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Review Article

Time-Cost-Risk Trade-off in Construction - A Multi-Objective Optimization Approach

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ABSTRACT

This study explores a multi-objective optimization approach to the Time-Cost-Risk (TCR) trade-off in construction projects, aiming to improve decision-making and project outcomes. The methodology centers on applying advanced optimization algorithms to simultaneously manage the often-conflicting objectives of time, cost, and risk. Through a detailed analysis of various algorithmic approaches, including comparisons of their performance and applicability, this paper demonstrates how these tools can aid in identifying the solutions, where no objective can be improved without compromising another. Case studies from the construction industry illustrate the practical implications of these algorithms, showing how TCR optimization can support more balanced and resilient project planning. This work aims to advance the understanding of multi objective optimization algorithms that approach TCR trade-off, providing a foundation for ongoing improvements in construction project management.

1. Introduction

Construction is a comprehensive process that transforms architectural design into physical structure through systematic planning, engineering, and building activities. The process encompasses critical stages, such as site preparation, foundation work, structural assembly, and finishing touches, each requiring specialized expertise and precise execution. Construction management orchestrates these operations by coordinating all aspects from initial planning to final completion, while ensuring adherence to budgets, timelines, and quality standards. This management discipline integrates various functions, including resource allocation, risk mitigation, safety oversight, and stakeholder coordination, to deliver successful projects. Through effective construction management, projects are completed efficiently while meeting regulatory requirements and stakeholder expectations, ultimately creating structures that serve their intended purposes safely and effectively.

Time management is essential for maintaining project schedules, cost management safeguards against financial overruns, and risk management minimizes potential disruptions caused by safety hazards, environmental issues, and other uncertainties. However, optimizing these factors simultaneously presents a challenge due to their interdependent nature; reducing project time, for instance, may lead to increased costs or heightened risks. This dynamic interplay highlights the need for a structured approach to assess and balance these competing objectives, making time-cost-risk (TCR) trade-off analysis a crucial aspect of modern construction project management.

Trade-offs have become so popular today because they allow managers to evaluate and prioritize competing objectives, making it easier to optimize outcomes based on the specific goals and constraints of each project. The topic of time-cost trade-offs in construction management has received significant attention in literature over the past few decades. Beyond the time-cost trade-off, other important trade-offs have been explored in the literature. The time-cost-quality trade-off introduces the complexity of maintaining high-quality standards while balancing time and cost. The time-cost-environmental trade-off is gaining increasing attention as sustainability becomes a critical aspect of modern construction practices. Through the application of diverse mathematical programming methodologies, researchers have proposed numerous models addressing trade-offs among time-cost, time-cost-quality, time-cost-quality-safety, and time-cost-quality-environment impact factors. Although risk plays a significant role in construction management, only a few studies have examined time-cost-risk trade-offs.

Optimization involves the minimization or maximization of a function with multiple variables, typically under equality or inequality constraints. Numerous engineering design challenges are highly complex and difficult to resolve with traditional optimization methods. (Sivanandam & Deepa, 2008). Since traditional approaches often lead to poor outcomes and increased vulnerability to unexpected events, multi-objective optimization algorithms offer a promising solution to trade-offs models. Multi-objective optimization algorithms have emerged as powerful techniques to address in construction management. These algorithms provide a systematic approach to simultaneously optimize multiple, often conflicting objectives, offering a range of Pareto-optimal solutions. By employing advanced technology and mathematical models, these algorithms can analyze extensive project information, evaluate various scenarios, and provide multiple best-fit solutions that align with conflicting objectives. This approach not only improves decision-making capabilities but also offers valuable insights into the trade-offs inherent in construction project management.

