WORK PACKAGE-BASED PROJECT PLANNING FOR OPTIMIZATION OF CARBON EMISSIONS IN MODULAR INTEGRATED CONSTRUCTION

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PhD

The Hong Kong Polytechnic University

This program is jointly offered by The Hong Kong Polytechnic University and Northwestern Polytechnical University

2026

The Hong Kong Polytechnic University

Department of Building and Real Estate

Northwestern Polytechnical University

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Work Package-Based Project Planning for Optimization of Carbon Emissions in Modular Integrated Construction

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

October 2025

CERTIFICATE OF ORIGINALITY

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Abstract

The construction industry faces mounting pressure to reduce its carbon footprint, as it accounts for approximately 38% of global energy-related CO_2 emissions. Modular Integrated Construction (MiC) has emerged as a promising approach to enhance sustainability in building projects, offering potential reductions in material waste, on-site construction impacts, and delay risks. However, existing efforts to improve MiC's carbon performance primarily focus on technical construction solutions, such as adopting low-carbon materials and implementing lean production practices to reduce waste. Research on using project management methods to improve MiC's carbon performance is notably limited. Work package–based project planning, an important project management method, has been shown to enhance cost-effectiveness and schedule performance by rationally sizing and sequencing work. It therefore also has significant potential to improve a project's carbon performance. This reveals a critical, underexplored opportunity for carbon mitigation through optimized work package configurations in MiC projects.

The primary aim of this study is to develop work package–based approaches to optimize carbon emissions in MiC projects while accounting for inherent trade-offs and economic considerations. The specific objectives are: (1) to establish a mathematical foundation linking work package characteristics to carbon emissions through a productivity-based framework; (2) to develop a single-objective genetic algorithm for minimizing carbon emissions in MiC work packages; (3) to formulate a multi-objective

optimization approach that balances carbon reduction with cost efficiency; (4) to develop an LLM-driven heuristic optimization framework to lower adoption barriers; and (5) to operationalize these approaches in an integrated platform for practical industry application.

This study first establishes the theoretical relationship between work package configurations and carbon emissions using the Cobb–Douglas production function. Building on this foundation, three complementary optimization approaches are developed: a Two-List Genetic Algorithm (TLGA) for single-objective carbon minimization; evolutionary algorithms (NSGA-II and SPEA2) for multi-objective optimization balancing carbon and cost; and a novel LLM-based heuristic framework that provides accessible optimization capabilities. These approaches are validated through comprehensive computational experiments using both simulated project instances and a real-world case study involving a large-scale MiC development.

The key findings demonstrate substantial carbon reduction potential through work package optimization. The TLGA achieved carbon emission reductions ranging from 49.93% to 81.15% compared with traditional work package schemes, while the multi-objective approaches identified balanced solutions achieving approximately 68% carbon reductions with only an 11% cost increase. The analysis revealed important patterns in carbon-optimized work packaging: larger projects benefit from smaller, more uniform work packages; different approaches are optimal for parallel factory production versus sequential on-site assembly; and the execution mode significantly influences optimal work package configurations. The LLM-based framework effectively bridged implementation barriers, with performance gaps narrowing markedly for larger projects and under more flexible scheduling conditions.

This study makes original contributions to sustainable construction management from both theoretical and practical perspectives. Theoretically, it establishes a productivity-based carbon emissions framework for MiC projects; advances genetic algorithm methodology through an innovative chromosome representation; develops a comprehensive multi-objective optimization approach that balances environmental and economic objectives; and introduces a paradigm for human–AI collaborative optimization through a structured prompt-chain methodology. Practically, it provides accessible decision-support tools for identifying carbon-efficient work package configurations, quantifies trade-offs between carbon reduction and cost, and offers implementation guidelines tailored to specific project characteristics. The integrated optimization platform operationalizes these approaches in a cohesive computational environment, addressing the persistent gap between theoretical optimization capabilities and practical implementation in MiC project management.

Publications Arising from the Thesis

Journal articles:

1. **Zhang, Y**., Li, X., Teng, Y., Shen, G. Q., & Bai, S. (2025). Multi-objective optimization of work package scheme problem to minimize project carbon emissions and cost. *Computers & Industrial Engineering*, 200, 110831.

2. **Zhang, Y**., Li, X., Teng, Y., Bai, S., & Chen, Z. (2024). Two-list genetic algorithm for optimizing work package schemes to minimize project costs. *Automation in Construction*, 165, 105595

3. **Zhang, Y.**, Li, X., Teng, Y., Shen, G. Q., & Bai, S. (2024). A heuristic rule adaptive selection approach for multi-work package project scheduling problem. *Expert Systems with Applications*, 238, 122092.

4. **Zhang, Y.**, Bai, S., Chen, Z., Liu, S., & Li, X. (2023). Real-time dynamic selection algorithm of RCPSP scheduling priority rules based on deep learning. *Systems Engineering Theory and Practice*.

5. Liu, Z., Li, X., Gao, Z., **Zhang, Y**., Teng, Y., & Wu, C. (2025). A Hybrid and Intuitive Work Packaging Approach with Multiple Task Relations, General Work Package Precedence, and BIM in Modular Construction. *Journal of Construction Engineering and Management*, 151(4), 04025019.

Conference articles:

1. **Zhang, Y.**, Li, X., Wu, C., & Chen, Z. (2022, December). A double deep Q-network-enabled two-layer adaptive work package scheduling approach. In International Symposium on Advancement of Construction Management and Real Estate (pp. 1027-

1041). Singapore: Springer Nature Singapore.

2. **Zhang, Y.**, Teng, Y., & Li, X. (2024, July). Tabu search-based multi-objective optimization of work package schemes to minimize project costs and carbon emissions. In ICCEPM 2024 (pp. 823-830).

3. **Zhang, Y.**, Li, X., Teng, Y., Shen, Q., & Bai, S. (2023, August). A Reinforcement Learning Framework for Maximizing the Net Present Value of Stochastic Multi-work Packages Project Scheduling Problem. In International Symposium on Advancement of Construction Management and Real Estate (pp. 733-756). Singapore: Springer Nature Singapore.

4. **Zhang, Y.**, Li, X., Teng, Y., Shen, G. Q., & Bai, S. Unlocking Large Language Models for Project Scheduling. In ICCREM 2024 (pp. 562-571).

5. **Zhang, Y.**, Xia Z., Teng, Y., Li, X., & Shen, G. Q. (2024, October) Carbon optimization based on three-echelon MC project supply chain network modeling. In International Symposium on Advancement of Construction Management and Real Estate (Accepted)

6. **Zhang, Y.**, Li, X., Teng, Y., Shen, Q., & Bai, S. Modular construction transportation scheduling considering hydrogen fuel cell vehicle substitution and temporary parking. In International Symposium on Advancement of Construction Management and Real Estate 2025 (Accepted)

Acknowledgements

My Ph.D. journey at The Hong Kong Polytechnic University over the past two years has been a transformative and unforgettable scholarly experience. The completion of this thesis was made possible by the guidance, encouragement, and assistance of many individuals to whom I am deeply grateful.

I owe my deepest gratitude to my Chief Supervisors, Prof. TENG Yue and Prof. LI Xiao, for their exceptional mentorship throughout this doctoral journey. Their clear vision, rigorous standards, and incisive feedback continuously sharpened my thinking and improved the quality of this work. I am especially thankful for the time and patience they devoted to discussing ideas, refining methodology, and guiding me through setbacks. Their encouragement to pursue independence while providing steady guidance helped me grow as a researcher. I also appreciate the opportunities they created for collaboration, conference presentations, and professional development. This thesis would not have taken its present shape without their steadfast support and trust.

I am sincerely grateful to Prof. SHEN Geoffrey Qiping (my Co-Supervisor at PolyU) and Prof. BAI Sijun (my Chief Supervisor at NWPU) for their guidance and steady support. Their complementary perspectives and practical suggestions greatly sharpened my arguments and improved the clarity of this thesis. I especially appreciate their readiness to discuss ideas, share resources, and provide constructive suggestions. Their timely advice at key junctures strengthened both the rigor and scope of my research.

My heartfelt gratitude goes to Prof. NI Meng and Prof. CHI Hung-lin for their valuable suggestions during the research process. I would like to thank all the researchers in related fields whose scientific spirit of exploration, knowledge-seeking, and sharing made this thesis possible. I would also like to thank the rest of my thesis committee: Prof. XIAO Zhongdong and Prof. KUO Yong Hong for their constructive comments and encouragement, and for the insightful question which incented me to improve my research from various perspectives.

The Department of Building and Real Estate has been instrumental in supporting this work, providing crucial funding, facilities, and equipment that enabled me to complete the thesis. In particular, I wish to acknowledge Ms. Chloe Shing and Ms. Irene Pang from the BRE General Office for their efficient administrative help and support.

I sincerely thank the China State Construction Hailong Technology Company Limited, CDO of PolyU, CR Construction Company Limited, and AluHouse Company Limited for providing project information support and field research opportunities. Their timely coordination, access to project sites and personnel, and provision of detailed records strengthened the practical relevance of this study. Special thanks to Mr. LUO Junjiang for his contribution to the design and beautification of the platform user interface in Chapter 7. His expertise in UI/UX transformed the platform into an intuitive and accessible prototype, significantly enhancing usability, visual coherence, and overall user experience.

Finally, I owe profound thanks to my parents. Their enduring patience, unwavering faith in my abilities, and boundless love have sustained me at every stage of this journey. I would like to express my sincere gratitude to comrade PENG Hongyu for her companionship and support over the past eight years, which has enriched my life and given me spiritual encouragement. I also thank Miss MA Shihui and Mr. LIU Zisheng for their help and support in my daily study and life, and I am grateful to all the people I have met in the research team.

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List of Abbreviations

ABM	Agent-based Models
AI	Artificial intelligence
AWP	Advanced Work Packaging
AWPS	Automatic Work Package Sizing
BIM	Building Information Modeling
CNN	Convolutional Neural Network
CPM	Critical Path Method
DfMA	Design for Manufacture and Assembly
DOM	Dynamic Ontology-based Mapping
EA	Evolutionary Algorithm
HVAC	Heating, Ventilation, and Air Conditioning
K-GAWP	Knowledge Graph-enabled Adaptive Work Packaging
LLM	Large Language Model
LSTM	Long Short-Term Memory
MC	Modular Construction
MiC	Modular Integrated Construction
MIP	Mixed Integer Programming
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PBS	Product Breakdown Structure
PERT	Program Evaluation and Review Technique
PMBOK	Project Management Body of Knowledge
SPEA2	Improved Strength Pareto Evolutionary Algorithm
TLGA	Two-List Genetic Algorithm
WBS	Work Breakdown Structure
WPS	Work Package Scheme
WPSP	Work Package Scheme Problem

Chapter 1 Introduction

1.1 Introduction

This chapter presents the framework of this study, beginning with the research background and the questions that will be addressed. It then establishes the research scope, aim, and specific objectives. The chapter then describes the research design and highlights the study's significance. The final section outlines the thesis's structure.

1.2 Research Background

1.2.1 Carbon Emission Reduction in the Construction Industry

Climate change, manifested through global warming, has triggered extreme weather events, including heavy rainfall, disruptions to marine ecosystems, rising sea levels, seasonal snow loss, and glacier melting. Research indicates that global warming is likely to exceed 1.5°C and 2°C in the 21st century unless greenhouse gas (GHG) emissions are drastically reduced in the coming decades. Carbon dioxide constitutes over 99% of energy- and industry-related GHG emissions (Masson-Delmotte et al., 2021). Recent data from the Copernicus Climate Change Service confirms the severity of this trend: on 22 July 2024, the daily global average temperature reached a record high in the ERA5 dataset. These developments underscore the urgent need to achieve net-zero emissions to mitigate global warming.

According to the 2023 Global Buildings and Construction Status Report, the buildings and construction sector contributes significantly to global climate change, accounting for approximately 21% of global GHG emissions. Buildings are responsible for 34% of global energy demand and 37% of energy- and process-related CO_2 emissions (UNEP, 2024). A substantial gap remains between current progress and the required decarbonization trajectory. To meet the 2030 milestone, an annual increase of ten decarbonization "points" is now required—up from the six points per year expected in 2015. Hong Kong faces similar challenges. The construction sector contributed HKD 133 billion to Hong Kong's GDP in 2023 and has a significant impact on the city's carbon footprint. Buildings in Hong Kong account for approximately 90% of electricity consumption and around 60% of carbon emissions (Wei et al., 2024). Consequently, reducing emissions in the construction industry is crucial for achieving Hong Kong's goal of carbon neutrality.

The construction industry is increasingly focused on reducing carbon emissions and enhancing sustainability (Abdi et al., 2018). Efforts include the use of low-carbon building materials (S. Chen, Teng, et al., 2023), optimized structural design (Y. Zhang et al., 2022; Hansen et al., 2024), and advanced digital and information technologies (J. Xu et al., 2022; Alsakka et al., 2024). In this context, Modular Integrated Construction (MiC) has emerged as a technologically mature and economically viable strategy for carbon reduction in the built environment. As an innovative construction method, MiC has significant potential to reduce carbon emissions. Studies indicate that MiC projects can achieve lower carbon footprints than conventional methods, primarily through reduced material waste and improved energy efficiency in manufacturing (Loo et al., 2023; Wei et al., 2024). As shown in Table 1.1, MiC has been valued and developed in many countries and regions worldwide.

Table 1.1 Current status of MiC development in some countries and regions

Countries or regions	The current state of development
Chinese Mainland	The market in the Chinese Mainland was valued at an estimated USD 19.12 billion in 2026.
Japan	The Japanese market was estimated to be valued at USD 5.89 billion in 2026.
United Kingdom	The government's goal to build approximately 300,000 new homes annually presents a major opportunity for the modular sector.
United States	In 2024, the U.S. modular construction market reached $20.3 billion.
Sweden	Sweden builds a remarkable 45% of its homes in factories, providing a proven model for other European nations.
Hong Kong	As of 2024, more than 70 MiC projects were ongoing or at the planning stage in Hong Kong

Despite MiC’s potential, there is a significant gap in specialized project management methodologies tailored to its unique characteristics. Conventional approaches often fail to capture the distinct spatiotemporal dynamics of MiC projects, in which parallel factory production and on-site preparation require sophisticated coordination and resource allocation. During planning, traditional methods inadequately address decisions that strongly influence MiC's carbon performance, including module standardization, supply-chain configuration, manufacturing process optimization, and logistics planning. A well-calibrated MiC planning methodology would enable practitioners to identify carbon hotspots across the project lifecycle and implement targeted mitigation strategies. Moreover, integrated planning tools that incorporate carbon metrics alongside cost and schedule parameters would support evidence-based decision-making during early design, when interventions are most effective. Developing MiC-specific project management frameworks is therefore not merely an academic exercise but a practical imperative for realizing MiC's full carbon-reduction potential, particularly as the industry faces increasingly stringent carbon regulations and adopts life-cycle environmental performance as a core project success criterion.

1.2.2 The Practice of MiC in Hong Kong

The construction industry plays a significant role in economic development. As an investment-driven sector, it enhances national competitiveness and affects residents' quality of life. Global construction expenditures exceeded US$11 trillion in 2019 (Alaloul et al., 2021). The industry has likewise contributed substantially to Hong Kong's economy. Figure 1.1 shows the total receipts of Hong Kong's construction industry over the past decade. In 2024, total receipts—comprising the gross value of construction works performed and other business receipts—reached HK$473.7 billion, a 5.1% increase over 2023. Industry value added, which measures the sector's contribution to Hong Kong's GDP, rose to HK$133.0 billion in 2023, a 9.2% increase over 2022. Per establishment, value added was HK$4.9 million in 2023, up 6.6% from

2022 (Hong Kong Census and Statistics Department, 2024).

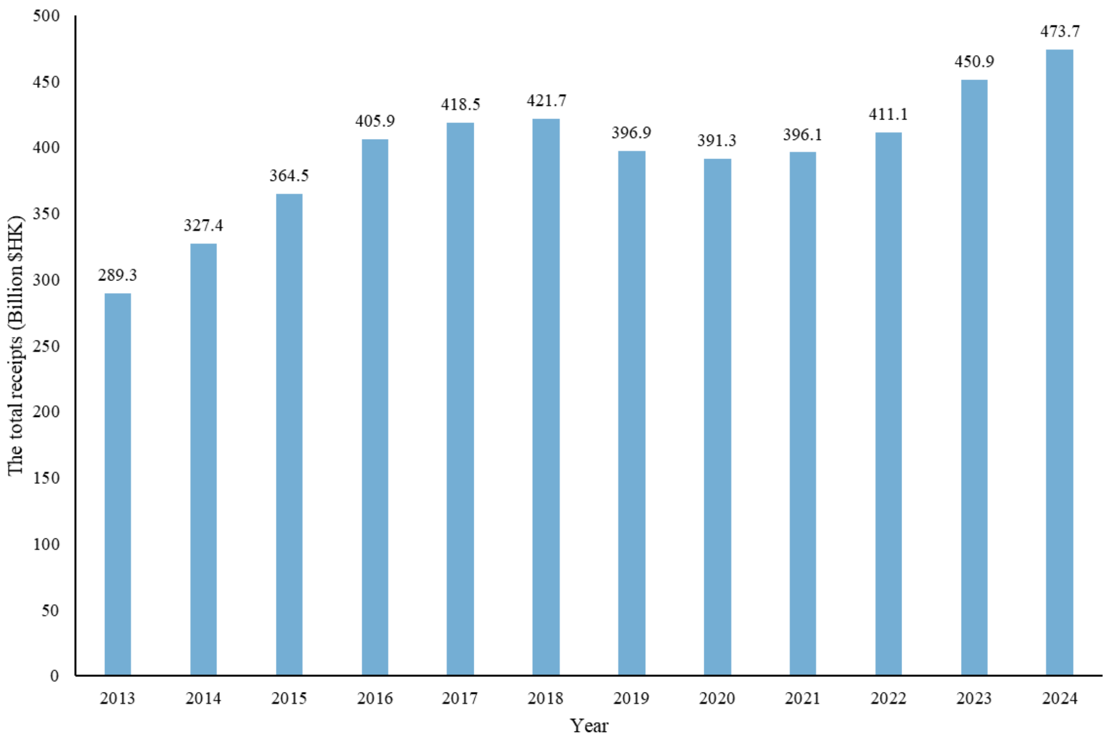


Figure 1.1 The total receipts of the construction industry in Hong Kong, 2013 to 2024

However, the construction industry continues to face challenges, including low productivity (Hasan et al., 2018), high waste rates (Y. Zhang, Pan, et al., 2024), and time and cost overruns (H. Li et al., 2024). To move beyond this stagnation, the industry must adopt contemporary technologies, with Modular Integrated Construction (MiC) representing one such approach. MiC is an innovative method in which building components are manufactured in a factory environment and then transported to the site for assembly (X. Li et al., 2022). MiC originates from modular construction (MC) but places greater emphasis on integrating advanced production technologies into the construction process (Pan & Hon, 2020). Because the concepts and scopes of MC and MiC are largely equivalent, this study uses "MiC"—the term commonly used in Hong Kong—to refer to the method. MiC incorporates principles of modularity, modularization, Design for Manufacture and Assembly (DfMA), and lean production to enhance cost efficiency (Pan & Hon, 2020). It has seen widespread adoption in the UK, US, Australia, Singapore, and elsewhere. Research shows that, when executed effectively, MiC can meet Construction 4.0 standards and deliver advantages over traditional cast-in-situ construction, including shorter construction times (Eriksson et al., 2014), improved quality assurance (Goh & Goh, 2019), and reduced labor requirements (Z. Xu et al., 2020).

As a subtropical, high-density city with limited land resources, Hong Kong faces one of the world's most acute housing challenges. Over the next 30 years, the city is projected to face a shortfall of approximately 3,000 hectares for housing. To address this, the Government has planned to build 308,000 public housing units from 2024 to 2033 (HKSAR, 2023). However, labor shortages and high construction costs make it challenging to deliver these plans using conventional methods. In 2017, the Government therefore proposed adopting MiC as a policy initiative to enhance productivity and cost-effectiveness and to shorten construction time. As of 2024, more than 70 MiC projects were ongoing or at the planning stage in Hong Kong (HKSAR, 2024). The Chief Executive's 2023 Policy Address further promotes MiC through measures to strengthen the component supply chain, foster collaboration with the Greater Bay Area, and encourage private-sector adoption (HKSAR, 2023). These initiatives aim to deliver construction more efficiently, reduce manpower requirements, and accelerate housing supply.

The rapid adoption of MiC in Hong Kong necessitates a corresponding evolution in project-planning methodologies tailored to the local context. Although the Government has shown strong policy commitment to MiC, a critical gap persists between technology adoption and the adaptation of the planning framework. Traditional planning approaches, developed for conventional construction, do not adequately address MiC's unique characteristics. In particular, they fail to account for the complex interdependencies among off-site manufacturing, logistics coordination, and on-site assembly—a limitation that is especially problematic in Hong Kong's dense urban environment. This misalignment often yields suboptimal outcomes that do not fully capitalize on MiC's benefits. An adaptive MiC planning framework calibrated to Hong Kong's construction ecosystem would help practitioners navigate regulatory requirements, spatial constraints, supply-chain configurations (including Greater Bay Area integration), and workforce capabilities. Moreover, as Hong Kong pursues the carbon-reduction targets in the Climate Action Plan 2050, MiC planning methodologies that explicitly incorporate carbon metrics would better align construction practices with broader sustainability objectives. Developing such approaches is both academically significant and practically imperative, providing decision-makers with tools to optimize MiC implementation across diverse project typologies, enhance the technology's contribution to meeting pressing housing needs, and advance environmental performance in the built environment.

1.2.3 The Work Package-based Project Planning

Project planning is a fundamental phase of project management that defines scope, objectives, and procedures to enable effective execution and control (Pellerin & Perrier, 2019). It establishes the groundwork for resource allocation, scheduling, and task integration, ensuring alignment with overall project goals. Effective planning also facilitates risk management by anticipating challenges and developing mitigation strategies, thereby increasing the likelihood of success and optimizing resource use (Schwindt & Zimmermann, 2015a).

To translate high-level project planning strategies into actionable execution, the project scope must be systematically decomposed. At the foundational level of the Work Breakdown Structure (WBS) lies the work package—the lowest hierarchical unit designed for granular management. More than simply a collection of tasks, a work package acts as a distinct control unit that encapsulates specific deliverables, resources, and responsibilities. By isolating these manageable segments, work packages allow for precise cost estimation, rigid scheduling, and targeted monitoring. Consequently, they serve as the essential interface between strategic planning and operational performance, ensuring that broader project objectives are met at the task level. Figure 1.2 (Y. Zhang, Li, et al., 2024) illustrates the relationship among work packages, scheduling, and planning across the project life cycle.

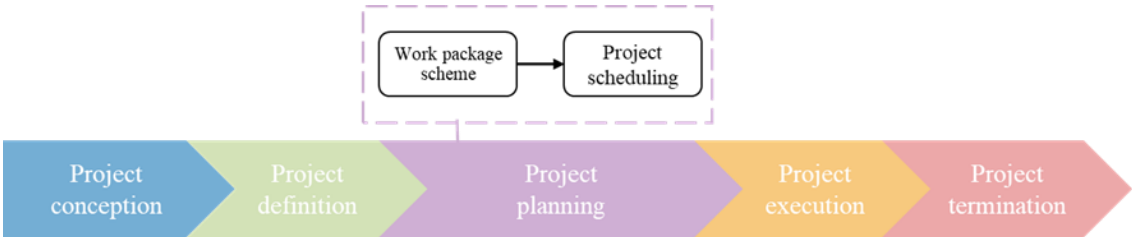


Figure 1.2 The relationship among work package formation, project scheduling, and project planning.

Work package–based planning has significant potential to reduce carbon emissions in MiC projects. Integrating this approach offers a strategic means to cut emissions, streamline execution, and enhance environmental performance by precisely managing each project segment. Work packages can facilitate carbon reduction by improving resource efficiency, optimizing production processes, enhancing transportation planning, and strengthening life-cycle management.

(1) Enhancing resource efficiency

Work package–based planning enables meticulous resource allocation and utilization. Each work package can be tailored to optimize material use, reduce waste, and control inventory (Choo et al., 1999). Such detailed planning reduces overuse and waste generation, both of which are directly correlated with construction-sector carbon emissions.

(2) Improving the production process

Work packages support detailed breakdowns of construction processes, enabling the identification and implementation of energy-efficient methods at each stage. In factory settings where MiC components are prefabricated, such optimizations can substantially reduce energy consumption and associated GHG emissions (Liu et al., 2023). The systematic reviews and refinements inherent in work package planning promote continuous improvement and process sustainability.

(3) Improving transportation planning

Strategic work package planning includes optimizing logistics and transportation. By carefully scheduling and consolidating shipments of prefabricated modules from the factory to the site, transportation-related emissions can be minimized. Efficient routing and load management further reduce fuel consumption and exhaust emissions (Y. Zhang, X. Li, et al., 2024).

(4) Lifecycle carbon management

Work package–based planning enables the integration of life-cycle carbon management from the outset. Each work package can incorporate end-of-life considerations for materials and structures, promoting reuse and recycling. This foresight supports a circular-economy approach, reducing carbon impacts associated with production and disposal. Overall, work package–based planning aligns with strategic environmental objectives by promoting efficiency, reducing waste, and embedding carbon-reduction practices throughout the project life cycle, thereby improving project performance and delivering economic, environmental, and social benefits.

Integrating work package–based planning into MiC projects is a critical step toward addressing MiC's complex carbon-management challenges. Although the literature recognizes the potential of work packages to improve resource efficiency, production processes, transportation planning, and life-cycle management, a significant methodological gap remains in systematically leveraging this approach to optimize carbon across MiC projects. Traditional work-package formations emphasize schedule and cost, often treating carbon performance as incidental rather than central. This siloed approach misses unique reduction opportunities at the interfaces among factory production, logistics, and on-site assembly that characterize MiC.

A carbon-centric work-package methodology would enable teams to identify and quantify emissions hotspots with granular precision, facilitating targeted interventions at the package level where mitigation potential is greatest. The structured nature of work packages provides an ideal framework for establishing carbon performance metrics, benchmarks, and improvement targets that can be tracked throughout execution. By integrating carbon accounting directly into work-package definition, planners can make informed trade-offs among competing objectives while maintaining clear visibility of carbon implications.

This integration is particularly relevant in Hong Kong, where government initiatives promoting MiC adoption create a favorable environment for innovative planning approaches that address both productivity and environmental imperatives. Developing a comprehensive work package–based planning methodology calibrated for carbon optimization in MiC projects would contribute significantly to both theory and practice in sustainable construction management.

1.3 Research Problems Statement

Generating appropriate work-package schemes (WPSs) during planning is critical to effective project management. Although tools such as the WBS, critical path method (CPM), and program evaluation and review technique (PERT) are widely used for planning and scheduling, they do not specifically address how to generate WPSs for carbon reduction. Key unresolved issues include: (1) determining the optimal work content of each work package; (2) identifying relationships among work packages; and (3) assessing how different work-package designs affect project carbon-emissions performance. The characteristics of these issues include:

First, existing studies have not adequately examined how trade-offs in work-package size affect project carbon emissions. When tasks are grouped into packages, size trade-offs arise: smaller packages increase coordination complexity and workload while reducing economies of scale; larger packages reduce concurrency and may adversely affect cash flow (C.-L. Li & Hall, 2019). These trade-offs influence not only cost but also emissions. For example, larger packages can share equipment, labor, and space, creating scale effects that reduce waste and emissions, yet they may be less suitable for fine-grained management and the implementation of new carbon-reduction technologies. Conversely, smaller packages facilitate refined management and technology deployment but at the expense of scale efficiencies. Moreover, the relationship between emissions and work content is often nonlinear; both under-pacing and expediting can trigger additional emissions (Jaber et al., 2013).

Second, suitable models and methodologies to handle different types of work-package precedence relations in carbon-emissions optimization are lacking. Practice and scholarship distinguish two perspectives (C.-L. Li & Hall, 2019): strictly precedence-constrained work packages and generally precedence-constrained work packages. Under strict precedence, if task a in package W precedes task a' in package W', then all tasks in W must precede all tasks in W'. Under generalized precedence, processing of W and W' may partially overlap even if a task in W precedes a task in W'. These differing precedence structures affect execution modes and, in turn, package-level emissions. Figure 1.3 illustrates their distinct impacts on project execution.

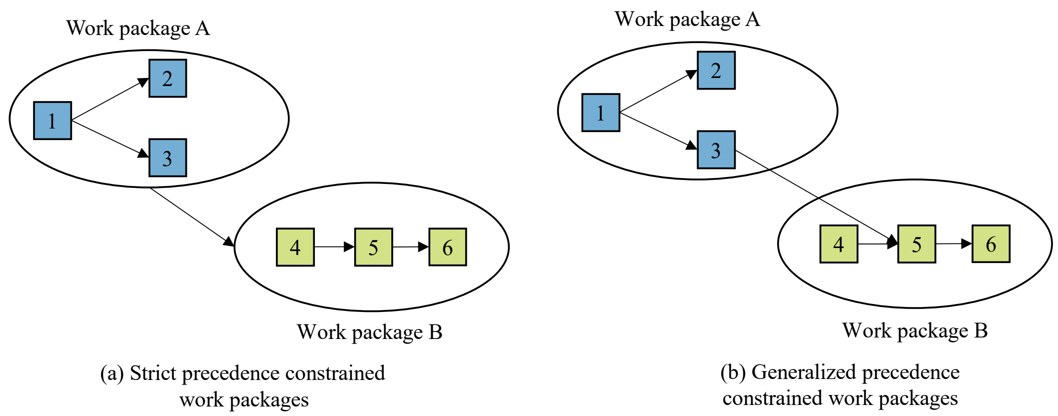


Figure 1.3 Precedence relations between work packages

In Figure 1.3(a), there are no time gaps among tasks within a work package; however, tasks in package B cannot begin until all tasks in package A are completed. Under strict constraints, packages remain more independent, reducing cross-package parallelism and potentially delaying overall progress. In Figure 1.3(b), package-level precedence derives directly from task-level precedence; for example, after task 4 is completed, task 5 cannot begin unless task 3 has also been completed. Under generalized constraints, packages require more collaboration. These relations increase cross-package parallelism but may introduce time gaps within a package. Accordingly, different models and methods are needed to address these two constraint types.

