{M_j}\sum_{q=t+1}^{t+d_{ijm}} r_{ijmk} * X_{ijmq} + \sum_{i=1}^{I}\sum_{\forall j'}\sum_{m=1}^{M_{j'}} r_{ij'mk} * Y_{ij'm(t+1)} - \sum_{i=1}^{I}\sum_{\forall j}\sum_{m=1}^{M_j}\sum_{q=t}^{t+d_{ijm}-1} r_{ijmk} * X_{ijmq} - \sum_{i=1}^{I}\sum_{\forall j'}\sum_{m=1}^{M_{j'}} r_{ij'mk} * Y_{ij'mt} + u_{\widehat{kt}}^{-} - u_{\widehat{kt}}^{+} = 0 \tag{7}$$

$$\sum_{\forall t} |desired\ rate - resource\ used| \tag{8}$$

$$\sum_{\forall t} |resource\ use\ at\ time(t) - resource\ use\ at\ time\ (t-1)| \tag{9}$$

$$c_{i1} \leq s_{j2} \quad and \quad s_{j2} \leq s_{j'} \;\; for\ all\ j' \text{ such that r } \in R^{re}_{m_{j'}},\ and \quad c_{j1} \leq s_{j'} \tag{10}$$

The Resource-Constrained Project Scheduling Problem (RCPSP) under Single-Objective and Multi-Objective Settings

The Resource-Constrained Project Scheduling Problem (RCPSP) can be formulated under both single-objective and multi-objective settings, depending on the decision-maker's priorities and the project environment. In single-objective formulations, the objective is typically to minimize project completion time, total cost, or schedule deviation, where objective functions are regular and non-decreasing with respect to activity start times. Minimization of the project makespan is one of the most widely studied objectives and can be formulated as: $Minimize\ z = \sum_{t=T}^{T+s} \beta_t * x_{Nt}$. where $x_{Nt}$is a binary variable corresponding to a dummy activity N, which starts and finishes at the end of period t; $\beta_t > 0$ is a weighting factor, and s is the allowable deviation in completion time (Davis et al, 1992). Another common objective focuses on minimizing total resource-related costs, expressed as: $Minimize\ z = \sum_{J=1}^{N} a * c$. where $(\mathrm{a}_1, .., \mathrm{a}_\mathrm{n})$ represents the vector of resource utilization, and$(\mathrm{c}_1, .., \mathrm{c}_\mathrm{n})$ denotes the corresponding cost vector, satisfying $0 < c_1 \leq c_2 \leq \cdots \leq c_n$ (Rodrigues & Yamashita, 2010; Liu & Wang, 2006). Financial performance objectives are often captured through the maximization of the Net Present Value (NPV), formulated as: $Maximize\ z = \sum_{J=1}^{n} \mathrm{e}^{-\alpha s_i} * c_i$. where α is the discount rate, s_i is the start time of activity i, and c_i the discounted cash flow (Schutt et al, 2012; Wiesemann et al, 2010; Nübel, 2001). Qual&riented objectives further extend RCPSP formulations by accounting for rework, inefficiencies, and skill mismatches. These objectives typically minimize a composite quality loss function, $Minimize\ z = Q_1 + Q_2$,where $Q_1 = \sum_{k=1}^{n} t_k + \sum_{k=2}^{n} \sum_{i=1}^{k-1} a_{ik} * d_i + \sum_{k=2}^{n} \sum_{i=1}^{k-1} \sum_{\substack{j=1 \\ j\neq i}}^{k} a_{ik} * a_{ji} * d_j$, $a_{ik} \epsilon (0,1)$ represents the rework coefficient of activity i due to k, t_k is the expected completion time, and d_i , the duration (Vandenheede et al., 2016; Icmeli-Tukel & Rom, 1997; Wen et al 2021). To enhance schedule robustness, Li and Demeulemeester (2016) and Li et al. (2015) proposed minimizing deviations in both resource utilization and activity start times, expressed as: $Minimize\ z = \sum_{k=1}^{K} \sum_{t=1}^{S_n} c_k * E * [(u_{kt} - \bar{u}_k)^+] + \sum_{i=1}^{n} w_i * E * [(\boldsymbol{s}_i - \bar{s}_i)^+]$,where u_{kt}denotes renewable resource K usage at time t ,E[·]is the expectation operator, and $\boldsymbol{w}_i$ epresents the penalty for deviation. In practice, multi-objective formulations provide a more realistic representation of project trade-offs. These models simultaneously address conflicting goals, such as minimizing critical path duration ($Minimize\ z_1 = \sum_{A \in CP} CTA_A$) and minimizing total project cost ($Minimize\ z_2 = \sum_A DC + IC\ (per\ day) * z_1 (in\ day)$) (Shrivastava & Pandey, 2024), or jointly maximizing NPV while minimizing project duration under uncertainty (Tirkolaee et al., 2019).

Materials and Methods

Conditions of the Resource-Constrained Project Scheduling Problem (RCPSP) under Top-Down and Bottom-Up Perspectives, and in Parallel or Sequential Activity Structures

For clarity and consistency, all parameters, symbols, and project performance indices used in this section are summarized in Tables 2 and Tables 3, which provide a unified reference for the mathematical notation and control indicators applied throughout the proposed framework Top-down project control evaluates schedule performance using Earned Value Management (EVM), relying on indicators such as SPI and SV to monitor schedule adherence over time (Bakhshi et al., 2022). To improve time-based sensitivity, Earned Duration Management (EDM) has been proposed as a complementary control mechanism (Khamoushi & Golafshani, 2014). However, neither EVM nor EDM explicitly accounts for resource constraints, which limits their effectiveness in resource-intensive project environments. To overcome this limitation, a work-content-based control perspective is adopted, enabling the integration of resource consumption into schedule performance evaluation through SPI_{wc}. In addition, tolerance limits and Project Buffer (PB) allocation are employed to enhance robustness against deviations and disturbances (Martens & Vanhoucke, 2017). Song et al. (2022) incorporated these control mechanisms into both top-down and bottom-up scheduling strategies under resource-conflict conditions, with the overall control logic illustrated in Figure 2.

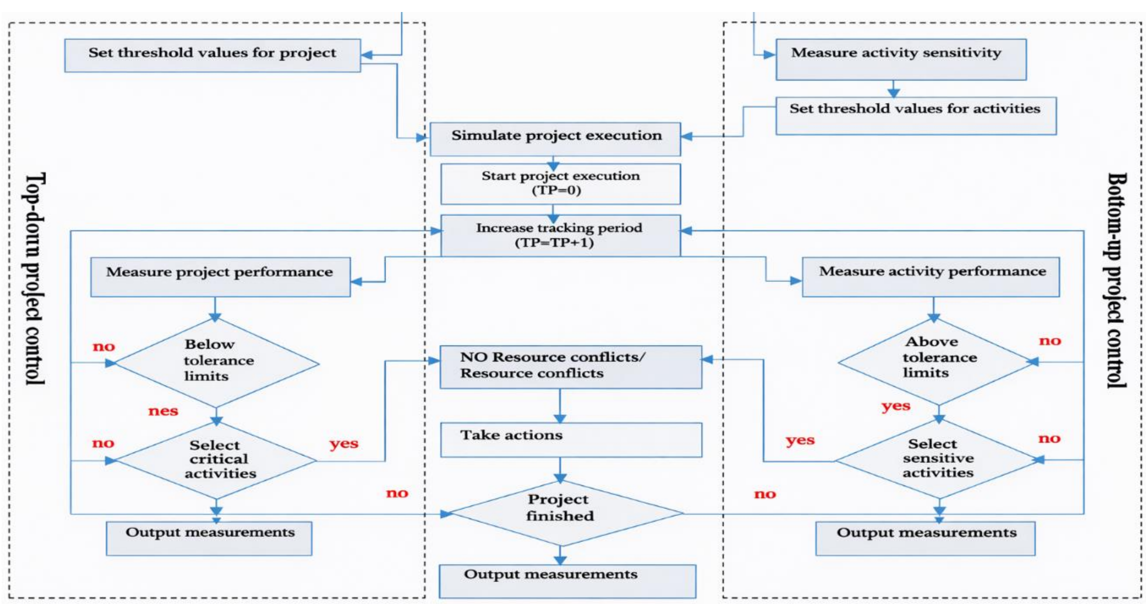

Figure 2. General Procedure of the RCPSP Simulation Model (Top-Down and Bottom-Up Views, Steps 4–7)"