This review article aims to investigate the application of multi-objective optimization algorithms in managing the Time-Cost-Risk (TCR) trade-off in construction projects. By synthesizing recent advancements in research and industry practices, it provides construction professionals, researchers, and decision-makers with a comprehensive understanding of how these algorithms can optimize TCR analysis. It not only provides a roadmap for selecting appropriate optimization techniques but also emphasizes the need for future research on algorithmic integration and hybrid approaches. It presents a thorough study of extensively applied algorithms such Genetic Algorithms (GA), Non-Dominated Sorting Genetic Algorithm (NSGA II and NSGA III) and along with newly developed methods such as Adaptive Multi-Objective Differential Evolution (AMODE) and hybrid models. By examining the strengths, limitations, and applicability of these methods, this review highlights opportunities for improving construction project outcomes. As construction projects grow in complexity, adopting these advanced optimization techniques is essential for enhancing decision-making, mitigating risks, optimizing time and cost efficiency, and achieving competitive, high-performing project outcomes.

2. Optimization of Time-Cost-Risk

2.1 Time Management

In construction, time management involves planning, scheduling, and monitoring project timelines to ensure tasks are completed on time. It includes defining project phases, estimating activity durations, and managing resources to minimize delays. Effective time management reduces delays, enhances efficiency, ensures project goals stay on track and drives successful project completion. Critical Path Method (CPM), Gantt charts, and the Program Evaluation and Review Technique (PERT) are widely used for managing time in construction projects. CPM helps identify the most important tasks that affect the project's timeline and optimizes the schedule. Gantt charts create a clear visual timeline, showing task progress and how different activities are connected, making it easier to spot and fix delays. PERT provides a flexible way to estimate task durations by accounting for uncertainties, helping managers plan for potential risks.

2.1.1 Minimizing Project Time PT

The PT is the total time required to complete all activities carried out along the project's longest path, called the critical path (CP).

$$\mathrm{PT} = \sum_{A \in CP} AT_A \tag{1}$$

In Eq. (1), AT_A denotes completion time of activity A lying on the critical path.

2.2 Cost Management

Cost management entails estimating, budgeting, and controlling project expenses to prevent cost overruns and ensure financial efficiency. It involves tracking costs throughout the project lifecycle, comparing actual costs to the budget, and adjusting as needed. Successful cost management supports profitability and ensures projects stay within financial constraints.

2.2.1 Minimizing Project Cost PC

PC factors are taken into consideration as project direct costs along with the indirect costs of activities. Consequently, Eq. (2) can be used to evaluate the PCC.

$$PC = \sum_{A} D.C + I.C \text{ per day } \times PT \text{ in days} \tag{2}$$

$$+ V_{d1} \times C_p \times (PT - PT_{\text{contract}}) -$$

$$V_{d2} \times C_r \times (PT_{\text{contract}} - PT)$$

$(\sum_A D.C)$ indicates the total direct cost of all project activities, including labor, raw materials, and equipment costs. On the other hand, the total indirect cost of the project is shown by (I.C per day $\times PT$ in days). If the PT is longer than PT_{contract}, the contractor will be penalized $\left(V_{d1} \times C_p \times (PT - PT_{\text{contract}})\right)$ where PT_{contract} is the project deadline specified in the contract document and C_p is the penalty for each day of delay. Moreover, V_{d1} is a decision variable that is binary decision variable. If the

PCT is less than PT_{contract} , $\left(V_{d2} \times C_r \times (PT_{\text{contract}} - PT)\right)$ serves as a reward for the contractor. V_{d2} is an additional binary decision variable, and C_r is the daily reward.

2.3 Risk Management

Risk management is the process of identifying, assessing, and mitigating potential risks that could impact the project's success. This includes analyzing factors like safety hazards, environmental issues, and financial uncertainties that might delay timelines or increase costs. Through proactive planning and monitoring, risk management aims to minimize negative impacts, ensuring the project progresses smoothly and safely.

2.3.1 Minimizing Project Safety Risk PSR

This method includes three phases: identifying significant safety concerns, assessing their likelihood and severity, and calculating a total risk score. The process begins by identifying significant safety risks for each activity. Based on data gathered from various government reports and publications, major risks for each activity were compiled in the first stage (Afshar & Zolfaghar Dolabi, 2014) .Following risk identification, the likelihood and severity of each risk are evaluated based on expert judgmental or historical data. (Cooke & Williams, 2024) provided a 6×6 matrix for scoring these risks. The matrix assesses likelihood on a scale from 1 (low probability) to 6 (high probability) and severity from 1 (minor injury) to 6 (fatality). After all the evaluations from experts were collected, Eq. (3) was used to determine the total safety risk score.

$$SR_{kj} = \sum_{i=1}^{n} R_{kji} \tag{3}$$

$$R_{kji} = l_{kji} \times s_{kji} \tag{4}$$

Where SR_{kj} is total safety risk score of the project of jth alternative of activity k. l_{ki}, is likelihood of safety risk, s_{kji}, is severity of safety risk and R_{kji} is safety risk score of safety risk item i.