Third, inappropriate work-package division creates resource inefficiencies and coordination problems that can significantly increase emissions. Poorly defined packages undermine resource allocation (materials, equipment, labor), leading to over- or under-use—both of which elevate emissions. For example, over-allocation can cause excess material consumption and waste, whereas under-allocation can cause delays and prolonged equipment operation. Clear, appropriately sized packages enable monitoring and management of package-specific emissions; poorly defined packages obscure sources and quantities, complicating targeted reductions. Ambiguous package boundaries also create confusion and miscommunication among stakeholders, driving process inefficiencies, overlapping efforts, and rework—each contributing to uncontrolled emissions.

1.4 Research Scope

This study is motivated by the need to reduce carbon emissions in MiC projects. When developing an approach to optimize work-package schemes, it is essential to define the study's boundaries. The project-management life cycle typically includes conception, definition, planning, execution, and termination. Work-package generation is only one component of the planning stage. Additionally, this study targets carbon optimization at a general level, representing emissions through abstract mathematical models rather than measuring them from detailed engineering quantities. Two specific boundaries are as follows:

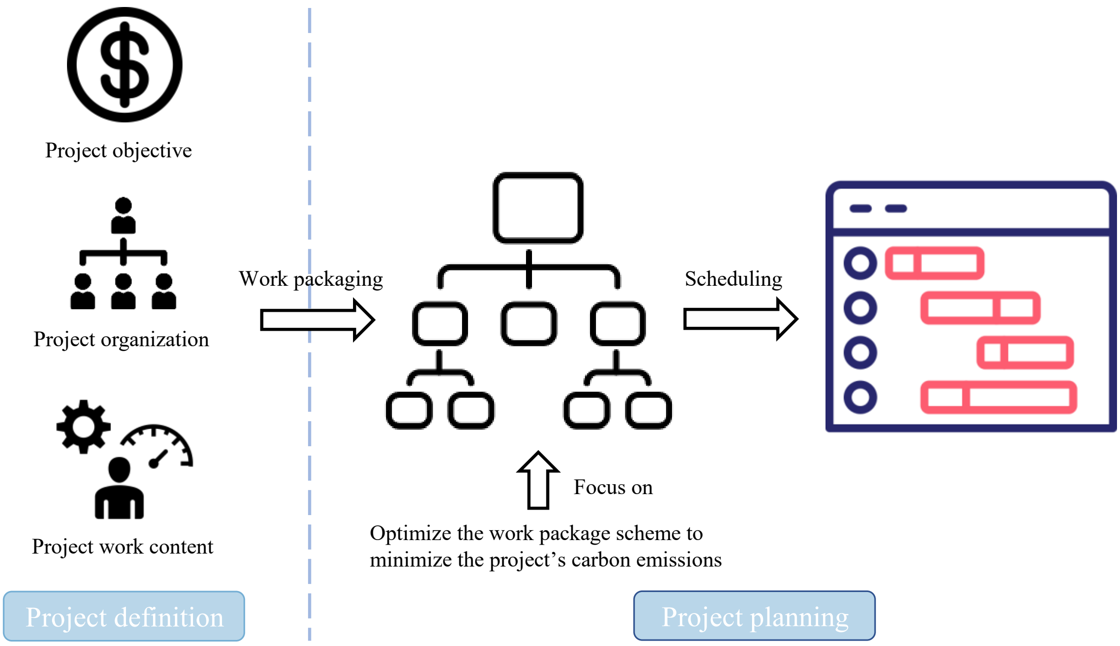


Figure 1.4 This study's scope in the project life cycle

(1) The study concentrates on generating WPSs, which serve as a critical bridge

between project definition and scheduling (see Figure 1.4). The project is decomposed into multiple work packages, each with specific durations, scope of work, and other attributes. These packages are then used as the lowest level for planning and scheduling. The study optimizes WPSs during the planning stage to minimize project-level carbon emissions.

Table 1.2 Comparison between the modeling and the measurement

Method	**Description**	**Key Features**	**Advantages**	**Disadvantages**
Mathematical Model	Uses statistical models to estimate emissions based on relationships from historical data and project parameters.	Predictive, generalizes across projects.	Scalable and useful for strategic planning, it can be quickly applied to new projects.	May lack accuracy for specific sites, heavily dependent on the quality and relevance of historical data.
Direct Measurement	Measures emissions directly by tracking resource consumption for each activity within a work package.	Direct measurement, highly specific to project activities.	Provides accurate, specific data, allows for precise monitoring and adjustments in real-time.	Labor-intensive, costly, may require recalibration for changes in project scope

(2) The study develops a generalized mathematical model linking work-package plans to total carbon emissions during the planning stage, rather than measuring emissions from engineering quantities. The model relates project work content (grouped into work packages) to associated emissions. It is designed for broad applicability across projects with similar characteristics and offers advantages in scalability and strategic planning. Once developed, it can be rapidly applied to new projects, reducing planning effort. It also supports high-level decision-making and scenario analysis, enabling evaluation of how changes in project scope or methods affect overall emissions. Table 1.2 summarizes the modeling versus measurement approaches.

1.5 Research Aim and Objectives

The primary aim of this study is to develop optimization approaches that generate work-package schemes (WPSs) minimizing carbon emissions in MiC projects, subject to task attributes, precedence relations, and project costs. The study focuses on the planning stage to enable appropriate and precise work-package division. The specific objectives are:

(1) Develop a mathematical optimization model for WPSs by specifying objective functions for carbon emissions and cost and formalizing constraints such as precedence relations, thereby laying the foundation for subsequent algorithms.
(2) Develop a single-objective optimization algorithm that minimizes project carbon emissions to improve sustainability performance.
(3) Develop a multi-objective optimization algorithm that simultaneously minimizes

carbon emissions and cost, enhancing realism and economic performance.

(4) Design LLM-based, prompt-engineering methods to heuristically optimize MiC WPSs. This approach aims to improve carbon-emissions performance while lowering the expertise barrier between project managers and optimization algorithms, thereby improving usability.

(5) Develop a user interface that integrates the optimization algorithms to enhance the usability of the proposed approaches.

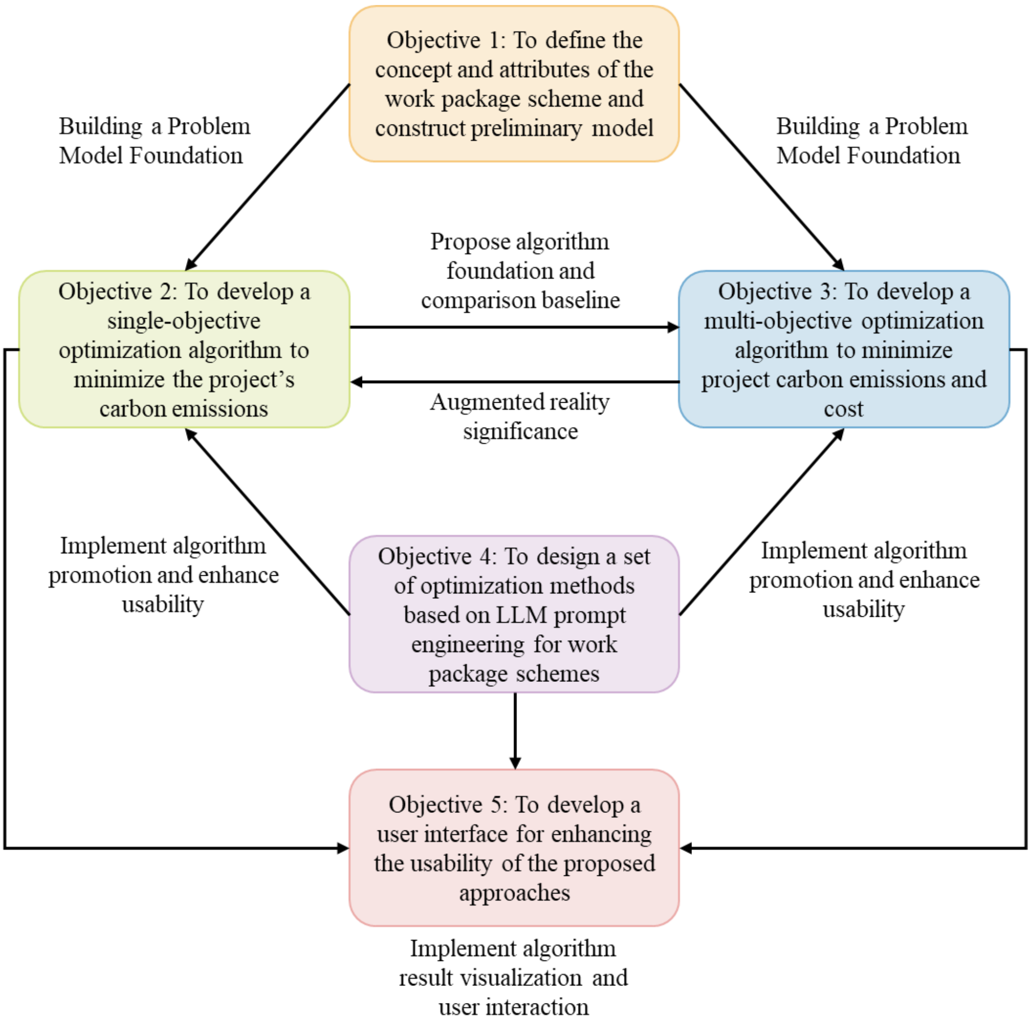


Figure 1.5 Logical relationship among the five objectives

Figure 1.5 delineates the structural coherence of the research objectives, illustrating a systematic progression from theoretical modeling to practical decision support. The framework is anchored by the mathematical formalization of Work Package Schemes (WPS) (Objective 1), which establishes the governing constraints and variables essential for all subsequent analysis. Building upon this foundation, the research advances through two complementary algorithmic pathways: a foundational single-objective approach to isolate and minimize carbon emissions (Objective 2), followed by a multi-objective expansion that integrates cost constraints to reflect economic realism (Objective 3). To bridge the gap between these sophisticated optimization techniques and construction practice, the study introduces an innovative LLM-driven heuristic method (Objective 4), designed to lower technical barriers and democratize access to optimization capabilities. The trajectory culminates in the development of an integrated user interface (Objective 5), which operationalizes these distinct computational engines into a cohesive platform. This evolution—from conceptualizing the problem space to engineering the solution and finally delivering the tool—ensures that theoretical rigor is directly translated into actionable strategies for sustainable MiC project management.

1.6 Research Path

To satisfy the aim and objectives, the research path is illustrated in Figure 1.6.

(1) Establish the conceptual foundation for the research. Using expert interviews and a comprehensive literature review, examine existing approaches to project planning,

work-package design, and carbon-emissions management in MiC. Identify research gaps at the intersection of work-package optimization and emissions reduction, and formalize a clear definition of "WPS." Develop a preliminary model to serve as the theoretical framework for subsequent algorithm development and testing.

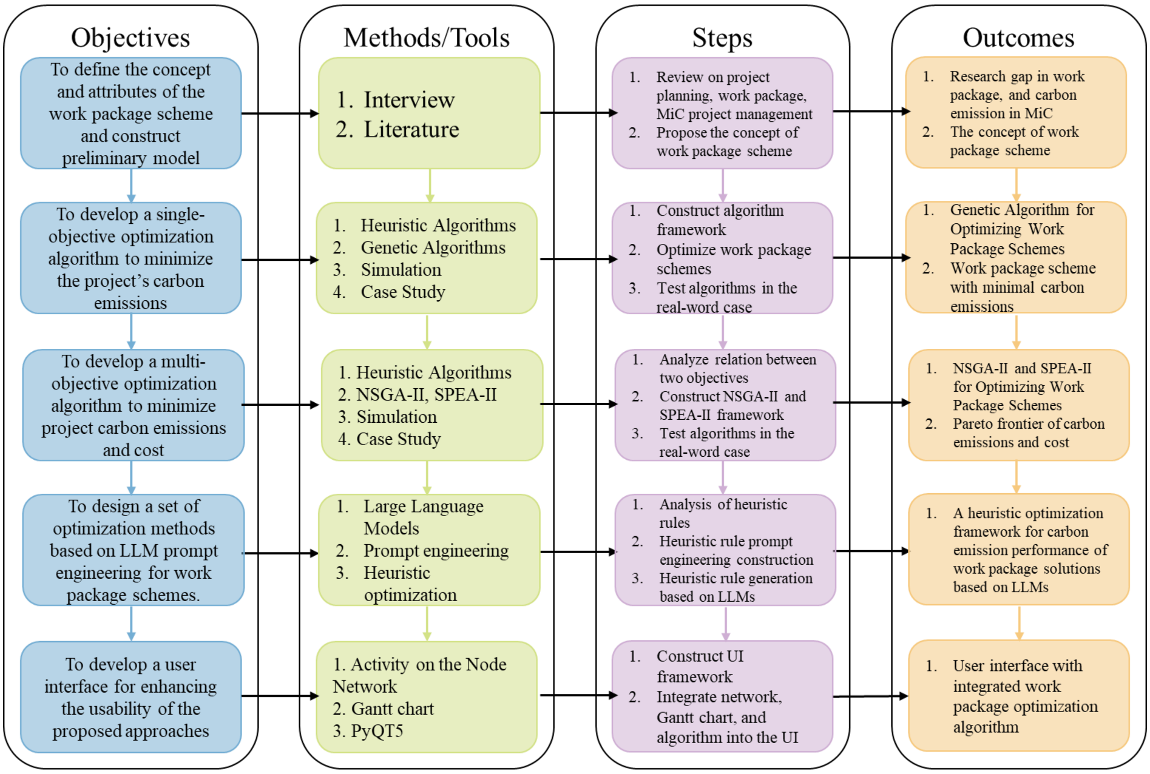


Figure 1.6 The overall research path

(2) Develop a single-objective optimization approach focused on minimizing carbon emissions. Construct an algorithmic framework based on a genetic algorithm, supported by heuristic methods and simulation. Target WPS configurations to minimize project-level emissions. Validate the approach through rigorous real-world case studies. Deliverables include a functional GA tailored to WPS optimization and documented

cases demonstrating measurable emissions reductions.

(3) Extend the approach to multiple objectives, explicitly addressing the trade-off between emissions and cost. Analyze the relationship between these objectives, then implement advanced multi-objective algorithms, including NSGA-II (Non-dominated Sorting Genetic Algorithm II) and SPEA-II (Strength Pareto Evolutionary Algorithm II). Build and validate the frameworks via simulation and case studies. The principal output is a Pareto frontier showing optimal trade-offs between emissions and cost, providing decision-makers with a spectrum of options aligned with their priorities.

(4) Integrate emerging LLM technologies into the optimization framework. Leverage prompt-engineering to generate heuristic rules for work-package optimization. Analyze existing heuristics, design prompt structures, and establish procedures for generating and evaluating new rules via LLM interactions. This stage combines traditional optimization with AI-assisted heuristic development, potentially uncovering novel emissions-reduction strategies not evident through conventional methods.

(5) Enhance practical applicability by developing a user-friendly interface for practitioners. Using PyQt5, build a comprehensive UI that integrates node-network visualization, Gantt-chart functionality, and the optimization algorithms into a cohesive tool. The interface will allow users to input project parameters, visualize alternative WPS configurations, and assess emissions and cost implications of different strategies. The final deliverable is a complete software solution that makes the research findings

accessible and implementable for construction project managers seeking to reduce project carbon footprints.

1.7 Significance and Contribution of the Research

The significance and contribution of this study can be reflected in the following four aspects:

Firstly, carbon-centric optimization model: The study develops a mathematical optimization model for generating WPSs in MiC that explicitly targets emissions reduction. Prior work lacks systematic formulations and optimization of WPSs with a carbon focus. The model links work-package configurations to quantifiable carbon footprints, translating high-level reduction goals into actionable planning decisions and providing a robust foundation for carbon-aware MiC planning.

Secondly, integrated single- and multi-objective algorithms: The study integrates algorithms that minimize emissions alone and jointly optimize emissions and cost. Whereas prior research prioritizes cost/schedule and treats carbon as incidental, these algorithms enable planners to systematically explore sustainability–economy trade-offs. The framework aligns with Hong Kong's tightening carbon-reduction targets while maintaining project viability.

Thirdly, LLM-enabled heuristic design: The study pioneers the use of LLM prompt engineering to generate and evaluate heuristics for WPS optimization, a novel approach in construction planning—especially for carbon optimization. This AI-assisted method lowers expertise barriers, connecting advanced optimization with practical project management and facilitating the adoption of carbon-reduction strategies.

Fourthly, end-to-end MiC planning framework and tool: The study develops a comprehensive work-package-based framework that targets carbon challenges at the interfaces of off-site production, logistics, and on-site assembly—junctures often overlooked but rich in reduction potential. Practically, it delivers both models and an integrated UI, enabling practitioners to implement carbon-optimized WPSs in real MiC projects, with particular relevance to Hong Kong’s dense urban context and pro-MiC policy environment.

1.8 Structure of the Thesis

Chapter 1 introduces the critical context of this study, including the research background, problem statement, scope, aim and objectives, design, significance and contributions, and thesis structure.

Chapter 2 conducts a comprehensive literature review of work package-based project planning and carbon reduction in MiC projects. The content analysis addresses two aspects: (1) identifying potential opportunities and gaps for carbon emission reduction in work package-based project plans from current research on project planning and work packages, and (2) examining the current status and research gaps in carbon emission reduction in MiC projects.

Chapter 3 establishes a comprehensive methodological framework for optimizing carbon emissions in MiC projects through work package planning. The methodology employs a mixed-methods approach, beginning with ontological foundations and scientific question formulation before proceeding to a research design in which quantitative analysis forms the core, supported by qualitative elements that ensure practical relevance. The chapter details specific methodological components for each research objective: data collection through field visits and document analysis; construction of mathematical models for WPSs; development of single- and multi-objective optimization algorithms using evolutionary computation; creation of LLM-based heuristic frameworks to bridge implementation gaps; and design of an integrated optimization platform.

Chapter 4 constructs a mixed-integer programming (MIP) model for work packages to minimize project carbon emissions. Based on the mathematical function defining work package carbon emissions, a Two-list Genetic Algorithm (TLGA) is developed to determine the optimal WPS for the project. The effectiveness of the proposed algorithm is demonstrated by comparing it with both the original WPS of an actual MiC project and schemes obtained using state-of-the-art heuristic algorithms.

Chapter 5 presents a novel multi-objective optimization model for the WPSP that minimizes both project carbon emissions and cost. Multi-objective evolutionary algorithms (EAs) are developed to solve this model. A multi-objective mixed-integer programming model establishes the functional relationship between work package attributes (duration and work content) and optimization objectives (carbon emissions and cost). Additionally, two multi-objective optimization EAs, NSGA-II and SPEA2, are developed to obtain the Pareto frontier.

Chapter 6 proposes a prompt engineering framework based on an LLM to address the problem that work package planning algorithms are too abstract and difficult to apply due to professional barriers. First, a set of structured thought-chain prompts is constructed to prompt the LLM to explore additional work package planning rules. Second, the rules generated by the LLM are used to develop WPSPs that optimize the project's carbon emissions performance. Finally, project instance dataset-based comparative experiments demonstrate the effectiveness of the proposed framework in improving project carbon emission performance and addressing professional barriers.

Chapter 7 develops a user-friendly platform that embeds both the work-package optimization algorithm and the LLM-based heuristic optimization framework introduced in previous chapters. This platform enhances the usability of the developed algorithms, paving the way for intelligent project management in MiC.

Chapter 8 synthesizes research on carbon-emission optimization in MiC projects using four complementary approaches. It analyzes the TLGA for single-objective optimization, which achieved substantial carbon reductions compared to traditional methods. The discussion examines multi-objective optimization that balances environmental and economic considerations, significantly reducing carbon emissions with minimal cost increases. It evaluates the LLM-based framework that bridged implementation gaps by making optimization accessible to project managers without specialized expertise. Finally, it discusses the integrated software platform that operationalized these advances through a user-friendly interface. The chapter articulates both theoretical contributions and practical implications, and identifies future research directions.

Chapter 9 synthesizes research findings on carbon-emission optimization in MiC projects using work-package-based approaches. It highlights five key contributions: a mathematical optimization model that establishes a productivity-based carbon-emission framework; a single-objective TLGA algorithm that achieves 49-81% carbon reductions; a multi-objective approach that balances environmental and economic considerations; an LLM-based framework that makes optimization accessible to practitioners; and an integrated software platform that operationalizes these advances. The chapter articulates both theoretical contributions to knowledge and practical benefits to industry, while acknowledging limitations in the emission modeling methodology and suggesting future research directions, including more nuanced emission models and enhanced LLM frameworks to further advance carbon-reduction MiC practices.

Chapter 2 Literature Review

2.1 Introduction

This chapter provides a comprehensive review of the literature on carbon reduction in the MiC project and work package. The content analysis is conducted in two aspects: (1) research status and challenges of carbon emission reduction in MiC project management, (2) the knowledge domains and the opportunities of work packages into MiC projects for project planning.

2.2 Carbon Reduction in MiC Projects

2.2.1 Opportunities for Carbon Reduction in MiC Projects

MiC is considered to have unique advantages for reducing carbon emissions compared with traditional construction methods (S. Chen, Zhang, et al., 2023). Numerous studies have shown that MiC creates numerous carbon-reduction opportunities across the design, construction, and operation stages of a project.

Research demonstrates that MiC delivers significant environmental benefits through two principal mechanisms. First, transferring up to 90% of construction activities to controlled factory environments substantially reduces on-site energy consumption and associated emissions (Abdelmageed & Zayed, 2020). Studies in Hong Kong confirm that decreased resource consumption from heavy equipment represents a major factor in overall emission reductions (Y. Wang et al., 2025). The factory setting enables streamlined, automated processes that consume less energy per construction unit compared to traditional methods (Guo et al., 2023). Second, MiC's inherent Design for Manufacturing and Assembly (DfMA) approach optimizes material use from the initial design stage. Research indicates MiC can reduce construction waste by over 80% through precise factory-based manufacturing (Loizou et al., 2021), with one study reporting an average 78.8% on-site waste reduction compared to conventional construction (Y. Zhang, Pan, et al., 2024). Additionally, DfMA facilitates the use of lower-carbon materials, such as engineered timber, instead of carbon-intensive concrete (Sajid et al., 2024), further reducing embodied carbon in construction projects.

In terms of construction, among various techniques, the traditional cast-in-situ method is known for higher carbon emissions and waste generation (Shen et al., 2019). Conversely, using precast concrete has been shown to reduce carbon emissions compared to cast-in-situ concrete (Dong et al., 2015). Furthermore, increasing the modularity of construction processes has been demonstrated to enhance efficiency, safety, quality, and reliability, while simultaneously reducing costs and waste (Chan et al., 2023). An agent-based model (ABM) is developed to simulate multi-threaded and multi-objective construction activities through collecting detailed project data of two case studies (one using the MiC method and the other one using the cast-in-situ method) in Hong Kong (Loo et al., 2023). The findings indicate that the MiC project offers substantial environmental benefits compared to the cast-in-situ project, particularly in terms of reducing CO_2 emissions and other harmful pollutants.

There are many studies on carbon-reduction operations in MiC's sustainability research (Nguyen et al., 2022). The controlled factory environment in which MiC modules are produced allows for precise installation of high-performance insulation, energy-efficient windows, and advanced heating, ventilation, and air conditioning (HVAC) systems, which are crucial for reducing energy consumption and, consequently, carbon emissions. For example, a study of energy consumption in MiC manufacturing facilities focused on reducing cycle time within the facility by identifying non-value-added activities that caused waste, thereby enhancing energy consumption (Xie et al., 2018). Moreover, the airtight construction achievable with modular units effectively minimizes thermal bridging and air leakage, leading to superior energy performance compared to traditional construction methods (Zhou & Xue, 2023).

2.2.2 Challenges of Carbon Reduction in MiC

Although MiC offers many opportunities to reduce carbon emissions in buildings, its widespread adoption has been hindered (Wuni & Shen, 2020). This section will identify some of the knowledge, technical, and management challenges that MiC faces in promoting carbon reduction.

Research identifies several significant barriers to reducing embodied carbon in MiC projects. Studies indicate that high material consumption, particularly concrete and steel, remains the primary contributor to embodied carbon in MC (X. Chen et al., 2025). This challenge is compounded by insufficient incentives and technical guidance for adopting green materials and low-carbon design strategies (Z. Li et al., 2024). Further research highlights how suboptimal module sizing and structural overdesign with excessive safety margins frequently result in unnecessary material use (Y. Zhang et al., 2022). The lack of standardization across modular components has been shown to complicate prefabrication processes, increase waste generation, and limit potential economies of scale (Jiang et al., 2022). Additionally, studies document how failure to achieve early design freeze often leads to late-stage modifications and rework, significantly increasing carbon emissions (Ramachandra & Ranadewa, 2023). Finally, despite their potential benefits, digital twin technology and BIM face limited adoption across various types of construction projects, including MiC, due to high implementation costs, integration complexity, and the absence of standardized protocols (Ba et al., 2025). The design and engineering of MiC projects differ significantly from conventional construction projects. Specifically, MiC necessitates intricate interfacing between modules, entails longer lead-in times, and demands highly restrictive tolerances (Pan et al., 2007). Furthermore, MiC exhibits low tolerance for dimensional and geometric variabilities, which can lead to errors during modular assembly, complicate rectification procedures, and result in prohibitive rework costs (Shahtaheri et al., 2017). Rather than helping to reduce carbon emissions, rework generates additional material waste and carbon emissions. In addition, the prerequisite for MiC to achieve carbon emission reduction through lean production is advanced, sophisticated production technology, but this process technology is still very underdeveloped in MiC's current production practice (Shahtaheri et al., 2017).

Compared to traditional cast-in-situ construction methods, MiC is characterized by a broader value and supply chain, including a complex network of stakeholders and processes. The sustainable supply chain for MiC includes various stages, including planning, modular design, obtaining statutory approvals, site preparation and development, modular manufacturing, transportation, storage, buffering, and the eventual on-site assembly and installation. Therefore, a project management mode compatible with MiC is essential (Wuni & Shen, 2020). The management process of MiC carbon reduction is notably complex due to the need for enhanced communication among a diverse web of stakeholders (Gan et al., 2018), each with distinct goals and value systems within the MiC supply chain (Luo et al., 2019). This complexity is further compounded by the need for extensive coordination of workflows, trades, resources, and stakeholders, both prior to and during the construction process (Hwang et al., 2018). All these require an advanced and efficient project planning method to be implemented in MiC projects.

2.2.3 Project Planning for Carbon Reduction in Construction Projects

Project planning is a critical phase for embedding carbon-reduction strategies into construction projects. Lessons from project planning for carbon emission reduction in conventional construction can provide valuable insights for MiC projects. A systematic framework employing Pinch Analysis tools has been developed to optimize energy and material resource management throughout construction processes, demonstrating potential for significant reductions in CO2 emissions in building projects (Aziz et al., 2017). Complementing this approach, researchers have developed minimum marginal abatement cost (Mini-MAC) curves specifically for construction activities, providing project managers with a clear methodology to identify and prioritize low-cost carbon-reduction pathways during planning phases (Lameh et al., 2022). Additionally, studies suggest integrating carbon-emission trading mechanisms into construction project planning to enhance the economic viability and implementation of carbon-capture techniques in building materials and processes (X. Zhang et al., 2014). Together, these methodologies offer construction planners a comprehensive toolkit for systematically reducing emissions through strategic project planning that combines technical optimization, economic analysis, and market-based incentives to achieve carbon reduction objectives.

A notable development is a mathematical modeling framework that integrates carbon-emission constraints alongside traditional project objectives, such as time and cost, enabling construction managers to optimize schedules that balance economic performance with environmental sustainability (Hussain et al., 2024). Complementing this approach, researchers have developed comprehensive frameworks for low-carbon construction site planning that demonstrate significant emissions reductions through systematic scheduling of resource-intensive activities and strategic energy integration throughout project timelines (Aziz et al., 2017). While primarily focused on agricultural settings, studies of land consolidation projects have revealed transferable scheduling methodologies that effectively reduce carbon footprints, highlighting how temporal sequencing of construction activities can substantially impact overall sustainability outcomes (Ertunç, 2023).

Additionally, project strategic planning methodologies provide construction stakeholders with sophisticated tools to systematically incorporate carbon reduction objectives throughout project lifecycles while maintaining flexibility to accommodate evolving sustainability requirements and technological developments, ultimately facilitating more effective emission reduction in construction projects. Exemplified by Canada's carbon capture project planning model, these are essential for optimizing the deployment of emission-reduction technologies in construction and for ensuring that environmental and social considerations are integrated into project decision-making processes (Usas & Ricardez-Sandoval, 2024). Complementing these frameworks, studies have demonstrated the effectiveness of multi-criteria decision-making methodologies in selecting sustainable construction initiatives that balance carbon reduction objectives with economic and social factors, enabling more holistic project evaluation (Yang et al., 2016). Further enhancing strategic planning capabilities, sensitivity analyses have proven valuable in revealing how variations in emission targets and resource allocation impact overall reduction strategies, allowing construction planners to develop robust approaches adaptable to changing conditions (Usas & Ricardez-Sandoval, 2024).

