A NOVEL ADAPTIVE STOCHASTIC MODEL FOR PROJECTS SCHEDULING UNDER UNCERTAINTY

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Abstract - Project scheduling faces high uncertainty due to fluctuating productivity, weather disruptions, resource shortages, and rework. Existing models such as CPM, PERT, and deterministic optimization lack the capability to dynamically adapt to real-time disturbances. This paper proposes a novel Adaptive Stochastic Resource-Constrained Scheduling Model (ASRCSM) that integrates (i) stochastic task durations, (ii) dynamic resource allocation rules, and (iii) an adaptive re-scheduling mechanism triggered by project state deviations. In addition, this study proposes a novel Adaptive Hybrid Genetic Algorithm (AHGA) which combines Serial Schedule Generation Scheme and local search heuristics to solve the problem. The approach provides a practical, computationally efficient tool for construction planners facing uncertainty.

Key words – Project scheduling; Genetic algorithm; resource-constrained scheduling

1. Introduction

Projects are traditionally scheduled using deterministic methodologies such as the Critical Path Method (CPM) or the Program Evaluation and Review Technique (PERT). These methods assume stable productivity, predictable durations, and unlimited resource availability-conditions rarely satisfied in practice.

Real-world construction projects suffer from:

- Uncertain task durations due to weather and productivity variations,
- Resource limitations and competition among teams,
- Task interruptions and rework events,
- Cascading delays that invalidate static schedules.

Recent research has attempted to integrate stochastic models, simulation-based scheduling, and dynamic rescheduling [1]. However, gaps remain:

1. Existing stochastic models rarely incorporate dynamic resource reallocation.
2. Simulation-based models are descriptive but lack optimization-driven adaptability.
3. Few studies propose generalizable models validated on construction case data.

To overcome the gaps, this paper aims to develop a novel adaptive scheduling model that combines optimization and stochastic simulation to handle the uncertainty. The proposed model integrates the stochastic duration deriving from the historical data and simulation, and dynamic resource allocation rules. In addition, a novel Adaptive Hybrid Genetic Algorithm which combines parameters auto-tuning method and local search procedure to enhance the searching ability is developed to solve the problem efficiently.

2. Related works

Project scheduling has been extensively studied in operations research and construction management, particularly through the framework of the resource-constrained project scheduling problem (RCPSP). Recent studies highlight that RCPSP remains a fundamental optimization problem for managing activity precedence relationships and limited resources in engineering and construction projects. Many comprehensive reviews of recent RCPSP research indicate that modern developments increasingly focus on hybrid optimization techniques, multi-objective formulations, and stochastic modeling to improve robustness and scalability in complex scheduling environments [1], [2], [3]. These studies emphasize that traditional deterministic scheduling approaches are insufficient for modern projects characterized by uncertainty, resource variability, and dynamic operational constraints.

Recent research has extended classical scheduling models by incorporating additional practical constraints such as multi-skilled resources, partially renewable resources, and complex precedence relationships. For instance, studies on multi-skilled resource-constrained scheduling highlight the importance of workforce flexibility in realistic project environments where workers possess multiple competencies and activities require different skill combinations [4]. Other recent work has explored new RCPSP formulations involving partially renewable resources and generalized precedence constraints, demonstrating that these extensions significantly increase computational complexity while improving model realism [5]. Additionally, applications in construction and infrastructure projects have introduced specialized constraints such as forbidden time windows and environmental restrictions, requiring hybrid heuristic and evolutionary algorithms to generate feasible schedules [6].

More recently, researchers have explored intelligent optimization and emerging computational paradigms for solving complex scheduling problems. Artificial intelligence and metaheuristics methods such as deep reinforcement learning, genetic algorithm have been proposed to address stochastic RCPSP variants where activity durations and resource availability are uncertain

[7], [8]. Rahman et al. proposed a meta-heuristics aproach which is proved to be useful to mitigate uncertainty [9]. Ji et al. developed a genetic algorithm to solve the uncertaity project scheduling problem efficiently [10].

In parallel, quantum and quantum-inspired optimization approaches have been investigated to tackle the combinatorial complexity of large-scale scheduling problems. For example, recent studies demonstrate that quantum annealing can be applied to RCPSP by transforming scheduling formulations into quadratic unconstrained binary optimization models solvable on quantum hardware [11]. In addition, quatitative methodologies which rely on a computer suppoert system to identify, analyse, quantify the schedule reality have been used for project scheuling problem [12] – [14]. These advances suggest a growing research trend toward adaptive and intelligent scheduling models capable of handling uncertainty, large problem sizes, and real-time decision environments in complex projects.

