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Intelligent Construction Scheduling Based on MOEA/D-DE, SPEA2+SDE, and NSGA-III by Integrating Safety Assessment with Resource Efficiency

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To improve the efficiency and safety of intelligent construction scheduling, this work explores an optimization method for construction schedules based on multi-objective optimization (MOO) algorithms. This work focuses on the generation and optimization processes of scheduling plans and conducts safety assessments and resource efficiency analyses of the generated plans. The proposed optimized model is compared with classical MOO algorithms. These algorithms include Multi-Objective Evolutionary Algorithm based on Decomposition with Differential Evolution (MOEA/D-DE), Strength Pareto Evolutionary Algorithm 2 with Shift-based Density Estimation (SPEA2+SDE), and Non-dominated Sorting Genetic Algorithm III (NSGA-III). Based on the experimental results, the proposed optimized model outperforms three classic MOO algorithms across multiple key performance indicators. In terms of Hypervolume, the value achieved by the proposed model is 0.722, indicating that its solution set covers the objective space more effectively, demonstrating stronger diversity and global search capability. Furthermore, on the indicators of Generative Distance and Inverse Generative Distance, the proposed model attains lower values of 0.008 and 0.061, suggesting that the solution set is closer to the optimal front, with higher precision. In addition, the Spacing Metric value of 0.011 further shows that the solution set generated by the proposed model is more evenly distributed in the objective space. It avoids excessive clustering and enhances the uniformity and adaptability of the solutions. This uniformity is critical in practical construction scheduling optimization. This is because, under multiple conflicting objectives, a well-distributed solution set provides decision-makers with more options, enabling a better balance between safety and resource efficiency. Regarding safety assessment, Plan C has a high score of 4.63, indicating that under the optimization of the proposed model, the construction plan can achieve excellent performance in resource utilization and provide better safety guarantees. Similarly, Plan D, which demonstrates the highest resource efficiency, receives an overall score of 4.72, showcasing its outstanding advantages in resource usage and scheduling efficiency. These results validate the proposed model's applicability and flexibility under different constraints and objective functions.

Povzetek: Opisano je inteligentno načrtovanje gradnje z uporabo večkriterijskih optimizacijskih algoritmov (MOEA/D-DE, SPEA2+SDE, NSGA-III), ki vključujejo oceno varnosti in učinkovitost virov. Eksperimenti potrjujejo izboljšano varnost in učinkovito rabo virov, kar omogoča boljše načrtovanje projektov in zmanjšanje tveganj v gradbeništvu.

1 Introduction

With the rapid advancement of the global construction industry, the complexity and scale of construction projects are continuously increasing, leading to more stringent requirements for construction management. Traditional construction scheduling methods often face issues such as low resource utilization efficiency, inadequate scheduling optimization, and poor safety management [1-3]. Intelligent construction technology has gradually become a focal point in the industry to address these challenges. Based on information technology, intelligent construction utilizes the Internet of Things (IoT), artificial intelligence (AI), big data, and other technological tools to achieve automation and intelligence in the construction process, thus improving construction efficiency and quality [4]. Multi-objective optimization (MOO) algorithms, known for their advantages in handling complex, nonlinear problems, have been extensively applied in intelligent construction scheduling. These algorithms can provide optimal construction scheduling solutions by balancing different objectives under multiple constraints. However, most current research focuses on optimizing single objectives and lacks comprehensive consideration of safety and resource efficiency [5]. In actual construction processes, safety issues and resource utilization efficiency are often critical factors that cannot be overlooked in decision-making. Therefore, incorporating safety assessment and resource efficiency into construction scheduling optimization models holds significant practical and theoretical value.

Against this backdrop, this work proposes applying MOO algorithms to intelligent construction scheduling and integrating comprehensive analysis of safety assessments and resource efficiency. This method aims to provide a more scientific and rational scheduling optimization method for construction projects. Adopting this method can improve the overall management level of construction projects, effectively reduce the occurrence of safety incidents, enhance resource utilization efficiency, and offer strong support for achieving green construction and sustainable development.