2.3 Work Packages

2.3.1 Source of Work Packages: WBS

A WBS represents a segmented depiction of the total scope of work required to achieve specific project objectives. Utilized persistently throughout a project, it provides the structure for work management (ISO 21511, 2018). WBS is an advantageous management tool that significantly reduces project complexity and offers the following benefits in project management (Siami-Irdemoosa et al., 2015): (1) It breaks down a project or program into distinct WBS elements and elucidates their interconnections. (2) It enables the evaluation of the costs, risks, and durations associated with each WBS element. (3) It simplifies the planning process and the allocation of management and technical responsibilities. While the Project Management Body of Knowledge (PMBOK® Guide, 2021) provides a general framework for creating appropriate WBSs, construction projects face unique challenges due to their complex nature. The coordination of various stakeholders, including subcontractors, contract administrators, and suppliers, complicates the development of WBSs (Torkanfar & Rezazadeh Azar, 2020). Numerous research studies have explored various aspects and applications of WBS in project management. Siami-Irdemoosa et al. (2015) used neural networks to identify relationships and trends among WBS components. This innovative approach facilitated the automatic generation of WBS configurations in complex construction projects. Park and Cai (2017) introduced an automated system for establishing connections between tasks and BIM objects. This system utilizes BIM databases to generate dynamic WBSs. A WBS matrix is created to specifically target the management of deliverables in off-site construction projects, aiming to enhance project management effectiveness in this context (Sutrisna et al., 2018). Integrating WBS with blockchain and BIM technologies enhances collaboration, security, and workflow efficiency in construction projects, offering a promising framework to overcome traditional industry challenges (Stas & Abrishami, 2024). Additionally, integrating 4D BIM with a WBS framework can enhance construction management in Asian contexts. For example, the development of the Civil Easy View platform demonstrated this by using standardized WBS codes to improve connectivity and synchronization between BIM objects and schedule data (Kim et al., 2025). However, existing research is based on established WBS standards or guidelines for creating and utilizing WBS. Limited research has been conducted on developing methods or tools to optimize the WBS.

2.3.2. Work Package Scheme Problem

As mentioned in Section 2.3.1, A WBS is a hierarchical decomposition of a project into work packages (Globerson, 1994). All planned work packages in a project can form the "WPS". The Work Package Scheme Problem (WPSP) is the problem of deciding which specific tasks to include in each work package to generate WPS. A WPS as a prerequisite for project scheduling belongs to the research scope of project planning (Schwindt & Zimmermann, 2015b). The effective development of WPS for a project poses a considerable challenge because it involves a sophisticated decision-making process to categorize project tasks into these packages. It should be noted that WPS is a prerequisite problem for the classic project scheduling problem. Table 2.1 summarizes the differences between work packaging and project scheduling with respect to decision-making, objectives, and constraints. Constructing a work package requires more than just considering task duration and content; it also involves managing inter-task precedence relations (X. Li et al., 2022; X. Li, Shen, et al., 2019). Several studies have been conducted on generating work packages using various methods to enhance project efficiency and reduce project costs. The work packaging process is expedited by integrating BIM data into design structure matrices and domain mapping matrices, automatically generating a list of proposed work packages with minimal interfaces (Isaac et al., 2017). To improve project scheduling efficiency, templates stored in BIM databases are employed to generate work packages (H.-W. Wang et al., 2020). The work package sizing problem is defined comprehensively by grouping tasks into distinct work packages. A heuristic method and a lower bound are proposed to solve this problem (C.-L. Li & Hall, 2019).

Table 2.1 Basic difference between project work packaging and project scheduling

	Project work packaging	Project scheduling
Decision	Decide which tasks should be included in each work package	Assign resources to each task or work package and determine their start time
Objective	Minimize total project cost	Minimize project makespan
Constraints	1) The precedence relations between the tasks; 2) The acyclic relations between the work packages; 3) Inactive tasks form separate work packages.	1) The precedence relations between the tasks; 2) Maximum resource availability.
Reference	(C.-L. Li & Hall, 2019)	(Schwindt & Zimmermann, 2015b)

In the context of MiC project production, an Automatic Work Package Sizing (AWPS) technique is proposed to optimize work package size and reduce production cost (Z. Liu et al., 2023). Collectively, these studies outline the critical role of work packages in accelerating project progress and controlling project costs. In addition to being closely related to the project schedule and cost, the work package attributes (i.e., duration and work content) also directly affect the project's carbon emissions. The carbon emissions of construction projects mainly come from the project's primary work content, such as the resources invested (e.g., materials) and the construction process (e.g., equipment energy consumption) (Lai et al., 2023). Work packages, which result from decomposing project work content, have significant potential to reduce project carbon emissions at a more detailed level. However, existing research still fails to consider the project's carbon emissions when forming work packages. Especially the relationship between the WPSs and their carbon emissions is not fully understood.

2.3.3. Work Package Research Method

In the field of work package research, various research methods have been used. Widely used research methods can be divided into two categories: (1) advanced work packaging (AWP) methods based on intelligent approaches; (2) work package modeling and solving based on optimization.

AWP can be defined as an approach to decompose the production or construction workflows (e.g., technical process) by product breakdown structure (PBS) of building systems that are made smart with augmented capacities of visualizing, tracking, sensing, processing, networking, and reasoning so that they can be executed autonomously, adapt to changes in their physical context, and interact with the surroundings to enable more resilient process (X. Li, Shen, et al., 2019). Many methods and technologies have been developed to achieve AWP. A building information modeling (BIM)-based method incorporates BIM data in Design Structure Matrices and Domain Mapping Matrices to automatically generate a list of proposed work packages with minimal interfaces (Isaac et al., 2017). A dynamic ontology-based mapping (DOM) approach is proposed to automatically generate semantic-enriched work packages, thereby significantly increasing the accuracy and efficiency of the dynamic work packaging process (X. Li et al., 2022). A knowledge graph-enabled adaptive work packaging (K-GAWP) approach is proposed to dynamically form semantic-enriched work packages with different granularities (X. Li et al., 2023). Since AWP has stringent requirements for constraint modeling, a hybrid deep learning model is built to extract constraint information from project documents to enhance AWP (Wu et al., 2021). In addition, AWP faces another difficulty: the data used are usually unstructured or semi-structured. Some adaptive AWP methods have been developed to improve data processing efficiency. A vision-based hybrid method, integrating a faster region-based convolutional neural network (CNN) with virtual finite-state machines for the capture of task motions and the dynamic generation of task sequences, is developed (Martinez et al., 2021). A method employing a two-layer long short-term memory (LSTM) as the encoder and a fully connected layer for output concatenation is proposed to learn and predict adaptive pairwise task relationships (Amer et al., 2022). Analysis of the literature on AWP shows that research on AWP is typically based on machine learning and knowledge-based methods to develop adaptive packaging approaches for efficient work package planning.

In early optimization research in project management, few studies are directly based on work packages. Discussions about work package optimization tend to stay in the realm of project management business and practice (Gardner, 2006). Until 2019, a comprehensive work package sizing problem model was proposed to solve the trade-off problem in work package sizing (C.-L. Li & Hall, 2019). The objective of minimizing the total project cost, subject to a project duration limit, is considered. For serial task networks, an efficient algorithm that determines optimal work package sizes is described. For acyclic task networks, a heuristic method along with a lower bound for the unary NP-hard problem is developed. A computational study demonstrates that this heuristic consistently yields near-optimal solutions, representing a significant improvement over those obtained via benchmark procedures. There is a growing body of literature focused on work package optimization research. A two-stage hierarchical model for assessing work packages is proposed in a balanced manner, revealing a link between sub-work size and work package configuration (Kafali et al., 2022). To address the problem of sizing work packages in MiC projects, a dynamic programming algorithm is developed to merge tasks into work packages at minimal cost (Liu et al., 2023). It can effectively package production tasks while reducing costs by 1.28%–16.25% compared with traditional task-organizing methods. In addition, some studies have attempted to bridge the gap in metaheuristic algorithms for work package optimization research. A TLGA is proposed to optimize WPSs with minimal project costs (Y. Zhang, Li et al., 2024). The minimum gap between TLGA and state-of-the-art heuristics is only 3.91%. And the running time of TLGA can be reduced by about 66% through parallel computing. Overall, the studies present these research methods for work package research. The methods used in work package research over the past five years are summarized in Table 2.2. These studies provide important insights into the work packages. However, work package research based on optimization methods is still less than other types of research. There is still a large research gap and potential in this area.

Table 2.2 Summary of previous research in work packages

Research	Concerns	Interpretations	Methods
(X. Li, Shen, et al., 2019)	Constraints management	To define and implement smart work packaging (SWP) for constraints management in PHP (prefabrication housing production).	Constraint modeling and optimization
(X. Li, Wu, et al., 2019)	Schedule reliability	To proposes an approach of smart work packaging (SWP)-enabled constraints modeling service.	Social network analysis (SNA) hybrid system dynamics (SD)-discrete event simulation (DES)
(C.-L. Li & Hall, 2019)	Costs	To consider the trade-off of work package size to minimize total project cost, subject to a deadline on project makespan.	Dynamic programming (DP), heuristic algorithms, exact algorithms
(X. Li et al., 2020)	Crane path planning	To achieve autonomous initial path planning, networked constraints classification, and adaptive decisions on path re-planning	Constraint optimization

Cont. Table 2.2Summary of previous research in work packages

Research	Concerns	Interpretations	Methods
(X. Li et al., 2021)	Privacy and security	To proposes a FedSWP framework, the federated transfer learning-enabled SWP for protecting the personal image information of construction workers in OHS management	Federated transfer learning
(X. Li et al., 2022)	Accuracy and efficiency	To proposes a DOM approach to automatically generate semantic-enriched work packages	Ontology-based mapping (DOM)
(Liu et al., 2023)	Costs	To describe an AWPS method in MC production to optimize work package sizing while minimizing costs.	Dynamic programming (DP)
(Y. Zhang, Li, et al., 2024)	Costs	To develop a TLGA to optimize WPSs with minimal project costs	Genetic algorithm (GA)

2.4 Research Gaps and Industry Needs

An extensive review of recent literature has covered a wide array of research topics concerning carbon reduction in MiC and work packages. These studies have enriched the knowledge base in these fields, offering insightful and practical information for both academics and professionals. While these contributions are significant, a critical gap in the literature persists: insufficient research on work package-based planning approaches for carbon reduction in MiC. The specific gaps are demonstrated as follows:

Firstly, although work packages are widely used as an effective project planning method, significant research gaps exist in project planning for carbon reduction implementation in MiC. First, there is a limited understanding of how work package-based planning can address the unique characteristics of MiC projects, including parallel factory production and on-site assembly processes that distinguish them from conventional construction. Second, the existing literature lacks comprehensive frameworks for integrating carbon accounting principles into work package definition and optimization, leading to carbon considerations being treated as secondary rather than primary planning parameters. Third, the relationship between work package configuration (size, boundaries, precedence relationships) and carbon performance remains largely unexplored, leaving project managers without evidence-based guidance for carbon-optimized work packaging decisions. Finally, there is a lack of specialized tools and methodologies that enable practitioners to systematically evaluate carbon implications across different WPSs while balancing other project objectives, such as cost and schedule. Addressing these gaps is essential to leveraging the full carbon-reduction potential of MiC through optimized project planning.

Secondly, despite advances in work package planning methodologies, a critical research gap remains in developing approaches that specifically prioritize carbon emission reduction in MiC projects. While previous research has improved the efficiency of generating work packages, existing algorithms predominantly focus on cost and schedule optimization, neglecting the carbon implications of different work package configurations. The unique structure of MiC projects—characterized by distributed production across factory and site environments—creates distinct carbon hotspots that require specialized consideration during work package formation. Current approaches fail to account for the carbon interdependencies between off-site manufacturing, transportation logistics, and on-site assembly phases of MiC delivery. Significant technical limitations further compound this research gap. Existing methods, such as the dynamic programming approach (Liu et al., 2023), can only create WPSs for projects with serial precedence relations, which is insufficient for the complex parallel processes inherent in MiC delivery systems. The unique carbon-emission patterns across factory production, transportation, and on-site assembly have not been adequately addressed in existing work packaging algorithms, particularly in productivity-based carbon accounting. Additionally, available methods lack the necessary flexibility to adapt to varying project scales, module configurations, and supply chain arrangements common in MiC implementation. There is an urgent need for algorithms that can automatically generate carbon-optimized WPSs. These algorithms must remain practical and user-friendly for industry implementation. The methods should integrate seamlessly with existing MiC planning workflows. They should provide a clear trade-off analysis between carbon performance and other project objectives. This supports evidence-based decision-making by project teams.

Thirdly, optimizing WPSs in MiC projects poses a complex challenge that requires balancing multiple objectives (carbon emissions, cost, and schedule) across interconnected work packages with varying precedence relationships. Traditional optimization algorithms, while powerful, often create a significant knowledge barrier for industry practitioners who lack specialized expertise in mathematical modeling and algorithm development. LLMs offer a revolutionary solution by bridging this gap through natural language interfaces that enable project managers to articulate project constraints, objectives, and priorities without advanced technical knowledge. LLMs can interpret project requirements, generate candidate WPSs, evaluate their performance against multiple criteria, and explain the rationale behind recommendations in accessible language. However, very little research currently exists on the application of LLMs to WPS optimization problems.

Fourthly, in addition to research gaps, the construction industry faces significant implementation challenges that hinder the adoption of carbon-optimized work-package planning in MiC projects. Current practices require specialized expertise in both work package theory and carbon management, which is a combination rarely found among project management teams. The absence of an efficient, intuitive platform creates a substantial barrier to entry, relegating advanced work package planning to academic exercises rather than practical application. The industry urgently needs an accessible digital platform that can guide practitioners through the work package formation process while automatically incorporating carbon considerations. Such a platform should feature intuitive interfaces, visualization capabilities, and decision support mechanisms that clarify the relationships between work package configurations and carbon outcomes. By eliminating these knowledge and expertise barriers, an integrated planning platform would democratize access to carbon-optimized work-package planning across the industry, enabling a wider range of project teams to implement carbon-reduction practices in MiC delivery while maintaining focus on project objectives.

2.5 Chapter Summary

This chapter first reviews the current status of MiC research, beginning with its development. It then discusses the opportunities and challenges of carbon reduction in MiC to identify research foundations and gaps. Through these reviews, work package-based project planning is identified as having significant potential to reduce carbon emissions in MiC projects. Consequently, literature on work packages is examined to explore how work package-based project planning can facilitate carbon reduction in MiC. The review covers work package sources, WBS, the WPS problem, and related research methods, providing important references for carbon reduction in MiC. Finally, research gaps and industry needs are thoroughly discussed.

Chapter 3 Research Methodology

This chapter establishes the methodological framework guiding this research on carbon-emission optimization in MiC projects. The methodology combines qualitative approaches for initial problem exploration with quantitative methods for mathematical modeling and the development of optimization algorithms. Beginning with the ontological foundation and the formulation of the scientific research question, this chapter systematically presents the mixed-methods research design, in which quantitative analysis serves as the core of the investigation, supported by qualitative elements that ensure practical relevance. The chapter then details the specific methodological approaches for each research objective: data collection through field visits and document analysis; construction of mathematical models for WPSs; development of single- and multi-objective optimization algorithms; creation of LLM-based heuristic frameworks; and design of a comprehensive optimization platform. These interconnected methodological components establish a rigorous foundation for the subsequent technical chapters, ensuring that the developed optimization approaches are both mathematically sound and practically applicable to real-world MiC projects. The methodological choices reflect the study's commitment to bridging the gap between theoretical optimization capabilities and their practical implementation in construction carbon management.

3.1 Scientific Research Question and Research Design

3.1.1 Establishing the Scientific Question

This study is founded on the ontological assumption that the physical processes, resource consumption, and resulting carbon emissions within MiC projects are objective, measurable phenomena that exist in the real world. This perspective acknowledges that there is a tangible reality to be studied and improved. Drawing on epistemological perspectives, this study posits that, while this reality is complex, knowledge about it can be effectively constructed and validated through systematic abstraction and empirical analysis. It is not assumed that a perfect representation of reality is possible, but rather that by creating mathematical models, this study can generate reliable and useful knowledge. These perspectives establish that carbon emissions in construction present a real challenge that can be addressed through mathematical analysis. This understanding leads directly to the central research question: How can WPSs be mathematically modeled and optimized to minimize carbon emissions in Modular Integrated Construction projects considering package relations and economic feasibility?

3.1.2 Research Design

The scientific research question leads to a mixed qualitative and quantitative methods research design where "quantitative analysis forms the core of the investigation", supported by an initial qualitative phase. This is not a balanced combination but rather a targeted approach in which qualitative methods serve as a crucial precursor to the primary quantitative work.

The main thrust of this thesis, however, is the quantitative analysis. This phase operationalizes the problem by translating the insights from the qualitative data into an MIP model. This quantitative framework provides a rigorous, objective means to analyze the problem, test hypotheses, and systematically search for optimal solutions. The development of optimization algorithms and the use of simulation are the central methods for generating the study's primary contributions. In this design, the qualitative work ensures the model's relevance, while the quantitative work provides a rigorous solution that directly aligns with the research aim of developing an optimization approach to minimize carbon emissions in MiC projects. Figure 3.1 shows the source of the scientific research question and the research design of this study.

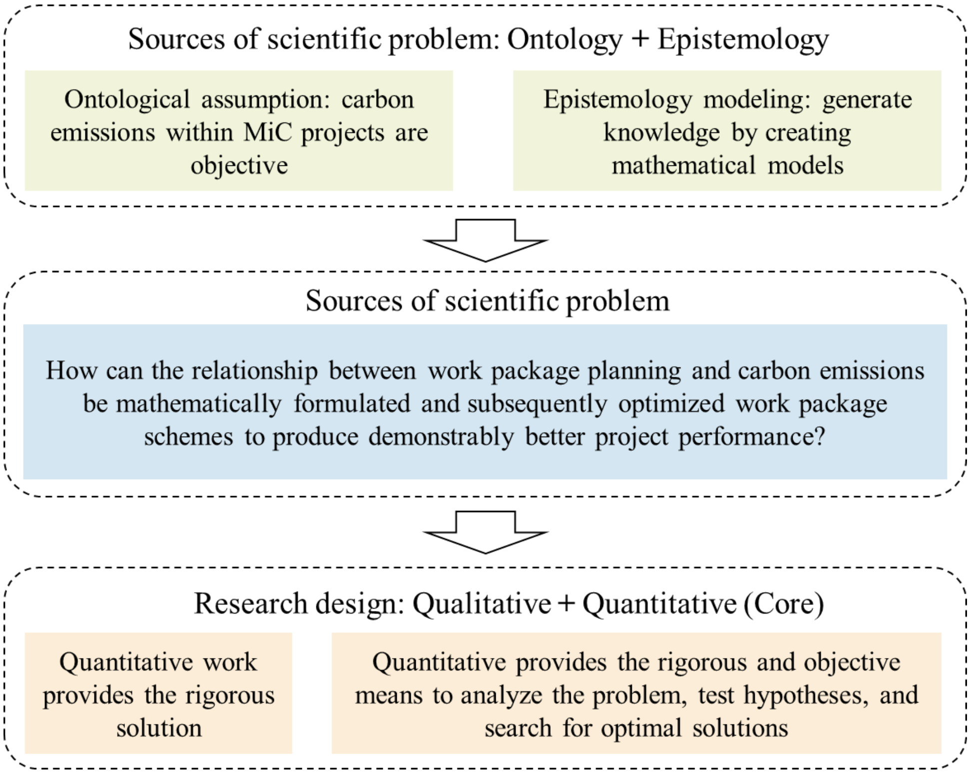


Figure 3.1 Scientific research question source and research design

To achieve the research objectives set out in Section 1.5, the following research methods will be used. The research methodology for defining WPSs employs field trips and literature review to gather foundational knowledge, followed by Project Network Technology and MIP, with subsequent verification using real MiC project processes. For single-objective carbon optimization, the approach combines literature review and simulation modeling with heuristic or metaheuristic algorithms, validated through sensitivity analysis on case studies and a simulation dataset. The multi-objective optimization methodology utilizes literature review and simulation to inform EAs and Pareto optimization techniques, with effectiveness evaluated through scenario analysis and quality indicators on case projects and a simulation dataset. LLM-based optimization methods are developed through a literature review and simulation, leveraging LLM technology and prompt engineering, refined with heuristic techniques, and evaluated across diverse project instances. Finally, the usability platform is created through visualization and simulation development that focuses on intuitive interfaces. Figure 3.2 summarizes the framework of methodology.

3.2 Definition and Mathematical Model Construction of Work Package Scheme Problem

3.2.1 Research Content

The first phase of this study established a mathematical framework for work package planning that minimizes project carbon emissions. This framework enables translating real-world construction planning challenges into mathematical optimization problems.

The research methodology involved two key phases. First, data collection was conducted through field visits to MiC projects to understand project structures and scheduling approaches. Second, the planning optimization problem was formally defined, and a mathematical model was developed based on existing literature and the collected project data.

3.2.2 Data Collection

Data collection was conducted through structured site visits to MiC projects and a comprehensive analysis of project documentation. These field investigations focused on gathering two essential types of planning materials: detailed task breakdowns and project schedules, which formed the foundation for developing the optimization framework. During site visits, tasks were systematically categorized based on their operational characteristics and requirements. Tasks were classified as either flexible or constrained based on whether they could be combined with other activities. Constrained tasks, such as high-risk lifting operations, required dedicated planning packages due to safety protocols, coordination demands, or specific responsibility assignments. These field observations provided crucial insights into which construction activities could be grouped together for efficient execution and which needed to remain separate due to their specialized requirements.

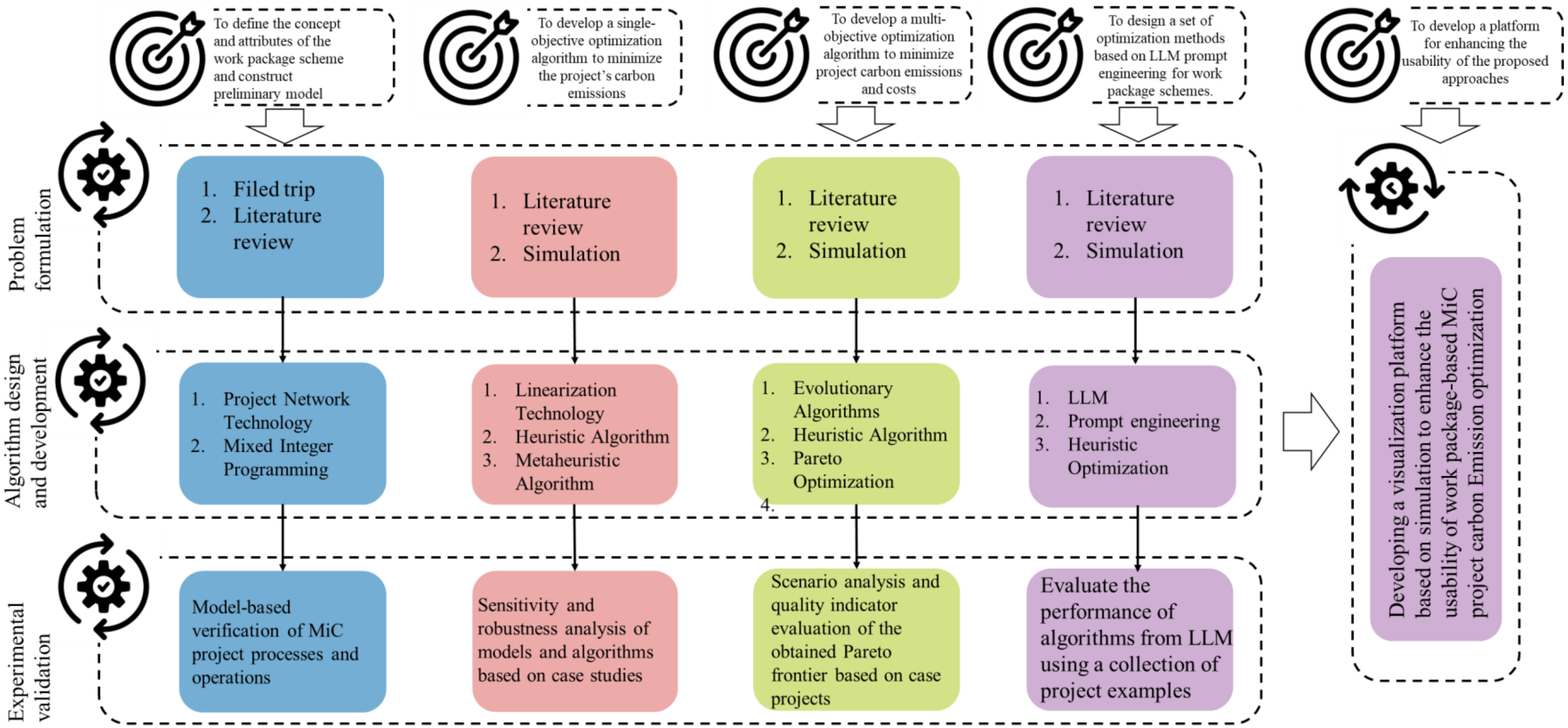
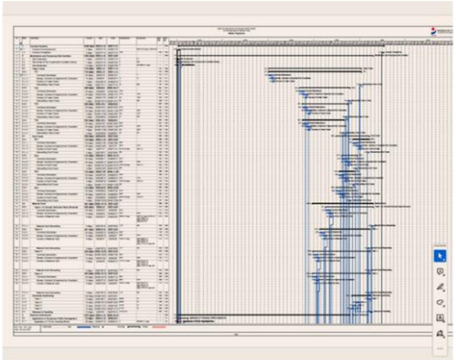


Figure 3.2 Framework of Methodology

(a) Equipment operation record



(b) Original project WBS and schedule

Figure 3.3 The original data from case project

For each construction task, essential parameters were documented, including completion timeframes and resource requirements measured in worker hours or cost units. Task dependencies were mapped to establish the sequence of activities, creating a project network that clearly visualizes individual tasks and their relationships. The data collection process also focused on establishing the connection between work package organization and carbon emissions. This involved gathering carbon emission factors for various construction activities and documenting production rates for different work package configurations. Historical project data was analyzed to understand how different planning strategies affected both performance and environmental outcomes, revealing practical constraints and optimization opportunities. Document analysis supplemented the field research by examining project records, industry standards, and academic literature on construction planning approaches. Particular attention was given to research demonstrating the mathematical relationship between production rates and carbon emissions, as this relationship forms a critical foundation for the optimization model. All collected information was systematically organized to support the development of a mathematical framework that links work package planning decisions to their environmental impacts.

Figure 3.4 MiC module production task information record

3.2.3 Problem Definition and Model Construction

The next phase involved translating the collected project data into a formal optimization framework. This systematic approach transformed real-world construction planning challenges into a structured mathematical representation that could be solved using optimization techniques. The problem definition process began by identifying the essential elements of work package planning and separating them from secondary considerations. This involved determining which decisions needed to be made (how to group tasks into work packages), which outcome to optimize (minimizing project carbon emissions), and which limitations must be respected (task dependencies and classifications). A critical step was establishing appropriate boundaries for the analysis, focusing specifically on work package formation while excluding resource scheduling decisions that occur in later planning phases. The mathematical model was constructed using established optimization principles for complex planning problems. Project structures were represented through interconnected networks that captured the relationships between construction tasks. This approach enabled systematic modeling of task dependencies and facilitated the identification of viable work package configurations by ensuring that proposed solutions maintained the required sequence of construction activities. Regarding the relationship between project carbon emissions and work packages, the carbon emissions can be expressed as a convex function of the production rate. The proof of this conclusion is as shown in following.

Theorem 3.1 The functional relationship between production ratio and carbon emissions is a convex function.

Proof

The Cobb-Douglas production function is a widely used mathematical model in economics that represents the relationship between two or more inputs (typically labor and capital) and the amount of output that can be produced. The Cobb-Douglas production function can be generally expressed as:

$$Y = A \times L^{\alpha} \times K^{\beta} \tag{3-1}$$

Where, Y is the total production (the real value of all goods produced in a year). L is the labor input. K is the capital input. A is total factor productivity (a constant scaling factor). α and β are the output elasticities of labor and capital, respectively. These parameters are constants determined by technology and indicate the percentage increase in output resulting from a one percent increase in labor or capital, holding all else constant.

Based on the basic Cobb-Douglas production function, Bogaschewsky and Mohamad Y. Jaber proposed and used the Cobb-Douglas production function considering environmental factor input measured by carbon emissions as Equation (3-2).

$$Y = A \times L^{\alpha} \times K^{\beta} \times C^{u} \tag{3-2}$$

Where C is carbon emissions, α, β are the capital and labor elasticities of output, respectively. $0 < \alpha, \beta < 1$. u is output elasticities of carbon emissions. $0 < u < 1$[1].

According to Equation (3-2), the production rate per unit time can be described as Equation (3-3).

$$P = \frac{A}{T} \times L^{\alpha} \times K^{\beta} \times C^{u}, (0 < \alpha, \beta, u < 1) \tag{3-3}$$

Thus, carbon emissions C can be described as Equation (3-4),

$$C = \left(\frac{PT}{A \times L^{\alpha} \times K^{\beta}}\right)^{\frac{1}{u}} \tag{3-4}$$

Based on Equation (4-6), calculate the second-order derivative of C with respect to P,

$$\frac{dC}{dP} = \frac{1}{u} \times (PT)^{\frac{1-u}{u}} \times \left(\frac{1}{A \times L^{\alpha} \times K^{\beta}}\right)^{\frac{1}{u}} \tag{3-5}$$

$$\frac{d^2C}{dP^2} = \frac{1-u}{u^2} \times (PT)^{\frac{1-2u}{u}} \times \left(\frac{1}{A \times L^{\alpha} \times K^{\beta}}\right)^{\frac{1}{u}} \geq 0 \tag{3-6}$$

Since the second-order inverse of $C = f(P)$ is greater than or equal to 0, it can be

[1] In the initial model, $0 \leq u < 1$. When $u = 0$, the model degenerates into a basic Cobb-Douglas production function that does not consider carbon emissions. This is inconsistent with the scope of this thesis. Therefore, in this thesis, $0 < u < 1$.

proved that there is a convex function relationship between carbon emissions C and production rate P.

The classification of tasks into flexible and constrained categories demonstrates how practical industry constraints can be effectively incorporated into theoretical models. This approach enhanced the model's real-world applicability while maintaining its mathematical solvability. Parameter definitions were carefully developed to ensure they could be measured consistently using available project data. The framework for connecting work package planning to carbon emissions was based on established production economics principles. This interdisciplinary approach integrated economic theory with construction management practices to establish the mathematical relationship between planning decisions and environmental outcomes. The research demonstrated that carbon emissions follow predictable patterns relative to production rates, which has important implications for selecting appropriate optimization methods. This theoretical foundation ensures that the problem can be solved efficiently using existing optimization techniques. The overall approach emphasized developing a flexible model structure that could be applied across different MiC projects while capturing the essential relationships between work package formation and carbon performance. This generalizability allows the framework to provide practical value across a range of construction contexts.