Table 2. Parameters and Symbols Used in RCPSP and URCPSP Models

Symbol	Description	Symbol	Description
i,j	Activity indices	WC_t	Work content of a project at time t
N	Set of activities	WC_t^{Ess}	Work content of a project that is scheduled according to ESS at time t
K	Set of resources	AT	Actual Time
s_i	Start time of activity (i)	WC_t^{Lss}	Work content of a project that is scheduled according to LSS at time t
d_i	Actual and planned duration of activity (i)	PC_i	Percentage completion of activity i
$\hat{d}_i$	Duration Planning in advance	ewc_i	Earned work content of activity i
r_{ik}	Demand for resource (k) by activity (i)	d^c_j	Duration of activity j after crashing d^e_j
R_k	Capacity of renewable resource (k)	C_t	Set of activities which have been completed at time t
t*	Warning time of disruption	O_t	Set of activities that are in progress at time t
d_i^C	Corrected duration after disruption	r_{jk}^c	Resource demand after the crash of activity j with resource type k
d^c_j	Duration of activity j after crashing d^e_j	S_t	A set of activities that start at time t
$\mathrm{P}(noS\|OT)$	On − time completion| if no control signal	F_t	Set of activities which will start after t
$ES_{min,t}$	Minimum feasible earned schedule at period t.	$\mathrm{P}(S\|Late)$	$Control\ signal\ \|\ if\ project\ finishes\ late$
PD	Planned duration	$PV_{t,LSS}$	planned value under the latest-start schedule
PB	Project Buffer	$PV_{t,shift_{max}}$	planned value under the maximum schedule
BAC	Budget at Completion	$N_i^{critical}$	Number of scenarios in which activity i has become critical
$x\%$	predefined reduction factor	N_{sim}	Total number of simulation runs (Monte Carlo / SRA)
β^m	activity under consideration	$R_{k,t}$	Available capacity of renewable resource (k) at time (t).
$(S_i(\beta))$	Start time of activity (i) under activity list β	$\varphi_i^{-1}(\tilde{d}_i)$	Inverse uncertainty distribution of activity (i)'s duration
β	Priority list of activities used in list-based scheduling	$\varphi_i^{-1}(\beta,\alpha)$	α level inverse uncertainty bound of activity (i) under list β
β^i	Position of activity (i) in activity list β	α	Belief (confidence) level, α [0,1]
β^m	Activity preceding (i) in activity list β	(I+2)	Index of the dummy project completion activity
$p^*{}_{pres}$	Set of precedence relations induced by the resource flow network	θ	Frame of discernment in Dempster–Shafer theory
$\tilde{d}_i$	Uncertain duration of activity (i)	$\bar{A}$	Complement of set (A) in θ
(A, B)	Subsets of the frame of discernment θ	(τ,δ)	Independent positive uncertain variables

(m(A))	Basic probability assignment (mass function) of set (A)	(R^+)	Set of positive real numbers
(Bel(A))	Belief measure of set (A)	(u)	Interval representing the sum of uncertain variables
(Pl(A))	Plausibility measure of set (A)	([s], [t])	Intervals of uncertainty associated with δ and τ
(Dou(A))	Doubt the function associated with set (A)	C_{max}	Project makespan

Table 3. Project Performance and Resource Control Indices

Index Name	Abbreviation	Control Perspective	Mathematical Formulation
Schedule Performance Index	SPI	Top-down (EVM / ES)	$\text{SPI(t)} = \frac{ES}{PV}$
Planned Value at time (t)	PV_t	Top-down	$PVt = BAC * PC_i$
Earned Value at time (t)	EV_t	Top-down	$EVt = \sum_{i \in N} BAC_i * PC_i$
Schedule Variance	$SV(t)$	Top-down (EVM)	$SV(t) = \text{ES} - \text{AT}$
Earned Schedule	ES_t	Top-down	$\text{ES}_\text{t} = x + \frac{\text{EV}_\text{t} - \text{PV}_x}{\text{PV}_{\text{x}+1} - \text{PV}_\text{x}}$
Earned Duration Management	EDM	Top-down	$\text{ED} = \text{\% Complete(project in actual time)} * \text{(PD)}$
Work Content of Activity	WC_i	Resource-based	$WC_i = \sum_{k=1}^{k} r_{ik} * \hat{d}_i$
Work-Content-based SPI	SPI_wc	Resource-based (Top-down)	$\text{SPI}_\text{wc} = \frac{ES}{t}$
Earned Work Content (activity)	EWC_i	Resource-based	$EWC_\text{i} = wc_i * pc_i$
Cumulative Earned Work Content	EWC_t	Resource-based	$EWC_t = \sum_{i=1}^{n} ewc_i$
Limited schedule performance index	$SPI_{t,limit}$	feasibility bounds	$SPI_{t,limit} = \frac{ES_{min,t}}{t}$
Resource Criticality Index	RCI_i	Resource-based	$RCI_i = \frac{N_i^{critical}}{N_{sim}}$
Resource Sensitivity Index	RSSI	Resource Sensitivity	$RSSI_i = \frac{S_{di}}{S_{Cmax}} * RCI_i$

Step 1: Project Buffer Allocation Using the Schedule Reserve Ratio (SRR): In the first step, the Project Buffer (PB) is allocated between the baseline Planned Value (PV) curve and schedule flexibility using the Schedule Reserve Ratio (SRR). The SRR quantifies the relative allocation of buffer between time flexibility and planned progress and is defined by Equation (11). An SRR

value of 0 assigns the entire Project Buffer to the PV curve, whereas an SRR value of 1 allocates the buffer fully to schedule flexibility, allowing maximum temporal adjustment.

$$SRR = \frac{ashift_{abs}}{shift_{max}} = \sum_{t=1}^{PD} \left(\frac{(PV_t - PV_{t,LSS}}{(PV_t - PV_{t,shift_{max}}} \right) \tag{11}$$

Step 2: Stage-Wise Distribution of the Project Buffer. Following buffer allocation, PB is distributed across project stages based on the cumulative flexibility ratio, which reflects the accumulation of schedule flexibility up to time ttt, as defined in Equation (12). This mechanism assigns larger buffer portions to stages with higher accumulated slack.

$$\%shift_t = \left(\frac{\sum_{i=1}^{t} (PV_i - PV_{i,LSS})}{\sum_{i=1}^{PD} (PV_i - PV_{i,LSS}} \right) \tag{12}$$

Step 3: Definition of Tolerance Limits and Schedule Performance Evaluation. Project performance is evaluated using Earned Schedule–based indicators with feasibility limits. The earned schedule is defined as ES_t . A limited schedule performance index is defined as $SPI_{t,limit}$. Efficiency and Reliability indicators, defined as Equation (15) and Equation (16). These indicators distinguish on-time (OT) and late completions (Late) under the presence or absence of control signals S (Colin & Vanhoucke, 2015; Martens & Vanhoucke, 2017). Two corrective control strategies are applied: the Roadrunner (RR) policy accelerates progress, while the Railway (RW) policy stabilizes schedules (Herroelen & Leus, 2004). The project network is characterized by Serial/Parallel (SP) and Resource Constraint (RC) indicators, with higher values indicating greater serial structure and tighter resource constraints. The framework integrates Buffer Management, EVM, and Schedule Risk Analysis (SRA) to assess activity importance and project completion risk (Vanhoucke, 2012; Ballesteros-Pérez et al., 2019).

$$efficiency = \mathrm{P}[Late|S] = \frac{\mathrm{P}(S|Late) * \mathrm{P}(Late)}{\mathrm{P}(S)} \tag{13}$$

$$reliability = \mathrm{P}[OT|noS] = \frac{\mathrm{P}(noS|OT) * \mathrm{P}(OT)}{\mathrm{P}(noS)} \tag{14}$$

Step 4: (1) Determining Threshold Limits for Project Control Top-Down Approach: Threshold limits under multiple resource constraints are derived from ESS and LSS schedules. Activity work content is computed as WC_i and The earned work content is defined as $EWC_i$and the cumulative earned value at time t expressed as EWC_t , with WC_t^{LSS} & WC_t^{ESS}, respectively denoting the minimum and maximum cumulative work content bounds. (2) In the bottom-up approach. Activity-level risk is assessed using Schedule Risk Analysis (SRA) through the Resource Sensitivity Index

(RSSI), which is defined as the total project duration and jointly reflects duration variability and resource criticality (Song et al., 2022).