2 Related work

With the swift development of the global construction industry, the complexity and scale of construction projects have been increasing. Wang studied the design of an intelligent construction system for prefabricated buildings based on an improved IoT architecture, proposing a system framework capable of markedly enhancing construction management efficiency and resource utilization. He indicated that integrating IoT technology could achieve data collection, transmission, and analysis throughout the prefabricated building construction process, providing support for real-time monitoring and dynamic scheduling on construction sites. Thus, it could enable optimal resource allocation and safety management in a complex and dynamic construction environment [6]. Chen proposed an economically intelligent decision-making platform based on AI technology, which applied machine learning (ML) and data mining techniques to analyze and predict economic data in construction projects. The platform could provide data support for the decision-making processes of construction enterprises, helping them make more rational investment and resource allocation decisions in the face of resource constraints and budget limitations. His research offered a new perspective on cost management and risk control in intelligent construction [7]. Li focused on dynamic cost estimation in reconstruction projects, improving the cost estimation model using particle swarm optimization (PSO) algorithms. The algorithm could quickly find the optimal solution and effectively handle uncertainties in the cost estimation process. The results indicated that this method could significantly improve the accuracy of cost estimates and support the rational allocation of resources, especially in construction projects with complex environmental constraints [8]. Feng et al. applied Building Information Modeling (BIM) technology to the intelligent project management of prefabricated buildings, proposing a management model that facilitated information sharing and process optimization. With the introduction of BIM technology, construction teams could track project progress in real-time, optimize resource allocation, and enhance the visualization and transparency of management, thereby reducing costs while improving construction efficiency and quality [9]. Wang studied the multi-objective task scheduling problem for drones under limited onboard resource constraints and proposed a scheduling strategy based on edge computing. This strategy dynamically adjusted resource allocation and optimized task execution sequences during the drone's performance of multiple tasks, thus improving task efficiency and accuracy. His research provided insights into task scheduling and resource optimization in intelligent construction, particularly for real-time monitoring and material delivery on construction sites [10]. Vijaya and Srinivasan found that multi-objective metaheuristic techniques could achieve efficient energy allocation for virtual machines in cloud data centers, thereby effectively enhancing resource utilization and energy savings in data centers [11]. Bendiaf et al. introduced an innovative task scheduling method using a knapsack algorithm for task distribution in heterogeneous computing systems, achieving efficient resource scheduling and optimization, which enhanced the overall system performance [12]. The analysis of related studies is detailed in Table 1.

Table 1: Summary of related work

Author	Year	Research focus	Performance indicators	Security assessment	Resource efficiency
Wang	2024	Design of an intelligent construction system for prefabricated buildings based on an improved IoT	Efficiency and resource utilization during construction	Real-time monitoring and security through IoT integration	Optimal resource allocation of prefabricated buildings
Chen	2024	Construction and application of an economically intelligent decision-making platform based on AI	Cost management, risk control, and resource allocation	Risk control in economic decision-making	Efficient resource allocation under budget constraints
Li	2023	Dynamic cost estimation in reconstruction projects using PSO	Accuracy of cost estimation and resource allocation	Not explicitly involved	Improvement of resource allocation in complex environments

Feng et al.	2022	The BIM technology-based intelligent project management of prefabricated buildings	Visualization of construction efficiency, quality, and management	Improvement of management transparency	Implementation of optimal resource allocation through BIM
Wang	2024	The multi-objective task scheduling strategy for drones based on edge computing	Task efficiency and scheduling accuracy	Not explicitly involved	Efficient resource utilization in drone task scheduling
Vijaya and Srinivasan	2024	Efficient energy allocation for virtual machines in cloud data centers based on multi-objective metaheuristic techniques	Resource utilization efficiency and energy conservation	Not explicitly involved	Implementation of resource allocation for virtual machines with high energy efficiency
Bendiaf et al.	2024	A task scheduling optimization in heterogeneous computing systems using a knapsack algorithm	System performance improvement and resource scheduling efficiency	Not explicitly involved	Implementation of efficient scheduling and utilization of resources

It can be observed that most existing methods have limited adaptability in dynamic construction environments. For instance, while many studies focus on optimizing resource allocation and scheduling efficiency, they lack a real-time response to changing working conditions. Intelligent construction requires an optimized model capable of dynamically adapting to changes in work conditions, enhancing robustness in uncertain environments. Although some studies have considered safety, many methods have not optimized safety under complex environments. For example, while real-time monitoring helps with risk control, existing methods do not achieve a balance between safety and resource efficiency. This work aims to construct a MOO model that comprehensively considers both safety and resource efficiency to ensure the safety and efficiency of construction scheduling. While resource efficiency is a focus in many studies, there is still room for improvement in optimizing resource allocation during the MOO process. Most studies achieve resource optimization in a single dimension, whereas the proposed model optimizes under multi-dimensional constraints, helping to comprehensively improve resource efficiency.

In summary, by combining MOO algorithms with dynamic scheduling strategies, this work achieves significant improvements in construction schedule optimization over current state-of-the-art (SOTA) methods.

3 Intelligent construction scheduling model based on MOO algorithms

3.1 Intelligent construction scheduling

Intelligent construction scheduling refers to the use of modern information technology, automation technology, and intelligent algorithms during construction, thus optimizing and managing the allocation, utilization, and coordination of construction resources. The goal is to improve construction efficiency, reduce costs, and ensure project quality and safety [13-15]. As the scale and complexity of construction projects have increased, traditional scheduling methods are no longer sufficient to meet the needs of the modern construction industry. Hence, intelligent construction scheduling has become a crucial means to enhance the competitiveness of the construction sector.

With the advancement of information technology, the construction industry is gradually evolving towards intelligent operations. As a critical component of construction management, construction scheduling is also transitioning from traditional manual management to intelligent management [16]. The rise of intelligent construction scheduling is attributed to advancements and applications in various technologies, as exhibited in Table 2:

Table 2: Technologies related to intelligent construction scheduling

Technology	Analysis
BIM	The application of BIM allows for collaborative work across different stages of a construction project (design, construction, and operation) within a single digital model [17]. Through this model, construction scheduling can achieve real-time data sharing and dynamic adjustments, improving the accuracy and efficiency of scheduling.