3.3 Single-objective Optimization of Work Package Scheme Problem to Minimize Project Carbon

3.3.1 Research Content

This section examines how construction work package planning can be optimized to minimize carbon emissions in modular building projects. The research addresses a critical gap in MiC project carbon reduction by recognizing that how work activities are organized and grouped significantly influences a project's environmental impact through production efficiencies, resource use patterns, and coordination requirements. The study transforms complex project planning decisions into a mathematical framework that enables systematic analysis of how different work packaging approaches affect carbon emissions throughout the construction process. The research methodology integrates three interconnected processes: defining the planning problem mathematically, developing solution algorithms, and validating results through real-world testing (H. Wang, 2024). This systematic approach follows established problem-solving principles where complex management challenges are first translated into mathematical models, then solved using computational methods, and finally tested through practical application.

3.3.2 Problem Formulation

The problem formulation methodology establishes the theoretical foundation for representing work package optimization as a mathematical problem. The process begins by modeling MiC projects as interconnected networks that capture the essential relationships between tasks without imposing artificial constraints. This network-based approach enables the formal definition of work packages and their schemes, providing mathematical rigor to concepts that are often treated qualitatively in construction management. A key theoretical innovation involves classifying tasks into flexible and constrained categories based on their operational characteristics. This distinction addresses a challenge in work package optimization: certain tasks, such as high-risk lifting operations or specialized testing procedures, require dedicated management and cannot be freely combined with other activities. This classification preserves the practical constraints of real-world project management while maintaining mathematical solvability, allowing the optimization model to generate solutions that respect operational realities.

The methodology connects work package configuration to carbon emissions through production economics theory. This framework establishes work package production rate as a key determinant of carbon efficiency, with mathematical evidence showing a predictable relationship between production rate and emissions per unit of work. This approach transcends traditional construction planning methods by integrating environmental performance directly into the mathematical representation of work package decisions. Rather than treating carbon emissions as an afterthought to be assessed after planning, the methodology embeds carbon efficiency into the fundamental decision-making process of work package formation. This enables optimization algorithms to directly target carbon reduction during the planning phase, creating a proactive approach.

3.3.3 Algorithm Design and Development

The algorithm design methodology uses evolutionary computation approaches to address the complex combinatorial nature of work package optimization. This problem belongs to a class of computationally challenging problems where traditional exact optimization methods become impractical for realistic project sizes. EAs offer particular advantages for this problem because they can efficiently explore large solution spaces without requiring mathematical derivatives or simplifying assumptions about the objective function. The methodology's most significant contribution lies in developing a specialized encoding scheme that effectively represents both task assignments and precedence relationships. This representation transforms the unstructured nature of work packages into an ordered sequence that maintains feasibility while enabling effective computational manipulation. The encoding preserves essential problem characteristics by maintaining task groupings within work packages and retaining precedence relationships between tasks, while creating a structure that supports evolutionary operations.

The algorithm incorporates specialized operators specifically adapted to the work package problem structure. These operators are designed with mathematical guarantees that all generated solutions remain valid throughout the optimization process. This ensures that the optimization results remain practically relevant by consistently respecting both task precedence and activity-type constraints. Rather than relying on penalty functions or repair mechanisms to handle invalid solutions, the methodology develops operations that inherently preserve feasibility. This approach improves both computational efficiency and solution quality by avoiding the common problem of generating invalid work package configurations that must be corrected or discarded during the optimization process. Figure 3.5 shows the basic steps of GA.

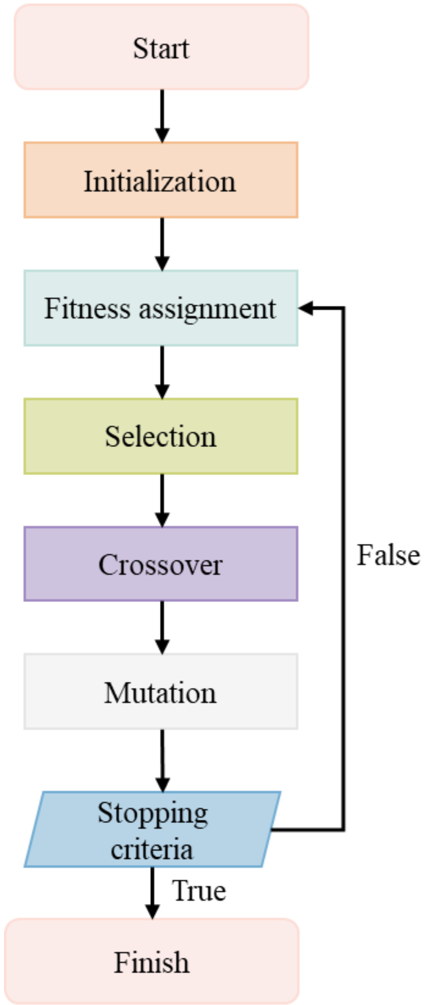


Figure 3.5 Basic steps of GA

3.3.4 Experimental Validation

The validation strategy combines real-world case studies with controlled experimentation to provide a comprehensive assessment of the optimization framework's effectiveness.

The case study methodology evaluates the optimization framework using an actual large-scale MiC project, determining whether theoretical benefits translate into practical applications with their inherent complexities. This approach recognizes that optimization models necessarily simplify reality, so validation must verify that these simplifications do not compromise practical usefulness. By comparing optimized work package plans against the approach actually implemented in practice, the methodology quantifies potential sustainability improvements while ensuring that optimized solutions remain operationally feasible.

The validation process includes comparative analysis that measures the developed approach against existing planning methods from the literature. This framework establishes objective performance measures and positions the research contribution within the current knowledge base. Rather than claiming improvement in isolation, this approach demonstrates measurable advancement over established techniques across multiple project scenarios with varying characteristics, ensuring that performance assessment considers algorithm effectiveness across diverse construction contexts. Controlled experimentation forms a core validation component, systematically varying project characteristics to identify relationships between project attributes and optimization outcomes. This approach isolates the effects of individual factors such as project size, task interdependencies, and construction methods.

3.4 Multi-objective Optimization of Work Package Scheme Problem to Minimize MiC Carbon Emissions and Cost

3.4.1 Research Content

This section addresses the critical challenge of balancing environmental sustainability with economic viability in MiC projects by optimizing work package planning. The research methodology employs a structured framework to simultaneously minimize both project carbon emissions and costs, recognizing the inherent trade-offs between these competing objectives. By establishing the optimal balance between environmental and economic performance, the methodology enables project managers to make informed decisions that reflect their specific priorities and constraints. The research methodology follows standard processes for solving optimization problems: problem formulation, algorithm design, and experimental validation. This approach first transforms the practical challenge of carbon-reduction work package design into a mathematical model that accounts for multiple objectives, then develops computational methods to efficiently identify optimal trade-off solutions, and finally validates the approach through rigorous testing across diverse project scenarios. This methodological framework bridges theoretical optimization concepts with practical construction management challenges, providing quantitative insights into how different work packaging strategies affect both environmental and economic performance throughout the MiC project lifecycle. The result is a decision-making tool that allows construction managers to systematically evaluate the sustainability implications of their planning choices while maintaining financial viability.

3.4.2 Problem Formulation

The problem formulation methodology establishes the theoretical foundation for optimizing work package planning by simultaneously considering both carbon emissions and cost objectives. This process begins with representing MiC projects as network structures that capture the relationships between tasks and their required sequence. The methodology then defines work packages as groups of tasks and establishes constraints to ensure operational feasibility, including proper handling of specialized tasks and maintaining required task sequences.

The approach develops two parallel objectives: one to measure project cost and another to calculate carbon emissions. The cost objective incorporates fixed expenses, work-related costs, and cash flow considerations, reflecting the economic dimensions of work package decisions. The carbon emissions objective builds upon production economics principles to establish the relationship between work package efficiency and environmental impact. This dual-objective approach represents a significant advancement over traditional single-focus optimization, recognizing that sustainable construction management must balance environmental performance with economic considerations. By formulating the work package planning problem as a mathematical model with dual objectives, the methodology creates a framework that captures the essential trade-offs between carbon reduction and cost efficiency. Pareto optimality theory is used to determine the optimal trade-off between a project's carbon emissions and costs. Figure 3.6 shows the relationship between Pareto optimal solutions and non-dominated solutions. The theoretical foundation uses established optimization principles to determine the optimal balance between a project's carbon emissions and costs. This approach provides the basis for subsequent algorithm development and experimental validation, enabling quantitative assessment of sustainability and economic balancing strategies in MiC project planning.

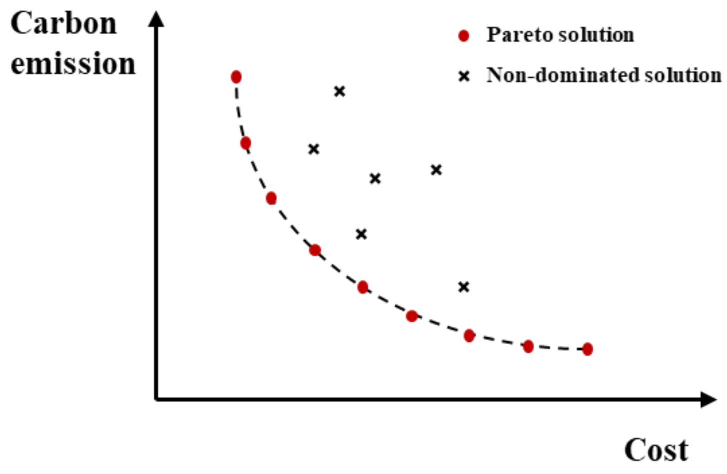


Figure 3.6 Pareto optimal solutions and non-dominated solutions

3.4.3 Algorithm Design and Development

The algorithm design methodology uses computational approaches inspired by natural evolutionary processes to address the complex optimization problem of work package planning with multiple objectives. This approach recognizes that traditional exact optimization methods become computationally impractical for realistic project sizes, particularly when multiple competing objectives must be simultaneously considered. EAs offer particular advantages for this problem because they can generate diverse optimal trade-off solutions in a single analysis without requiring predetermined preferences between different objectives.

The methodology incorporates two complementary computational algorithms to explore different approaches to multi-objective optimization. This dual-algorithm approach enables comparative analysis of different optimization strategies while providing methodological robustness through cross-validation. Both algorithms employ population-based search techniques that maintain and evolve a diverse set of candidate solutions to explore the trade-off space between carbon emissions and cost.

The algorithm design develops specialized solution-encoding schemes and computational operations tailored to the work-package planning problem structure. The solution representation effectively captures task assignments to work packages while enabling efficient computational manipulation. The methodology incorporates constraint-handling mechanisms to ensure that all generated solutions remain operationally feasible throughout the optimization process, addressing both task sequence constraints and specialized task requirements.

These problem-specific adaptations enhance the algorithms' ability to efficiently navigate the complex solution space of possible work package configurations. The result is a computational framework that can systematically identify optimal trade-offs between environmental and economic performance in construction project planning.

3.4.4 Experimental Validation

To validate the proposed optimization model, a comprehensive evaluation strategy is implemented. This strategy assesses the model's effectiveness at balancing costs and carbon emissions across a range of project scenarios. The approach combines theoretical testing with practical application, using systematic experiments and comparing the model's performance against established methods. The validation process includes both small, controlled simulations and large-scale, real-world case studies to provide a thorough understanding of the model's capabilities and applicability.

The methodology involves benchmarking the new optimization approach against current state-of-the-art software and specialized algorithms. This comparison evaluates the model not only on its ability to find a well-rounded set of optimal solutions but also on its performance in extreme cases that prioritize either minimizing carbon footprint or reducing costs. By measuring the model against both general and problem-specific tools, a comprehensive assessment of its effectiveness in reducing carbon emissions is achieved. A key component of this validation is sensitivity analysis, which systematically examines how changes in project variables and assumptions influence the optimization outcomes. This analysis investigates the impact of project characteristics, such as the number of tasks and their sequence, as well as model parameters like execution methods and resource conversion rates. The quality of the trade-off solutions is quantified using the hypervolume indicator. This allows for an objective comparison between different project setups and model variations, ensuring the robustness of the findings.

3.5 Large Language Models-based Heuristic Optimization Framework for Work Package Scheme Problem

3.5.1 Research Content

This section addresses the significant gap between advanced carbon optimization methods and their practical use in construction project management. To bridge this divide, the study introduces an innovative framework that uses LLMs, a form of artificial intelligence (AI). This approach positions the AI as an intermediary, tasked with translating complex mathematical techniques into actionable strategies that construction professionals can readily apply. The methodology involves developing carefully structured instructions that guide the AI to generate simple, step-by-step optimization procedures. This process empowers project managers to utilize powerful carbon-reduction strategies without needing specialized training in complex algorithms. The research is based on the understanding that theoretical breakthroughs in optimization are of little practical value unless they are made accessible and user-friendly for industry professionals. By systematically developing these AI instructions, generating practical solution methods, and confirming their effectiveness, this study creates a vital link between sophisticated theory and real-world application. This work paves the way for the practical implementation of carbon optimization in MiC projects, making carbon-reduction practices easier to adopt across the industry.

3.5.2 Problem Formulation

This chapter's methodology begins by redefining the problem of optimization. Instead of treating construction expertise and algorithm design as separate fields requiring distinct specialists, this research positions LLMs as a bridge between them. The framework uses AI as an intelligent agent, capable of converting the practical requirements of a construction project into the principles of mathematical optimization.

Following this principle, the research structures the task of creating an optimization procedure as a logical, language-based reasoning process for the AI. This approach breaks down the complex process of algorithm design into a series of manageable, sequential steps: first, understanding the problem; then, identifying patterns; and finally, specifying the implementation. By deconstructing the task in this manner, the methodology mirrors the problem-solving techniques of human experts and aligns perfectly with the AI's capacity for structured reasoning. This effectively transforms algorithm development from a highly specialized technical activity into a guided dialogue, making advanced optimization accessible through natural language.

3.5.3 Algorithm Design and development

The algorithm design methodology uses a structured approach to translate the vast knowledge within LLMs into practical optimization procedures for carbon reduction. This method is based on the understanding that while an AI contains extensive knowledge of optimization and mathematics, it requires carefully designed instructions, or prompts, to apply that knowledge to a specific problem. The methodology, therefore, focuses on developing a sequence of prompts that guide the AI through a logical reasoning process. This process mirrors how a human expert would design a solution, yet the final output is simple enough for non-specialists to use.

The sequence of instructions follows a deliberate progression. It begins by providing the AI with complete context for the problem, including the specific mathematical model used to calculate carbon emissions for a project. This foundational step ensures that the AI's reasoning is grounded in the project's unique details, rather than relying on generic solution patterns. From there, the instructions guide the AI through a series of stages: identifying relevant patterns, creating a basic solution template, defining the implementation steps, and verifying the result. Each prompt builds upon the AI's previous response, progressively refining the solution.

A key innovation of this method is its ability to generate a variety of optimization strategies, not just a single one. Rather than pursuing a single path, the methodology systematically explores multiple decision-making rules for core project operations. This structured exploration yields a diverse set of procedures that leverage different mathematical properties of the emissions model. Ultimately, this provides construction professionals with a toolkit of flexible approaches that can be adapted to the needs of various projects.

3.5.4 Experimental Validation

To test the effectiveness of the AI-generated procedures, this study conducts a comprehensive comparison with established optimization methods across a range of project scenarios. This approach acknowledges that the value of these new, user-friendly tools depends on balancing their performance with their ease of implementation. Therefore, the validation strategy evaluates both the quantitative results and the practical usability of the AI-based approach, providing a complete picture of its benefits.

The methodology involves systematically testing procedures across different construction scenarios by varying key project characteristics, such as the number of tasks and the schedule's complexity. This process identifies the specific contexts in which the AI-generated methods are most competitive. Rather than making a broad claim about performance, this practical approach aims to provide clear guidance to professionals on when and how to apply these accessible optimization tools to their project's specific needs.

The experimental process includes several measures to provide a thorough performance evaluation. The primary metric is the performance gap between AI-generated solutions and state-of-the-art optimization tools, providing a numerical basis for comparison. Furthermore, statistical analysis is used to measure the reliability and consistency of these methods. This assessment spans different project types. Reliability is a critical factor for practical use in real-world applications. By applying this consistent evaluation to multiple AI-generated algorithms, the research also offers insights into which approaches are most effective for solving the carbon optimization problem.

3.6 Work Package-based MiC Carbon Emission Optimization Platform

3.6.1 Development Framework and System Architecture

This section outlines the development of a software platform designed to optimize carbon emissions in MiC. The goal is to put the theoretical research from previous chapters into practice by transforming complex algorithms into an accessible and practical tool. By bridging the gap between academic models and real-world construction management, this platform enables professionals to deploy advanced carbon-reduction strategies without specialized mathematical knowledge. The development process focused on balancing powerful performance with a user-friendly experience, creating a system that is both effective and easy to use.

The development process began by selecting PyQt5 as the software framework, chosen to meet the specific needs of this project. This framework was chosen because it works across different operating systems, has strong capabilities for creating clear visuals, such as charts and graphs, and integrates easily with the mathematical tools needed to run the optimization algorithms. Using this framework, the methodology focuses on building a user interface that presents complex project information in an intuitive way to construction professionals. This includes clearly displaying work package structures. It also involves presenting carbon emission data in an accessible format.

The software is built on a three-layer structure that separates data management, algorithm processing, and the user interface. This architectural choice makes the system easier to develop and maintain by creating clear divisions between its core functions. The data layer securely manages all project and production information. The processing layer contains the various optimization algorithms from the preceding research, allowing users to select the best approach for their project. Finally, the presentation layer provides a user-focused experience that guides construction professionals through the optimization workflow, hiding the complex calculations behind a simple interface to make powerful carbon-reduction strategies accessible to all.

3.6.2 Functional Implementation Methodology

The platform's design is organized into three distinct optimization modules that turn complex theories into practical, easy-to-use tools (as shown in Figure 3.7). This is achieved through clear workflows and easy-to-understand visuals. This approach is founded on the principle that a successful tool must not only be accurate but also guide construction professionals as they engage with increasingly advanced optimization methods. Each module offers a complete workflow. This includes data input, processing, and visualization of results. Modules can be used independently. Alternatively, they can be combined with others to solve specific project challenges.

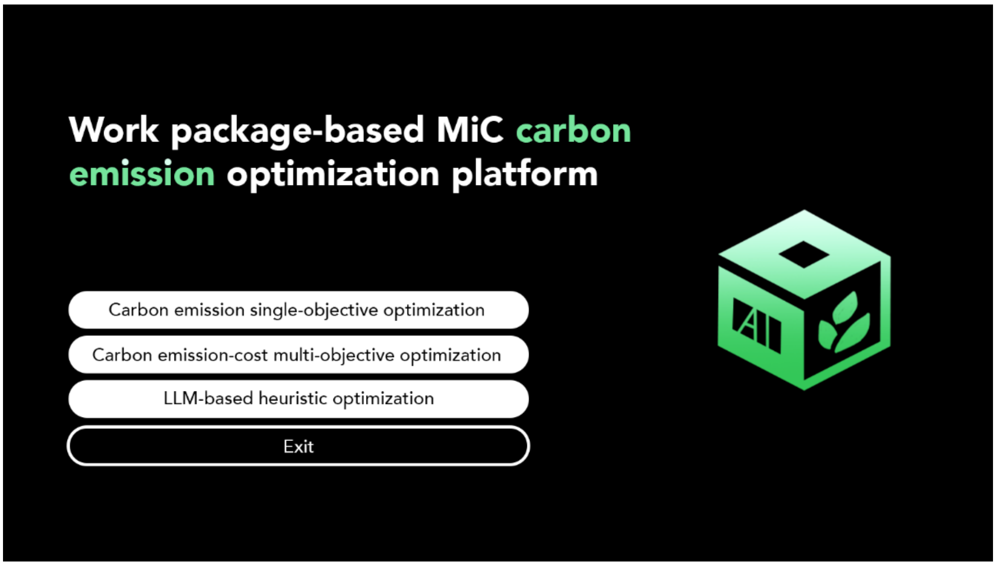


Figure 3.7 Example of a simulated platform

Across all modules, a consistent design helps users become familiar with the process, making it easier for them to move from simple to more advanced optimization techniques. This consistency smooths the learning curve, allowing users to build their expertise gradually as they tackle more complex problems. By integrating these complementary optimization methods into a single, unified interface, the platform provides a comprehensive solution that meets the diverse needs of carbon-efficient design for a wide range of MiC projects.

3.7 Chapter Summary

This research developed a comprehensive method for reducing carbon emissions in MiC by optimizing project planning at the work package level. The entire study was founded on the principle that the physical processes and carbon emissions in MiC projects can be objectively measured and understood through systematic analysis. The core of the investigation involved numerical analysis, which was supported by an initial real-world study phase to ensure the final models were both relevant and practical.

To begin, data was gathered through site visits to MiC projects and by analyzing project documents to understand task details and the order in which they must be completed. This information was used to create a mathematical model that links how work is organized to its carbon footprint, establishing a clear relationship between production speed and environmental impact (objective 1). Subsequently, a specialized algorithm was developed to determine the optimal project plan to minimize carbon emissions (objective 2). To address more complex scenarios, advanced algorithms were then used to find optimal trade-offs between reducing carbon emissions and lowering costs, ensuring all solutions were practical for real-world operations (research objective 3).

A key innovation was the use of LLMs to act as a bridge between complex mathematical techniques and the practical needs of construction professionals. This was achieved by using a series of carefully designed instructions that guide the AI through a logical reasoning process to create effective optimization strategies (objective 4). The research culminated in the development of a comprehensive software platform that integrates all these concepts. Built with a three-layer architecture that separates data, processing, and the user interface, the platform transforms theoretical research into an accessible, user-friendly tool (objective 5).

Finally, the entire methodology was rigorously tested through case studies, comparisons with leading methods, and experiments with varying project parameters. This validation process confirmed the system's performance across diverse scenarios, providing construction professionals with clear, context-specific guidance on applying these carbon-optimization techniques in practice.

Chapter 4 Single-Objective Optimization of Work Package Scheme Problem to Minimize Project Carbon

This chapter develops a single-objective optimization approach for WPSs to minimize carbon emissions in MiC projects. As the foundation of the optimization framework established in this thesis, it introduces the mathematical relationship between work package configuration and project carbon emissions, demonstrating how production rates at the work package level directly influence environmental performance. The primary contribution is the development of a TLGA that effectively searches the complex solution space of possible work package configurations, leveraging parallel computing to handle the interdependencies among work packages and their associated carbon emissions. The TLGA development serves two primary objectives: (1) to provide a specific WPS that minimizes the project's total carbon emissions through optimal configuration, and (2) to establish a productivity-based framework for defining and calculating carbon emissions at the work package level that accurately reflects the unique characteristics of MiC delivery methods. This implementation addresses research objective 2 of this thesis by developing an effective single-objective optimization algorithm for carbon reduction. The mathematical framework established here provides the foundation for subsequent multi-objective optimization in Chapter 5 and the LLM-based heuristic approaches in Chapter 6. Through experimental validation on both real-world MiC project data and simulation datasets, this chapter demonstrates significant carbon reductions achievable through improved project planning methods before implementing technological interventions. The chapter is organized as follows: Section 4.1 presents a formal statement of the WPSP; Section 4.2 introduces project carbon emissions based on work package production rate; Section 4.3 describes the TLGA's processes; Section 4.4 validates the algorithm using a real-world case study; and Section 4.5 summarizes the chapter.

4.1 Work Package Scheme Problem Statement

The problem model used in this paper was first proposed by Li and Hall and can effectively compare TLGA with the baseline for this problem (C.-L. Li & Hall, 2019). As shown in Figure 4.1, a project can be represented by a directed acyclic graph $G(N, E)$, where the nodes $N = \{1, \dots, n\}$ represent the *tasks,* and arcs $E \subset N \times N$ represent zero-lag finish-start *precedence relations* between tasks. The precedence relations are given by sets of immediate P_a, indicating that a task j cannot start before all of its predecessors are completed. Each task $a \in N$ has a given *duration* $t_a \geq 0$ and given *work content* $x_a \geq 0$. The WBS falls under project planning, while allocating required resources to tasks falls under project scheduling. Thus, task resource allocation is not considered at this stage.

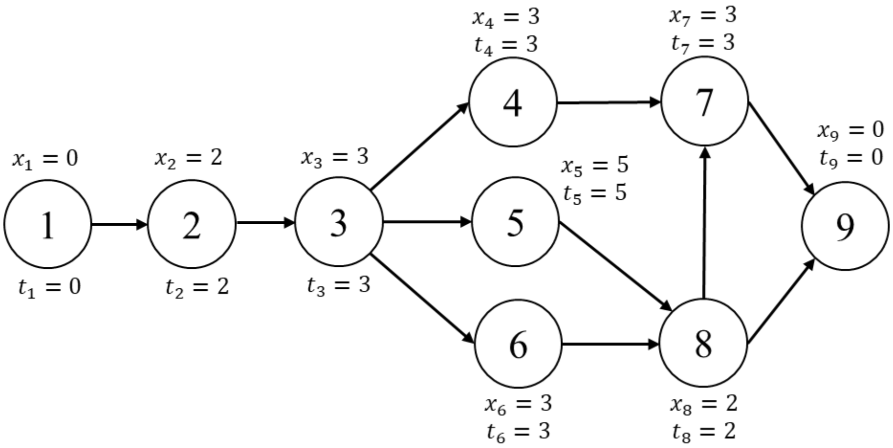


Figure 4.1 Project networks

Tasks are grouped into work packages in a project. There are two types of tasks in the project: active and inactive. A work package may contain one or more tasks. However, it is necessary to meet the specific requirements of specific tasks when forming a work package. These special tasks should be organized into a separate work package, and they are not suitable for inclusion in a work package with other tasks because they may affect the coordination between tasks or distract the responsible person. These special tasks are considered inactive in this thesis. Inactive tasks cannot be freely combined with other tasks in forming a work package. For example, lifting operations in a construction project can be seen as a group of inactive tasks. Lifting operations are used extensively on construction projects and present two typical risks: 1) Crane collapse, such incidents present significant potential for multiple fatal injuries, both on and off-site; 2) Load falling, these events also present a significant potential for death and major injury. Other dangers have involved people being struck by moving loads, cranes contacting overhead conductors, and cranes colliding. Therefore, all lifting operations involving lifting equipment should be properly planned by a competent person, appropriately supervised, and carried out safely. The above tasks need to be organized into separate work packages and cannot be combined with other tasks to form a single work package. High-risk tasks are just one example of inactive tasks. Other tasks may also be considered inactive due to the need for internal coordination and the assignment of responsibilities (C.-L. Li & Hall, 2019). In contrast, Active tasks are other tasks that can be freely combined to form work packages of any size.

The work package formed by active tasks is denoted as W, and the work package formed by inactive tasks is denoted as R. Assume that task 1, task 8, and task 9 in Figure 4.1 are inactive tasks, and the other tasks are active tasks. Therefore, the project can form the following work package network (Figure 4.2). When forming work packages, precedence relations also exist between them, inherited from task-level precedence relations. The relations between work packages are defined as *strict precedence*. That means that if task a in work package W is a predecessor of task a' in work package W', then all tasks in W precede all tasks in W'. Strict precedence is commonly used in project management practice and aligns with the WBS's purpose of decomposing and simplifying the project (C.-L. Li & Hall, 2019). The formed work packages have work package durations t_W and work content x_W. t_w is the critical path length of the tasks in the work package W. x_W is the sum of the task work content in the work package W. A work package scheme is a set of work packages within a project. Each work package is represented by a set of tasks The WPS of the project in Figure 4.2 is: $\{\{1\},\{2,3,4\},\{5,6\},\{7\},\{8\},\{9\}\}$.

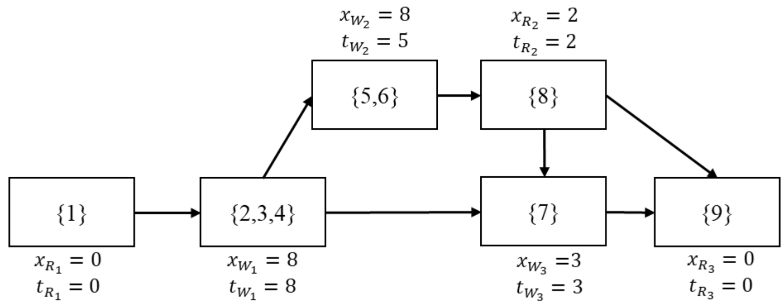


Figure 4.2 Work packages network

A project has multiple WPSs, but some are infeasible. As shown in Figure 4.3, there is a cycle between work package $\{6,7\}$ and work package $\{8\}$, therefore WPS $\{\{1\},\{2,3,4,5\},\{6,7\},\{8\},\{9\}\}$ is infeasible.

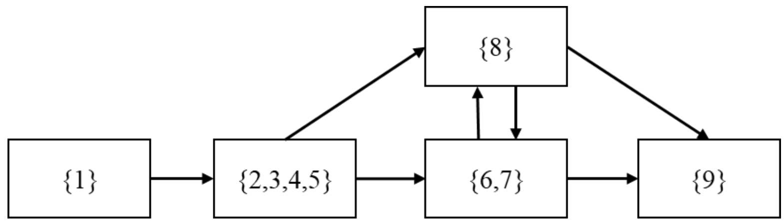


Figure 4.3 Infeasible WPS

4.2 Work Package Production Rate-based Project Carbon Emissions

Current studies still lack a generalized definition of the relationship between project carbon emissions and WPSs. This article calculates project carbon emissions based on work package durations and work content. The relevant variable relationships are shown in Figure 4.4 The calculation details are as follows.