Step 5: Project Performance Assessment via Thresholds :(1) Top-Down Control: Project performance is assessed against threshold limits via Equation (21); deviations of cumulative earned work content ($\mathrm{EWC_t}$) show if the project is ahead, on, or behind schedule (Song et al., 2022). (2) Bottom-Up Project Control: Project performance is evaluated against threshold values of the Resource Sensitivity Analysis Index (RSSI) using Equation (22); deviations indicate if progress aligns with the plan.

$$\mathrm{EWC_t} = \begin{cases} > WC_t^{\mathrm{Ess}} & Project\ ahead\ of\ schedule \\ [\,WC_t^{\mathrm{Lss}}, WC_t^{\mathrm{Ess}}\,] & Project\ on\ schedule \\ < WC_t^{\mathrm{Lss}} & Project\ delay \end{cases} \tag{15}$$

$$\mathrm{RSSI} = \begin{cases} RSSI\ value > RSSI\ \ threshold\ value & Project\ ahead\ of\ schedule \\ RSSI\ value = RSSI\ \ threshold\ value & Project\ on\ schedule \\ RSSI\ value < RSSI\ \ threshold\ value & Project\ delay \end{cases} \tag{16}$$

Step 6: Activity Selection and Corrective: Actions. In top-down control, activities are selected based on critical chain and threshold deviations, whereas in bottom-up control, they are selected based on RSSI deviations. Corrective actions reduce remaining activity duration by allocating additional renewable resources, as shown in Equations (17) and (18). The corresponding post-disturbance resource demand is given by Equation (19). (Vanhoucke, 2011; Song et al., 2021).

$$d_j^R = \left[d_j^e * x\%\right] \tag{17}$$

$$d_j^C = d_j^e - d_j^R \tag{18}$$

$$r_{jk}^C = \left[\frac{wC_{jk}}{d_j^C}\right] \tag{19}$$

Step 7: Resource Conflict Analysis and Scenario Classification: This step examines whether a resource conflict occurs within the interval$\left[\mathrm{t}^*, \mathrm{t}^* + \mathrm{d_i^C}\right]$ following an activity failure. Activities at time t are classified into four sets, such that $C_t \cup O_t \cup S_t \cup F_t = N$.If the total resource demand within the specified time window does not exceed the available amount a_k , no resource conflict occurs in Equation (21). Three resource conflict scenarios are distinguished: No Resource Conflict (NRC), Local Resource Conflict (LRC), and Global Resource Conflict (GRC). Empirical results indicate that top-down control is more effective in sequential projects under high resource constraints (Song et al., 2022). whereas SRA performs better in parallel networks, with differences diminishing (Song et al., 2022).

$$r_{jk}^{c} + \sum_{i\varepsilon(O_t \setminus \{j\} \cup s_t)}^{k} r_{ik} \leq a_k \tag{20}$$

$$C_{max} = \bar{S}_{I+2} \tag{21}$$

$$Prob\ (S_I \leq \ \bar{S}_{I+2}) \geq \alpha \tag{22}$$

Uncertain Resource-Constrained Project Scheduling (URCPSP)

Motivation and Sources of Uncertainty

Large-scale projects are inherently exposed to multiple sources of uncertainty, including natural disasters, economic fluctuations, regulatory changes, and organizational disruptions, all of which can significantly affect project schedules and budgets. To explicitly address this variability, uncertainty-aware extensions of the Resource-Constrained Project Scheduling Problem (RCPSP), commonly known as URCPSP, have been developed. These models account for uncertainty in activity durations, resource availability, and external conditions, thereby enhancing schedule robustness and decision reliability.

Probabilistic and Evidence-Theoretic Modeling Approaches

Probabilistic and evidence-theoretic models constitute a major class of URCPSP formulations. In particular, evidence theory enables the representation of incomplete, imprecise, or conflicting information by defining belief and plausibility intervals, resulting in schedules that remain feasible under parameter fluctuations. These models are frequently combined with chance-constrained programming and advanced metaheuristics to optimize uncertain activity durations and support adaptive scheduling in response to disruptions. Additional uncertainty-handling approaches include reactive, stochastic, fuzzy, and GERT-based scheduling, as well as proactive robust scheduling and sensitivity analysis (Herroelen & Leus, 2005)

Chance-Constrained URCPSP with Reactive Scheduling

Rahman et al. (2021) proposed a chance-constrained RCPSPD model incorporating real-time reactive scheduling to address uncertainty in activity durations. The problem was solved using advanced metaheuristics, namely IGFBIS and IGFBID. The objective function minimizes the project makespan as Equation (22) and Equation (23), where $\bar{S}_{I+2}$ often interpreted as a subjective probability or fuzzy confidence level (Wang et al., 2017). The set of ongoing activities at time t is defined as $M_t = [\, i|S_i \leq t \leq \ S_i{+}d_i]$. Due to duration uncertainty, the completion time of each activity becomes a variable (Rahman et al., 2021).

Resource Flow Networks under Uncertain Durations

Artig and Roblat (2000) introduced a resource flow network to define precedence relations $p^{*}{}_{pres}$in classical RCPSP with deterministic durations. This concept was subsequently extended to uncertain environments. For uncertain activity durations, Wu et al. (2016) defined the start time of each activity i as Equation (23). This formulation remains valid under dynamic resource capacities $R_{k,t}$ and uncertain resource demands. Given that duration uncertainty follows an inverse uncertainty distribution$\varphi_i^{-1}(\tilde{d}_i)$, with $\varphi_i^{-1}(\beta,\alpha)$, α∈[0,1], the chance-constrained limit can be formulated as Equation (24). Finally, the objective function of the chance-constrained RCPSPD model is $minimize\ C_{max} = \ \varphi_{I+2}^{-1}(\beta,\alpha)$ representing the project makespan under a belief level α (Rahman et al, 2021).

$$S_i(\beta) = max_{[\beta^m < \beta^i]}\,(S_m(\beta)) \vee \ max_{(i,j)\in p^{*}{}_{pres}}\,\widetilde{F}_j(\beta) \tag{23}$$

$$\varphi_i^{-1}(\beta,\alpha) = max_{[\beta^m < \beta^i]}\left(\varphi^{-1}(\beta,\alpha)\right) \vee \ max_{(i,j)\in p^{*}{}_{pres}}\,(\varphi_j^{-1}(\beta,\alpha) + \ \varphi_j^{-1}(\alpha) \tag{24}$$

Robust, Scenario-Based, and Evidence-Theoretic URCPSP Models

Moradi et al. (2019) investigated RCPSP under simultaneous uncertainty in resource availability and activity durations, adopting a robust optimization and multi-objective framework to minimize makespan, maximize renewable resource utilization, and increase profit. Uncertainty was modeled via scenario sets, ensuring feasibility across all scenarios. Earlier, Molavi et al. (1995) introduced scenario-based modeling for uncertain durations and resources, treating the net present value (NPV) as a random variable across multiple scenarios. Gharouki et al. (2023) applied a multi-objective Dempster–Shafer (D–S) evidence theory framework to model duration uncertainty. Belief functions are defined as $Bel(A) = \sum_{B\subset A} m(B)$ with $\sum_{A\in 2^{\theta}} m(A) = 1$, $Bel(\varphi) = 0$, $Bel(\theta) = 1$, while plausibility functions are as in Equation (25), providing upper bounds for Bel(A). For two independent positive-real variables $(\sigma,\tau)\epsilon \mathrm{R}^{+}$ (Mean and variance of distribution), their sum is modeled as Equation (26), forming a theoretical foundation for URCPSP modeling (Shafer, 1976; Huynh, 2009; Choi et al., 2009; Yager, 1968).

$$PL(A) = 1 - Dou\ (\mathrm{A})\ \&\quad Pl(A) = 1 - Bel(\bar{A}) \tag{25}$$

$$m(\sigma + \tau\ \epsilon\ [u]) = \sum_{[s]+[t]=[u]} m(\sigma\ \epsilon\ [s]) * m(\tau\ \epsilon\ [t]) \tag{26}$$

Fuzzy, Stochastic, and Proactive–Reactive URCPSP Models

Salah and Moslehi (2016) proposed a multi-objective fuzzy URCPSP using triangular fuzzy numbers, with defuzzification applied to obtain crisp solutions minimizing variability and resource idle time. Lamas and Demeulemeester (2016) introduced chance-constrained RCPSP (CC-RCPSP) as a proactive approach to minimizing project duration at a specified confidence level. Other notable models include stochastic proactive RCPSP (SRCPSP) and proactive–reactive RCPSP (PR-RCPSP), which combine robust baseline schedules with real-time adjustment policies (Brucker et al., 1998; Van de Vonder et al., 2006; Leus et al., 2015). Wang et al. (2015) incorporated explicit risk preference a^0 ($\mathcal{M}\{s_n \leq \bar{s}_n\} \geq a^0$) minimizing $Min\ \Psi_n{}^{-1}(AL, a^0)$ into CC-RCPSP formulations, where uncertain durations follow inverse uncertainty distributions $\varphi_i{}^{-1}(\alpha)$ Similarly, Ki et al. (2015) developed a robust URCPSP for logistics projects with uncertain linear durations $d = \{\ \widetilde{d_1}, \widetilde{d_2}\ , \ldots\ldots, \widetilde{d_{10}}\}$, and the objective function $Min\ E[\sum_{i\epsilon n} w_i\ (s_i - s_i) + p(0, s_n - \sigma)^+]$ where p denotes a penalty for deadline violations.