IoT	IoT technology connects key elements of the construction site, such as equipment, materials, and personnel, enabling real-time monitoring and data collection throughout the construction process.
Big Data Analytics	By analyzing large volumes of construction data, intelligent scheduling can predict potential issues such as resource bottlenecks and schedule delays, allowing for preemptive optimization measures.
AI	Through ML algorithms, construction scheduling systems can continuously learn and optimize scheduling strategies, enhancing overall construction efficiency [18].
Automation Technology	Utilizing automated devices (such as automated construction machinery and drones) makes operations on the construction site more precise and efficient, thus improving the execution and reliability of scheduling.

Intelligent construction scheduling involves multiple key elements that work together to ensure both the intelligence and efficiency of scheduling. First, there is construction resource management, including labor, equipment, materials, and funds. Intelligent scheduling systems dynamically manage and optimize these resources to ensure optimal resource usage during construction, reduce waste, and improve utilization rates. Next, progress control is managed by real-time monitoring of construction progress, combined with historical data and predictive analysis to develop reasonable construction plans and schedules, ensuring timely project completion [19-21]. Besides, quality control is addressed by real-time monitoring of critical control points during construction to promptly identify and correct quality issues, ensuring that project quality meets design requirements. Lastly, safety management is vital in construction management. The intelligent scheduling system uses real-time site monitoring and risk analysis to detect potential safety hazards and take preventative measures, ensuring construction safety.

Despite the many advantages of intelligent construction scheduling in practice, it also faces challenges. For instance, the complexity and uncertainty of construction sites require scheduling systems to have strong adaptability and responsiveness. Additionally, high demands for data collection and analysis on construction sites mean that the accuracy and timeliness of data directly impact the effectiveness of intelligent scheduling [22]. In the future, with the further development of information technology and advancements in intelligent algorithms, intelligent construction scheduling is expected to become more widespread and refined. Particularly with the advancement of 5G, AI, and IoT technologies, construction scheduling could become more intelligent and automated, further enhancing the construction project management level and efficiency. Through ongoing technological innovation and practical experience accumulation, intelligent construction scheduling can provide stronger support for developing the construction industry [23].

3.2 The use of MOO algorithms in construction scheduling

MOO algorithms have significant application value in construction scheduling, effectively addressing the conflicts among multiple objectives, such as cost, duration, quality, and safety. As the complexity of construction projects increases, traditional single-objective optimization methods are no longer sufficient to meet practical needs. MOO algorithms are increasingly becoming effective tools for solving complex scheduling problems [24-26]. Table 3 illustrates their application scenarios.

Table 3: Application scenarios of MOO algorithms

Scenario	Analysis
Resource Allocation Optimization	In construction, the efficient allocation of various resources (such as labor, equipment, and materials) is key to ensuring the smooth progress of the project. MOO algorithms can balance cost, project duration, and resource utilization to find the optimal allocation plan. For instance, in a large construction project, genetic algorithms can be used to optimize the scheduling and distribution of construction equipment, minimizing idle time and rental costs.
Construction Schedule Optimization	The efficient scheduling of construction progress directly affects the overall project duration and cost. MOO algorithms can create the optimal construction schedule by simultaneously considering various factors, such as task priorities, resource availability, and changes in construction conditions. Particle swarm optimization algorithms perform exceptionally well in such scenarios, quickly identifying scheduling solutions that meet multiple objectives.
Balancing Cost and Duration	In construction, shortening the project duration often increases costs, while reducing costs frequently extends the timeline. MOO algorithms can help decision-makers find the optimal balance between cost and duration. For example, using Pareto optimal solutions, project managers can obtain a set of

	different cost and duration combinations and select the one that best fits the project's requirements.
Quality and Safety Management	Quality and safety are two crucial objectives in construction management, often requiring optimization within the constraints of cost and schedule. MOO algorithms can help develop a construction plan that meets quality and safety requirements while controlling costs and timelines. For example, differential evolution algorithms can optimize the configuration of construction quality control measures, maximizing quality and safety within limited resources.
Risk Management and Emergency Scheduling	During construction, unforeseen risks and emergencies often impact the original schedule. MOO algorithms can be used to develop emergency scheduling plans by considering multiple potential risk scenarios, optimizing resource allocation, and scheduling to minimize the impact of risks on the project. Ant colony optimization algorithms excel in these situations, quickly adapting to changes and finding the optimal emergency scheduling solutions.

As AI technology advances, the application of MOO algorithms in construction scheduling becomes more extensive and in-depth. With the advancement of big data and ML, intelligent algorithms can better understand and address complex construction scheduling issues, offering more accurate and efficient solutions [27].