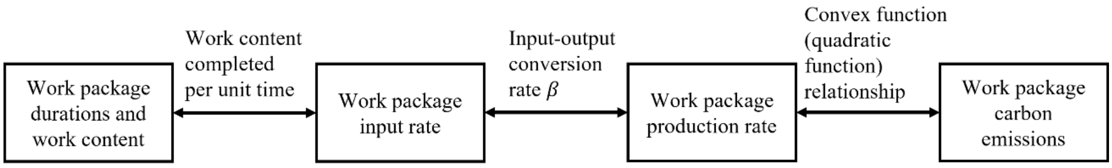


Figure 4.4 The relevant variable relationships

The total carbon emissions of the project TE are the sum of the carbon emissions of each work package E_{W_k}. That is,

$$TE = \sum_{k=1}^{k=n} E_{W_k} \tag{4-1}$$

The carbon emissions of each work package are the carbon emissions per unit of work content of the work package ε_{W_k} multiplied by the work content of the work package v_{W_k}.

$$E_{W_k} = v_{W_k} \times \varepsilon_{W_k} \tag{4-2}$$

The key to the problem now is to determine the carbon emissions per unit of work content of the work package ε_{W_k}. Existing studies have proven the correlation between production rate and carbon emissions (Jaber et al., 2013; Jauhari et al., 2022). The production rate in the above studies is described as the number of products delivered per unit of time. Work content can be measured in worker hours or monetary units required to complete the work package (C.-L. Li & Hall, 2019), so it can be considered as the input of the work package. The products of a work package can be measured in proportion to the input, $\beta \cdot v_{W_k}$. Similarly, the *work package production rate* γ_W is the number of work package's product per unit time, $\gamma_{W_k} = \frac{\beta v_{W_k}}{t_{W_k}}$.

The views of reference (Jaber et al., 2013) are used in this article. ε_{W_k} is a quadratic function of γ_{W_k}, that is,

$$\varepsilon_{W_k} = a \cdot {\gamma_{W_k}}^2 - b \cdot \gamma_{W_k} + c = a \cdot (\frac{\beta v_{W_k}}{t^*_{W_k}})^2 - b \cdot \frac{\beta v_{W_k}}{t^*_{W_k}} + c \tag{4-3}$$

a, b, c are the coefficients of the function. In summary, the total carbon emissions of the project are calculated as shown in Equation (4-10).

$$TE = \sum_{k=1}^{n}(a \cdot \frac{\beta^3 v^3_{W_k}}{t^{*2}_{W_k}} - b \cdot \frac{\beta^2 v^2_{W_k}}{t^*_{W_k}} + c \cdot \beta v_{W_k}) \cdot y_{W_k} \tag{4-4}$$

4.3 The Two-list Genetic Algorithm (TLGA)

4.3.1 Overview of TLGA

To optimize the WPSs and minimize the project's total carbon emissions, a TLGA-based approach is proposed. As illustrated in Figure 4.5, task duration, task work content, and task precedence relations are extracted as project information. The project information serves as input to the TLGA, and the WPSs are the outputs after iterative optimization. The WPSP with makespan has been proved to be a unary NP-hard problem. A state-of-the-art study has developed a heuristic method and a lower bound (C.-L. Li & Hall, 2019). Meta-heuristics have been proven to perform well in solving NP-hard problems in project planning (Ma et al., 2019), such as Tabu search (He et al., 2021) and genetic algorithm (Debels & Vanhoucke, 2007). Among them, genetic algorithms have been widely used in project planning and have consistently delivered outstanding results (Gómez Sánchez et al., 2023; Pellerin et al., 2020). Therefore, an improved genetic algorithm, the TLGA, is designed to address the WPSP because of its advantage for permutation problems (Soares & Carvalho, 2020). Although the WPS is an unordered set (defined in Section 4.2), it can be transformed into an ordered set when considering the task precedence relations. In addition, the TLGA is well-suited to parallel computing because it operates on a population of solutions, enabling independent and simultaneous processing of individuals during fitness evaluation, selection, crossover, and mutation (Cheng & Gen, 2019).

4.3.2 Encoding and Decoding

In genetic algorithms, chromosome encoding and decoding are vital for representing problem solutions. The coding process transforms the solutions' natural representation into a form suitable for genetic operations. The main contribution of the TLGA is to improve a genetic algorithm's adaptability to the WPSP by encoding it as a *Two-list*. As stated in Section 3, two key issues should be addressed in determining a WPS: 1) the number of tasks included in the formed work package and 2) the specific tasks information included in the formed work package. Therefore, a two-list is used to encode the WPS, which includes two lists: 1) the task list and 2) the work packaging list. Each $task\ list = \{a_1^T, a_2^T, \dots, a_n^T\}$ is coded by n genes, namely the number of tasks in the project. The task list is assumed to be a precedence feasible permutation of the set of tasks $\{1,2,\dots,n\}$, that is, it is an ordered set $\{a_1^T, a_2^T, \dots, a_n^T\}$ and $P_{a_i^T} \subseteq \{a_1^T, \dots, a_{n-1}^T\}$ for $i = 1,2,\dots,n$ [46]. The $work\ packaging\ list = \{a_1^W, a_2^W, \dots, a_n^W\}$ is an n-bit binary set consisting of 1 and 0. $a_n^W = 1$ means that a_n^T forms a new work package, and the $a_n^W = 0$ means that a_n^T forms the same work package with $\{a_m^T | a_m^W = 1\ and\ max_m(m < n)\}$.

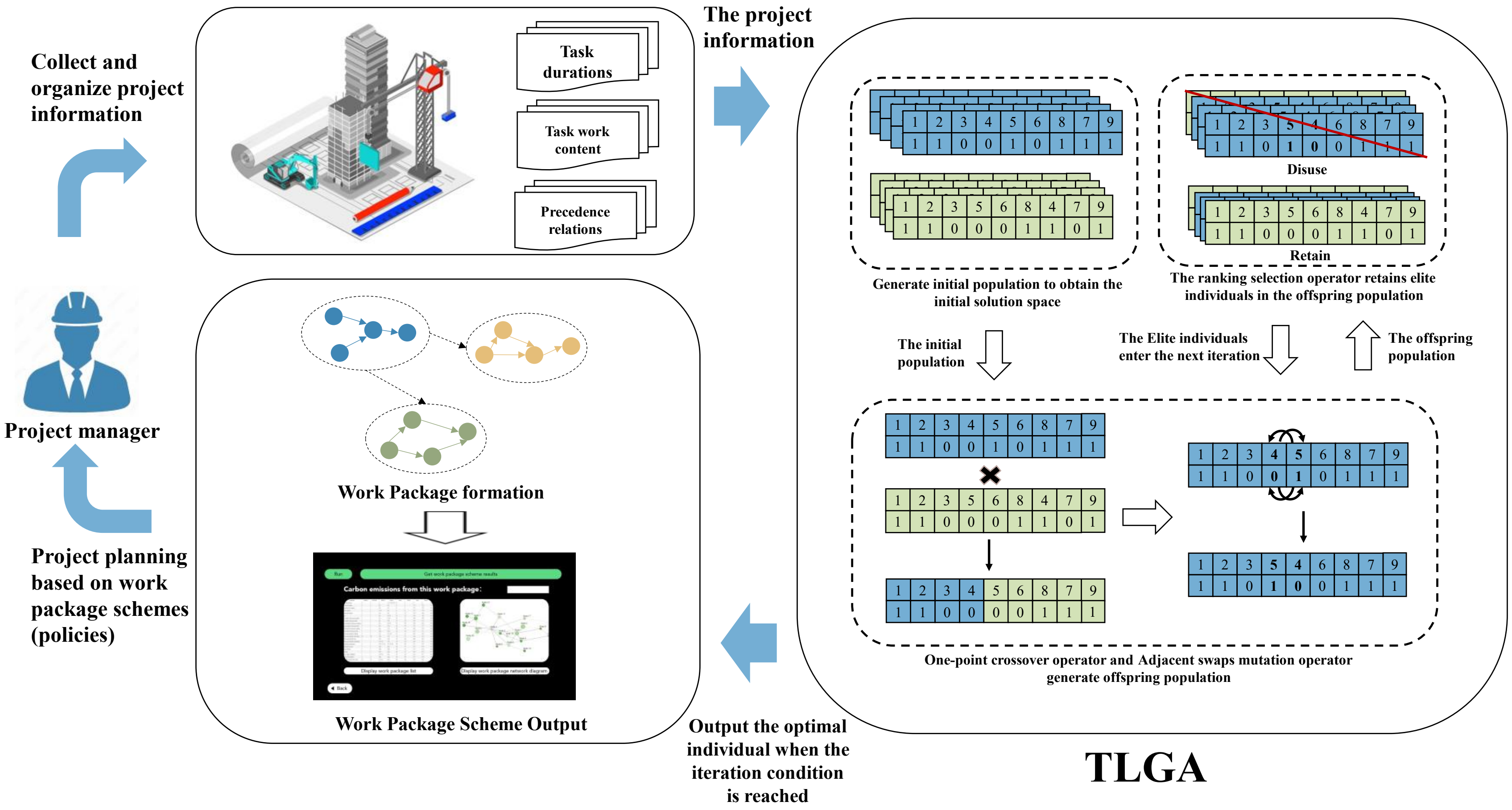


Figure 4.5 Overview of the TLGA

The work packaging list addresses the first issue: the number of tasks included in the formed work package. The 1 in the list and all the 0s before the next 1 together represent the number of tasks in a work package. The task list addresses the second issue: the specific tasks included in the formed work package. The position of the work packaging list corresponds to the task list, which is the specific tasks included in the work package. The Two-list is the key to characterizing the WPSP and is the foundation for subsequent algorithm processes.

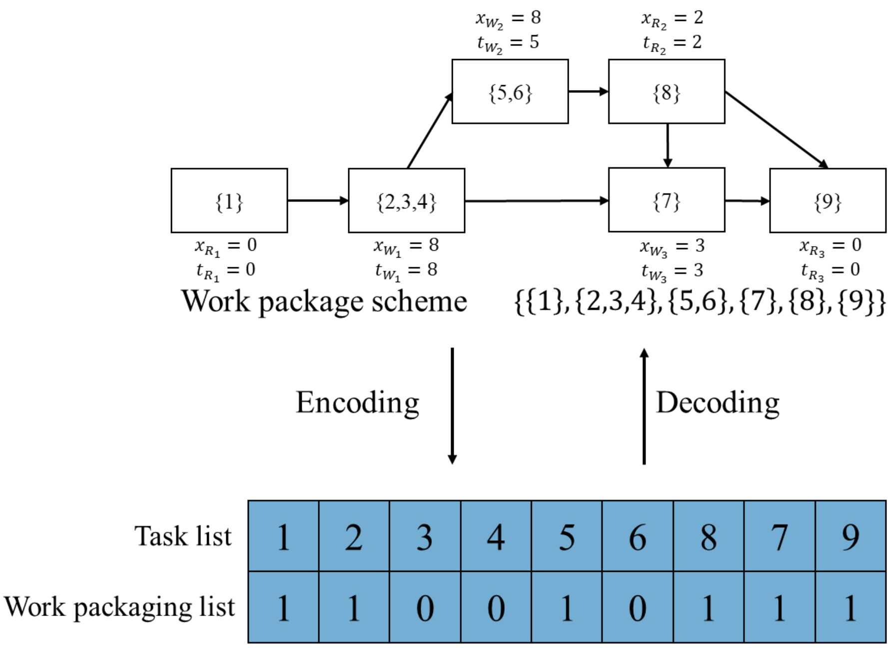


Figure 4.6 Encoding and decoding process

The encoding and decoding process of the WPS in Figure 4.2 is shown in Figure 4.6. Take work package {2,3,4} as an example; {1,0,0} represents this work package with three tasks. Its position corresponds to the task list {2,3,4}. Therefore, tasks 2, 3, and 4 are grouped into a single work package. It should be noted that multiple two-lists may correspond to the same WPS since it is unordered. For example, two-list$\{\{4,5,6\},\{1,0,0\}\}$ and two-list $\{\{4,6,5\},\{1,0,0\}\}$ represent the same WPS $\{4,5,6\}$.

4.3.3 Population Initialization

Population initialization creates a diverse initial population of potential solutions, enabling the genetic algorithm to effectively search the solution space for an optimal solution. As mentioned above, each individual comprises a precedence-feasible task list and a work packaging list. The task list is used to determine the specific tasks grouped in the work package. The work packaging list is used to determine the number of tasks in a work package. The following steps implement the process of generating the initial population.

Step 1: A Task list is generated randomly according to the precedence relations.

Step 2: A work packaging list consisting of 0s and 1s is generated. The following conditions are considered when the work packaging list is generated: 1) To satisfy inactive task constraints, it is necessary to pre-set the value of the inactive task position and the subsequent position to 1 (except the last dummy task) to ensure that inactive tasks form a separate work package. 2) To increase the flexibility of the generated solution, inactive tasks that are immediately related to each other form a work package only if they are adjacent in the task list. In this step, pre-setting the number 1 can speed up the iterative process.

Step 3: Combine the task list and work packaging list to obtain an initial population of individuals.

Step 4: Repeat Steps 1 to 3 until the number of individuals reaches the initial population size.

The subsequent theorem guarantees that the conditions for work package feasibility have been met, namely, that it is acyclic.

Theorem 4.1: If a task list of a work packaging list is precedence-feasible, the WPS decoded by the work packaging list TWL satisfies the work package feasibility condition, namely, acyclicity.

Proof

Set

a_x^T: The task at position x in the Task List (TL);

W_k: The kth work package in a solution;

$P_{a_x^T}$: A set of predecessor tasks of task a_x^T.

Original proposition: If the TL of a TWL is precedence-feasible, the solution of the TWL satisfies the work package feasibility criterion, namely, acyclicity.

Hypothesis: the original proposition is not true. There is a network of work packages generated by a two-list in which at least one cycle exists, that is,

$$\exists TL = \left\{a_1^T, \dots, a_x^T, a_y^T, a_z^T, \dots a_n^T\right\} \; and \; Solution = \{W_1, W_2, \dots, W_k \dots, W_p\}$$

$$\exists W_k \in \{W_1, W_2, \dots, W_k \dots, W_p\},$$

$$\exists \; task \; a_x^T \epsilon W_k; a_y^T, a_z^T \epsilon W_j; a_y^T \in P_{a_x^T}, a_x^T \in P_{a_z^T}; j < k$$

$$\because j < k, \therefore y, z < x \therefore a_x^T \in P_z \nsubseteq \{1, a_1^T, \dots, a_{z-1}^T\}$$

This contradicts the definition of TL. Thus, the hypothesis is not true, and the original proposition is true.

4.3.4 Evaluation Function

The evaluation function assesses each chromosome's quality within a given population. As the aim of optimizing the WPS is to obtain the best total carbon emission, Equation (4-4) is used as the evaluation function of the TLGA. The process of evaluating a population can be accomplished in two simple steps. Each individual two list in the population is decoded into a WPS. Each WPS calculates corresponding total cost according to Equation (4-4).

4.3.5 One-point Crossover Operator

The crossover operator promotes diversity in the population and allows for exploring new areas in the solution space, thereby enhancing the potential for identifying optimal or near-optimal solutions. Various crossover operators, such as single-point crossover, two-point crossover, etc., have been developed in project planning and scheduling. The one-point crossover (Hartmann, 1998) is used in the TLGA because it has higher computational efficiency and can better preserve the genotype of the parents. The process of one-point crossover is implemented as follows.

Step 1: Any two individuals in the population are selected for crossover, a mother M and a father F. Then, a random integer q with $1 \leq q < n$ is drawn as the crossover point. Two new individuals, a daughter D and a son S, are produced from the parents.

Step 2: Take an example as daughter D, which is defined as follows: In the task list of D, positions $i = 1, \ldots, q$ are taken from the mother, that is, $a_i^D \coloneqq a_i^M$. The positions $i = q + 1, \ldots, n$ in D are taken from the father. The tasks already selected from the mother cannot be considered again, that is:

$$a_i^D := a_k^F,\ \ where\ k\ is\ the\ lowest\ index\ such\ that\ a_k^F \notin \{a_1^D, \ldots, a_{i-1}^D\}$$

Step 3: WL performs the same crossover following task list under conditions for inactive tasks. The value of work packaging list in the offspring is entirely inherited from the parents.

Step 4: To satisfy inactive task constraints, if the complete inheritance of work packaging list violates the premise that inactive tasks should form work packages separately, work packaging list is corrected to ensure this premise.

At this point, an individual daughter D is generated by a one-point crossover. Individual Son S is also obtained through the same one-point crossover. However, positions $1, \ldots, q$ in the task list of S are taken from the father, and the remaining positions are from the mother. ***Theorem 4.2*** guarantees that all offspring individuals obtained through one-point crossover have work package feasibility.

Theorem 4.2 If parent individuals are work package-feasible genotypes, all their offspring generated by one-point crossover are also work package-feasible.

Proof

Set

M: The chromosome as mother;

F: The chromosome as father;

D: The chromosome as daughter.

a_n^M: The task at position n in the M;

$P_{a_n^M}$: A set of predecessor tasks of task a_n^M.

Original proposition: If applied to work package-feasible parent individuals, the one-point crossover operator for the TWL-based genetic encoding result is a work package-feasible offspring genotype.

Because of ***Theorem 4.2***, the original proposition is equivalent to If applied to precedence feasible parent individuals, the one-point crossover operator for the TL-based genetic encoding result is a precedence feasible offspring genotype.

Hypothesis: the original proposition is not true. If applied to precedence feasible parent individuals, exiting a one-point crossover operator for the TL-based genetic encoding result is a precedence infeasible offspring genotype, that is,

$$\exists M = \{a_1^M, a_2^M, \dots, a_n^M\}, F = \{a_1^F, a_2^F, \dots, a_n^F\}$$

$$And\ P_{a_i^M} \subseteq \{a_1^M, \dots, a_{i-1}^M\}, P_{a_i^F} \subseteq \{a_1^F, \dots, a_{n-1}^F\}\ for\ i = 1,2, \dots, n$$

$$\forall position\ q \in [1, n), D = \{a_1^M, \dots, a_q^M, a_k^F, \dots, a_n^F\},$$

$$where\ k\ is\ the\ lowest\ index\ such\ that\ a_k^F \notin \{a_1^M, \dots, a_q^M\}$$

$$Obviously, \{a_1^M, \dots, a_q^M\}, \{a_k^F, \dots, a_n^F\}\ are\ both\ feasible$$

$$if\ exit\ infeaible\ precedence, it\ must\ be\ between\ \{a_1^M, \dots, a_q^M\} and\ \{a_k^F, \dots, a_n^F\}$$

$$\therefore\ \exists a_i^M \in \{a_1^M, \dots, a_q^M\}, \qquad P_{a_i^M} \cap \{a_k^F, \dots, a_n^F\} \neq \emptyset$$

$$\because \{a_1^M, \dots, a_q^M\} \cap \{a_k^F, \dots, a_n^F\} = \emptyset \therefore P_{a_i^M} \nsubseteq \{a_1^M, \dots, a_q^M\}$$

This contradicts the definition of TL. Thus, the hypothesis is not true, and the original proposition is true.

Figure 4.7 shows the process of obtaining a daughter D by one-point crossover from the parent individuals. Given $q = 4$, the first four genotypes in the task list for D are derived from M. The last five genotypes are derived from F. The genotype of the work packaging list is then inherited from the parents, but task 7 is an exception. To ensure that task 8 can form a separate work package, the work packaging list genotype for task 7 is corrected to 1.

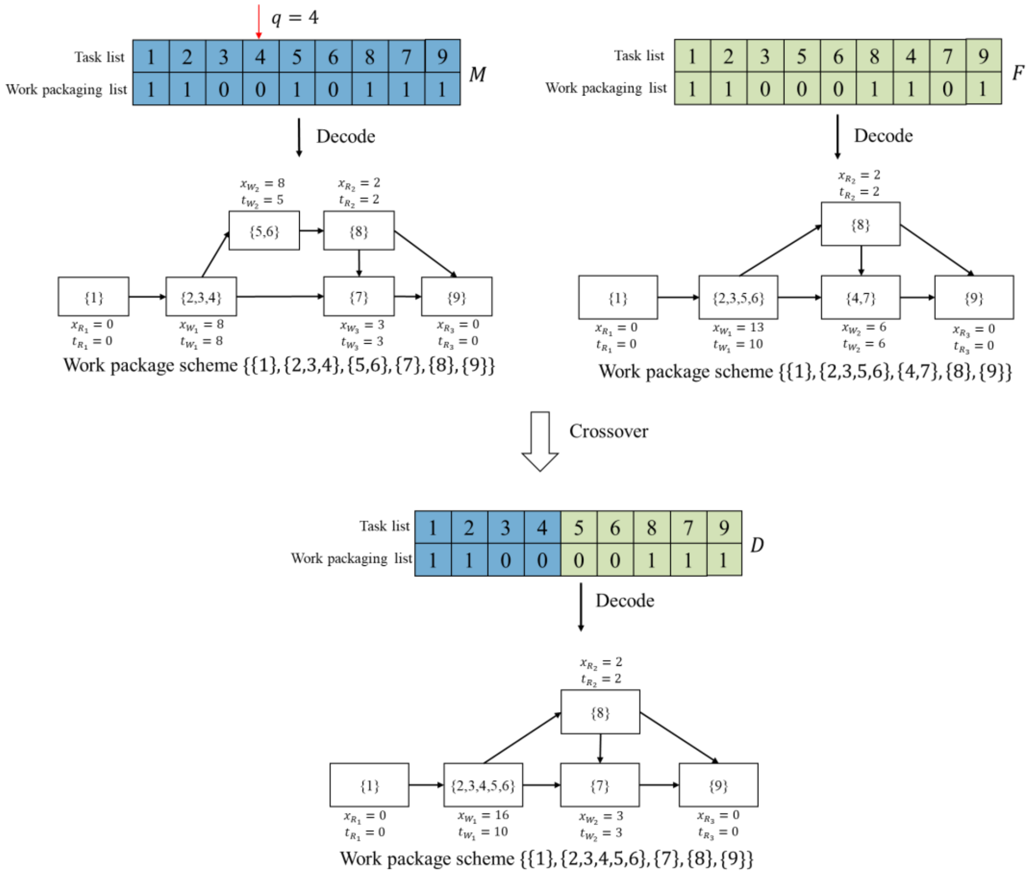


Figure 4.7 Process of one-point crossover

4.3.6 Adjacent Swaps Mutation Operator

After the one-point crossover produces the offspring population, individuals in the population need to apply mutation operators to increase its diversity. The TLGA uses the adjacent swaps mutation operator because of its applicability and ease of operation to permutation problems. The process of adjacent swaps mutation is implemented as follows.

Step 1: For each position $i = 1,2, \ldots, n-1$ swap the tasks a_i and a_{i+1} with probability $p_{mutation}$. The work packaging list performs the same mutation following the task list.

Step 2: Check whether the swapped task list satisfies the task precedence relations. If so, go to Step 3. Otherwise, cancel this swap and swap the next position.

Step 3: To satisfy inactive task constraints, if the swapped two-list violates the premise that inactive tasks should form work packages separately, the work packaging list is corrected to ensure this premise.

Figure 4.8 shows the process of adjacent swaps mutation of task 4.

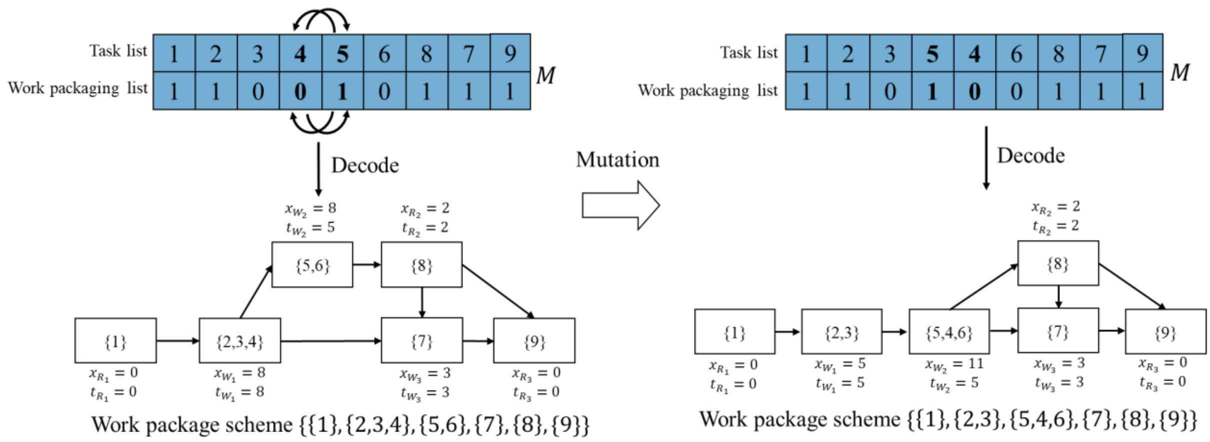


Figure 4.8 Process of adjacent swaps mutation

The offspring population produced by crossover and mutation operators must use a selection operator to retain excellent genotypes (i.e., better solutions) into the next generation. The ranking selection can maximize retention of elite individuals into the next generation, thereby speeding up the algorithm's convergence. At the same time, to ensure the consistency of the number of individuals in each generation and the diversity of the population, two rounds of 'crossover-mutation-selection' are used in each generation for optimization. Suppose there are M mothers and M fathers. M daughters and M sons will be obtained after crossover and mutation operators. $\frac{1}{2}M$ better daughters and $\frac{1}{2}M$ better sons are remained by ranking selection operator. Repeat the above process once, and $2M$ elite individuals are obtained. They will form M pairs of parents in the new iteration. A delay penalty is added to individual fitness to relax the deadline constraint and avoid local optima. The pseudocode for the TLGA is shown as Algorithm 1.

4.4 Experiments and Results

This section uses the TLGA to conduct two sets of experiments: a MiC project case adapted from a real-world, large-scale setting and a set of project instances specifically for work package problem research. The TLGA generates a WPS for a project case adapted from the real world. The TLGA's WPS is also compared with the original WPS of the project case and the WPS generated by a state-of-the-art heuristic (C.-L. Li & Hall, 2019) to prove the TLGA's effectiveness. Given that the WPSP is an NP-hard problem, exact algorithms are computationally prohibitive for large-scale instances. Li's heuristic is selected as the benchmark because previous studies have demonstrated its ability to produce solutions that converge closely to the theoretical lower bound, thereby providing a rigorous standard for evaluating the proposed algorithm's performance.

Algorithm 1: TLGA

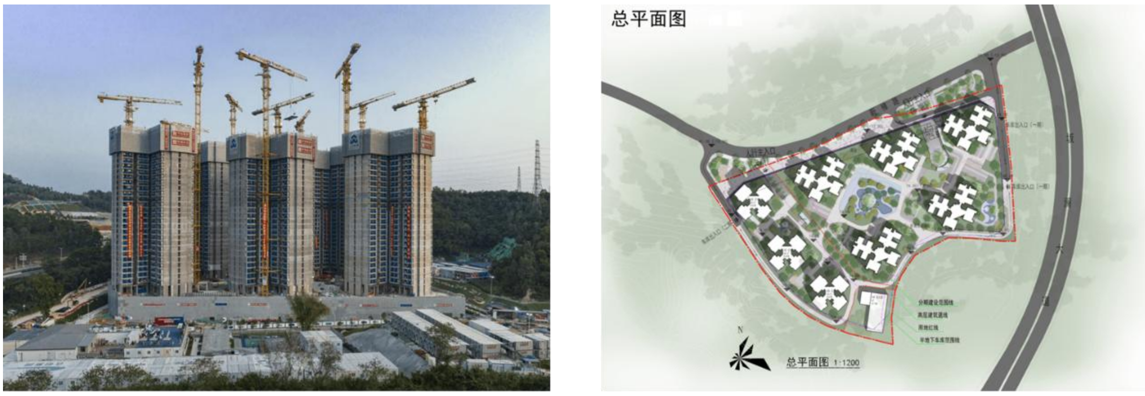
Data: initial population size $init\_pop$, population pop, mutation probability $p_{mutation}$, maximum generation max_gen, project information pro_info

Result: the best individual $best\_indi$ and its $fitness$

1 **while** *The number of individuals in the first generation population* $i\_init < init\_pop$ **do**
2   randomly generate $TL = \{a_1^T, a_2^T, ..., a_n^T\}$ according to the precedence relations in the pro_info;
3   obtain inactive task set $I = \{a_1^I, a_2^I, ..., a_n^I\}$;
4   corresponding to TL randomly generated binary list $WL = \{a_1^W, a_2^W, ..., a_n^W\}$;
5   **if** $a_i \in TL \bigcap I$ **then**
6         $a_i^W = 1, a_{i+1}^W = 1$;
7   **if** $a_i \in I \bigcap P_{a_{i+1}}$ **then**
8             $a_{i+1}^W = 0$
9   **end**
10   **end**
11 **end**
12 select $\frac{1}{2}pop$ individuals by ranking selection from initial population as mothers Ms;
13 select $\frac{1}{2}pop$ individuals by random selection from initial population as fathers Fs;
14 **while** *iterations* $iter < max\_gen$ **do**
15   given a random position $1 \leq q < n$;
16   In TL of a daughter D, position $i = 1, ..., q$ is from a M: $a_i^D := a_i^M$;
17   position $i = q+1, ..., n$ in a D is from a F: $a_i^D := a_k^F$ here k is the lowest index such that $a_k^F \notin \{a_1^D, ..., a_{i-1}^D\}$;
18   WL follows the same crossover and repeat Step5 to Step10;
19   Swap the M and the F in Step16 to Step18, get a S;
20   **for** *each indi in* Ds *and* Ss **do**
21         $a_i \in TL(i = 1, .., n-1)$ given a probability $p \in [0, 1]$;
22   **if** $p \leq p_{mutation}$ *and* $a_i \notin P_{a_{i+1}}$ **then**
23   swap a_i^T and a_{i+1}^T;
24   WL follows the same swap and repeat Step5 to Step10;
25   **end**
26   **end**
27   compute the $fitness$ of each $inid$;
28   select $\frac{1}{4}pop$ individuals from Ds and $\frac{1}{4}pop$ individuals from Ss as remained elite by ranking selection;
29   repeat Step15 to Step28, Ds of $\frac{1}{2}pop$ individuals and Ss of $\frac{1}{2}pop$ individuals are remained into next generation as Ms and Fs;
30 **end**
31 obtain the best individual $best\_indi$ and its $fitness$

4.4.1 Experiments on Large-scale Project Case

The initial task information for the project, including task durations, task work content, and task precedence relations, is derived from a construction project in Shenzhen, China (as shown in Figure 4.9). This is a five-tower MiC project comprising 4658 modules and 28-29 storeys. The entire construction process, from module production to installation, is adapted to form the original WPS, which comprises 289 tasks. To minimize the total cost, the TLGA and state-of-the-art heuristics will divide these tasks into work packages. The largest number of tasks in the project case used in state-of-the-art research is 160 (C.-L. Li & Hall, 2019). The project used in this paper is about 1.8 times that size.