Classification of Uncertainty and Research Gap

In practice, uncertainty is commonly classified as internal (organizational, resources, work content) or external (environmental, socio-political, market, and technical). Mitigation strategies include reactive, stochastic, fuzzy, sensitivity-analysis-based, and robust approaches. However, most reactive scheduling studies remain focused on machine scheduling environments, highlighting a critical gap in project-oriented URCPSP research (Hazır, 2015; Hazır & Ulusoy, 2020). Table 4 summarizes and contrasts the key characteristics of RCPSP and URCPSP under deterministic and uncertain conditions, providing a structured comparison that motivates the need for the unified analytical framework proposed in this study.

Table 4. Comparison of two models (RCPSP & URCPS)

Parametters	RCPSP Model	URCPSP Model
Capacity	Fixed and Definite	Unstable and in transition
Resource requests	Fixed and Definite	Unstable and in transition
Duration	Deterministic	Uncertain
Modeling approach	Deterministic	Uncertainty RCPSP Models
Resource breakdowns (here, disruptions)	It does not happen.	May happen due to unforeseen
Algorithm solution	Exact, meta-heuristic, heuristic, and local search	Exact, meta-heuristic, heuristic, and local search
Approach for Tracking Uncertainties	No	Yes
Rescheduling	No need	Managers have better control
Resources and Budgets	allocation	better allocation
Base Approach	RCPSP Classic Model	Uncertainty RCPSP Models
Duration–Resource Uncertainties	No	Yes
Adaptive Scheduling	No	Yes

Solution Algorithms for the Resource-Constrained RCPSP

The Resource-Constrained Project Scheduling Problem (RCPSP) can be addressed using three main categories of solution algorithms: exact, heuristic, and metaheuristic approaches (Abdolshah, 2014). These categories primarily differ in their trade-off between solution optimality and computational tractability, particularly as problem size and resource complexity increase. Exact methods aim to guarantee global optimality, but they are computationally prohibitive for large-scale or highly constrained instances. Among exact techniques, the Branch and Bound (B&B) algorithm remains the most widely adopted, as it efficiently resolves resource conflicts by combining discrete arc representations with a depth-first search strategy. Its effectiveness is further enhanced by dominance rules and tight bounding mechanisms, which significantly reduce the search space (Christofides, 1987). Other exact approaches, such as Mixed-Integer Programming (MIP) and Constraint Programming (CP), offer high modeling flexibility and expressive constraint handling; however, their practical applicability remains limited due to exponential growth in solution time as project size increases. In contrast, heuristic methods focus on generating high-quality near-optimal solutions within acceptable computational times, making them suitable for medium- to large-scale RCPSP instances. These approaches typically rely on priority-rule-based scheduling, such as Minimum Latest Finish Time (min LFT) and Longest Processing Time (LPT), implemented within either Serial Scheduling Schemes (SSS) or Parallel Scheduling Schemes (PSGS). In PSGS, activities are selected dynamically from the set of eligible activities based on priority rules, whereas in SSS, activities are first ordered according to predefined priorities and then scheduled sequentially (Van Eynde & Vanhoucke, 2022; Villafáñez et al., 2019; He et al., 2022). Random tie-breaking mechanisms are commonly incorporated to introduce stochasticity and enhance solution diversity. Heuristic frameworks are often structured around Activity Selection (AS), Resource Transfer (RT), and Transition Mode (TM) rules, which collectively determine activity sequencing, resource reallocation, and schedule evolution. Table A1 summarizes the number of existing (E) and newly proposed (N) priority rules for each heuristic category, highlighting the continued methodological development in this area (Mittal & Kanda, 2009; Lova & Tormos, 2001). Recent advances have extended classical heuristic rules to uncertainty-aware environments, as demonstrated by Liu et al. (2025), who proposed a comprehensive framework that explicitly considers the time-dependent reliability of renewable resources. To further improve performance for large-scale, highly complex RCPSP instances, hybrid optimization approaches combining heuristics and metaheuristics have attracted increasing attention. For example, the Hybrid Immune Genetic Algorithm with Local Search (HIGALS) integrates evolutionary exploration with local intensification, resulting in faster convergence and enhanced solution robustness (Farahmand-Mehr & Mousavi, 2025). Similarly, the Subpopulation Genetic Algorithm (SPGA) effectively identifies Pareto-optimal solutions for multi-objective RCPSPs by maintaining diversity across multiple subpopulations (Rezaeian et al., 2015). The Two-List Genetic Algorithm (TLGA) addresses stochastic activity durations by simultaneously managing deterministic and stochastic priority lists, enabling more adaptive scheduling decisions (Soares & Carvalho, 2020; Zhang et al., 2024). Finally, metaheuristic approaches—including Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), Ant Colony Optimization (ACO), and Neural Network-based methods—have demonstrated strong performance on complex, large-scale RCPSP variants. These methods are commonly classified into local-search-based, population-based, and learning-based algorithms, offering robust solution quality when exact methods become infeasible (Agarwal et al., 2015; Ding et al., 2023).

Results

Unified Analytical Framework Integrating RCPSP and URCPSP

This section introduces a unified analytical framework that integrates deterministic RCPSP and uncertainty-aware URCPSP models within a single multi-stage decision structure. Unlike most existing studies, which treat deterministic scheduling and uncertainty modeling as separate research streams, the proposed framework explicitly links these environments, enabling project data to transition dynamically between deterministic and uncertain settings based on disruption intensity, uncertainty propagation, and resource behavior. The framework is organized into sequential decision stages, beginning with classical RCPSP modeling under deterministic assumptions and progressively extending to URCPSP formulations when uncertainty in activity durations, resource availability, or external conditions becomes significant. This staged architecture supports both proactive planning and reactive rescheduling, thereby transforming uncertainty from a post-hoc adjustment into an integrated decision component. As a result, this study's contribution moves beyond a descriptive literature synthesis, offering instead a coherent methodological integration that bridges deterministic optimization and uncertainty-aware scheduling. Figure 3 illustrates the conceptual transition between deterministic and uncertain scheduling environments and highlights the decision logic governing this shift, including the conditions under which uncertainty-driven rescheduling is triggered.

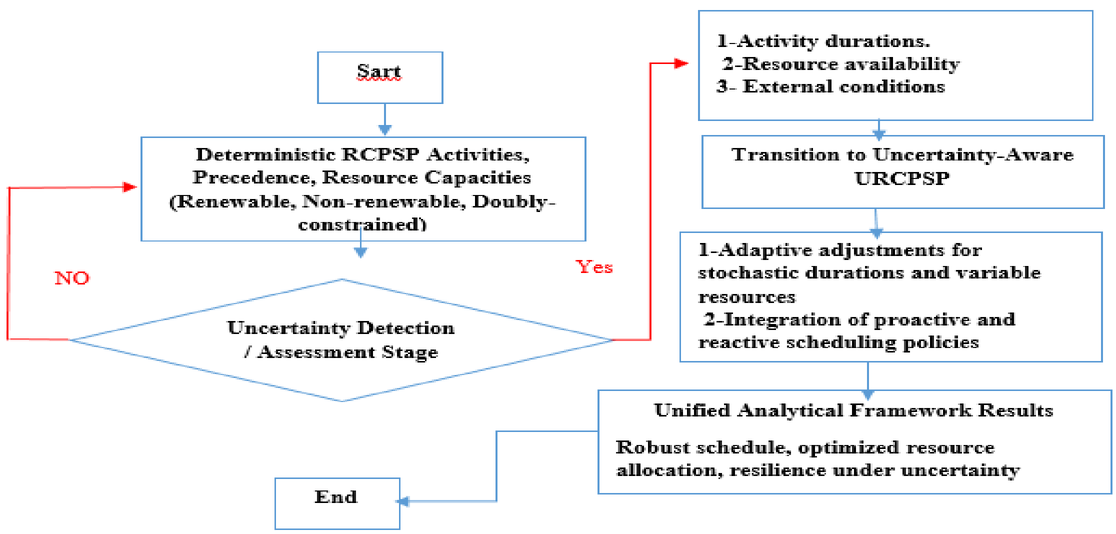

Figure 3. Unified Analytical Framework Integrating Deterministic RCPSP and Uncertainty-Aware URCPSP

Positioning with Respect to Recent Studies (2022–2025)

Table 5 provides a structured comparison between the proposed unified framework and representative studies published between 2022 and 2025. While prior research has addressed specific uncertainty sources, individual algorithmic strategies, or limited resource categories, none of these studies explicitly unify deterministic RCPSP and URCPSP environments within a single analytical structure. Moreover, existing approaches typically focus on either renewable or non-renewable resources, whereas the proposed framework accounts for renewable, non-renewable, and doubly-constrained resources simultaneously. This comprehensive integration positions the proposed framework as a methodological advancement, offering a systematic foundation for future research on hybrid deterministic–uncertain project scheduling and data-driven decision support under resource and uncertainty constraints.