3. Introduction to Multi-Objective Optimization

Multi-objective optimization (MOO) is a method for optimizing two or more conflicting objectives simultaneously, commonly used in fields like engineering, economics, and logistics, where trade-offs among different objectives must be carefully balanced. For instance, in construction, time, cost, and quality may all need to be optimized, but improving one can negatively impact the others. MOO has been defined as the simultaneous optimization of multiple objective functions. (Deb, 2002). Central to this methodology is the concept of Pareto optimality, which describes solutions where no single objective can be improved without threatening others. The set of all Pareto optimal solutions is known as the Pareto front.

3.1 Review of Multi-Objective Optimization

3.1.1 Genetic Algorithms

A Genetic Algorithm (GA) introduced by (Holland,1975) is a specific type of evolutionary algorithm inspired by the process of natural selection. GAs evolves a population of candidate solutions over multiple generations, using operators such as selection, crossover, and mutation to search for optimal solutions. GAs is highly adaptable and can be applied to a wide range of optimization problems, including multi-objective optimization where GA excel at finding diverse solutions along a Pareto front. Their stochastic nature makes them less prone to getting stuck in local optima. GAs can be computationally expensive, particularly for complex problems with large search spaces. Parameter tuning is often necessary to achieve optimal performance. Convergence can be slow compared to derivative-based optimization methods in cases where the objective function is smooth. To overcome shortcomings of mathematical and heuristic approaches, metaheuristic algorithms genetic algorithm, is widely used to solve both single and multi-objective TCO problems (Feng, Liu, & Burns, 1997).

3.1.2 Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II (Nondominated Sorting Genetic Algorithm II), introduced by (Deb et al., 2002) is a widely used multi-objective evolutionary algorithm (MOEA). Its main purpose is to find a diverse set of optimal solutions for problems with multiple objectives, which are often in conflict with each other. NSGA-II is designed to address the limitations of its predecessor, NSGA, resulting in enhanced performance and efficiency. NSGA-II is a popular multi-objective evolutionary algorithm (MOEA) that improves upon the original NSGA by addressing computational complexity and enhancing performance for solving problems with multiple objectives. It efficiently groups solutions into non-dominated fronts through fast sorting, where the first front includes the best, non-dominated solutions. NSGA-II incorporates elitism by merging parent and offspring populations to retain the top solutions, accelerating convergence. Using crowding distance, it promotes a well-spread Pareto front by favoring solutions in less dense areas, while the crowded comparison operator combines non-domination rank with crowding distance to guide selection, balancing both solution quality and diversity. NSGA-II enhances multi-objective optimization with faster convergence and effective diversity maintenance, thanks to its elitist strategy, non-dominated sorting, and crowding distance. By eliminating the need for a sharing parameter, it simplifies usage and is adaptable for handling constraints in the search space. However, it faces challenges with computational demands in many-objective problems, and parameter interactions can slow convergence in interdependent decision-variable scenarios. As a stochastic method, NSGA-II may fall into local optima without guaranteed global Pareto solutions, and its performance is still influenced by crossover and mutation settings.