(a) Project Overview　　(b) General Layout

Figure 4.9 Overview of the case project

Small-scale project instances are used to test multiple hyperparameter combinations of the TLGA. Four hyperparameters involved: initial population size, population size per generation, the maximum number of generations, and mutation probability, are set to low, medium, and high values, with a total of 81 combinations tested (Table 4.1). Among them, the maximum number of generations is chosen as a hyperparameter that controls the algorithm's execution process. It facilitates predictability and control, enabling straightforward estimation of computational effort and ensuring that the algorithm's runtime is bounded, easy to implement, and easy to understand. The selected values of the four hyperparameters based on experimental results are as as shown in Table 4.1.

Table 4.1 Hyperparameters of the TLGA

Parameter	Test value	Selected value
Initial population size	{1000,1500,2000}	2000
Population size per generation	{200,500,1000}	1000
Maximum number of generations	{100,200,500}	500
Mutation probability	{0.2,0.5,0.8}	0.2

Initial population size: A larger initial population size can improve optimization performance. In addition, the case project has an extremely large solution space due to its 289 tasks. Therefore, the largest initial population size of 2000 is selected. 2) Population size per generation: similar to 1), the largest population size per generation (i.e., 1000) is selected. 3) Maximum number of generations: Although most combinations can reach convergence around 50 to 100 generations, some combinations still produce new and better solutions after 200 generations. Therefore, the largest maximum number of generations (i.e., 500) is selected to maximize the optimization performance. 4) Mutation probability: The mutation probabilities show interesting experimental results. A higher mutation probability does not improve optimization performance, whereas a lower mutation probability performs better. The reason may be that lower mutation probabilities preserve elite individuals to a greater extent. Therefore, the smallest mutation probability (i.e., 0.2) is selected. The TLGA and the heuristics are implemented in Python 3.11 on a computing platform with an Intel Xeon Gold 6226R CPU at 2.90GHz and 16 cores.

Table 4.2 The carbon emission of WPSs provided by the state-of-the-art heuristics, TLGA, and original WBS

Mode_Inputoutput	WP by Heuristic	WP by TLGA	Original_WP	Performance improvement by Heuristic	Performance improvement by TLGA
Delay_0.8	17752.0000	17818.6200	48619.0515	63.49%	63.35%
Delay_1.0	23077.6000	23331.6026	94818.6656	75.66%	75.39%
Delay_1.2	30888.4800	31671.1573	168051.8830	81.62%	81.15%
Standard_0.8	17924.0936	18374.1699	41998.6639	57.32%	56.25%
Standard_1.0	22190.0000	22374.0743	82477.2100	73.10%	72.87%
Standard_1.2	27693.1200	28129.3631	148362.9709	81.33%	81.04%
Rush_0.8	18090.8784	18424.1137	36798.4363	50.84%	49.93%
Rush_1.0	22401.9767	23027.4169	71910.9544	68.85%	67.98%
Rush_1.2	26628.0000	26854.3047	130804.2989	79.64%	79.47%

As shown in Table 4.2 and Figure 4.10, the analysis focuses on the performance of the proposed TLGA algorithm relative to a state-of-the-art heuristic and the original WBS across various scenarios. The scenarios are categorized by different input-output ratios levels (0.8, 1.0, and 1.2) and execution modes (Delay, Standard, and Rush). The carbon emissions of the optimized work packages and the corresponding performance improvements are discussed below.

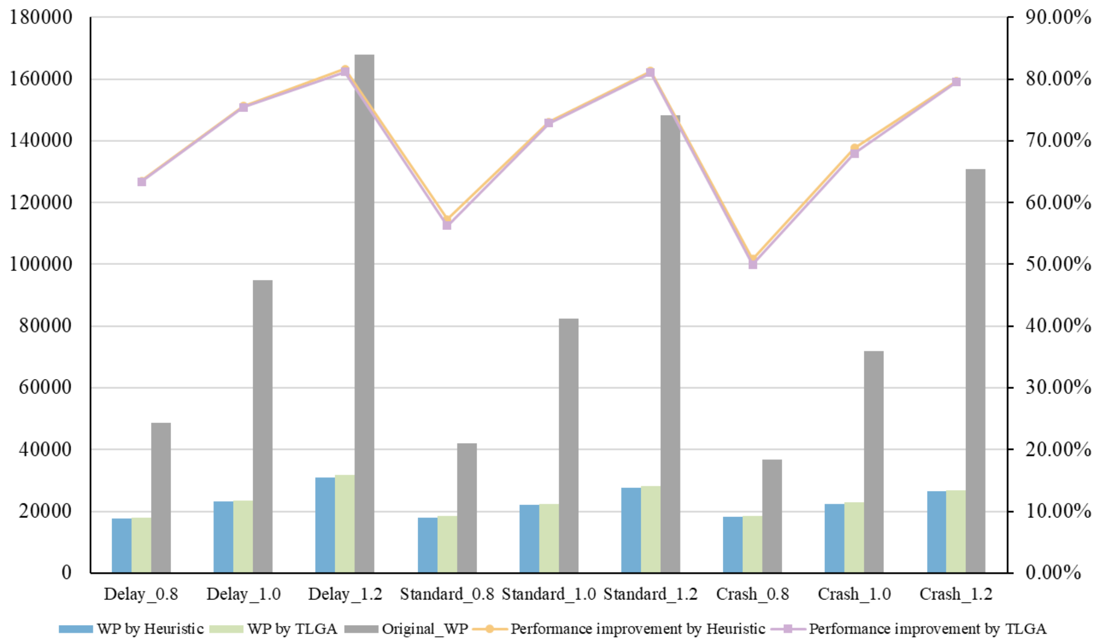


Figure 4.10 The optimization performance of TLGA and heuristics

Table 4.2 presents a comprehensive comparison of carbon emissions generated by the proposed TLGA, the state-of-the-art heuristic method, and the original WBS across nine distinct project scenarios. The results unequivocally demonstrate the superior environmental performance of both optimization approaches compared to traditional planning methods. While the original WBS consistently yielded high carbon emissions, peaking at approximately 168,052 units in the most demanding scenario, the optimization algorithms maintained significantly lower levels, typically ranging between 17,752 and 31,671 units. This stark contrast highlights that traditional manual planning becomes increasingly inefficient as project demands rise, whereas algorithmic approaches effectively mitigate these inefficiencies, enabling substantial carbon reductions. A closer examination of the data reveals a positive correlation between project complexity and the magnitude of performance improvement. In lower-complexity scenarios, such as “Rush_0.8,” the algorithms achieved approximately a 50% improvement over the baseline. However, as the input-output ratio increased to 1.2, representing greater project constraints and complexity, the performance gap widened significantly. In these high-demand scenarios, the optimization algorithms delivered improvements exceeding 81%. This trend suggests that the proposed methods are particularly valuable in complex construction environments where manual coordination struggles to manage resource and schedule constraints effectively. Finally, the comparative analysis between the two optimization methods indicates that the TLGA is highly competitive with the state-of-the-art heuristic. Although the heuristic method achieved marginally lower emissions in most cases, the performance difference was consistently negligible. For instance, in the “Rush_1.0” scenario, the heuristic outperformed the TLGA by less than 1%. This narrow margin confirms that the TLGA provides a robust and reliable alternative for solving complex work packaging problems, achieving near-optimal results that are statistically comparable to established benchmarks.

The performance of TLGA closely aligns with that of the heuristic algorithm, particularly in the “Delay” and “Standard” modes. For example, in the “Delay_1.2” scenario, the heuristic improves performance by 81.62%, while TLGA achieves a similar improvement of 81.15%. This trend is consistent across other scenarios, reflecting the algorithm's robustness and reliability. However, in certain "Rush" mode scenarios (e.g., "Rush_0.8" and "Rush_1.0"), TLGA's improvement lags slightly behind the heuristic, suggesting room for further refinement in high-intensity project settings. Despite the heuristic algorithm's slight edge in performance, TLGA offers several noteworthy advantages. The algorithm proposed in this study, TLGA, provides results comparable to the heuristic while introducing methodological innovations that may be more adaptable to specific project requirements. Its results indicate it is a viable alternative to existing methods, particularly for delay-tolerant scenarios (e.g., "Delay_1.2") where its performance is nearly indistinguishable from the heuristic. Moreover, TLGA consistently delivers significant emissions reductions compared to the original WBS, achieving more than 49% improvement in all scenarios. This highlights its effectiveness as a carbon reduction optimization tool for project work packages.

As shown in Figure 4.11, the proposed optimization framework demonstrates significant efficacy even under the rigorous stage-wise constraints of MiC. By enforcing a strict separation of tasks into distinct production, transportation, and on-site assembly zones, the study ensures that the generated WPSs remain operationally feasible, avoiding the impracticality of cross-stage task grouping. Despite these restrictive boundaries, which inherently limit the solution space compared to free task combination, both the heuristic and TLGA methods achieve substantial carbon mitigation. The analysis reveals that the optimization algorithms consistently outperform the original WBS, delivering emission reductions ranging from approximately 50% in lower-complexity scenarios to over 81% in high-delay conditions. This performance indicates that imposing practical stage restrictions does not materially compromise the potential for environmental optimization. While the heuristic algorithm retains a slight edge in specific high-intensity "Rush" scenarios, the TLGA demonstrates robust competitiveness, achieving near-identical results in standard and delay-tolerant modes. These findings validate the practical applicability of the proposed approach, confirming that it can successfully balance the logistical necessity of stage-separated work packaging with the objective of maximizing carbon efficiency.

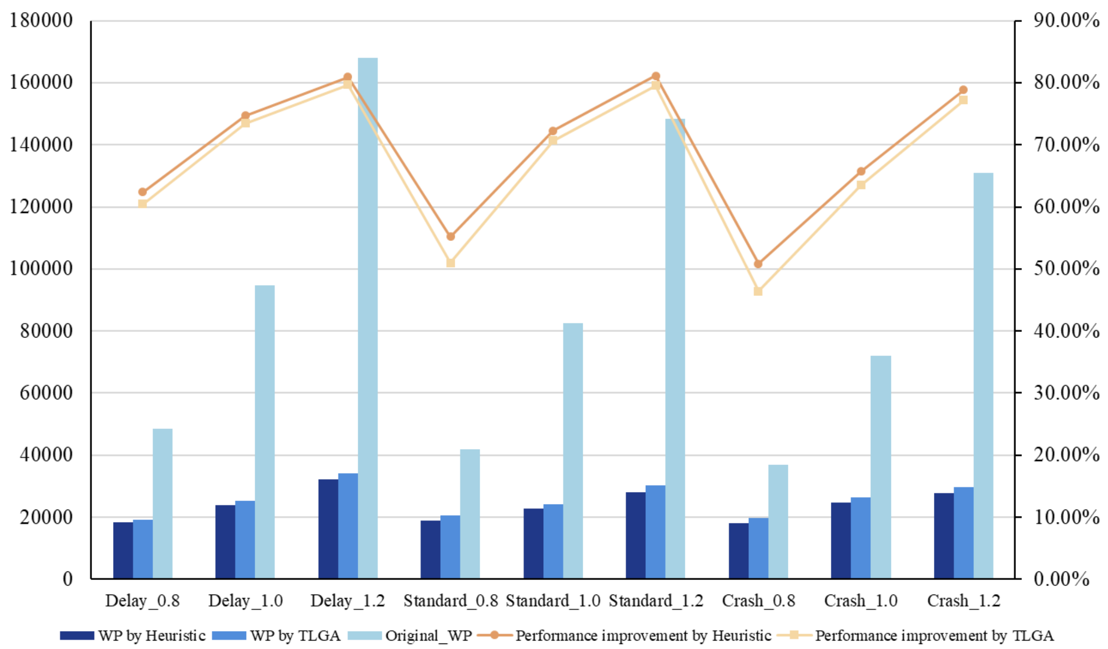


Figure 4.11 The optimization performance of TLGA and heuristics under MiC stage setting

In summary, the TLGA algorithm demonstrates strong performance in reducing carbon emissions and improving sustainability in project work packages. While the heuristic algorithm slightly outperforms TLGA in most scenarios, the differences are marginal, and TLGA remains competitive across all tested conditions. Its adaptability and methodological contributions position it as a valuable approach for carbon-reduction project management, particularly in scenarios with high tolerance for delays. Further research could refine it for high-pressure “Rush” scenarios to enhance overall performance.

4.4.2 Experiments on Project Instance Dataset

To comprehensively assess the impact of work package size on the project's total carbon emissions, a subset of project instances from a project instance dataset (C.-L. Li & Hall, 2019) used in previous research is used to generate work package sizes using the TLGA. This dataset is generated based on two indicators: the network size indicator I_1 and the serial or parallel indicator I_2. $I_1 \in \{40,80,120\}$, which means the number of tasks in a project. $I_2 \in \{0.2, 0.4,0.6,0.8,1.0\}$, which is larger, the project networks project networks tend to be more serial. When $I_2 = 1.0$, the project network is a fully serial network. Two work package indicators are used to evaluate the size of the work packages formed: (1) the average number of tasks in each work package; and (2) the standard deviation of the number of tasks in the work package.

(1) Mean and standard deviation experimental results and analysis

The size of work packages, evaluated by the average number of tasks per work package, and their consistency, assessed via the standard deviation, are analyzed across varying project parameter settings. These settings include the number of tasks in the projec (I_1), the serial or parallel indicator (I_2), the input-output ratio, and the work package execution mode (Rush, Standard, and Delay). This analysis explores how these parameters influence the scale and balance of work packages to minimize carbon emissions.

The results in Table 4.3 indicate that the average number of tasks per work package decreases as the total number of tasks in the project (I_1) increases. For instance, in the "Rush" mode with I_2=0.2 and an input-output ratio of 1.2, the average number of tasks per work package diminishes from 3.14 (I_1=40) to 2.52 (I_2=120). This trend holds consistently across all modes and input-output ratios. Larger projects inherently distribute tasks across more work packages to optimize carbon emissions, resulting in smaller individual packages. The consistency of work package sizes, as reflected in the standard deviation results (Table 4.4), also improves with an increase in I_1. For example, in the "Rush" mode with I_2=0.2 and an input-output ratio of 1.2, the standard deviation decreases from 0.57 (I_1=40) to 0.20 (I_1=120). This suggests that larger projects not only reduce the average size of work packages but also achieve a more uniform distribution of tasks across packages, contributing to a balanced organizational structure.

The degree of network seriality (I_2) significantly affects the scale and consistency of work packages. As I_2 increases, indicating a shift toward more serial project structures, the average number of tasks per work package increases. This is particularly evident in highly serial projects (I_2=1.0), where the average number of tasks in the “Delay” mode with an input-output ratio of 1.2 rises to 9.04 (I_1=40), compared to only 2.98 in projects with I_2=0.2. Serial projects tend to group tasks into larger packages to streamline sequential execution and minimize the emissions associated with interdependencies. The standard deviation results show that higher I_2 values generally lead to increased variability in work package sizes. For example, in the “Standard” mode with I_1=40 and an input-output ratio of 1.2, the standard deviation rises from 0.55 (I_2=0.2) to 2.00 (I_2=1.0). This variability suggests that optimization algorithms prioritize larger packages in serial networks, creating more disparity in size to align with the network’s structural constraints. The input-output ratio also influences work package scale. Lower ratios (e.g., 0.8) result in slightly larger work packages on average, as seen in the “Rush” mode with I_1=40 and I_2=0.6, where the average size decreases from 8.43 (input-output ratio=0.8) to 5.48 (input-output ratio=1.2). A lower ratio indicates fewer task dependencies, allowing more tasks to be grouped per package while maintaining emission efficiency. However, the impact of the input-output ratio on standard deviation is less pronounced, with only minor fluctuations observed across scenarios. For instance, in the “Delay” mode with I_1=80 and I_2=0.4, the standard deviation ranges from 0.48 to 0.32 as the input-output ratio increases. This suggests that the ratio primarily affects the average size of work packages rather than their variability.

The execution mode (Rush, Standard, Delay) has a notable impact on work package scale and consistency. Rush mode, which prioritizes rapid task execution, results in larger work packages on average. For example, in projects with I_1=40 and I_2=0.6, the average work package size in Rush mode is 8.43, compared to 5.38 in Standard mode. and 4.69 in Delay mode. This reflects the need to consolidate tasks to minimize emissions under time-critical conditions. In terms of consistency, Rush mode tends to exhibit higher variability in work package sizes, as seen in Table 4.4. For projects with I_1=40 and I_2=0.6, the standard deviation in Rush mode is 2.30, compared to 1.43 in Standard mode and 1.05 in Delay mode. This variability highlights the challenges of balancing task distribution under accelerated execution conditions.

Table 4.3 The average number of tasks in each work package in the minimum carbon emission WPS

		I_1=40			I_1=80			I_1=120		
		0.8	1	1.2	0.8	1	1.2	0.8	1	1.2
I_2=0.2	Rush	3.4617	3.1999	3.1438	2.9484	2.8281	2.6520	2.8838	2.6724	2.5154
	Standard	3.1665	3.1372	3.1372	2.8083	2.8657	2.6367	2.6347	2.4955	2.3403
	Delay	2.9945	2.9938	2.9825	2.5942	2.6670	2.5631	2.4850	2.4026	2.1761
I_2=0.4	Rush	4.6273	3.9302	4.0458	4.0436	3.4181	3.3803	3.6460	3.2479	3.0729
	Standard	4.1351	3.9623	3.8588	3.5732	3.3028	3.2276	3.2669	3.0351	2.8146
	Delay	3.4949	3.7773	3.8752	3.3457	3.0955	3.1440	2.9151	2.9076	2.8069
I_2=0.6	Rush	6.4603	5.3254	4.7668	4.6734	4.1984	3.6861	4.0497	3.6401	3.3950
	Standard	5.3762	4.6128	4.4909	4.1596	4.1593	3.7151	3.8464	3.3939	3.3091
	Delay	4.6859	4.3462	4.5240	3.7491	3.5849	3.5471	3.3939	3.3070	3.1081
I_2=0.8	Rush	8.4333	6.9540	5.4825	5.1910	4.7500	4.5166	4.0847	3.9924	3.7764
	Standard	6.9540	5.6365	5.4873	4.9649	4.6488	3.7151	3.8330	3.7762	3.7402
	Delay	6.2206	5.3159	5.5714	4.3186	4.3341	4.1977	3.8904	3.5869	3.7254
I_2=1.0	Rush	5.8286	7.4492	8.3048	4.3531	4.7641	5.1938	3.7029	4.0479	4.2290
	Standard	6.9270	8.2000	8.5714	4.7205	5.7003	4.2930	3.8827	4.1793	4.3398
	Delay	8.2381	8.1048	9.0381	5.4515	5.4070	5.2563	4.1366	4.2584	4.1011

Table 4.4 The standard deviation number of tasks in each work package in the minimum carbon emission WPS

		40			80			120		
		I_1=0.8	I_1=1	I_1=1.2	I_1=0.8	I_1=1	I_1=1.2	I_1=0.8	I_1=1	I_1=1.2
I_2=0.2	Rush	0.6359	0.6584	0.5676	0.3428	0.3576	0.2422	0.2461	0.3917	0.2033
	Standard	0.4732	0.5518	0.5518	0.2496	0.3059	0.2865	0.2318	0.1944	0.3085
	Delay	0.4220	0.5972	0.5639	0.1881	0.2709	0.1968	0.2696	0.2226	0.2487
I_2=0.4	Rush	1.1220	0.6920	1.4606	0.3090	0.3122	0.3988	0.3403	0.3690	0.3218
	Standard	0.6611	1.4604	0.8397	0.4286	0.3430	0.4215	0.4177	0.3292	0.2827
	Delay	0.6654	1.1155	1.0491	0.4833	0.3081	0.3270	0.4142	0.2768	0.2493
I_2=0.6	Rush	2.7753	0.8522	0.7392	0.6027	0.5428	0.3536	0.3869	0.4320	0.3403
	Standard	1.4329	0.5573	0.8770	0.4012	0.3851	0.4821	0.5663	0.3359	0.2767
	Delay	1.0510	0.6409	0.6100	0.3025	0.5704	0.3724	0.2813	0.3501	0.4220
I_2=0.8	Rush	2.3000	1.6409	1.0133	0.9042	0.6951	0.3176	0.3594	0.2805	0.2370
	Standard	1.6409	1.1684	1.6929	0.6667	0.6197	0.4821	0.3019	0.3184	0.3054
	Delay	1.6120	1.1191	1.4124	0.2726	0.3790	0.3597	0.2886	0.3659	0.3507
I_2=1.0	Rush	1.4898	1.9846	1.5444	0.3563	0.3751	0.4208	0.3622	0.3565	0.2847
	Standard	1.8468	1.3013	2.0045	0.4133	0.6183	0.3998	0.3124	0.4264	0.3260
	Delay	1.7824	1.4377	2.1552	0.5186	0.4624	0.3835	0.3145	0.3704	0.3890

The analysis underscores the interplay between project parameters and the scale and consistency of work packages in optimizing carbon emissions. Larger projects (higher I_1) result in smaller, more consistent work packages, while highly serial networks (higher I_2) favor larger, less consistent packages due to structural constraints. The input-output ratio primarily affects average work package size, with lower ratios yielding larger packages. Execution modes, particularly Rush mode, significantly influence both the scale and variability of packages, reflecting the trade-offs between speed and balance. These insights provide a nuanced understanding of the factors shaping work package optimization strategies in sustainable project management.

(2) Distribution experiment results and analysis

To further evaluate the WPS results for minimizing the project's carbon emissions across different project parameter settings, the distribution of the average number of tasks per work package is analyzed. The three sets of boxplots illustrate the distribution of the average number of tasks per work package across various project parameter settings (I_1, I_2, input-output ratio, and execution mode). Each set corresponds to distinct project sizes (I_1 = 40, 80, and 120), providing insights into how project size influences the scale and variability of work packages. By examining these distributions across parameter dimensions, the interplay between project characteristics and carbon emission performance can be understood.

The overall trends across the boxplots indicate that as project size (I_1) increases, the average number of tasks per work package decreases, and the distribution's variability narrows. For instance, in "Rush" and "Standard" modes, the interquartile range and whisker lengths are smaller for $I_1 = 120$ than for $I_1 = 40$, reflecting greater consistency in work package sizes for larger projects. This result aligns with the broader flexibility available in larger projects, where the optimization process can distribute tasks more evenly across work packages. Smaller, more uniform work packages enhance carbon emission efficiency by reducing task handoffs and resource idling.

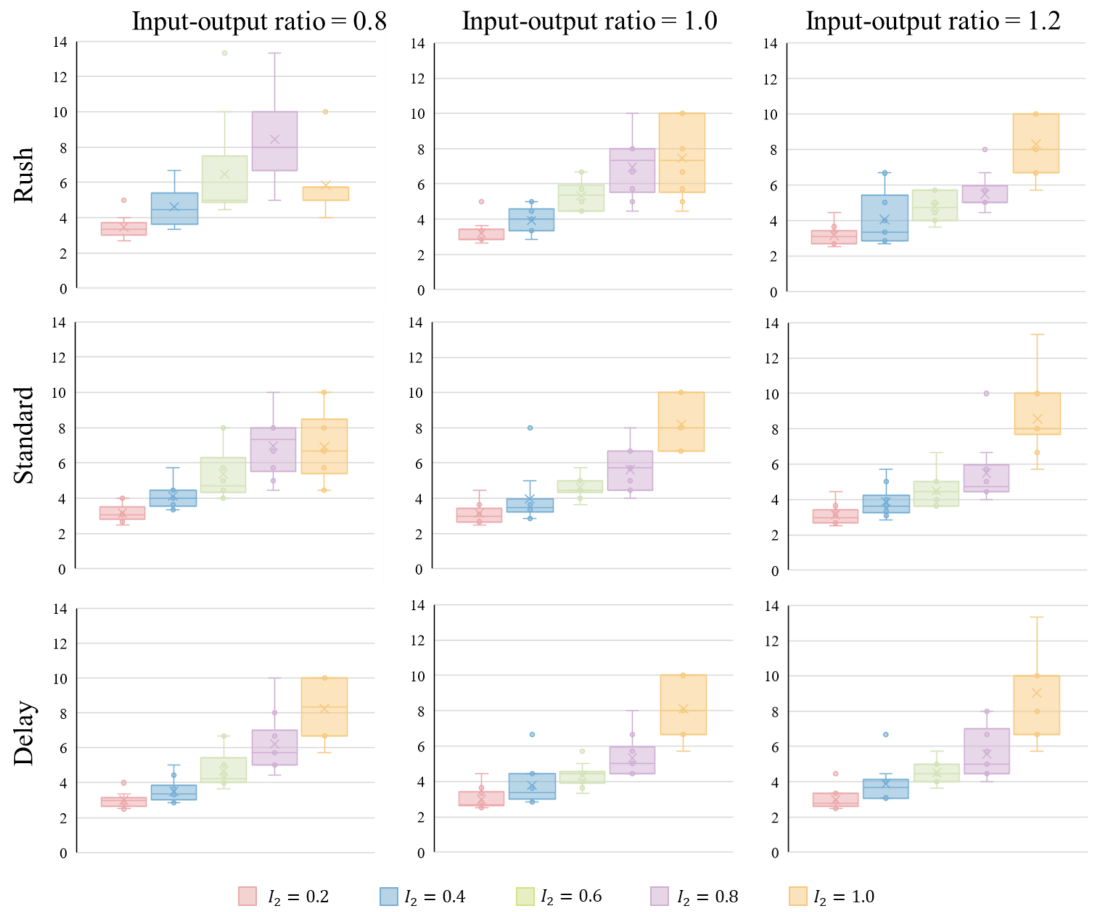


Figure 4.12 Distribution of the average number of tasks in each work package for a project instance with I_1=40

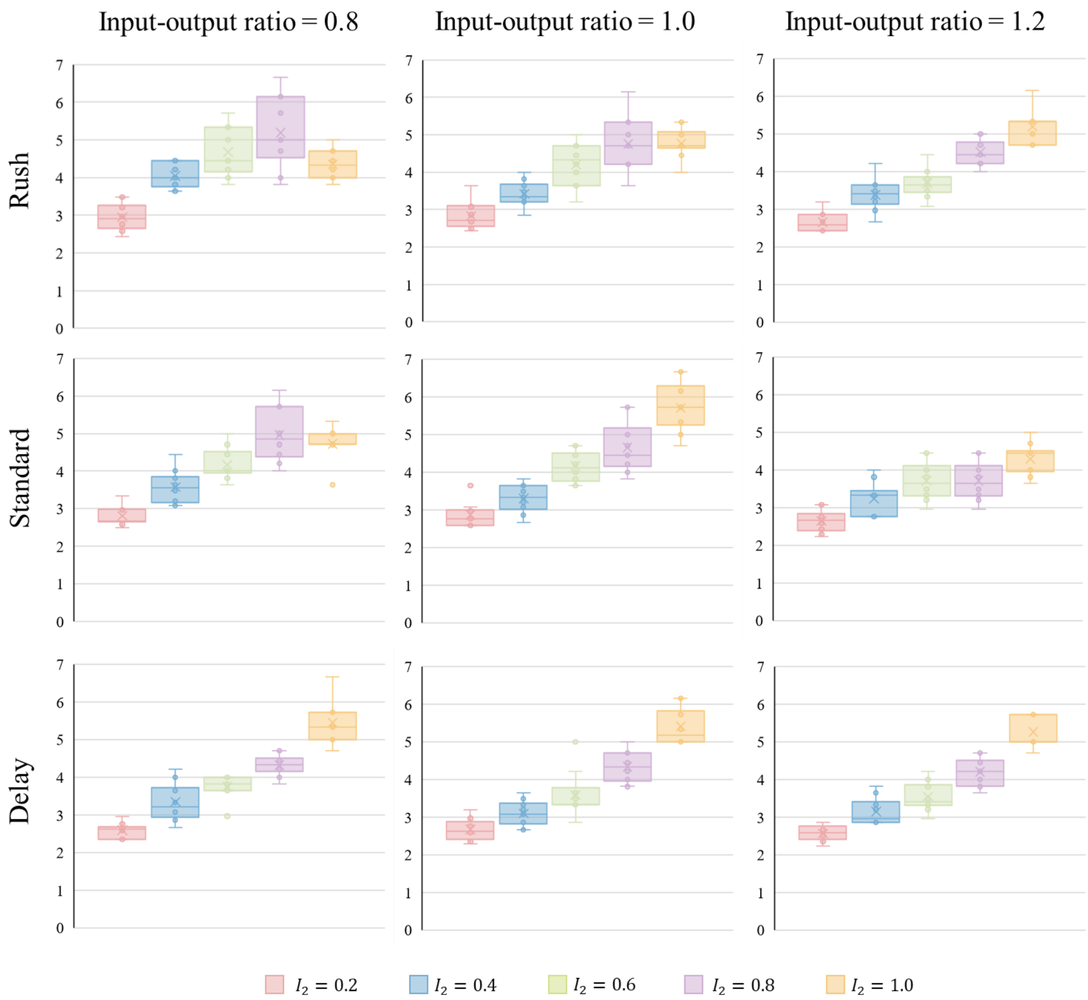


Figure 4.13 Distribution of the average number of tasks in each work package for a project instance with I_1=80

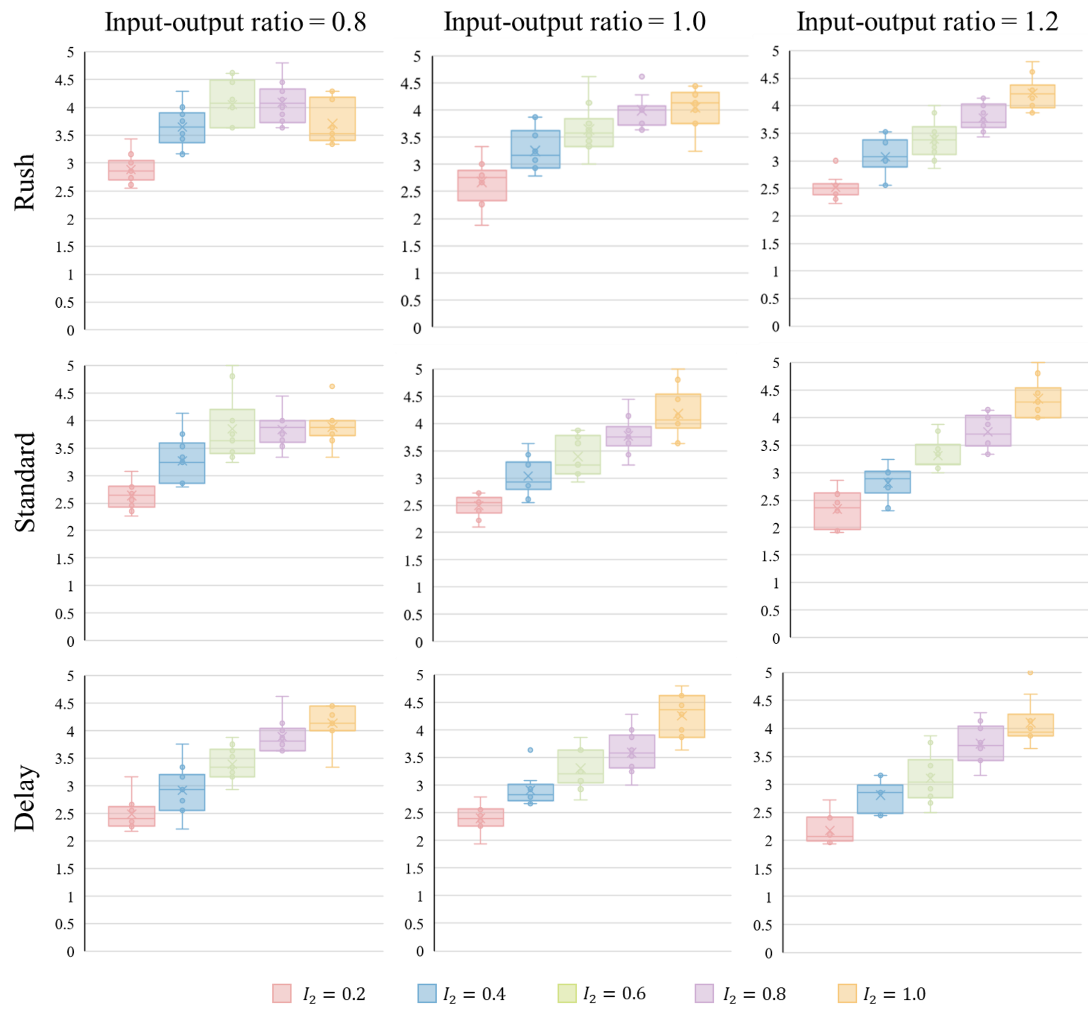


Figure 4.14 Distribution of the average number of tasks in each work package for a project instance with I_1=120

Comparing the three project sizes (I_1 = 40, 80, 120) reveals consistent patterns in the relationship between parameter settings and work package scale. However, larger projects (I_1 = 120) exhibit reduced variability across all settings, as evidenced by the narrower IQRs and shorter whiskers in the boxplots. This indicates that larger projects achieve greater uniformity in task distribution, which is advantageous for carbon emission optimization. In contrast, smaller projects (I_1 = 40) show greater sensitivity to parameter changes, with wider variability in work package sizes, particularly in Rush and high-seriality (I_2 = 1.0) scenarios. These results suggest that smaller projects face greater challenges in balancing task distribution and emission performance due to limited flexibility.