Table 5. Comparative Analysis of Proposed Framework vs Recent Studies (2022–2025)

Study	Resource Types	Uncertainty Considered	Scheduling Strategy	Key Limitation
Kolisch & Drexl (1997)	Renewable	None	Deterministic RCPSP	Ignores uncertainty
Hartmann & Briskorn (2010)	Renewable	Limited	Heuristic RCPSP	No reactive mechanism
Moradi et al. (2019)	Renewable	Scenario-based duration	Robust optimization	No integration with deterministic RCPSP
Rahman et al. (2021)	Renewable, Non-renewable	Duration uncertainty	Reactive scheduling	No unified framework
Song et al. (2022)	Renewable	Disruptions	Project control heuristics	Limited resource-type coverage
Nie et al. (2023)	Renewable	Dynamic disruptions	Buffer-based control	No doubly-constrained resources
Hu et al. (2024)	Renewable, Non-renewable	Multi-source uncertainty	Metaheuristic	Deterministic–uncertain gap remains
Zhang et al. (2025)	Renewable, Doubly-constrained	Stochastic duration	Genetic algorithm	Focused on a single uncertainty type
Proposed Framework (This Study)	Renewable, Non-renewable, Doubly-constrained	Duration, resource availability, external uncertainty	Multi-stage proactive–reactive framework	Bridges deterministic RCPSP and URCPS

Developing a Comprehensive Model for the Resource-Constrained Project Scheduling Problem (RCPSP)

This section presents an integrated algorithmic structure consolidating deterministic and uncertainty-aware RCPSP models (Figure 4).

Step 1: Define the baseline model by analyzing project data, activities, precedence relations, durations, resources, and the project structure (serial or parallel). This step forms the foundation for selecting both the control strategy and the solution method for the scheduling model. Determining whether the project structure is serial or parallel helps researchers and project managers choose the appropriate control strategy.

Step 2: Identify whether the project data (start times, activity durations, processing times, resources, and scenarios) are deterministic or uncertain.

Step 3: The nature of the data determines the corresponding model type:1) Deterministic data → RCPSP or DRCPSP.2) Uncertain data → URCPSP.

Step 4: Based on the type of data and the degree of uncertainty, an appropriate model is selected:1) RCPSPD: Activities with uncertain durations (disturbance conditions).2) RO-RCPSP: Robust optimization model with uncertainty scenarios.3) DST-RCPSP: Uncertain processing times modeled via Dempster–Shafer Theory.4) SRCPSP: Stochastic proactive scheduling model. 5) PR-RCPSP: Stochastic reactive scheduling model. 6) FRCPSP: Fuzzy-based scheduling model.

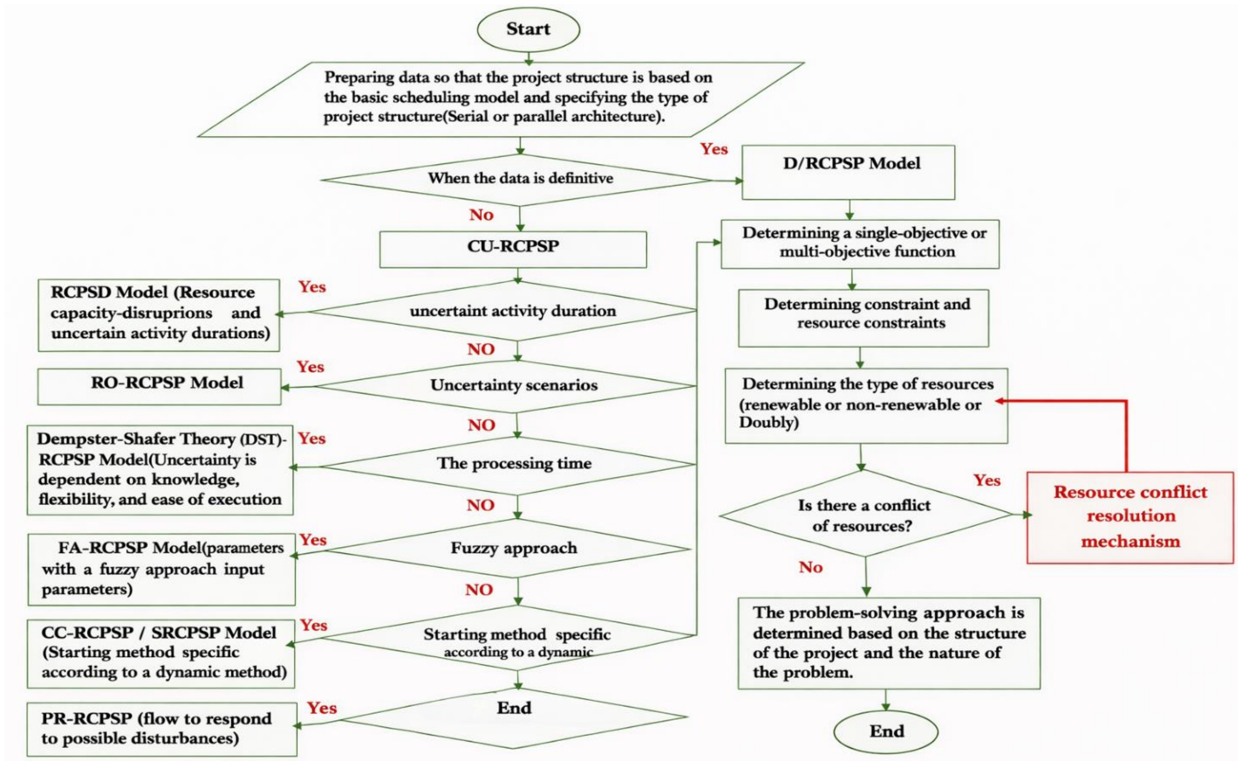

Figure 4. Comprehensive RCPSP Algorithm (No Resource Conflicts)

Step 5: Define the project constraints, distinguishing between resource-dependent and resource-independent constraints, with the primary focus on resource conflicts.

Step 6: Classify resource types, which are generally divided into three main categories:1) Renewable resources – reusable over the planning horizon (e.g., labor, equipment).2) Nonrenewable resources – consumable and not reusable (e.g., limited raw materials).3) Doubly constrained resources – limited both per period and over the total project duration (e.g., financial budgets).

Step 7: Detect resource conflicts, which play a crucial role in estimating project completion time and overall efficiency.

Step 8: Select the appropriate solution algorithm for the RCPSP. Depending on the project's structural characteristics (serial or parallel) and scheduling nature, the solution may rely on one of the following categories: 1. Exact methods, 2. Heuristic methods, 3. Metaheuristic methods, 4. Hybrid approaches.

Discussion and Conclusion

This study provides a unified analytical perspective that systematically integrates deterministic RCPSP and uncertainty-aware URCPSP within a single decision-oriented framework. Unlike prior studies that treat deterministic and uncertain scheduling environments separately (Song et al., 2022; Rahman et al., 2021), the proposed framework reveals a structural relationship between the intensity of resource conflicts and the required level of scheduling reactivity. Specifically, as resource conflicts become more frequent or severe under uncertainty, reactive and hybrid control mechanisms outperform static deterministic policies, particularly in parallel project structures (Nie et al., 2023; Hu et al., 2024). A second theoretical insight concerns the differentiated behavior of renewable and non-renewable resources under uncertainty. While renewable resources primarily induce short-term feasibility violations due to capacity fluctuations, non-renewable and doubly constrained resources generate long-term feasibility risks that cannot be mitigated solely through local rescheduling. This finding is consistent with recent robust and stochastic RCPSP studies highlighting the cumulative nature of non-renewable resource disruptions (Zhang et al., 2025; Barbalho et al., 2025). Third, the results support the development of a decision-oriented taxonomy for selecting RCPSP/URCPSP models. Deterministic RCPSP models remain effective in low-uncertainty environments with stable renewable resources, whereas robust and stochastic formulations are more suitable when uncertainty affects activity durations or transfer times (Hu et al., 2024; Zhang et al., 2025). Reactive and hybrid models become essential when uncertainty propagates dynamically across multiple resource types, as observed in recent learning-based and hybrid optimization studies (Martin et al., 2024; Geibinger et al., 2024). Overall, these findings shift the discussion from algorithm-centered comparisons toward structure-aware and resource-aware decision logic, strengthening the analytical depth of the literature and directly addressing limitations identified in recent RCPSP surveys (Van Eynde & Vanhoucke, 2022; Ballesteros-Pérez et al., 2019)