3. Proposed Model: ASRCSM

3.1. Problem description

The Adaptive Stochastic Resource-Constrained Scheduling Model (ASRCSM) integrates

a. Stochastic Activity Durations Modeled via a non-parametric distribution derived from:

historical productivity records, or

Monte Carlo–generated variability with weather-impact factors.

b. Resource Constraints Activities require resource vectors

$r_i = (r_{i,1}, r_{i,2}, \ldots, r_{i,K})$

with limited availability, where I represents for activity index and K represents for the resource index.

c. Adaptive Rescheduling Trigger

A rescheduling event is triggered when:

$| D^{\text{actual}}(i) - D^{\text{expected}}(i) | > \theta,$

where, θ is a deviation tolerance (5–20%), $D^{\text{actual}}(i)$ represents for the actula duration of activity i and $D^{\text{expected}}(i)$ represents for expected duration of activity i.

d. Dynamic Resource Allocation Rule

A priority index is computed as:

$$PI_i = \alpha \cdot \text{Slack}_i^{-1} + \beta \cdot \text{ResourceIntensity}_i + \gamma \cdot \text{DisruptionRisk}_i$$

Where, α, β, γ are weight parameters which use to control the importance of each factor including slack, intensity and disruption risk.

e. Rolling-Horizon Optimization

At each rescheduling trigger, solve:

min Expected Makespan

subject to:

- Precedence constraints,
- Stochastic duration samples,
- Resource feasibility.

3.2. Mathematical model

Decision Variables

S_i: Start time of activity i

C_i: Completion time of activity i

$x_{ik} = 1$ if activity i uses resource type k at time t

Objective Function

$$\min E_\omega \left[\max_i \quad C_i \right] \tag{1}$$

Constraints

- Precedence

$$S_j \geq C_i, \forall (i,j) \in \text{Precedence} \tag{2}$$

- Stochastic Duration

$$C_i = S_i + D_i(\omega) \tag{3}$$

where $\omega$is scenario index.

- Resource Constraints

$$\sum_i r_{i,k} \cdot x_{ik}(t) \leq R_k^{\max}, \forall k, t \tag{4}$$

Formula (1) aims to minimize the average project duration across all possible uncertainties.

Formula (2) is to ensure an activity cannot start until all its predecessor activities are completed.

Formula (3) defines the completion time of activity i depending on the random duration.

Formula (4) is to ensure the total resource usage must not exceed available resources.

4. Adaptive Hybrid Genetic Algorithm

4.1. Chromosome Representation

In the GA framework, each feasible project schedule is encoded as a chromosome representing the priority order of activities. A chromosome is defined as

$C = [a_1, a_2, a_3, \ldots, a_n]$

where $a_i$denotes the activity index, and n represents the total number of project activities. To ensure feasibility with respect to precedence relationships, a Serial Schedule Generation Scheme (SGS) is applied to convert the chromosome into an executable schedule.