The degree of network seriality (I_2) significantly influences the scale and variability of work packages. As I_2 increases, the average work package size rises, with noticeable differences between lower and higher levels of seriality. For example, in the boxplots for I_1= 40 and I_1= 80, the median work package size in highly serial networks (I_2= 1.0) is substantially larger than in parallel-oriented networks (I_2=0.2). This trend reflects the structural constraints of serial networks, in which tasks are more interdependent, requiring larger work packages to minimize emissions associated with frequent task switches. Additionally, variability tends to increase at higher I_2 values, particularly for smaller projects (I_1=40), as the algorithm prioritizes emission performance over uniformity in task distribution.

The input-output ratio influences how tasks are grouped within work packages. Across all project sizes, lower input-output ratios (e.g., 0.8) result in larger average work package sizes, while higher ratios (e.g., 1.2) lead to smaller packages. For instance, in the “Rush” mode for I_1 = 80, the median work package size decreases from approximately 5 tasks (input-output ratio = 0.8) to 3 tasks (input-output ratio = 1.2). This behavior is consistent with the reduced interdependencies at lower ratios, enabling the grouping of more tasks into larger packages. Conversely, higher ratios reflect increased interdependencies, which necessitate smaller, more granular packages to accommodate the complexity of task relationships while maintaining emission efficiency.

The execution mode has a pronounced effect on both the scale and variability of work packages. Rush mode consistently results in the largest work packages across all project sizes and input-output ratios. For instance, in the boxplots for I_1 = 40, the median work package size in Rush mode surpasses that of Standard and Delay modes. This reflects the need to consolidate tasks for rapid execution, thereby reducing emissions by minimizing handoff delays. However, variability in Rush mode is higher, particularly in smaller projects, due to the trade-off between speed and the balance of task distribution. Standard mode exhibits moderate work package sizes and a relatively consistent distribution across all parameter settings. The lower variability in Standard mode highlights its balanced approach, optimizing both carbon emissions and task allocation. Delay mode results in the smallest average work package sizes, particularly at higher input-output ratios. For example, in the boxplots for I_1=120 and an input-output ratio of 1.2, the median work package size in Delay mode is the smallest among all execution modes. This reflects the flexibility of the Delay mode, which allows for finer-grained task allocation to minimize emissions over extended timeframes.

The analysis of the boxplots highlights how project parameter settings influence the distribution of work package sizes in carbon emission optimization. Larger projects achieve smaller, more consistent work packages, while highly serial networks and low input-output ratios result in larger packages to accommodate structural constraints. Execution modes further shape the distribution, with Rush mode favoring larger packages for speed and Delay mode allowing finer-grained task allocation. These insights emphasize the need to tailor optimization strategies to specific project conditions to achieve both sustainability and operational efficiency.

(3) Analysis of the impact of work package size on carbon emissions

The trends observed in work package scale (average number of tasks) and consistency (standard deviation) are strongly influenced by the interplay between practical work package management strategies and efforts to minimize carbon emissions. Each project parameter influences the optimization process in ways that align with the realities of task execution, resource allocation, and carbon footprint reduction. The next delves into the reasons behind these results, considering the relationship between work package scale and carbon emission performance.

As the number of tasks in a project (I_1) increases, work packages become smaller and more consistent. This is because larger projects provide greater flexibility for task allocation during optimization. With more tasks to distribute, the algorithm can create smaller, more balanced work packages while still ensuring that dependencies and carbon emissions are effectively managed. Smaller work packages in larger projects reduce the likelihood of bottlenecks and promote parallel execution, minimizing idle time for resources and reducing emissions from prolonged task delays. Furthermore, consistent work package sizes streamline resource allocation and scheduling, reducing inefficient use of resources and potentially increasing carbon emissions. Hence, the optimization algorithm naturally trends toward smaller, more uniform work packages as the number of tasks grows.

Increased seriality (higher I_2) forces tasks into larger work packages due to the inherent structural constraints of serial networks. In highly serial networks, tasks depend heavily on the completion of preceding tasks, which reduces opportunities for parallelization. As a result, the algorithm consolidates tasks into fewer, larger work packages to minimize emissions associated with frequent task transitions and interdependencies. Larger work packages in serial networks help reduce the overhead of task handoffs, which can lead to unnecessary delays and increased energy consumption. However, the increased variability in work package sizes (higher standard deviation at higher I_2 values) reflects the difficulty in balancing the conflicting goals of maintaining emission efficiency and adhering to the network's structural constraints. The optimization process prioritizes emission reduction, even if it means sacrificing uniformity in work package sizes.

The input-output ratio affects the degree of task interdependence, influencing how tasks can be grouped into work packages. Lower ratios (e.g., 0.8) indicate fewer interdependencies, allowing the algorithm to group more tasks into larger packages without violating constraints. This grouping reduces the need for frequent task handoffs, which minimizes emissions associated with coordination and resource reallocation. As the input-output ratio increases, the network becomes more interconnected, which limits the size of work packages the algorithm can form without creating dependency conflicts. Smaller work packages in these scenarios help mitigate the risk of delays and inefficiencies caused by interdependent tasks, ensuring that carbon emissions remain low despite the increased complexity of task relationships.

The execution mode plays a critical role in shaping work package scale and consistency, as it directly affects the balance between speed and emission performance. In Rush mode, which prioritizes rapid execution, larger work packages dominate because consolidating tasks minimizes time spent coordinating between them. However, this mode often results in greater variability in package sizes, as the optimization algorithm sacrifices uniformity to achieve the dual objectives of speed and emission reduction. Larger packages in this mode also reduce emissions by minimizing resource idling and repeated task handoffs, which are energy-intensive. Standard mode reflects a balanced approach where task execution aligns with typical resource constraints. The work package sizes are moderate and relatively consistent, as the algorithm prioritizes carbon emission reduction without the time pressures of Rush mode or the extreme flexibility of Delay mode. Delay mode offers the greatest flexibility in task execution, resulting in smaller, more consistent work packages. The algorithm leverages the extended time frame to optimize task grouping, reducing emissions by ensuring balanced resource allocation and minimizing inefficiencies. Smaller work packages in Delay mode also reflect the reduced pressure to consolidate tasks for rapid execution, allowing for more granular optimization.

From a practical perspective, these results demonstrate the nuanced trade-offs between work package scale and carbon emission performance under different project conditions. These are ideal for minimizing emissions in scenarios with high task counts (large I_1) or flexible execution modes (e.g., Delay). They improve resource utilization and reduce the energy waste associated with idle resources or inefficient task transitions. In highly serial networks (high I_2), larger work packages are necessary to streamline execution and reduce emissions from frequent task dependencies. However, this comes at the cost of increased variability, which may require careful planning to avoid introducing inefficiencies. In Rush mode, prioritizing speed results in larger, less consistent work packages. Practical implementation in such scenarios must focus on mitigating the risks of uneven task distribution, such as resource bottlenecks, while leveraging the emission reductions enabled by rapid task execution. The work package size and consistency in carbon emission optimization are shaped by the interplay of project parameters and practical considerations of task execution. Larger projects and flexible networks enable smaller, more uniform work packages, thereby enhancing emission performance by streamlining resource use. In contrast, highly serial networks and time-constrained execution modes necessitate larger, less consistent packages to balance structural and temporal constraints. These insights highlight the importance of tailoring optimization strategies to project-specific conditions to achieve carbon reduction and efficient project management. Table 4.5 summarizes the impact of work package size results under different project parameters.

Table 4.5 Impact of work package size results under different project parameters

Parameter	Impact on Work Package Scale	Impact on Consistency	Reasoning
Number of tasks (I_1)	Larger projects (higher I_1) result in smaller work packages.	Greater consistency in larger projects due to improved task distribution flexibility.	Larger projects allow for more balanced allocation, reducing bottlenecks and promoting parallel execution.
Network seriality (I_2)	Higher seriality (higher I_2) leads to larger work packages.	Higher variability in highly serial networks due to structural constraints.	Serial networks require task consolidation to minimize emissions from frequent transitions and dependencies.
Input-output ratio	Lower ratios (e.g., 0.8) result in larger work packages; higher ratios (e.g., 1.2) yield smaller packages.	Minimal impact on consistency.	Fewer interdependencies at lower ratios allow for larger groups; higher ratios limit grouping due to complexity.
Execution mode	Rush: Larger packages for rapid execution. Standard: Moderate, balanced sizes. Delay: Smaller, flexible packages.	Rush: High variability. Standard: Moderate consistency. Delay: High consistency.	Rush mode prioritizes speed; Delay mode allows finer optimization; Standard mode balances emission performance.

4.5 Chapter Summary

This chapter has presented a comprehensive approach to optimizing WPSs to reduce carbon emissions in MiC projects. Beginning with a formal problem statement of the WPSP, this chapter established the theoretical foundation for carbon emissions based on work package production rates through the Cobb-Douglas production function. This productivity-based framework provided the mathematical basis for quantifying how work package configurations influence overall project carbon emissions across the factory production, transportation, and on-site assembly phases characteristic of MiC delivery.

The core methodological contribution of this chapter is the development of the TLGA, specifically designed to address the complexities of work package optimization in MiC projects. The TLGA's innovative chromosome representation effectively handles two types of tasks. It manages active tasks that can be freely combined. It also handles inactive tasks that require dedicated management. This distinction is particularly important in MiC projects. In these projects, certain operations, such as module lifting, require specialized attention. Through carefully designed crossover, mutation, and selection operations, the algorithm efficiently explores the vast solution space of possible work package configurations to identify those that minimize carbon emissions. Experimental validation using both a large-scale real-world MiC project case study and a comprehensive set of project instances demonstrated the TLGA's effectiveness across diverse project scenarios. The algorithm consistently achieved substantial carbon emission reductions ranging from 49.93% to 81.15% compared to traditional WPSs, performing comparably to state-of-the-art heuristic methods. These results highlight the significant untapped potential for carbon reduction through systematic optimization of work packages in MiC projects.

Analysis of the experimental results revealed important patterns in carbon-optimized work packaging that directly inform MiC project management. Larger projects benefit from smaller, more uniform work packages, despite the increased coordination requirements they entail. Different project phases warrant different approaches to work packaging. Smaller packages are appropriate for parallel factory production. Larger packages are better suited for serial site assembly. The execution mode significantly influences optimal work package size: time-critical assembly phases require larger packages to minimize coordination-related emissions, while factory production benefits from smaller, more consistent packages that optimize resource utilization. These findings provide valuable guidance for MiC project managers seeking to enhance the sustainability advantage that MiC already offers over conventional methods. By thoughtfully designing work packages based on project characteristics, execution modes, and the distinct nature of factory versus site operations, significant carbon reductions can be achieved without compromising project delivery.

While this chapter has demonstrated the substantial potential for carbon reduction through optimized work packaging, it has focused exclusively on carbon emissions as the optimization objective. In practice, MiC project managers must balance environmental performance with other critical project objectives, particularly cost efficiency. The inherent trade-offs between carbon reduction and cost minimization present significant challenges for decision-makers in the increasingly sustainability-conscious construction industry. Chapter 5 will address this limitation by extending the optimization approach to incorporate both carbon emissions and project costs in a multi-objective framework. Building on the productivity-based carbon emission model and TLGA methodology established in this chapter, Chapter 5 explores the Pareto frontier of WPSs that offer optimal trade-offs between environmental impact and economic performance. By identifying the set of non-dominated solutions across competing objectives, the multi-objective approach provides MiC project managers with a comprehensive decision-support tool for selecting WPSs that align with specific project priorities and stakeholder requirements.

Chapter 5 Multi-objective Optimization of Work Package Scheme Problem to Minimize MiC Project Carbon Emissions and Cost

This chapter develops a multi-objective optimization framework for WPSs to simultaneously minimize carbon emissions and project costs in MiC projects. Building on the single-objective carbon-optimization approach established in Chapter 4, this chapter recognizes that sustainable construction management must balance environmental performance with economic considerations to be practically viable. The primary contribution is the implementation of two evolutionary algorithms (NSGA-II and SPEA2) to generate Pareto-optimal solutions that quantify the trade-offs between carbon reduction and cost implications across various project configurations. In multi-objective optimization, EAs for identifying the Pareto frontier exhibit distinct advantages over other optimization techniques. Compared to weighted-sum methods, EAs generate a diverse set of optimal solutions that represent various trade-offs among objectives without requiring predefined weights, thereby avoiding the subjective biases often inherent in traditional methods (Drake et al., 2020). Furthermore, EAs are less susceptible to issues related to nonlinearity and nonconvexity than other Pareto methods, such as ε-constraint approaches. Since the WPSP has been proven to be NP-hard (C.-L. Li & Hall, 2019), EAs are particularly suitable for its resolution. The population-based nature of these algorithms enables parallel search, significantly enhancing computational efficiency and scalability (Thiele et al., 2009). This chapter addresses research objective 3 outlined in Chapter 3: developing multi-objective optimization techniques that enable project managers to make informed decisions by explicitly quantifying sustainability-cost relationships. The work aims to achieve three objectives: (1) to construct a MIP model to minimize project carbon emissions and cost; (2) to solve the multi-objective optimization problem using two representative algorithms, NSGA-II (Deb et al., 2002) and SPEA2 (Zitzler et al., 2001); and (3) to test the robustness of the proposed models and algorithms under varying parameters and constraints. The multi-objective approach demonstrated remarkable effectiveness, achieving approximately 68% reductions in carbon emissions with only an 11% increase in cost compared to traditional methods across diverse project parameters. The chapter is organized as follows: Section 5.1 presents the problem statement considering both project carbon emissions and cost; Section 5.2 introduces the algorithms for obtaining the Pareto frontier; Section 5.3 validates their effectiveness using a project instance dataset and a real-world construction project, with comparisons to Gurobi and a state-of-the-art heuristic algorithm; Section 5.4 implements sensitivity analysis of parameters and constraints; and Section 5.5 summarizes the chapter content.

5.1 Problem Statement of WPSP Considering both Project Carbon Emissions and Cost

5.1.1 The General Description

Similar to Chapter 4, A project can be represented by a directed acyclic graph $G(N, E)$, where the nodes $N = \{1, \dots, n\}$ represent the tasks, and arcs $E \subset N \times N$ represent zero-lag finish-start precedence relations between tasks. Each task $a \in N$ has a given duration $t_a \geq 0$ and given work content $v_a \geq 0$. The first and the last tasks are dummy tasks, and their work content and durations are both 0. Figure 5.1shows the process of tasks being packaged into work packages. Two constraints are considered in this process: (1) inactive tasks. A set of tasks $a \in R \subseteq N$, with special requirements (e.g., risk control) and dummy tasks can only form a single-task work package. For example, tasks 1, 8, and 9 in Figure 5.1. (2) The task precedence relations. Since there is a precedence relationship between tasks, there is also a precedence relationship between work packages formed by tasks. There are two main perspectives on precedence relations between work packages (C.-L. Li & Hall, 2019). The first is strict precedence-constrained work packages. That means that if task a in work package W is a predecessor of task a' in work package W', then all tasks in W precede all tasks in W'. The second is generalized precedence constrained work packages. Under this perspective, the processing of work package W and W' may be partially overlapped even though one of the tasks in W is a predecessor of one of the tasks in W'. Since previous research paid more attention to the strict precedence constrained work packages (C.-L. Li & Hall, 2019; Liu et al., 2023). This section considers the generalized precedence-constrained work packages to supplement insights. Based on the above two constraints, the WPS in Figure 5.1 can be recorded as $\{\{1\},\{2,3,4\},\{5,6\},\{7\},\{8\},\{9\}\}$.

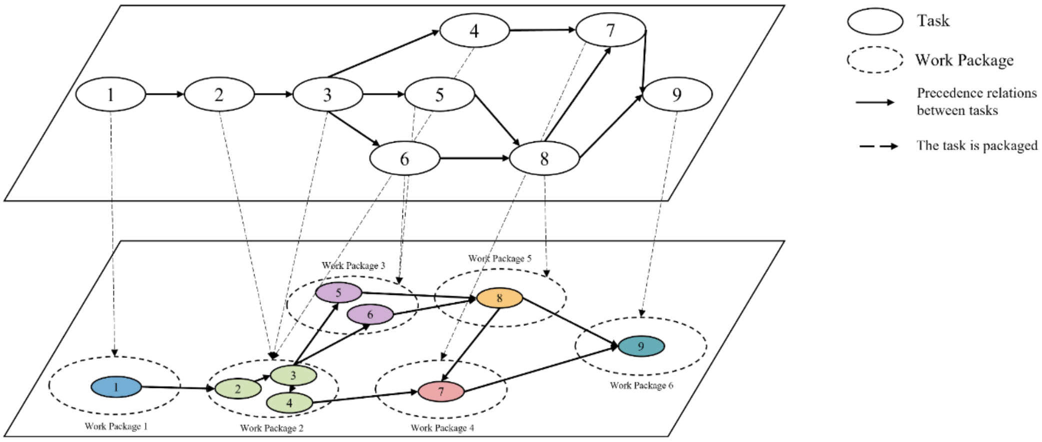


Figure 5.1 Project tasks are packaged into work packages

5.1.2 The Mathematical Description

This section presents details of objective functions and constraints of the WPSP. The project cost objective and the carbon emissions objective are described as functions of work package durations and work content. Decision variables are introduced to describe the task packaging process.

(1) Objective 1: The project cost based on work package durations and content

The total project cost equals the sum of all work packages formed. The cost of a work package is related to fixed cost ω, the work content of the work package v_w and the completion time C_W of the work package (C.-L. Li & Hall, 2019). That is,

$$TC = \omega\left(\sum_{k=1}^{k=n} y_{W_k} - 2\right) + \sum_{k=1}^{k=n} H\left(v_{W_k}\right) \cdot y_{W_k} + \xi \sum_{k=1}^{k=n} y_{W_k} L(v_{W_k}, C_{W_k}) \cdot y_{W_k} \quad (5\text{-}1)$$

TC is the sum of the cost of all work packages in the project. The cost of a work package consists of three parts: fixed cost ω, work content cost function $H(v_W)$, and cash flow cost function $L(v_W, C_W)$.

$H(v)$ is a cost composite function related to the content of the work package, which consists of three functions:

(1) Cost and schedule estimation, $f(v)$, is concave, non-decreasing, and contingent upon the work content of the work package. When estimating the time required for a work package, discrepancies can be mitigated by allocating additional resources, such as an additional workforce. Conversely, inaccuracies in cost estimation may be counterbalanced by setting aside a larger budget in advance. The required buffer can be determined based on experience with similar projects or established industry benchmarks. Notably, the cost of these extra resources and the budget earmarked for this buffer relies on the work content encapsulated within the work package.

(2) The cost associated with tracking and managing the progress of a work package are expressed as a function $g(v)$ of its work content. Notably, this function is convex and non-decreasing.

(3) The economies of scale, derived from repetition and similarity of tasks within a work package, are expressed as a function $h(v)$ of its content.

The view of Li et al. (C.-L. Li & Hall, 2019) is used in this article. $f(v) = h(v) = 3v^{0.8}, g(v) = v^{1.2}$ and $H(v) = f(v) + g(v) + h(v)$. This function is concave and non-decreasing.

$L(v_W, C_w)$ is the total discounted cash flow cost with discount rate α, $L(v_W, C_w) = \xi v_W(1 - e^{-\alpha C_W})$.

(2) Objective 2: The project carbon emissions based on work package production rate

Objective 2 has been given and proved in detail in Chapter 4. Therefore, this chapter will directly use the optimization objective in Chapter 4. It should be noted that in order to more easily calculate the actual execution time of the work package in the generalized precedence relations, this chapter simplifies the "SS (Start-Start)" precedence relations used in previous studies to deal with the generalized precedence relations. As shown in Figure. 5.2, time gaps (t_2 to t_3) may arise because predecessor tasks may exist in other work packages. The actual execution time of a work package $t^*_{W_k}$ is the work package makespan minus all time gaps. For example, it is $(t_4 - t_1) - (t_3 - t_2)$ in Figure 5.2.

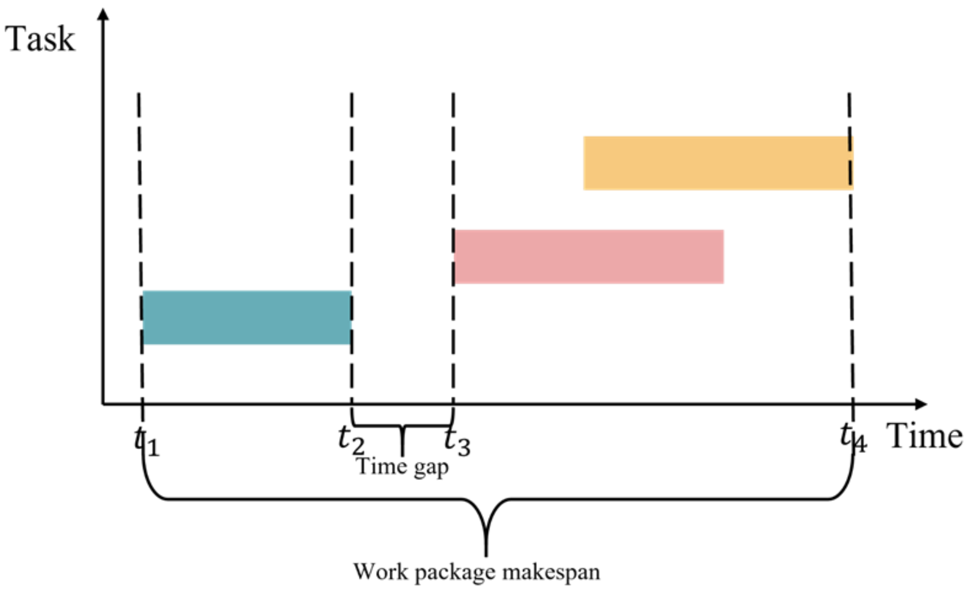


Figure 5.2 The actual execution time of a work package

(3) Model

Based on the total project carbon emissions and cost defined previously, the model of the WPSP of minimizing total project carbon emissions and cost is described as follows.

$$\text{Obj. } Min\ (TE, TC) \tag{5-2}$$

$$\text{s.t. } \sum_{k=1}^{k=n} x_{ak} = 1\ , for\ a = 1,2, \dots, n \tag{5-3}$$

$$\sum_{a=1}^{a=n} x_{ak} \leq n \cdot y_{W_k}, for\ k = 1,2, \dots, n \tag{5-4}$$

$$\sum_{a \in R} \sum_{k=1}^{k=n} x_{ak} = 1 \tag{5-5}$$

Equation (5-2) is the objective function to minimize the total project carbon emissions and cost. To more comprehensively balance the two objectives of project carbon emissions and cost, β is also be considered in work content in TC. Equation (5-3) ensures that each task is assigned to a work package. Equation (5-4) ensures that the work package being used is assigned at least one task. Equation (5-5) ensures that each inactive task needs to be assigned to a single work package without other tasks. As mentioned in Section 2, this model can be considered as a variant of the MKP. Tasks and work packages are MKP's items and knapsacks, respectively. Since such problems have high computational complexity (Lalonde et al., 2022; C.-L. Li & Hall, 2019) and consider multi-objective trade-offs between carbon emissions and cost. Two multi-objective EAs, NSGA-II and SPEA2, are used to obtain the Pareto frontier for this problem.

5.2 Multi-objective Optimization EA

Unlike traditional weighted sum methods that aggregate conflicting objectives into a single scalar value using subjective weights, the Pareto-based approach adopted in this study treats carbon emissions and cost as independent variables. Weighted methods often struggle to capture the full complexity of trade-offs and require repeated execution to approximate a solution frontier. In contrast, Pareto optimization allows for the simultaneous generation of a diverse set of non-dominated solutions within a single computational run. This methodology is particularly advantageous for Modular Integrated Construction planning, where the relationship between environmental impact and economic cost is non-linear and often competing. By avoiding a priori weight assignments, this approach empowers project managers to evaluate the explicit trade-offs along the Pareto frontier, selecting the most appropriate work package scheme based on specific project constraints rather than predetermined preference structures.

EAs, which are metaheuristic search techniques derived from the biological concept of evolution (Eiben & Smith, 2015), encompass a range of approaches, including multi-objective EAs. These algorithms are designed to address multiple objectives concurrently and have been widely utilized across diverse problem domains, demonstrating their effectiveness as robust, general-purpose search methods. The suitability of EAs for multi-objective optimization is particularly notable; a population-based approach enables the simultaneous exploration of multiple segments of the Pareto frontier within a single execution of the algorithm (Drake et al., 2020). The following outlines two motivations for using NSGA-II and SPEA2 in this article. (1) NSGA-II is currently the most widely employed algorithm in multi-objective optimization research. The Pareto frontier derived from NSGA-II typically exhibits superior diversity and better coverage of the true Pareto frontier (Deb et al., 2002). Its population-based encoding is adaptable to the precedence relationships of tasks in the project (Xiao et al., 2016). (2) However, NSGA-II may have problems maintaining diversity in dense regions of the Pareto frontier. SPEA2's enhanced fitness assignment and advanced clustering techniques can effectively address these limitations. Therefore, SPEA2 is also used as a complementary method.

5.2.1 NSGA-II

The implementation of NSGA-II primarily involves the following steps: encoding and decoding, initialization, fitness evaluation, non-dominated sorting, crossover and mutation, and selection. There are two common methods to handle WPSP constraints in EAs: (1) treat individuals according to the constrained dominance principle in the iterative selection process (J. Xu et al., 2024); (2) integrate the problem constraints in generating individuals and populations. Both methods can eliminate non-dominated solutions and accelerate algorithm convergence. The constrained dominance principle is used in NSGA-II. Integrating constraints is used in SPEA2.

(1) Encoding and decoding

Each solution in the population is represented by a chromosome consisting of n genes, where each gene g_a corresponds to the work package number assigned to task a. This encoding scheme is an integer representation where $g_a \in \{1,2,\dots,n\}$.