Conclusion

This paper makes three main contributions to the RCPSP and URCPSP literature. First, a unified analytical framework is proposed that explicitly links deterministic RCPSP models with uncertainty-aware extensions, allowing project scheduling decisions to evolve coherently as uncertainty intensity increases. This integration addresses a long-standing fragmentation in the literature, where deterministic and uncertain models are typically developed in isolation (Song et al., 2022; Rahman et al., 2021). Second, the study demonstrates that resource type plays a decisive role in scheduling performance under uncertainty. Renewable, non-renewable, and doubly constrained resources exhibit fundamentally different disruption patterns, requiring differentiated modeling and control strategies. Ignoring these distinctions may lead to systematically infeasible or overly optimistic schedules, particularly in large-scale or multi-project environments (Zhang et al., 2025; Barbalho et al., 2025). Third, the proposed framework provides practical guidance for project managers. Sequential project structures benefit from top-down control and proactive buffering, while parallel structures require bottom-up, reactive, or hybrid scheduling policies to effectively manage uncertainty propagation. This insight aligns with recent empirical and heuristic studies on adaptive project control (Nie et al., 2023; Martin et al., 2024).

Future Work and Limitations

The framework primarily focuses on single-project environments and assumes predefined uncertainty representations. Future research should extend this work toward multi-project settings, longer planning horizons, and data-driven uncertainty modeling, including reinforcement learning and graph neural network approaches for RCPSP under uncertainty (Geibinger et al., 2024; Zhang et al., 2025). By explicitly integrating deterministic and uncertainty-aware scheduling models, this study addresses a key methodological gap in the literature and provides structured, actionable guidance for both researchers and practitioners engaged in complex project environments. Despite these contributions, several avenues for future research remain open. In particular, future studies may focus on:

1. Integrating machine learning techniques to dynamically estimate and update RCPSP and URCPSP parameters;
2. Extending the proposed framework to longer planning horizons and large-scale project portfolios;
3. Investigating the role of critical path dynamics under uncertainty and their interaction with resource constraints;
4. Analyzing how different types of resource conflicts (local versus global) influence scheduling outcomes and control effectiveness.
5. Integrating machine learning techniques to dynamically estimate and update RCPSP and URCPSP parameters;

6. Extending the proposed framework to longer planning horizons and large-scale project portfolios;
7. Investigating the role of critical path dynamics under uncertainty and their interaction with resource constraints;
8. Analyzing how different types of resource conflicts (local versus global) influence scheduling outcomes and control effectiveness.

Data Availability Statement

Data available on request from the authors.

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The authors have witnessed the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

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References

Abdolshah, M. (2014). A review of resource-constrained project scheduling problems (RCPSP) approaches and solutions. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies*, *5*(4), 253–286. http://tuengr.com/V05/0253.pdf

Agarwal, A., Colak, S., & Erenguc, S. (2015). Metaheuristic methods. *Handbook on Project Management and Scheduling*, *1*, 57–74. https://doi.org/10.1007/978-3-319-05443-8_4

Aghileh, M., Tereso, A., Alvelos, F., & Lopes, M. O. M. (2025). Multi-Project Scheduling with Uncertainty and Resource Flexibility: A Narrative Review and Exploration of Future Landscapes. *Algorithms*, *18*(6), 314. https://doi.org/10.3390/a18060314

Baharum, Z., Venkatesan, Y. R., Raidzuan, S. N. M., & Qureshi, M. I. (2018). The development of simulation model on environmental uncertainty factors for interval project completion. *International Journal of Engineering & Technology*, *7*(2.29), 62–66. https://doi.org/10.14419/ijet.v7i2.29.13130

Bakhshi, R., Moradinia, S. F., Jani, R., & Poor, R. V. (2022). Presenting a hybrid scheme of machine learning combined with metaheuristic optimizers for predicting final cost and time of project. *KSCE Journal of Civil Engineering*, *26*(8), 3188–3203. https://doi.org/10.1007/s12205-022-1424-3

Bakry, I., Moselhi, O., & Zayed, T. (2016). Optimized scheduling and buffering of repetitive construction projects under uncertainty. *Engineering, Construction and Architectural Management*, *23*(6), 782–800. https://doi.org/10.1108/ECAM-05-2014-0069

Ballesteros-Pérez, P., Cerezo-Narváez, A., Otero-Mateo, M., Pastor-Fernández, A., & Vanhoucke, M. (2019). Performance comparison of activity sensitivity metrics in schedule risk analysis. *Automation in Construction*, *106*, 102906. https://doi.org/10.1016/j.autcon.2019.102906

Barbalho, T.J., Laredo, J.L.J. & Santos, A.C. (2025). The resource-constrained project scheduling problem for risk reduction after industrial disasters involving dangerous substances. *OR Spectrum*. https://doi.org/10.1007/s00291-025-00822-1

Brucker, P., Knust, S., Schoo, A., & Thiele, O. (1998). A branch and bound algorithm for the resource-constrained project scheduling problem. European Journal of Operational Research, 107(2), 272–288.https://doi.org/10.1016/S0377-2217(97)00335-4

Chakrabortty, R. K., Sarker, R. A., & Essam, D. L. (2016). Multi-mode resource constrained project scheduling under resource disruptions. *Computers & Chemical Engineering*, *88*, 13–29. https://doi.org/10.1016/j.compchemeng.2016.01.004

Challa, S., & Koks, D. (2004). Bayesian and Dempster-Shafer fusion. *Sadhana*, *29*, 145–174. https://doi.org/10.1007/BF02703729

Chand, S., Singh, H., & Ray, T. (2019). Evolving heuristics for the resource constrained project scheduling problem with dynamic resource disruptions. *Swarm and evolutionary computation*, *44*, 897–912. https://doi.org/10.1016/j.swevo.2018.09.007

Chao, Y., Zhuang, C., Guo, H., & Liu, J. (2026). A genetic programming hyper-heuristic with whale optimization algorithm for the dynamic resource-constrained multi-project scheduling problems. *Expert Systems with Applications*, *295*, 128881. https://doi.org/10.1016/j.eswa.2025.128881

Chen, S. M., Chen, P. H., & Chang, L. M. (2013). A framework for an automated and integrated project scheduling and management system. Automation in Construction, 35, 89–110. https://doi.org/10.1016/j.autcon.2013.04.002

Cheng, J. R., & Gen, M. (2019). Accelerating genetic algorithms with GPU computing: A selective overview. *Computers & Industrial Engineering*, *128*, 514–525. https://doi.org/10.1016/j.cie.2018.12.067

Choi, H., Katake, A., Choi, S., Kang, Y., & Choe, Y. (2009). Probabilistic combination of multiple evidence. In *Neural Information Processing: 16th International Conference, ICONIP 2009, Bangkok, Thailand, December 1-5, 2009, Proceedings, Part I 16* (pp. 302–311). Springer Berlin Heidelberg.. https://doi.org/10.1007/978-3-642-10677-4_34

Chou, J. S., & Yang, J. G. (2012). Project management knowledge and effects on construction project outcomes: An empirical study. *Project Management Journal*, *43*(5), 47–67. https://doi.org/10.1002/pmj.21293

Colin, J., & Vanhoucke, M. (2015). A comparison of the performance of various project control methods using earned value management systems. *Expert Systems with Applications*, 42, 3159–3175. https://doi.org/10.1016/j.eswa.2014.12.007

Davis, K. R., Stam, A., & Grzybowski, R. A. (1992). Resource constrained project scheduling with multiple objectives: A decision support approach. *Computers & operations research*, *19*(7), 657–669. https://doi.org/10.1016/0305-0548(92)90035-4

Demeulemeester, E., & Herroelen, W. (2010). Robust project scheduling. Foundations and Trends® in Technology, Information and Operations Management, 3(3–4), 201–376.http://dx.doi.org/10.1561/0200000021

Ding, H., Zhuang, C., & Liu, J. (2023). Extensions of the resource-constrained project scheduling problem. *Automation in Construction*, *153*, 104958. https://doi.org/10.1016/j.autcon.2023.104958

Farahmand-Mehr, M., & Mousavi, S. M. (2025). Resource-constrained multi-project scheduling problems considering time-dependent reliability of resources: a new immune genetic local search algorithm. *Kybernetes*. https://doi.org/10.1108/K-04-2024-0895

Geibinger, T., Mischek, F. & Musliu, N. (2024). Investigating constraint programming and hybrid methods for real-world industrial test laboratory scheduling. *J Sched* **27**, 607–622 https://doi.org/10.1007/s10951-024-00821-0

Ghoroqi, M., Ghoddousi, P., Makui, A., Shirzadi Javid, A. A., & Talebi, S. (2023). An integrated model for multi-mode resource-constrained multi-project scheduling problems considering supply management with sustainable approach in the construction industry under uncertainty using evidence theory and optimization algorithms. *Buildings*, 13(8), 2023. https://doi.org/10.3390/buildings13082023

H. Nübel. (2001). The resource renting problem subject to temporal constraints, *OR Spectr*. 23 359–381.https://doi.org/10.1007/PL00013357.