3.3 Construction of MOO algorithms combined with models

Constructing a MOO model for intelligent construction scheduling is crucial for achieving intelligent scheduling and optimized management [28]. This model integrates multiple key objectives in the construction process, such as project duration, cost, quality, and safety, to balance these objectives and find the optimal scheduling plan. Implementing an efficient MOO model requires detailed design and analysis of various aspects, including this model's objective functions, constraints, and solution algorithms. Figure 1 illustrates the model proposed here.

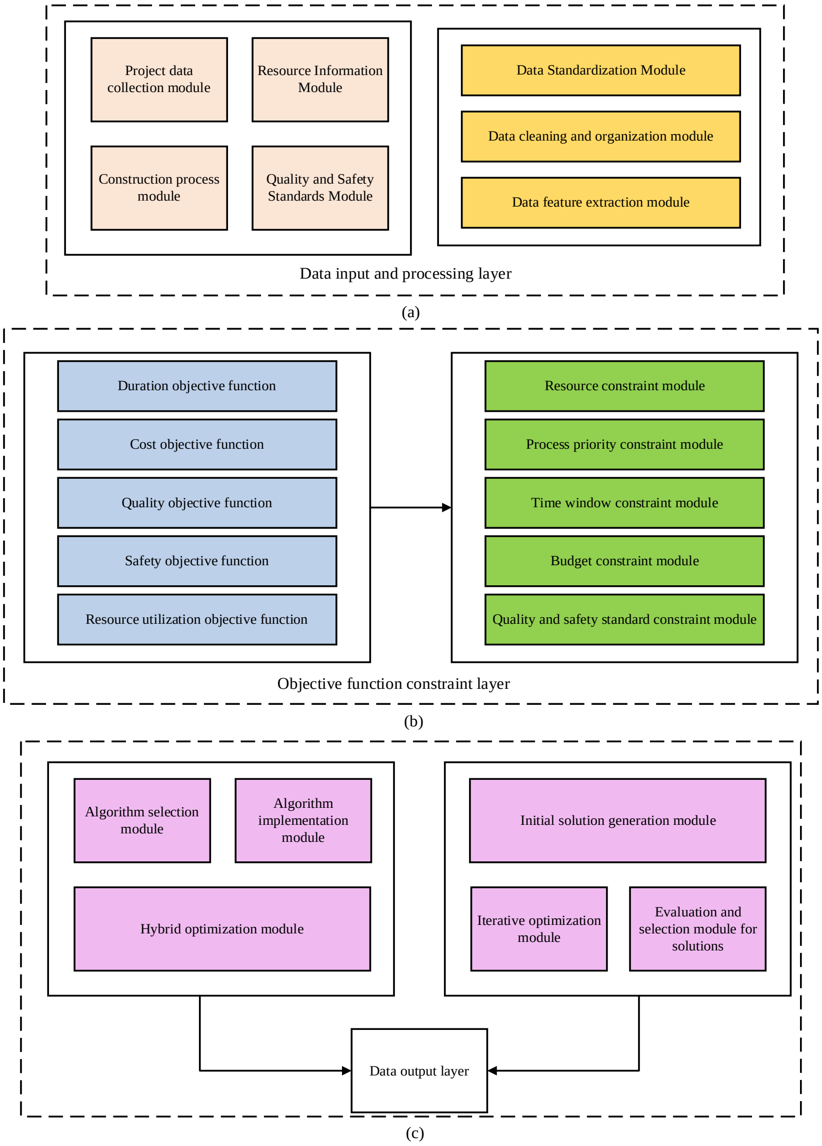

Figure 1: The MOO model ((a): The data input and processing layer; (b): The objective function constraint layer; (c): The data output layer)

First, the objective of the model is to minimize the construction duration, as shown in equation (1):

$$T_{total} = \max_{i\in\{1,2,\ldots,N\}} (T_i + D_i) \tag{1}$$

T_{total} represents the minimized construction duration, T_i refers to the start time, and D_i is the duration. Subsequently, the minimized total construction cost is calculated as equation (2):

$$C_{total} = \sum_{i=1}^{N} (C_{labor,i} + C_{material,i} + C_{equipment,i}) \tag{2}$$

C_{total} represents the minimized total construction cost; $C_{labor,i}$, $C_{material,i}$, and $C_{equipment,i}$ denote the labor, material, and equipment costs for each operation, respectively. N means the total quantity of the project. To ensure high-quality construction, the model is designed to maximize construction quality:

$$Q_{total} = \sum_{i=1}^{N} w_i \cdot Q_i \tag{3}$$

Q_{total} represents the maximized construction quality, w_i is the weight coefficient, and Q_i refers to the quality score. Similarly, maximizing construction safety is also an important objective of the model:

$$S_{total} = \sum_{i=1}^{N} v_i \cdot S_i \tag{4}$$

S_{total} refers to the maximized construction safety, v_i denotes the weight coefficient, and S_i represents the safety score.