3.1.3 Ant Colony Optimization (ACO)

Ant colony optimization (ACO) (Dorigo, Birattari, & Stutzle, 2006) is a metaheuristic algorithm that takes inspiration from the foraging behavior of ants to solve optimization problems. The foundation of ACO lies in the concept of stigmergy, an indirect form of communication between ants using pheromone trails. When ants forage for food, they leave pheromones on the paths they traverse. Paths with higher pheromone concentrations attract more ants, creating a positive feedback loop that enables the colony to discover and converge on efficient paths to food sources. ACO algorithms simulate this behavior to find optimal or near-optimal solutions to various optimization problems. ACO’s robustness against local optima arises from its inherent randomness and the gradual decay of pheromone trails, which together maintain search diversity. Another strength is its flexibility, as ACO can be applied to diverse optimization problems, particularly those involving combinatorial optimization, such as scheduling. However, ACO algorithms require careful parameter tuning, as their performance depends on factors like the number of ants, pheromone evaporation rate, and the balance between pheromone and heuristic information. Slow convergence is another potential drawback, especially for problems with large search spaces. The sources offer specific examples of ACO applications. One source discusses multi-objective ACO (MOACO) algorithms designed for multi-objective combinatorial optimization problems. It proposes a taxonomy for categorizing MOACO algorithms based on characteristics like pheromone model, solution construction, evaluation method, and handling of Pareto optimal solutions. The source also examines various existing MOACO algorithms and offers design guidelines.

3.1.4 The Artificial Bee Colony (ABC) algorithm

(Karaboga & Basturk, 2008) developed Artificial Bee Colony (ABC) Algorithm. ABC is an optimization algorithm based on the intelligent behavior of honeybee swarms. The Artificial Bee Colony (ABC) algorithm is valued for its simplicity and ease of implementation, as its structure is straightforward with minimal parameter tuning requirements, making it accessible to non-experts and adaptable across various programming environments. Its robustness and adaptability to complex problems are notable due to its unique bee roles, allowing it to avoid local optima and handle challenging search spaces. Additionally, the ABC algorithm effectively manages multimodal and multivariable optimization, often outperforming algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) on benchmark functions. However, its parameter sensitivity can affect performance, and its convergence speed may be slower for high-dimensional problems, making it less suitable for time-sensitive applications. Furthermore, the ABC algorithm lacks a strong theoretical foundation, which limits rigorous analysis of its behavior and performance across diverse optimization problems.

3.1.5 Adaptive Multiple Objective Differential Evolution (AMODE)

The capacity of DE to provide effective solutions for complex problems through relatively simple operations has motivated numerous researchers to establish MODE-based methodologies (Das & Suganthan, 2011). Building on the foundations of Differential Evolution (DE), which is known for its simplicity and effectiveness in single-objective optimization, Adaptive Multi-Objective Differential Evolution (AMODE) extends DE’s capabilities to multi-objective optimization by incorporating adaptive mechanisms. While DE operates with fixed parameters, AMODE dynamically adjusts parameters such as mutation and crossover rates based on the progress of the optimization. This adaptability allows AMODE to balance exploration and exploitation more effectively, making it ideal for complex scenarios with multiple conflicting objectives (Cheng et al., 2016). AMODE also enhances DE’s performance in high-dimensional spaces by improving solution diversity across the Pareto front, maintaining a well-distributed set of optimal solutions for multi-objective challenges.

3.1.6 Non-Dominated Sorting Genetic Algorithm III (NSGA-III)

Traditional approaches, such as the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), have been effective for two or three objectives. They often struggle with high-dimensional problems where maintaining diversity and efficiency becomes challenging. To address this, the new algorithm NSGA-III was developed by (Deb & Jain, 2014). NSGA-III uses a reference point-based approach, guiding solutions toward a diverse Pareto front and enhancing its capability to handle many-objective optimization problems. Among its advantages, NSGA-III is known for maintaining a well-distributed set of solutions, improved scalability, and faster convergence toward optimal solutions in complex objective spaces. However, it also has challenges such as selecting an appropriate set of reference points that can be difficult, as this step often requires either prior knowledge or experimentation. Additionally, NSGA-III can be computationally intensive and may not offer significant performance gains for certain objective structures. Despite these limitations, NSGA-III is widely used in fields like engineering, logistics, and finance, where balancing numerous objectives is critical for effective decision-making.