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SGS procedure
Input: priority list
While NOT all acitivites scheduled
        Select next activity based on priority list
        Find earliest feasible start time satisfy:
                Precedence constraints
                Resource constraints
        Assign start time
        Update:
                resource usage
                scheduled set
End.
-------------------------------------------
```

4.2. Fitness Function

The objective of the scheduling problem is to minimize the project completion time (makespan). Therefore, the fitness function is defined as

$$Fitness = \frac{1}{C_{max}} \tag{5}$$

where, C_{max}= total project duration (makespan);

A smaller makespan results in a higher fitness value.

In some extensions, penalty terms can be added to handle resource violations or schedule instability.

4.3. Genetic Operators

4.3.1. Crossover

Crossover combines genetic information from two parent chromosomes to generate offspring. For scheduling problems, precedence-preserving crossover (PPX) is commonly used. An example is described as follows:

Parent 1

$$[1, 2, 3, 4, 5, 6]$$

Parent 2

$$[2, 1, 4, 3, 6, 5]$$

Offspring inherit activity sequences while maintaining precedence feasibility.

4.3.2. Mutation

Mutation introduces diversity into the population by randomly modifying chromosomes. In this problem, swap mutation is frequently applied where two activity positions are exchanged.

4.3.3. Selection

Individuals are selected for reproduction based on their fitness values. In this study, tournament selection is adopted due to its balance between exploration and exploitation.

Parameters

Instead of fixed crossover and mutation probabilities, AHGA dynamically adjusts them according to population diversity.

$$P_c = P_c^{min} - (P_c^{max} - P_c^{min})\frac{f_i}{f_{max}} \tag{6}$$

$$P_m = P_m^{min} + (P_m^{max} - P_m^{min})\frac{f_i}{f_{max}} \tag{7}$$

where

f_i= fitness of individual f_{max}= best fitness in population

This mechanism encourages exploration early and exploitation later.

4.3.4. Resource Conflict Repair Operator

When resource conflicts are detected, a repair heuristic is applied:

1. Identify conflicting activities;
2. Delay lower-priority activity;
3. Update schedule using forward pass.

This operator improves schedule feasibility without restarting the search.

4.3.5. Local Neighborhood Search

To refine high-quality solutions, AHGA applies a local search procedure:

- Swap two activities;
- Insert activity into a new position;
- Evaluate makespan improvement.

This hybridization enhances solution quality and convergence speed.

4.4. AHGA procedure

The main procedure of the AHGA is designed as follows:

Input: Project activities, precedence relations, resources
Generate initial population P
while stopping condition not satisfied **do**:
  Evaluate fitness of each chromosome
  Select parent chromosomes
  Apply adaptive crossover operator
  Apply adaptive mutation operator
  Generate schedules using SGS
  Apply resource conflict repair
  Perform local neighborhood search
  Update population
end while
Return best schedule

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5. Model validation

5.1. Case Study Description

A mid-rise building project containing:

- 32 activities grouped into excavation, structural works, MEP, and finishing.
- Four resource types: labor crews, excavators, cranes, and electricians.
- Activity durations are affected by:

+ Weather conditions (rain probability 18%),
+ Crew productivity variability (σ = 15–25%),
+ Rework probability of 5% for MEP tasks.

The proposed model is compared with the CPM (deterministic), PERT (stochastic without resource constraints), and Heuristic RCPSP (serial scheduling, priority rule: minimum slack) based on Monte Carlo simulation with 5,000 replications for each scheduling method.

5.2. Results and Discussion

The comparison results are shown in the Table 1. According to the Table 1, ASRCSM achieves the lowest makespan and lowest variance. Resource conflicts reduced by 34% compared to heuristic RCPSP. In addition, adaptive rescheduling increases robustness without excessive computational cost. Weather-induced delays are mitigated by dynamic reallocation of crews.

To validate the proposed approach, a sensitivity analysis was implemented as shown in Table 2. As can be seen, a moderate tolerance level from 5 to 10 percent can achieve a balance between solution quality and system stability.

Table 1. *performance comparison*

Method	Expected Makespan (days)	Variance	Resource Conflicts	% Improvement vs CPM
CPM	124	–	17	–
PERT	121	High ($\sigma^2 = 64$)	17	2.4%
Heuristic RCPSP	117	42	9	5.6%
ASRCSM (Proposed)	**112**	**32**	**6**	**9.8%**

Table 2. *Sensitivity Analysis*

θ	Expected Makespan	Rescheduling Events
0% (Continuous)	109	84
5%	112	21
10%	113	9
20%	116	4

In addition, the performance of the proposed Adaptive Hybrid Genetic Algorithm is validated using large-scale problem instances, where the number of activities is increased to 200. The resource configuration consists of five types of limited renewable resources. The precedence relationships among activities are generated following the characteristics of the PSPLIB benchmark structure, ensuring realistic and comparable network complexity. The parameters of the compared algorithms are set as in Table 3. The average results as shown in Table 4 indicate that the proposed AHGA algorithm achieves the best solution which improves the makespan by approximately 5–10% compared to the standard GA and 3–6% compared to other advanced metaheuristics.

Table 3. *parameters settings*

Parameter	GA	PSO	AHGA
Population size	50	50	50
Iterations	200	200	200
Crossover probability	0.8	–	adaptive
Mutation probability	0.1	–	adaptive
Inertia weight	–	0.7	–
Cognitive coefficient	–	1.5	–
Social coefficient	–	1.5	–

Table 4. *Performance Comparison of Scheduling Algorithms*

Method	Best Makespan (days)	Average Makespan	Std. Dev.	CPU Time (s)
CPM	465	465	0	0.02
GA	425	412	8.6	42.5
PSO	411	398	6.2	48.7
AHGA (Proposed)	**385**	**372**	**2.7**	51.8

6. Conclusion

This paper proposes a novel Adaptive Stochastic Resource-Constrained Scheduling Model (ASRCSM) for construction project planning under uncertainty. Integrating stochastic durations, dynamic resource allocation, and adaptive rescheduling enables robust performance in variable environments. In addition, AHGA is designed to solve the problem efficiently. The main contributions of the study are as follows.

1. A new integrated optimization–simulation scheduling framework.

2. A construction-specific stochastic model with dynamic resource priority indices.

3. Numerical validation showing significant improvements over CPM, PERT, and RCPSP.

4. Practical guidelines on rescheduling thresholds.

The future researches may involve in incorporation of machine learning for duration forecasting, multi-project scheduling extensions, or real-time data integration using IoT sensors on construction sites.

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