The proposed optimized model architecture consists of three layers: the data input and processing layer, the objective function constraint layer, and the data output layer. These layers work collaboratively to achieve MOO in construction scheduling. Firstly, the data input and processing layer includes modules for project data collection, resource information, construction processes, and quality and safety standards. This layer is responsible for gathering real-time data and resource information from the construction process and performing preprocessing through data standardization, data cleaning and organization, and feature extraction. These steps ensure the accuracy and consistency of the data, providing reliable inputs for the subsequent optimization process. Secondly, the objective function constraint layer focuses on MOO. It optimizes the construction schedule, total cost, quality, safety, and resource utilization through the duration objective function, cost objective function, quality objective function, safety objective function, and resource utilization objective function. This layer also includes modules for resource constraints, process priority constraints, time window constraints, budget constraints, and quality and safety standard constraints, ensuring that the generated scheduling solutions meet the project's practical needs and construction standards. Finally, the data output layer is responsible for executing the optimization algorithm and outputting the results. This layer encompasses modules for algorithm selection, algorithm implementation, hybrid optimization, initial solution generation, iterative optimization, and solution evaluation and selection. By choosing the appropriate optimization algorithms and combining them with hybrid optimization methods, this layer continuously generates and refines the scheduling solutions. Ultimately, it selects the best scheduling plan based on indicators such as safety, resource efficiency, and scheduling time. Overall, the proposed model achieves efficient, safe, and resource-optimized construction scheduling through a multi-layered modular design, offering effective support for intelligent construction management projects.

This framework design ensures that the MOO model for intelligent construction scheduling has flexibility, scalability, and efficiency, enabling it to handle complex scheduling requirements and provide optimized decision support.

4 Performance comparison and scheduling results analysis of intelligent construction scheduling models

4.1 Experimental results of performance comparison for intelligent construction scheduling model

The dataset used for the experiment is the Construction Project Management dataset from Kaggle. This dataset includes detailed information on various construction projects, such as project schedules, resource allocation, and cost estimates, and is suitable for analyzing resource optimization issues in construction scheduling. The dataset can be downloaded from Kaggle's official website (https://www.kaggle.com/). The experiments are conducted in a high-performance computing environment to ensure the MOO algorithm's effectiveness and efficiency in intelligent construction scheduling. The experiments utilize an Intel Xeon Gold 6248R processor, which features 24 physical cores and 48 threads with a clock speed of 3.0 GHz, enabling efficient parallel computation. To meet the memory demands of the algorithm's computations, the system is equipped with 128 GB of DDR4 RAM, ensuring ample memory resources for data processing and algorithm training. For storage, a 2 TB NVMe solid-state drive is used to provide fast data read and write speeds, further accelerating the overall execution efficiency of the experiments. The operating system version of the experiment is Ubuntu 20.04 LTS, and the programming language and version are Python 3.8. The main libraries and versions are as follows:

1. TensorFlow: 2.5.0
2. PyTorch: 1.9.0
3. NumPy: 1.21.0
4. Pandas: 1.3.0
5. Matplotlib: 3.4.2

The model selects Non-dominated Sorting Genetic Algorithm II (NSGA-II) as the benchmark algorithm. It has a population size of 200, 100 generations, a crossover probability of 0.9, a mutation probability of 0.1, and an objective function weight of 0.5. The comparison models include Multi-Objective Evolutionary Algorithm based on Decomposition with Differential Evolution (MOEA/D-DE), Strength Pareto Evolutionary Algorithm 2 with Shift-based Density Estimation (SPEA2+SDE), and Non-dominated Sorting Genetic Algorithm III (NSGA-III). Performance comparison metrics are Hypervolume (HV), Generational Distance (GD), Inverted Generational Distance (IGD), and Spacing. The experimental results are presented in Figure 2.