Table 1. Algorithms Comparison Table

Algorithm	Key Characteristics	Pros	Cons
Genetic Algorithms (GA)	Evolutionary algorithm using selection, crossover, and mutation operations	Finds diverse solutions, effectively avoids local optima, highly adaptable, handles discrete and continuous variables	Computationally expensive, sensitive to parameter settings, slow convergence, performance depends on population diversity
Ant Colony Optimization (ACO)	Inspired by ant colony behavior and pheromone trail following	Strong capability in avoiding local optima, excellent for combinatorial problems, inherently parallel, adapts to changes	Generally slow convergence requires careful parameter tuning, critical pheromone update rules, difficult theoretical analysis
Non-Dominated Sorting Genetic Algorithm II (NSGA-II)	Multi-objective genetic algorithm with fast non-dominated sorting and crowding distance	Efficient sorting mechanism, excellent diversity maintenance, widely used for 2-3 objective problems, effective constraint handling	Performance decreases with many objectives, computationally intensive for large populations, crowding distance less effective in high dimensions, parameter tuning can be challenging
Artificial Bee Colony (ABC)	Inspired by foraging behavior of honeybees	Simple to implement, good at handling multimodal problems, minimal parameter tuning, balances exploration and exploitation	May converge slowly in high-dimensional spaces, performance depends on bee role balance, can struggle with constrained optimization, limited theoretical foundation
Non-Dominated Sorting Genetic Algorithm III (NSGA-III)	Enhanced version of NSGA-II for many-objective optimization	Excellent for problems with more than 4 objectives, maintains good solution diversity, robust in high-dimensional objective spaces, effective reference point adaptation	Computationally demanding, complex implementation requires careful reference point selection, may struggle with irregular Pareto fronts
Adaptive Multi-Objective Differential Evolution (AMODE)	Enhanced DE algorithm with adaptive parameter control	Better exploration-exploitation balance, self-adaptive parameter tuning, good for complex multi-objective problems, robust performance across different problems	Higher computational overhead, complex adaptive mechanisms, may require initial parameter calibration

4. Review of Previous Case Studies on Time-Cost-Resources Trade-off (TCRT)

Table 2. Previous Case Studies

References	Year	Trade-off Model							Approach
		Time	Cost	Risk	Quality	Environment	Resource	CO2	
Lakshminarayanan et al.	2010	✓	✓	✓					Ant Colony Optimization
Afshar & Zolfaghar Dolabi	2014	✓	✓	✓					Genetic Algorithm
Amoozad Mahdiraji et al.	2016	✓	✓	✓	✓				Grey Multi-Objective Linear Programming
Mohammadipour & Sadjadi	2016	✓	✓	✓	✓				Goal attainment
Mahmoudi & Feylizadeh	2018	✓	✓	✓	✓				Grey Linear Model
Tran & Long	2018	✓	✓	✓					Adaptive Multiple Objective Differential Evolution
Duc Long et al.	2019	✓	✓	✓					MOABCDE
Hosseinzadeh et al.	2020	✓	✓	✓	✓				Dolphin Hunting Algorithm
Askarifard et al.	2021	✓	✓	✓	✓	✓			Robust Programming
Panwar & Jha	2021	✓	✓	✓	✓				Nondominated Sorting Genetic Algorithm III)
Kaveh et al.	2021	✓	✓	✓	✓	✓	✓		Differential Evolution (DE)
Sharma & Trivedi	2022	✓	✓	✓	✓				LHS-based NSGA III
Avsar & Onut	2022	✓	✓	✓	✓				Goal Programming, AHP
Shishehgarkhaneh et al.	2022	✓	✓	✓	✓			✓	Fire Hawk Optimizer (FHO), BIM
Banihashemi & Khalilzadeh	2022	✓	✓	✓	✓				Fuzzy Logic and Genetic Algorithm
Sharma et al.,	2023	✓	✓	✓	✓				Particle Swarm Optimization (PSO)
Anh Nguyen et al	2023	✓	✓	✓				✓	Chaotic Adaptive Multi-Objective Sea Horse (CAMOSH)
Sharma & Trivedi	2023	✓	✓	✓	✓	✓			Opposition-based NSGA III
Yılmaz & Dede	2024	✓	✓	✓					NDSII-Rao-2, NDSII-GWO, NDSII-WOA