Han, S. H., Yun, S., Kim, H., Kwak, Y. H., Park, H. K., & Lee, S. H. (2009). Analyzing schedule delay of mega project: Lessons learned from Korea train express. *IEEE Transactions on Engineering Management*, 56(2), 243–256.https://doi.org/10.1109/TEM.2009.2016042

Hazır, Ö. (2015). A review of analytical models, approaches and decision support tools in project monitoring and control. *International Journal of Project Management*, *33*(4), 808–815. https://doi.org/10.1016/j.ijproman.2014.09.005

Hazır, Ö., & Ulusoy, G. (2020). A classification and review of approaches and methods for modeling uncertainty in projects. *International Journal of Production Economics*, *223*, 107522. https://doi.org/10.1016/j.ijpe.2019.107522

He, N., Zhang, D. Z., & Yuce, B. (2022). Integrated multi-project planning and scheduling-a multiagent approach. *European Journal of Operational Research*, *302*(2), 688-699. https://doi.org/10.1016/j.ejor.2022.01.018

Herroelen, W., & Leus, R. (2004). The construction of stable project baseline schedules. *European journal of operational research*, *156*(3), 550–565. https://doi.org/10.1016/S0377-2217(03)00130-9

Herroelen, W., & Leus, R. (2005). Project scheduling under uncertainty: Survey and research potentials. *European Journal of Operational Research*, *165*(2), 289–306. https://doi.org/10.1016/j.ejor.2004.04.002

Huynh, V. N. (2009, November). Discounting and combination scheme in evidence theory for dealing with conflict in information fusion. In *International Conference on Modeling Decisions for Artificial Intelligence*. 217–230. https://doi.org/10.1007/978-3-642-04820-3_20

Jin, S. (2024). Measuring complexity in mega construction projects: fuzzy comprehensive evaluation and grey relational analysis. *Engineering, Construction, and Architectural Management*. https://doi.org/10.1108/ecam-07-2024-0951

Kannimuthu, M., Ekambaram, P., Raphael, B., & Kuppuswamy, A. (2018). Resource unconstrained and constrained project scheduling problems and practices in a multiproject environment. *Advances in Civil Engineering*, *1*, 9579273. https://doi.org/10.1155/2018/9579273

Ke, H., Wang, L., & Huang, H. (2015). An uncertain model for RCPSP with solution robustness focusing on logistics project schedule. *International Journal of e-Navigation and Maritime Economy*, *3*, 71–83. https://doi.org/10.1016/j.enavi.2015.12.007

Khamooshi, H., & Golafshani, H. (2014). EDM: Earned Duration Management, a new approach to schedule performance management and measurement. *International Journal of Project Management*, *32*(6), 1019–1041. https://doi.org/10.1016/j.ijproman.2013.11.002

Lamas, P., & Demeulemeester, E. (2016). A purely proactive scheduling procedure for the resource-constrained project scheduling problem with stochastic activity durations. *Journal of Scheduling*, *19*, 409–428. https://doi.org/10.1007/s10951-015-0423-3

Leus, R., Rostami, S., & Creemers, S. (2015, December). New benchmark results for the stochastic resource-constrained project scheduling problem. In 2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM). 204–208. IEEE. https://doi.org/10.1109/IEEM.2015.7385637

Li, H., & Demeulemeester, E. (2016). A genetic algorithm for the robust resource leveling problem. *Journal of Scheduling*, *19*, 43–60. https://doi.org/10.1007/s10951-015-0457-6

Li, H., Xu, Z., & Demeulemeester, E. (2015). Scheduling policies for the stochastic resource leveling problem. *Journal of Construction Engineering and Management*, *141*(2), 04014072. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000936

Liu, W., Zhang, J., Vanhoucke, M., & Guo, W. (2025). Resource allocation models and heuristics for the multi-project scheduling with global resource transfers and local resource constraints. *Computers & Industrial Engineering*, *200*, 110843. https://doi.org/10.1016/j.cie.2024.110843

Liu, Z., & Wang, H. (2006). Heuristic algorithm for RCPSP with the objective of minimizing activities' cost. *Journal of Systems Engineering and Electronics*, *17*(1), 96–102. https://doi.org/10.1016/S1004-4132(06)60018-2

Lova, A., & Tormos, P. (2001). Analysis of scheduling schemes and heuristic rules performance in resource-constrained multiproject scheduling. *Annals of Operations Research*, *102*, 263–286. http://dx.doi.org/10.1023/A:1010966401888

Ma, W., Che, Y., Huang, H., & Ke, H. (2016). Resource-constrained project scheduling problem with uncertain durations and renewable resources. *International journal of machine learning and cybernetics*, *7*, 613–621. https://doi.org/10.1007/s13042-015-0444-4

Martens, A., & Vanhoucke, M. (2017). A buffer control method for top-down project control. *European Journal of Operational Research*, 262(1), 274–286. https://doi.org/10.1016/j.ejor.2017.03.034

Martens, A., & Vanhoucke, M. (2017). The integration of constrained resources into top-down project control. *Computers & Industrial Engineering*, *110*, 277–288. https://doi.org/10.1016/j.cie.2017.05.020

Martin, X. A., Herrero, R., Juan, A. A., & Panadero, J. (2024). An Agile Adaptive Biased-Randomized Discrete-Event Heuristic for the Resource-Constrained Project Scheduling Problem. *Mathematics*, *12*(12), 1873. https://doi.org/10.3390/math12121873

Mittal, M. L., & Kanda, A. (2009). Scheduling of multiple projects with resource transfers. *International Journal of Mathematics in Operational Research*, *1*(3), 303–325. http://dx.doi.org/10.1504/IJMOR.2009.024288.

Moradi, M., Hafezalkotob, A., & Ghezavati, V. (2019). Robust resource-constrained project scheduling problem of the project's subcontractors in a cooperative environment under uncertainty: Social complex construction case study. *Computers & Industrial Engineering*, *133*, 19–28. https://doi.org/10.1016/j.cie.2019.04.046

Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations Research*, *43*(2), 264–281. https://doi.org/10.1287/opre.43.2.264

Nassreddine, G., Abdallah, F., & Denoux, T. (2009). State estimation using interval analysis and belief-function theory: application to dynamic vehicle localization. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *40*(5), 1205–1218. https://doi.org/ 10.1109/TSMCB.2009.2035707

Nie, X., Li, M., Lu, J., & Wang, B. (2023). Research on Buffer Calculation Model of Critical Chain Based on Adjacency Information Entropy. *Buildings*, *13*(4), 942. https://doi.org/10.3390/buildings13040942

Nonobe, K., Ibaraki, T. (2002). Formulation and Tabu Search Algorithm for the Resource Constrained Project Scheduling Problem. In: Essays and Surveys in Metaheuristics. *Operations Research/Computer Science Interfaces Series Springer Boston MA*, 15. https://doi.org/10.1007/978-1-4615-1507-4_25

Nudtasomboon, N., & Randhawa, S. U. (1997). Resource-constrained project scheduling with renewable and non-renewable resources and time-resource tradeoffs. *Computers & Industrial Engineering*, *32*(1), 227–242. https://doi.org/10.1016/S0360-8352(96)00212-4

Ock, J. H., & Han, S. H. (2010). Measuring risk-associated activity's duration: A fuzzy set theory application. *KSCE Journal of Civil Engineering*, *14*(5), 663-671. https://doi.org/10.1007/s12205-010-1003-x

Pritsker, A. A. B., Waiters, L. J., & Wolfe, P. M. (1969). Multiproject scheduling with limited resources: A zero-one programming approach. *Management science*, *16*(1), 93–108. https://doi.org/10.1287/mnsc.16.1.93