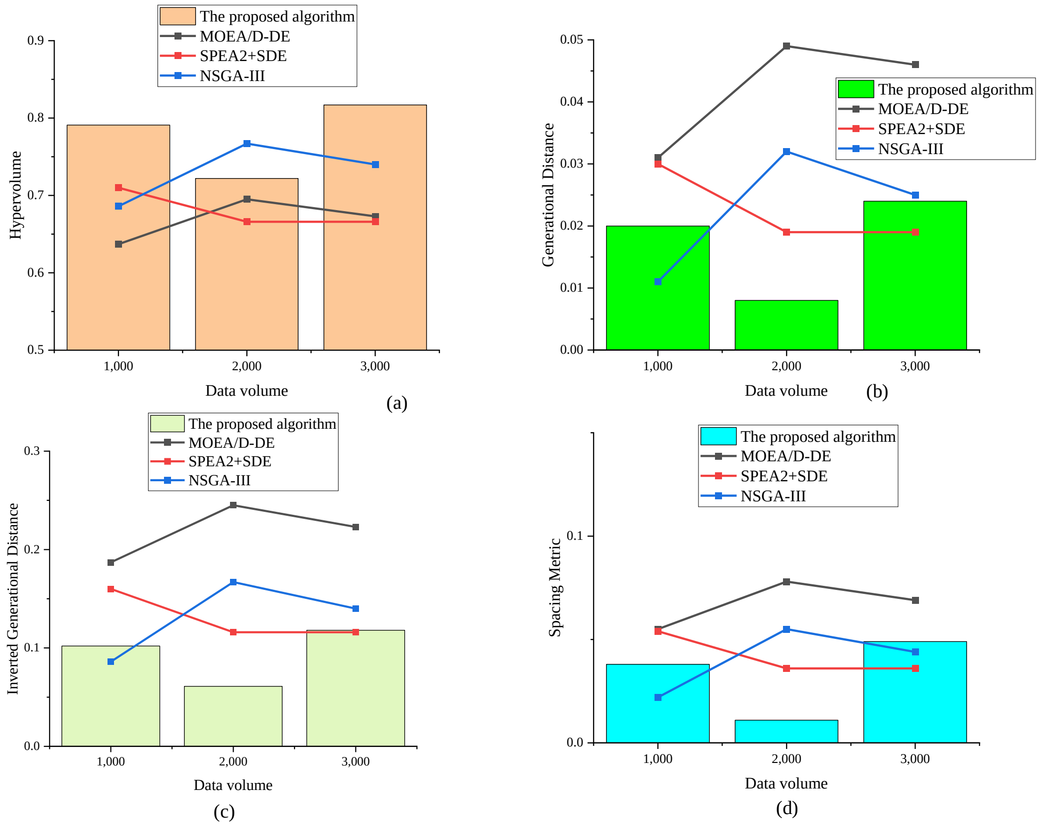

Figure 2: Performance comparison results ((a): HV; (b): GD; (c): IGD; (d): Spacing)

Figure 2 shows that for the HV metric, with a dataset size of 1000, the optimized model's HV value is 0.791, significantly exceeding the other three models. This indicates that the optimized model better covers the objective space in smaller datasets. MOEA/D-DE and NSGA-III have HV values of 0.637 and 0.686, respectively, showing relatively weaker performance, while SPEA2+SDE performs slightly better with an HV value of 0.710, surpassing MOEA/D-DE. With a dataset size of 2000, the HV value of the optimized model is 0.722, maintaining a leading position, though its performance slightly decreases compared to other dataset sizes. NSGA-III performs better with an HV value of 0.767, illustrating strong adaptability to medium-sized datasets. MOEA/D-DE's HV value rises to 0.695, while SPEA2+SDE decreases to 0.666. When the dataset size reaches 3000, the optimized model's HV value reaches 0.817, showcasing its advantage with large datasets. NSGA-III also performs relatively well with a value of 0.740, while MOEA/D-DE and SPEA2+SDE have HV values of 0.666, showing no significant advantage. Regarding GD, the optimized model performs exceptionally well across diverse dataset sizes, particularly with a dataset size of 2000, where it achieves the smallest GD value of 0.008, demonstrating strong convergence. This indicates that the solution set generated by the proposed model is very close to the true Pareto front across all dataset sizes, exhibiting excellent optimization capability. NSGA-III performs best when the dataset size is 1000, but its convergence decreases with increasing dataset size, particularly with a GD value rising to 0.032 when the dataset size reaches 2000. However, NSGA-III's performance with a dataset size of 3000 is similar to the proposed model, indicating adaptability to large-scale datasets. MOEA/D-DE's GD values are consistently high across all dataset sizes, especially reaching 0.049 with a dataset size of 2000, demonstrating insufficient convergence performance for large-scale data. In contrast, SPEA2+SDE shows stable performance, but its GD values are generally higher than those of NSGA-III and the optimized model, reflecting less favorable convergence compared to both. For IGD, with a dataset size of 1000, NSGA-III achieves the best IGD value of 0.086, indicating its excellent coverage of the true Pareto front. The optimized model's IGD value is 0.102, slightly higher than NSGA-III, but still shows strong coverage capability. SPEA2+SDE has an IGD value of 0.160, showing moderate performance, while MOEA/D-DE has a relatively high IGD value of 0.187, indicating slightly weaker coverage capability. With a dataset size of 2000, the optimized model's IGD value drops to 0.061, demonstrating outstanding coverage of the solution set and significantly surpassing other models. SPEA2+SDE's IGD value is 0.116, showing relatively good performance, while NSGA-III's IGD value is 0.167, indicating a notable decrease in coverage performance. MOEA/D-DE's IGD value is 0.245, reflecting the weakest coverage capability at this dataset size. For a dataset size of 3000, the optimized model's IGD value is 0.118, slightly increasing the value for the 2000 dataset, but still maintaining strong coverage performance. NSGA-III's

IGD value increases to 0.140, showing relatively good solution set coverage. SPEA2+SDE's IGD value remains at 0.116, consistent with the 2000 dataset size, showing stable performance. MOEA/D-DE's IGD value is 0.223, still the weakest among all models. In terms of the Spacing metric, the optimized model performs the best. In particular, with a dataset size of 2000, the Spacing value is only 0.011, indicating an extremely uniform distribution of solutions in the objective space. This means the optimized model generates solutions close to the optimal and ensures a good distribution of these solutions in the objective space. NSGA-III performs excellently with a dataset size of 1000, with a Spacing value of 0.022. However, the uniformity of the solution set decreases with increasing dataset size, especially with a Spacing value rising to 0.055 for a dataset size of 2000, signaling instability in distribution uniformity. SPEA2+SDE shows stable performance across different dataset sizes, with Spacing values between 0.036 and 0.054. Although it does not reach the level of NSGA-III or the optimized model, its stability demonstrates adaptability across various dataset sizes. MOEA/D-DE performs relatively weakly in the Spacing metric, particularly with a dataset size of 2000, where the Spacing value is 0.078. It displays an uneven distribution of solutions, indicating that MOEA/D-DE lacks uniformity in the solution set when handling large-scale data.