The paper by (Afshar & Zolfaghar Dolabi, 2014) presents a multi-objective optimization model that integrates time, cost, and overall safety risk (OSR) using a Genetic Algorithm (GA). Thus, this paper aims to propose a multi-objective GA-based model to incorporate safety analysis in discrete TCO problem and present pareto-optimal front that consists of nondominated solutions. An Excel VBA macro is also developed to facilitate the use of the model and make it more practical. A case study involving 18 activities was analyzed under two distinct scenarios. The first scenario focused on minimizing both time and cost, while the second scenario aimed to optimize time, cost, and safety risk. To achieve optimal performance in both scenarios, the genetic algorithm (GA) parameters were carefully tuned. The results indicated that the Time-Cost-Safety Risk Optimization model provided a broader range of nondominated solutions compared to traditional approaches. Furthermore, the integration of safety risk assessments significantly enhanced the overall safety risk management within the model, demonstrating its effectiveness in addressing safety concerns alongside time and cost optimization.Using the ant colony optimization approach, (Vijayan et al., 2018) presented a multi-objective optimization model for time-cost risk management. Ant colony optimization algorithm (ACO) is a probabilistic technique for dealing with computational problems that can be simplified by identifying effective pathways through graphs. The optimal solution for time and cost obtained from the algorithm proposed are compared to problem solutions obtained from the MAWA (modified adaptive weight approach) and MOACO (multi objective ant colony optimization) approach. It was discovered that the model developed provides efficient results when compared to MAWA and comparable results when compared to MOACO. By analyzing the results of the sample project, the authors observed the inverse relationships between time and cost and between time and risk. However, the variation in risk values across different solutions was less pronounced compared to the changes in time and cost, this led the authors to conclude that although time and cost are the primary drivers in decision-making, the risk factor is also relevant, particularly when comparing solutions with similar time and cost values.

To tackle the Time-Cost-Risk Trade-off (TCRT) challenges in construction projects, (Tran & Long, 2018) introduced a novel algorithm known as adaptive multiple objective differential evolution (AMODE). The authors developed the AMODE-TCR algorithm, which integrates the strengths of differential evolution (DE) with an adaptive mutation strategy. This approach enhances the algorithm's ability to explore diverse solution spaces while maintaining effective exploitation of promising solutions. The adaptive mechanism prevents the optimization process from becoming overly random or greedy, ensuring a balanced search for optimal solutions. The performance of the AMODE algorithm is evaluated through a numerical case study involving a construction project with 10 activities. The results are compared against established algorithms, including NSGA-II (Non-dominated Sorting Genetic Algorithm II), MOPSO (Multi-Objective Particle Swarm Optimization), and MODE (Multi-Objective Differential Evolution), using various performance metrics. The results indicate that AMODE generates a better Pareto front compared to other widely used algorithms, showcasing improved greater diversity, balanced compromises, and higher degrees of satisfaction. The study also demonstrates that the proposed model significantly enhances the efficiency and effectiveness of project scheduling, making it a valuable contribution to the field of construction management.

Hybrid multi-objective optimization algorithm called MOABCDE, which combines the strengths of the Artificial Bee Colony (ABC) algorithm and Differential Evolution (DE) was used by (Duc Long et al., 2019) to solve Time-Cost-Risk Trade-off (TCRT) problems in construction projects. ABC and DE were chosen by authors for their complementary strengths. ABC is proficient at exploring different solution spaces but has limitations in efficiently exploiting solutions, frequently converging slowly on complex issues. DE, which is noted for its resilience and fast convergence optimization, balances ABC's limitations by effectively refining solutions. Together, these algorithms create a balanced hybrid (MOABCDE), which improves both exploration and utilization in challenging optimization problems. The performance of MOABCDE is evaluated through a case study of an eight-activity construction project and compared against NSGA-II (Non-dominated Sorting Genetic Algorithm II), MOPSO (Multi-Objective Particle Swarm Optimization), MODE (Multi-Objective Differential Evolution) and MOABC (Multi-Objective Artificial Bee Colony) using C-metric, Spread, and Hyper-Volume metrics. The results showed that MOABCDE stands out among other algorithms, showing a stronger ability to converge smoothly, maintain diverse options, and provide well-balanced solutions for the TCRT problem.