Qiu, K., Chen, L., & Dauzère-Pérès, S. (2025). Robust optimization approach for the resource-constrained project scheduling problem with uncertain activity release times. *Computers & Operations Research*, 107215. https://doi.org/10.1016/j.cor.2025.107215

Rahman, M. H. F., Chakrabortty, R. K., & Ryan, M. J. (2021). Managing uncertainty and disruptions in resource constrained project scheduling problems: A real-time reactive approach. *IEEE Access*, *9*, 45562–45586. https://doi.org/ 10.1109/ACCESS.2021.3063766

Rezaeian, J., Soleimani, F., Mohaselafshary, S., & Arab, A. (2015). Using a meta-heuristic algorithm for solving the multi-mode resource-constrained project scheduling problem. *International Journal of Operational Research*, *24*(1), 1–16. https://doi.org/10.1504/IJOR.2015.070859

RezaHoseini, A., Noori, S., & Ghannadpour, S. F. (2021). Integrated scheduling of suppliers and multi-project activities for green construction supply chains under uncertainty. *Automation in Construction*, *122*, 103485. https://doi.org/10.1016/j.autcon.2020.103485

Rodrigues, S. B., & Yamashita, D. S. (2010). An exact algorithm for minimizing resource availability costs in project scheduling. *European Journal of Operational Research*, *206*(3), 562–568. https://doi.org/10.1016/j.ejor.2010.03.008

Sadeghloo, M., Emami, S., & Divsalar, A. (2024). A Benders decomposition algorithm for the multi-mode resource-constrained multi-project scheduling problem with uncertainty. *Annals of Operations Research*, *339*(3), 1637–1677. https://doi.org/10.1007/s10479-023-05403-5

Salah, A., & Moselhi, O. (2016). Risk identification and assessment for engineering procurement construction management projects using fuzzy set theory. *Canadian Journal of Civil Engineering*, *43*(5), 429–442. https://doi.org/10.1139/cjce-2015-0154

Salama, T., & Moselhi, O. (2019). Multi-objective optimization for repetitive scheduling under uncertainty. *Engineering, Construction and Architectural Management*, *26*(7), 1294–1320. https://doi.org/10.1108/ECAM-05-2018-0217

Salvadori, I., Agnetis, A. (2025). The impact of the number of preemptions in resource-constrained project scheduling problems with time-varying resources: computational experiments and a case study. *Ann Oper Res*. https://doi.org/10.1007/s10479-025-06892-2

Schutt, A., Chu, G., Stuckey, P. J., & Wallace, M. G. (2012). Maximising the net present value for resource-constrained project scheduling. In *International conference on integration of artificial intelligence (AI) and Operations research (OR) techniques in constraint programming* , Berlin, Heidelberg: Springer Berlin Heidelberg. 362–378. https://doi.org/10.1007/978-3-642-29828-8_24

Shafer, G. (1976). A mathematical theory of evidence. *Princeton University Press.* 42. https://doi.org/10.2307/j.ctv10vm1qb

Shrivastava, A., & Pandey, M. (2024). Integrating quality in resource-constrained time-cost trade-off optimization for civil construction projects using NSGA-III technique. *Asian Journal of Civil Engineering*, *25*(6), 4619–4632. https://doi.org/10.1007/s42107-024-01068-y

Soares, L. C. R., & Carvalho, M. A. M. (2020). Biased random-key genetic algorithm for scheduling identical parallel machines with tooling constraints. *European Journal of Operational Research*, *285*(3), 955–964.https://doi.org/10.1016/j.ejor.2020.02.047

Song, J., Martens, A., & Vanhoucke, M. (2021). Using schedule risk analysis with resource constraints for project control. *European Journal of Operational Research, 288*, 736–752. https://doi.org/10.1016/j.ejor.2020.06.015

Song, J., Martens, A., & Vanhoucke, M. (2022). Using Earned Value Management and Schedule Risk Analysis with resource constraints for project control. *European Journal of Operational Research*, *297*(2), 451–466. https://doi.org/10.1016/j.ejor.2021.05.036

Tirkolaee, E. B., Goli, A., Hematian, M., Sangaiah, A. K., & Han, T. (2019). Multi-objective multi-mode resource constrained project scheduling problem using Pareto-based algorithms. *Computing*, *101*, 547-570. https://doi.org/10.1007/s00607-018-00693-1

Van de Vonder, S., Demeulemeester, E., Leus, R., & Herroelen, W. (2006). Proactive-reactive project scheduling trade-offs and procedures. Perspectives in modern project scheduling, 25–51. https://doi.org/10.1007/978-0-387-33768-5_2

Van Eynde, R., & Vanhoucke, M. (2020). Resource-constrained multi-project scheduling: benchmark datasets and decoupled scheduling. *Journal of Scheduling, 23,* 301–325. http://dx.doi.org/10.1007/s10951-020-00651-w

Van Eynde, R., & Vanhoucke, M. (2022). New summary measures and datasets for the multi-project scheduling problem. *European Journal of Operational Research*, 299(3),853–868. http://dx.doi.org/10.1016/j.ejor.2021.10.006

Vandenheede, L., Vanhoucke, M., & Maenhout, B. (2016). A scatter search for the extended resource renting problem. *International Journal of Production Research*, *54*(16), 4723-4743. https://doi.org/10.1080/00207543.2015.1064177

Vanhoucke, M. (2011). On the dynamic use of project performance and schedule risk information during project tracking. *Omega The International Journal of Management Science*, 39, 416–42. https://doi.org/10.1016/j.omega.2010.09.006

Vanhoucke, M. (2012). Measuring the efficiency of project control using fictitious and empirical project data. *International journal of project management*, *30*(2), 252–263. https://doi.org/10.1016/j.ijproman.2011.05.006

Vanhoucke, M. , & Batselier, J. (2019). A statistical method for estimating activity uncertainty parameters to improve project forecasting. *Entropy*, 21(10), 952. https://doi.org/10.3390/e21100952

Villafáñez, F., Poza, D., López-Paredes, A., Pajares, J., & Olmo, R. D. (2019). A generic heuristic for multi-project scheduling problems with global and local resource constraints (RCMPSP). *Soft Computing*, *23*(10), 3465–3479. https://doi.org/10.1007/s00500-017-3003-y

Wang, H., Wang, W., Sun, H., Cui, Z., Rahnamayan, S., & Zeng, S. (2017). A new cuckoo search algorithm with hybrid strategies for flow shop scheduling problems. *Soft Computing*, *21*, 4297–4307 .https://doi.org/1 0.1007/s00500-016-2062-9

Wang, L., Huang, H., & Ke, H. (2015). Chance-constrained model for RCPSP with uncertain durations. *Journal of uncertainty analysis and applications*, *3*, 1–10. https://doi.org/10.1186/s40467-015-0034-8

Wang, Y., Xu, D., Zhou, L., & Li, Z. (2025). Standard Revision Project Scheduling Problem Considering Coordination Degree of Standards Systems. *Systems*, *13*(8), 685. https://doi.org/10.3390/systems13080685

Wen, M., Lin, J., Qian, Y., & Huang, W. (2021). Scheduling interrelated activities in complex projects under high-order rework: A DSM-based approach. *Computers & Operations Research*, *130*, 105246. https://doi.org/10.1016/j.cor.2021.105246

Wiesemann, W., Kuhn, D., & Rustem, B. (2010). Maximizing the net present value of a project under uncertainty. *European Journal of Operational Research*, *202*(2), 356–367. https://doi.org/10.1016/j.ejor.2009.05.045

Yager, R. R. (1986). Arithmetic and other operations on Dempster-Shafer structures. *International Journal of Man-Machine Studies*, *25*(4), 357–366. https://doi.org/10.1016/S0020-7373(86)80066-9

Zaman, F., Elsayed, S. M., Saker, R., & Essam, D. (2020). Resource constrained project scheduling with dynamic disruption recovery. *IEEE Access*, *8*, 144866–144879.https://doi.org/10.1109/ACCESS.2020.3014940

Zhang, L., Zhou, L., Yao, Z., & Li, Y. (2024). Reactive scheduling for repetitive projects based on integrated crew interruption and soft logic strategies. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2024.3394852

Zhang, Y., Chang, R., Omrany, H., Zuo, J., Burry, J., & Gu, N. (2025). Policy-gradient scheduling optimisation under multi-skill constraints: A comparative study on computational algorithms. *Journal of Building Design and Environment*, *3*(3), 202571–202571. http://dx.doi.org/10.70401/jbde.2025.0017

Zhang, Y., Li, X., Teng, Y., Bai, S., & Chen, Z. (2024). Two-list genetic algorithm for optimizing work package schemes to minimize project costs. *Automation in Construction*, *165*, 105595. https://doi.org/10.1016/j.autcon.2024.105595