4.2 Safety assessment and resource efficiency analysis

In optimizing intelligent construction scheduling, safety assessment and resource efficiency analysis are crucial for assessing the quality of scheduling plans. By evaluating the safety and resource utilization efficiency of the generated scheduling plans, it is possible to ensure that construction projects operate efficiently under safety regulations, maximize resource utilization, and reduce potential risks. Safety assessment is a key step in construction scheduling, aimed at effectively preventing and controlling various potential safety risks during execution. To this end, this work employs a comprehensive evaluation system that integrates multiple safety indicators for a thorough assessment. Table 4 presents the details.

Table 4: The safety indicator system

Indicator	Description
Accident Rate	It evaluates the frequency of safety incidents occurring during construction, typically calculated per 1,000 work hours.
Safety Distance	It measures the minimum distance between construction site personnel and hazard sources.
Personnel Protective Measures	It checks whether all construction personnel are equipped with necessary protective gear (such as helmets and safety belts).
Equipment Operation Safety	It assesses the stability of construction equipment under different operating conditions to prevent equipment failure or accidents.

A safety risk analysis model based on the fuzzy comprehensive evaluation method is established to assess the scheduling plans quantitatively. By scoring each safety indicator (from 1 to 5) and combining expert weight analysis, a comprehensive safety score is calculated for each scheduling plan. The fuzzy comprehensive evaluation method-based safety risk analysis model quantitatively evaluates the scheduling plans. Figure 3 presents the experimental results.

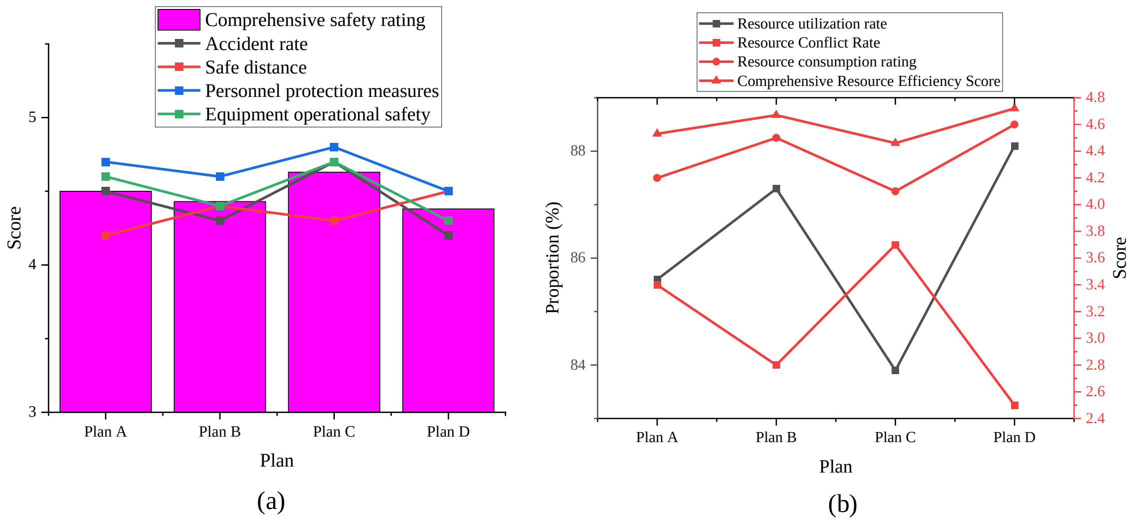

Figure 3: Safety assessment and resource efficiency analysis ((a): Safety assessment; (b): Resource efficiency)

According to the safety assessment scores, Plan C has the highest overall safety score of 4.63, indicating that it performs best in safety. Its safety indicators are all rated highly, particularly in personnel protective measures and equipment operation safety. This suggests that Plan C can effectively reduce safety risks on the construction site and ensure smooth project implementation. In contrast, Plan D has the lowest safety score of 4.38, illustrating deficiencies in some critical safety indicators. Moreover, Plan D has the highest overall resource efficiency score of 4.72, demonstrating high resource utilization, low conflict rate, and reasonable resource consumption. Plan D excels particularly in the key indicators of resource utilization and conflict rate, implying that it achieves optimal configuration and maximizes construction efficiency under limited resources. Plan B follows closely with a resource efficiency score of 4.67, while Plans A and C score slightly lower at 4.53 and 4.46, respectively.