In the context of optimizing time, cost, and risk in construction projects, the study by (Panwar & Jha, 2021) provided a significant example of how quality and safety can be integrated into scheduling optimization. Utilizing the Non-Dominated Sorting Genetic Algorithm III (NSGA-III), the authors addressed the complexities involved in achieving optimal trade-offs among multiple objectives, including time, cost, quality, and safety. The researchers compared the model's performance against existing model examples from past case studies. The model's performance was assessed using standard metrics such as degree of convergence, diversity, and speed of convergence. Compared to existing models, the developed model consistently showed better average values across all three metrics, signifying superior convergence, solution diversity, and computational efficiency.

(Sharma et al., 2023) demonstrated a Particle Swarm Optimization (PSO)-based model to address the multi-objective optimization problem of balancing quality and safety in construction project management, while also considering constraints of duration and cost. The authors adopted the standard PSO algorithm to handle the complexities of the construction domain, including the use of non-dominated sorting to identify the Pareto-optimal solutions that represent the trade-offs between the competing objectives. Through comprehensive experiments using real-world construction project data, the authors demonstrate that their PSO-based approach is effective in identifying optimized project plans that achieve desirable outcomes across the key performance metrics of quality, safety, time, and cost. The results highlight the potential of PSO as a valuable decision-support tool to aid construction stakeholders in making informed decisions that align with their specific project requirements and priorities.

Table 2 provided valuable insights into the various multi-objective optimization algorithms in managing the Time-Cost-Risk Trade-off (TCRT) in construction projects. Most of the studies focus on optimizing time, cost, and risk, with some extending to other objectives such as quality, environment, and CO2 emissions. Algorithms such as Genetic Algorithms (GA), Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and Non-Dominated Sorting Genetic Algorithm III (NSGA-III) are commonly applied due to their efficiency in maintaining diverse Pareto fronts. Adaptive Multi-Objective Differential Evolution (AMODE) and Multi-Objective Artificial Bee Colony (MOABCDE) had been used for their adaptability and ability to optimize complex multi-objective problems in TCRT scenarios.

In addition to these demonstrated methodologies, novel algorithms such as Robust Programming used by (Askarifard et al., 2021) and Chaotic Adaptive Multi-Objective Sea Horse (CAMOSH) (Anh Nguyen et al., 2023) demonstrate potential in enhancing robustness and dynamic adaptation in TCRT problems. Moreover, Fire Hawk Optimizer (FHO) combined with Building Information Modeling (BIM), as demonstrated by Shishehgarkhaneh et al. (2022), introduces an innovative approach by integrating optimization with real-time construction data, improving decision-making and efficiency. Hybrid approaches, such as Fuzzy Logic combined with Genetic Algorithms (Banihashemi & Khalilzadeh, 2022) and LHS-based NSGA III (Sharma & Trivedi, 2022), further enhance the performance of TCRT optimization by addressing uncertainty and improving the exploration of the solution space.

Overall, these case studies illustrate the progression of multi-objective optimization in construction project management, showcasing how both traditional and emerging algorithms contribute to more effective TCRT solutions.

5. Conclusion

Effectively managing time, this review shows that although current project management methods have improved individual aspects, the construction industry would benefit from a more integrated approach that considers time, cost, and risk together. Time and cost overruns continue to plague construction projects worldwide, emphasizing the critical need for more effective management strategies. Risk in construction projects covers a wide range of factors, yet in the studies reviewed, the focus has been primarily on safety risks, resource risks, and total float risks. While these are critical areas, expanding the scope of risk analysis to include other dimensions such as environmental risks, financial risks, and stakeholder-related risks could provide a more comprehensive understanding of the Time-Cost-Risk trade-off. A broader risk perspective could lead to more robust and adaptive project management strategies, helping to mitigate delays and cost overruns more effectively.

Comparative analyses of various optimization algorithms could reveal which methods are most efficient and accurate across diverse project scenarios. Future research should aim to test and evaluate a wider array of algorithms, enhancing their applicability to complex construction projects. Understanding the influence of problem characteristics, parameter choices, and algorithm implementation on performance is crucial for successfully applying these tools to multi-objective optimization problems. By addressing these gaps, construction project managers can gain deeper insights into the trade-offs between time, cost, and risk, leading to more informed and resilient project outcomes.

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