The analysis indicates that while Plan C excels in safety, it is slightly inferior to Plan D in resource efficiency. This suggests that a balance between safety and resource efficiency may be necessary in practical construction scheduling, and the most suitable scheduling plan should be chosen based on the specific project needs. The final scheduling decision should integrate safety assessment with resource efficiency to ensure smooth project progress and effective resource utilization.

5 Discussion

This work primarily analyzes the performance differences of the optimized model under varying dataset sizes. First, NSGA-III performs quite well on large datasets but shows weaker adaptability on smaller datasets. This phenomenon may be related to NSGA-III's strategy for managing the diversity of the solution set, as the algorithm relies on reference points to ensure the uniform distribution of solutions. However, on smaller datasets, the reference point configuration may cause sparse solution distributions, thereby affecting the optimization results. As the dataset size increases, the increased number of reference points helps the algorithm better capture the multi-dimensional objective space, resulting in stronger adaptability on large datasets. Nevertheless, the suboptimal performance on smaller datasets highlights its sensitivity to dataset size, particularly in scenarios requiring finer granularity control. In contrast, the proposed optimization model demonstrates strong robustness across all dataset sizes, especially showing an advantage in the Spacing metric. The Spacing metric reflects the uniformity of the solution set's distribution in the objective space; The proposed model ensures a balanced distribution of solutions across different dimensions through the design of the objective function and iterative strategies. This uniformity enhances solution diversity and enables decision-makers to select solutions suited to various contexts from a multi-dimensional solution set, further showcasing the model's robustness.

Regarding safety assessment, although this work provides a detailed analysis of safety scores, these scores should be understood in terms of their practical impact on construction. Higher safety scores indicate that the solutions are more effective at reducing safety incidents during construction and meeting the high standards for personnel and equipment protection in construction projects. This satisfies industry safety standards and helps reduce the risk of project delays due to accidents, ensuring timely project delivery. Furthermore, solutions with high resource efficiency are of significant practical value in construction projects. High resource efficiency means that the project has been more rationally planned in terms of resource allocation, reducing material and equipment waste. Hence, it directly contributes to lowering the total cost of the project and improving construction progress. This efficient use of resources is critical in projects with tight budgets or limited resources, as it ensures compliance with project deadlines while minimizing environmental impact, and aligning with sustainable development goals.

Overall, through its high scores in safety and resource efficiency, the proposed model's practical application value in real-world construction scenarios has been further validated. The model's robustness and multi-scenario applicability highlight its potential in the intelligent construction field, particularly in complex construction projects that require a balance between safety and resource optimization, demonstrating its strong practical utility.

6 Conclusion

This work systematically investigates intelligent construction scheduling using MOO algorithms, to generate optimal scheduling plans that balance safety and resource efficiency. A new optimization model is proposed, validated, and compared with classical MOO algorithms such as NSGA-III, MOEA/D-DE, and SPEA2+SDE. The proposed model demonstrates significant advantages in MOO problems. Comparative analysis of experimental data reveals that the model consistently outperforms the comparison models on key indicators such as HV, GD, IGD, and S, particularly when dealing with larger datasets. This indicates that the proposed model can better balance the conflicts between various objective functions and generate higher-quality solution sets while ensuring the scheduling plan meets MOO requirements. This work confirms that safety and resource efficiency are interdependent yet indispensable factors in practical construction scheduling through safety assessment and resource efficiency analysis of the generated scheduling plans. The assessment methods and the proposed models effectively balance these factors, providing a scientific basis for construction management. This comprehensive approach not only enhances the feasibility and rationality of the scheduling plans but also offers valuable insights for future intelligent construction management practices.

The optimized model proposed in this work performs excellently under specific data volumes and static construction environments but still exhibits certain limitations in dynamic adaptability. Specifically, the model's applicability may be limited in dynamic scenarios, such as fluctuations in resource availability or construction delays. This work does not test the model in dynamic construction environments. However, future research could validate its real-time adaptability through case studies or hypothetical scenarios, such as how it handles scheduling adjustments due to resource shortages or unexpected events. The model's ability to respond in real-time to changes in the construction environment remains an area for further research. Additionally, the model faces high computational complexity when handling large-scale datasets or high-dimensional multi-objective problems, potentially resulting in slower convergence and impacting real-time performance in practical applications. This limitation suggests that in high-computation-demand scenarios, the model may encounter computational constraints. It indicates that future research should focus on simplifying the computational steps without compromising the quality of the solution set to enhance the model's practical usability. To address these limitations, future research could focus on enhancing the model's dynamic adaptability and computational efficiency. For example, dynamic scheduling algorithms or adaptive optimization mechanisms could be introduced to improve the model's responsiveness to resource changes and unexpected events. Furthermore, integrating other optimization techniques, such as metaheuristic algorithms, distributed computing, and parallel computing, could help reduce computational time and accelerate convergence. Additionally, future work could explore applying the model to more complex, large-scale construction scenarios to test its applicability and robustness in different environments, thus enhancing its practical value in the intelligent construction field.

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