Decoding involves constructing the set of task allocations to work packages from the gene values. For a chromosome (each chromosome also represents an individual) $X =$

$[g_1, g_2, \dots, g_n]$, the allocation can be decoded as $W_k = \{a|g_a = k\}, for\ k = 1,2, \dots, n$. Take Figure 5.1 as an example, the corresponding relationship between work packages and coding is shown in Figure 5.3.

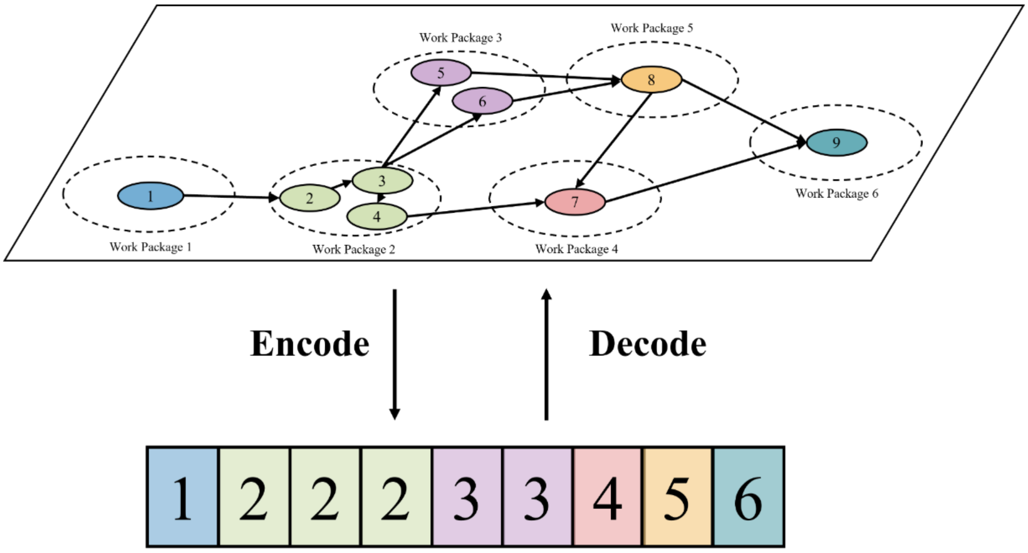


Figure 5.3 Encoding and decoding of work packages

(2) Initialization

The initial population P_0 of size Ω is generated randomly while ensuring all constraints are satisfied. For tasks in R, they require to be single work packages respectively without other tasks: if $a \in R$, then $g_a = W_{R_k}$, where W_{R_k} is the single-task work package. For each individual i in the population, $CV(i)$ is initialized to zero. The initial population P_0 s sorted using non-dominated sorting that takes into account $CV(i)$ to handle constraints. Individuals with lower $CV(i)$ values (fewer constraint violations) are considered better.

(3) Non-dominated sorting

Non-dominated sorting is used to classify the solutions into different frontiers. A solution Φ is said to dominate Ψ (denoted as $\Phi \prec \Psi$) if it is no worse in all objectives and better in at least one objective:

$$\forall O \in \{TC, TE\}, f_O(\Phi) \leq f_O(\Psi) \wedge \exists O \in \{TC, TE\}, f_O(\Phi) < f_O(\Psi) \quad (5\text{-}6)$$

This process partitions the population into several frontiers $F_1, F_2, \dots, F_m$, where F_1 is the set of non-dominated solutions.

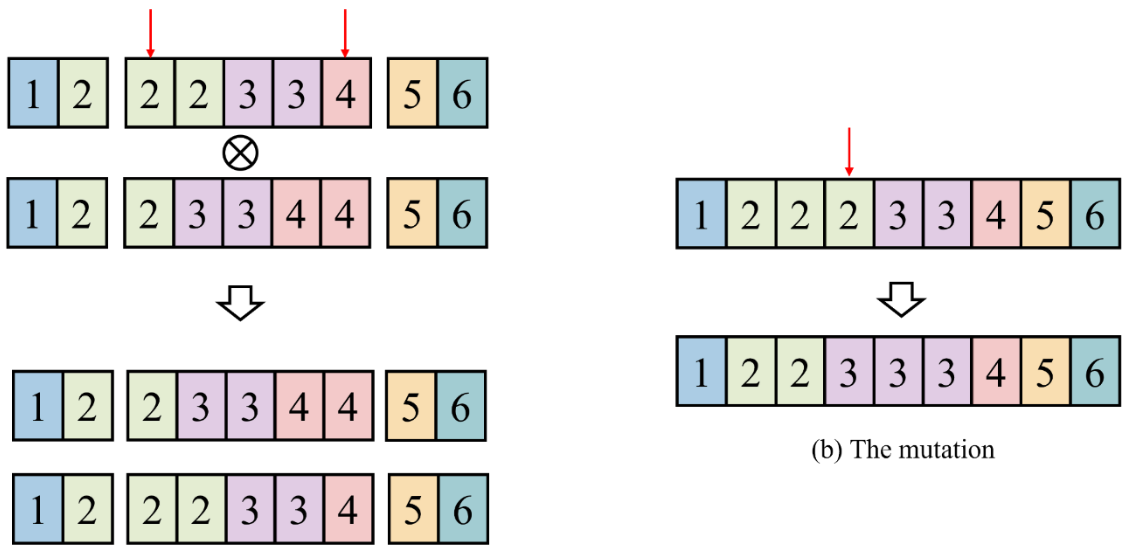
(4) Crowding distance calculation

Within each frontier, the crowding distance is calculated to preserve diversity in the population. For each solution, Φ in frontier F, the crowding distance $d(\Phi)$ is calculated as:

$$d(\Phi) = \sum_{O=1}^{2} (f_O(\Phi^{(i+1)}) - f_O(\Phi^{(i-1)}))/(f_O^{max} - f_O^{min}) \quad (5\text{-}7)$$

(5) Crossover and mutation

A two-point crossover is used (Figure 5-4 (a)), combining segments from two parents to form new offspring, respecting the constraints for tasks in R. Two-point represent two randomly selected crossover points, and the genotypes between the crossover points are exchanged. Mutation is applied with a probability p_m (Figure 5-4 (b)). Selected genes are reassigned to different work packages, respecting the constraints for tasks in R.



(a) The two-point crossover

(b) The mutation

Figure 5.4 The crossover and mutation

(6) Fitness evaluation and selection

A combined population undergoes non-dominated sorting. The next generation is formed by selecting individuals based on their rank and crowding distance, using a binary tournament selection method. This method balances exploration and exploitation effectively and is particularly suited for GA like NSGA-II, where maintaining diversity is crucial. The binary tournament selection method is implemented according to the following steps. Each new generation is formed by combining and sorting the current population and their offspring using the constrained non-dominated sorting approach based on CV.

Step1. Random selection of pairs: Randomly select two individuals X_i and X_j from the population P, where $i,j \in \{1,2,3,\dots,\Omega\}$ and $i \neq j$.

Step2. Determination of fitness: For each individual X, a fitness measure of a combination of rank from non-dominated sorting and the crowding distance:

$$F(X) = rank(X) + \frac{1}{1+crowding\_distance(X)} \tag{5-8}$$

Here, a lower rank is better, and a higher crowding distance is better, making the $\frac{1}{1+crowding\_distance(X)}$ term smaller for crowded individuals.

Step 3. Selection based on fitness and CV: Compare the fitness values of X_i and X_j. Select the individual with the better fitness. best individuals are selected based on their non-domination rank and crowding distance to form the new population.

Step 4. Repetition for selection: Repeat steps 1 to 3 N times to select N individuals for the next generation.

The above contains the entire process of implementing NSGA-II. The pseudocode of NSGA-II is shown in Algorithm 2. The algorithm complexity of NSGA-II is $O(G \cdot \Omega^2 \cdot (T + S))$, where G is the number of generations; Ω is population size; T is the number of tasks; S is the number of inactive tasks. The calculation process is provided as ***Theorem 5.1***.

```
Algorithm 2: NSGA-II
  Input: Population size Ω, number of generations G
  Output: Pareto-optimal front
  Initialize population P_0 with Ω chromosomes
  foreach individual i in P_0 do
      Evaluate fitness of i considering task assignments
      CV(i) ← 0
      foreach task t in tasks do
          if task t is not assigned to any work package then
              CV(i) ← CV(i) + 1
              // Constraint 1
      foreach inactive task s in inactive tasks do
          if inactive task s is not assigned to a dedicated work package
           then
              CV(i) ← CV(i) + 1
              // Constraint 2
  Perform constrained non-dominated sorting on P_0 using CV(i)
  Assign crowding distance to each individual in P_0
  for generation r = 1 to G do
      P_r ← ∅
      while |P_r| < Ω do
          Select two individuals X_i, X_j from P_{r-1} based on tournament
           selection with CV
          Apply crossover and mutation to X_i, X_j to form Y_i, Y_j
          Evaluate fitness of Y_i, Y_j
          CV(Y_i), CV(Y_j) ← 0
          foreach task t in tasks do
              if task t is not assigned to any work package then
                  CV(Y_i) ← CV(Y_i) + 1
                  // Same for Y_j CV(Y_j) ← CV(Y_j) + 1
          foreach inactive task s in inactive tasks do
              if inactive task s is not assigned to a dedicated work package
               then
                  CV(Y_i) ← CV(Y_i) + 1
                  // Same for Y_j CV(Y_j) ← CV(Y_j) + 1
          if CV(Y_i) + fitness(Y_i) ≤ CV(Y_j) + fitness(Y_j) then
              Add Y_i to P_r
          else
              Add Y_j to P_r
      Combine P_r and P_{r-1} into R_r
      Perform constrained non-dominated sorting on R_r using CV
      Assign crowding distance to each individual in R_r
      Select Ω individuals from R_r to form new population P_r
  return Non-dominated individuals from P_G
```

Theorem 5.1 The algorithm complexity of NSGA-II is $O(G \cdot \Omega^2 \cdot (T + S))$

Proof

Initialization of population P_0: $O(\Omega)$

Evaluation of fitness and constraint violations for each individual in P_0:

$$O(\Omega) + O(\Omega \cdot T) + O(\Omega \cdot S) = O\big(\Omega \cdot (T + S)\big)$$

Constrained non-dominated sorting on P_0: $O\big(\Omega^2 \cdot (T + S)\big)$

Assigning crowding distance to each individual in P_0: $O(\Omega \cdot log\Omega)$

Main loop for G generations:

$$O(\Omega) + O\big(\Omega \cdot (T + S)\big) + O(\Omega) + O\big(\Omega^2 \cdot (T + S)\big) + O(\Omega \cdot log\Omega) + O(\Omega \cdot log\Omega)$$

$$= O(\Omega^2 \cdot (T + S) + \Omega \cdot log\Omega)$$

Total complexity for the main loop: $O\big(G \cdot (\Omega^2 \cdot (T + S) + \Omega \cdot log\Omega)\big)$

Returning non-dominated individuals from P_G: $O(\Omega)$

Overall complexity:

$$O\big(\Omega^2 \cdot (T + S)\big) + O\big(G \cdot (\Omega^2 \cdot (T + S) + \Omega \cdot \log \Omega)\big) = O\big(G \cdot \Omega^2 \cdot (T + S)\big)$$

Where:

G: The number of generations.

Ω: The population size.

T: The number of tasks.

S: The number of inactive tasks.

5.2.2 SPEA2

SPEA2 uses a different strength-based fitness assignment method from NSGA-II, which is specifically reflected in the following three aspects (Zitzler et al., 2001). (1)

Individual strength value. Each individual in the population is assigned a strength value that reflects the number of solutions it dominates. The fitness of an individual is then defined as the sum of the strengths of all individuals that dominate it, inversely. Thus, less dominated individuals have better fitness. (2) Clustering mechanism. SPEA2 incorporates a clustering mechanism to prune the population size and ensure diversity. (3) External archive. The external archive maintained by SPEA2, which stores the best solutions found so far, is another distinctive feature that helps preserve elite solutions across generations. Since the initialization, crossover, and mutation of SPEA2 are similar to those of NSGA-II, only the process of obtaining the dominant solution is introduced.

Step 1. Setup of parameters: Let P represent the population of individuals with $|P| = N$. And let A be an external archive that stores potentially of solutions that individuals X_i dominates.

$$S(X_i) = \left|\{X_j \in P \cup A: X_i\ dominates\ X_j\}\right| \tag{5-9}$$

Step 2. Fitness assignment: The fitness of each individual X_j in both P and A is calculated based on the strength of the individuals who dominate X_j.

$$F(X_j) = \sum_{X_i \in P \cup A: X_i\ dominates\ X_j} S(X_i) \tag{5-10}$$

This fitness calculation ensures that individuals dominated by many others or by highly dominant individuals will have a higher fitness value.

Step 3. Density estimation: To maintain diversity among solutions, SPEA2 incorporates a density estimation technique, typically using the k-th nearest neighbour method. The density $D(j)$ of an individual X_j is inversely proportional to the distance to its k-th nearest neighbour in the combined set $P \cup A$.

$$D(X_j) = \frac{1}{distance\ to\ k\text{-}th\ nearest\ neighbour\ of\ j+2} \tag{5-11}$$

Step 4. Raw fitness and density: The raw fitness $F'(X_j)$ and the density $D(X_j)$ are combined to give a total fitness score $F''(j)$ for each individual. This total fitness is used to select individuals for the archive and reproduction.

$$F''(X_j) = F'(X_j) + D(X_j) \tag{5-12}$$

Step 5. Environmental selection. The archive A is updated using the following rule: All non-dominated individuals from $P \cup A$ are added to A. If $|A| > N_A$, reduce A that removes individuals based on their density measure, retaining those with lower density. If $|A| < N_A$, fill A with dominated individuals from $P \cup A$ based on their fitness values F''. The pseudocode of SPEA2 is shown in Algorithm 3. The algorithm complexity of NSGA-II is $O\big(G \cdot ((\Omega + \Omega_A)^2 \cdot log(\Omega + \Omega_A) + \Omega_A \cdot log\,\Omega_A)\big)$, where G is the number of generations; Ω is the population size; Ω_A is the archive size. The calculation process is provided as ***Theorem 5.2***.

Algorithm 3: SPEA2

Input: Population size Ω, Archive size Ω_A, number of generations G, set of tasks T, set of inactive tasks $T_s \subseteq T$

Output: Pareto-optimal front

Initialize population P_0 with Ω individuals:;
for *each individual* $i \leftarrow 1$ **to** Ω **do**
  Assign each task $t \in T$ to a work package W_j ensuring all tasks are covered;
  Ensure each inactive task $t_s \in T_s$ is assigned to a separate work package W_k;
  Validate or adjust assignments if necessary;
end
Initialize archive A_0 to empty;
Evaluate fitness of each individual in P_0;
for *each generation* $r \leftarrow 1$ **to** G **do**
  Calculate strength $S(X_i)$ for each individual X_i in $P_{r-1} \cup A_{r-1}$;
  Assign fitness $F(X_i)$ based on strength values for each individual in $P_{r-1} \cup A_{r-1}$;
  Calculate density $D(X_i)$ using distance to k-th nearest neighbor for each individual in $P_{r-1} \cup A_{r-1}$;
  Update fitness $F''(X_i) = F(X_i) + D(X_i)$ for each individual;
  if $|A_{r-1}| < \Omega_A$ **then**
    Add non-dominated individuals from $P_{r-1} \cup A_{r-1}$ to A_{r-1};
    Fill remaining slots in A_r with dominated individuals based on $F''(X_i)$ until $|A_r| = \Omega_A$;
  else
    Truncate A_{r-1} by removing individuals with worst $F''(X_i)$ until $|A_r| = \Omega_A$;
  end
  Select individuals from A_r and P_{r-1} to reproduce and form P_r with size Ω;
  Apply crossover and mutation to generate offspring Q_r;
  Evaluate fitness of each individual in Q_r;
  Combine P_r and Q_r into R_r;
end
Select non-dominated individuals from A_G to form the final set of solutions;
return *Pareto-optimal solutions from* A_G;

Theorem 5.2 The algorithm complexity of NSGA-II is $O(G \cdot \Omega^2 \cdot (T + S))$

Proof

Initialize population $P_0: O(\Omega \cdot T)$

Initialize archive $A_0: O(1)$

Evaluate the fitness of each individual in $P_0: O(\Omega)$

Main loop for G generations:

Calculate strength $S(X_i): O((\Omega + \Omega_A)^2)$

Assign fitness $F(X_i): O(\Omega + \Omega_A)$

Calculate density $D(X_i): O((\Omega + \Omega_A)^2 \cdot \log(\Omega + \Omega_A))$

Update fitness $F''(X_i): O(\Omega + \Omega_A)$

Update archive A_r:

If $|A_{r-1}| < \Omega_A: O\big((\Omega + \Omega_A) \cdot \log(\Omega + \Omega_A)\big)$

Else: $O(\Omega_A \cdot \log \Omega_A)$

Select, reproduce, and form $P_r: O(\Omega)$

Apply crossover and mutation: $O(\Omega)$

Evaluate fitness of $Q_r: O(\Omega)$

Combine P_r and $Q_r: O(\Omega)$

Total: $O((\Omega + \Omega_A)^2 \cdot \log(\Omega + \Omega_A) + \Omega_A \cdot \log \Omega_A)$

Overall complexity:

$$O(\Omega \cdot T) + O(\Omega) + O\big(G \cdot ((\Omega + \Omega_A)^2 \cdot \log(\Omega + \Omega_A) + \Omega_A \cdot \log \Omega_A)\big) + O(\Omega_A \cdot \log \Omega_A) = O\big(G \cdot ((\Omega + \Omega_A)^2 \cdot \log(\Omega + \Omega_A) + \Omega_A \cdot \log \Omega_A)\big)$$

Where:

G: The number of generations.

Ω: The population size.

Ω_A: The archive size.

T: The number of tasks.

5.3 Experiments

This section details the experimental strategy employed to evaluate the optimization capabilities of the proposed NSGA-II and SPEA2 algorithms. The assessment is structured into two distinct phases to ensure a comprehensive validation. Initially, the study utilizes a dataset of small-scale project instances to benchmark the proposed methods against established state-of-the-art optimization solvers, thereby demonstrating their algorithmic superiority in controlled environments. Subsequently, the research expands the scope to include a large-scale scenario derived from an actual construction project. This second phase aims to verify the algorithms' effectiveness and robustness in handling complex, real-world conditions by comparing their performance against leading heuristic methods.

5.3.1 Experiments on Small-scale Project Instances

(1) Optimization solver and data preparation

To establish a rigorous performance baseline for the proposed NSGA-II and SPEA2 algorithms, Gurobi was selected to solve small-scale instances of the Work Package Sizing Problem (WPSP). Recognized as a premier optimization solver within operations research (Nadarajah & Cire, 2020; Rostami et al., 2021), Gurobi provides a reliable standard for comparative analysis. The experimental data is drawn from a specialized project instance dataset (C.-L. Li & Hall, 2019) containing 200 variations defined by the project size (I_1) and the seriality indicator (I_2). In this context, I_1 denotes the number of non-dummy tasks, while I_2 measures network topology on a scale from 0 to 1, where higher values indicate increasingly serial structures.

For this comparative study, ten instances characterized by the minimum parameter values ($I_1 = 40$ and $I_2 = 0.2$) were specifically chosen to accommodate the computational constraints of exact solvers. Although Gurobi represents the state of the art, it faces significant challenges with NP-hard problems like WPSP, often proving unable to resolve large-scale instances; however, it can reliably generate suboptimal solutions for smaller projects within a finite timeframe, necessitating the selection of the smallest project size. Furthermore, the choice of the minimum I_2 value leads to highly parallel network structures, significantly expanding the solution space. This complexity imposes greater demands on the solver, ensuring that the comparative evaluation creates a sufficiently challenging testing environment to validly assess algorithmic performance.

Table 5.1 Basic information of the project instance dataset

Dataset parameters	**Values**
Total number of project instances	200
I_1	$\{40,80,120,160\}$

I_2	$\{0.2,0.4,0.6,0.8,1.0\}$
Number of project instances for each combination of I_1 and I_2	10

(2) Parameter settings

To ensure a comprehensive evaluation of the proposed framework, this study requires precise definitions of both model parameters and algorithm hyperparameters. The manipulation of model parameters enables the simulation of diverse problem scenarios, while calibration of algorithm hyperparameters is essential for achieving optimal computational performance. Regarding the total cost function, the study adopts the parameter values established in previous research (C.-L. Li & Hall, 2019) to maintain consistency and facilitate direct comparisons. For the carbon emissions function, the coefficients a, b, and c must be predetermined, as the theoretical minimum occurs when the work package production rate equals $b/2a$.

To rigorously test the model across different operational contexts, the ratio $b/2a$ is set to 1.0, 0.8, and 1.2, corresponding to standard, delay, and rush modes, respectively. In the standard mode ($b/2a = 1.0$), the optimal low-carbon production rate involves completing one unit of work per unit of time. Since the total work content of the project remains constant, the parameter c does not influence the optimization results; however, specific mathematical constraints are satisfied to ensure the model reflects real-world feasibility. Additionally, the input-output conversion parameter β is varied to 80%, 100%, and 120% to represent different efficiency levels. All adopted parameter values for the problem model are consolidated in Table 5.2.

Table 5.2 Parameter values of the problem model

The parameters	Values	Basis
α	0.001	Previous research (C.-L. Li & Hall, 2019)
ξ	100	
ω	50	
β	80%;100%;120%	Classification discussion
a	10	
b	16;20;24	
c	20;24.4;16.4	

The efficacy of evolutionary algorithms, such as NSGA-II and SPEA2, relies heavily on the precise calibration of hyperparameters, including population size, generation limits, and crossover and mutation probabilities. Identifying the optimal configuration for these variables is a decisive yet complex task in multi-objective optimization, as the specific settings directly dictate both the quality of the solution and the efficiency of convergence. Because theoretical determination of these values is often infeasible, empirical validation through systematic testing is required. A widely accepted approach for this calibration is grid search, a technique that involves systematically testing specific parameter intervals while holding other variables constant to isolate their effects (G. Li et al., 2021).

This method offers several distinct advantages for the current study. Primarily, it is conceptually straightforward and can be implemented without complex statistical tools. Furthermore, its exhaustive nature ensures that any optimal combination within the defined search space will be identified. Crucially, grid search operates independently of assumptions regarding the response surface, making it particularly robust for navigating the irregular solution landscapes often encountered in complex optimization problems where traditional models may falter. Given that evolutionary algorithms are specifically designed for large-scale applications, the grid search was conducted using the adapted case project to determine the final settings for population size, maximum generations, and crossover and mutation probabilities. The results of the grid search as shown in Figure 5.5 and Figure 5.6. The algorithm hyperparameter values are summarized in Table 5.3.

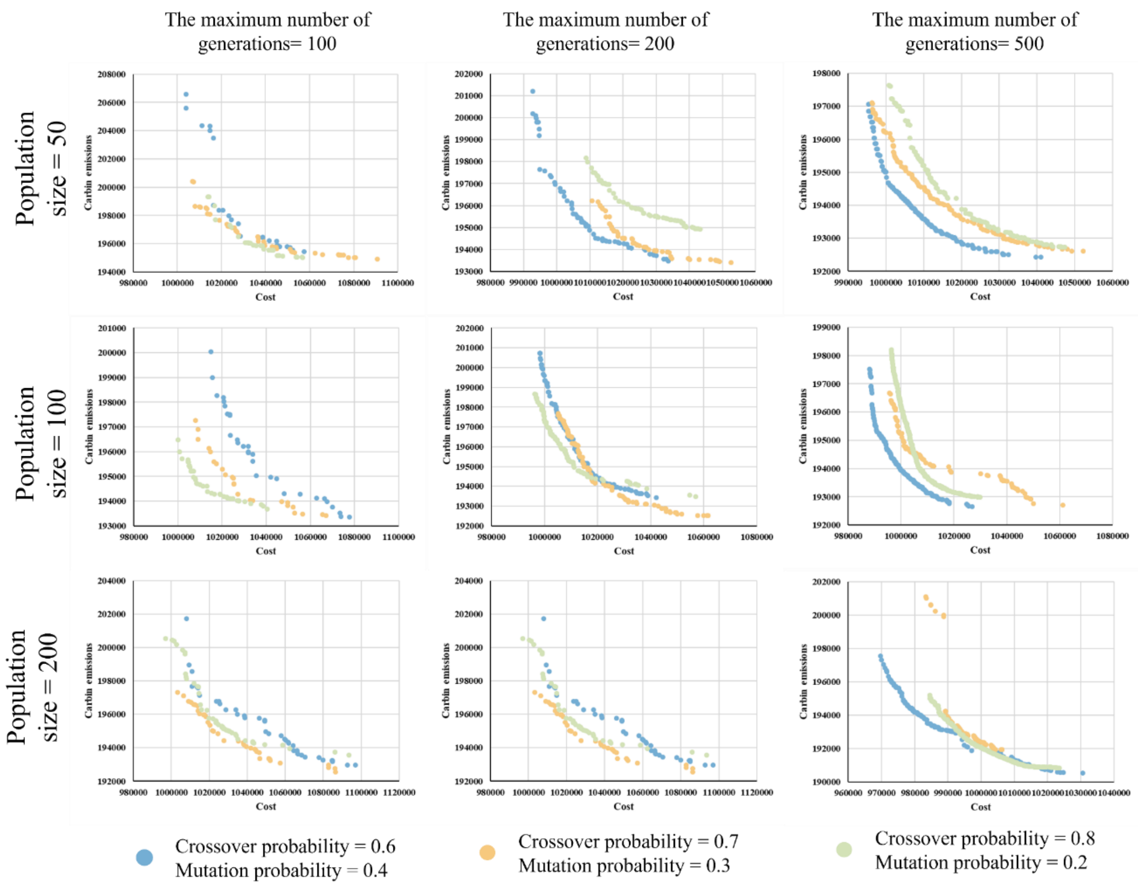


Figure 5.5 Grid search results using NSGA-II

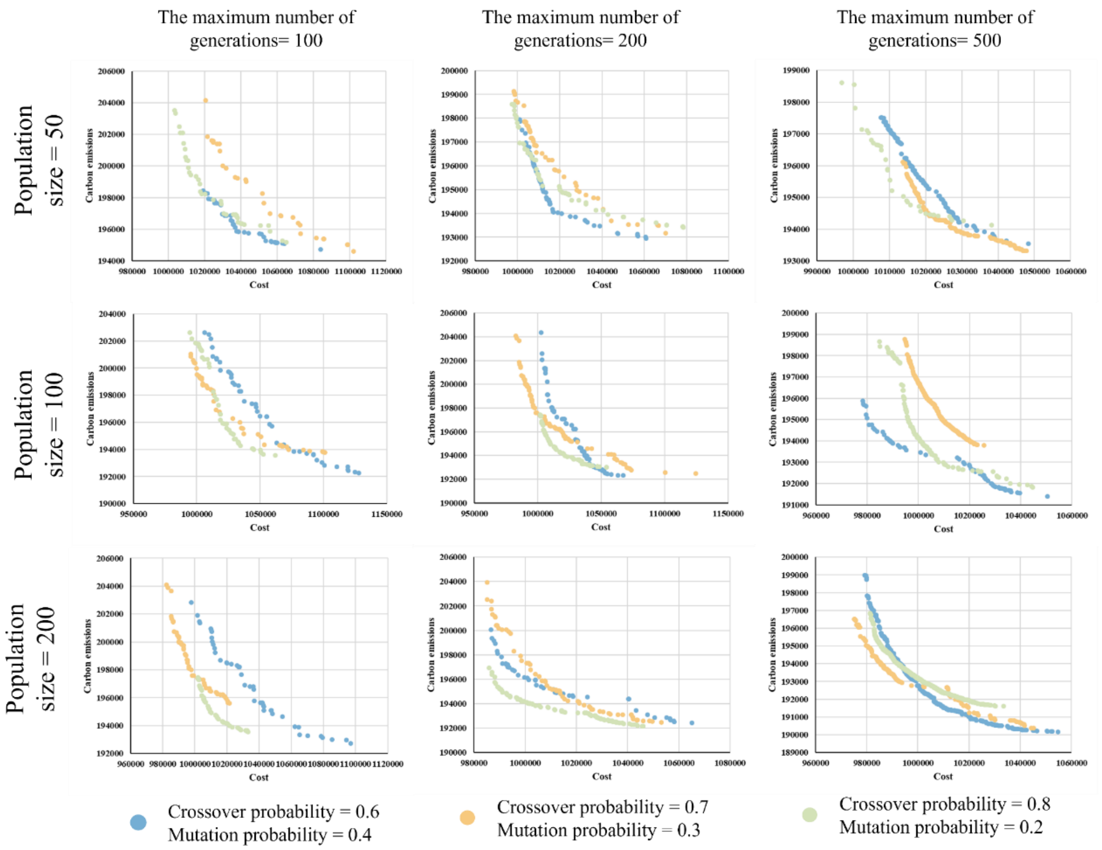


Figure 5.6 Grid search results using SPEA2

Table 5.3 The hyperparameter values of the algorithm

The hyperparameters	Values	Basis
Population size	200	
The maximum number of generations	500	Grid search results
Crossover probability	0.8	

Mutation probability	0.2

(3) Experimental results

To validate the efficacy of the proposed algorithms, the solutions generated by Gurobi for small-scale project instances serve as the benchmark for assessing NSGA-II and SPEA2. Specifically, the analysis contrasts the minimum cost obtained by the exact solver with the corresponding values on the evolutionary algorithms' Pareto frontiers. Recognizing that the inherent complexity of the Work Package Sizing Problem (WPSP) may prevent Gurobi from guaranteeing a global optimum, the solver nevertheless yields the highest-quality feasible solutions. Consequently, the carbon emissions and cost values derived from these baseline solutions are utilized as the reference standard for computing the performance metric, Gap_1, as defined in Equation (5-13).

$$Gap_1 = \frac{Carbon/Cost_{EAs} - Carbon/Cost_{Gurobi}}{Carbon/Cost_{Gurobi}} \times 100\% \tag{5-13}$$

A positive Gap_1 indicates that the result of EAs is worse than that of Gurobi, and a negative Gap_1 indicates that the result of EAs is better than that of Gurobi. The average values of Gap_1 for the ten project instances under different model parameters are summarized in Table 5.4.

The data presented in Table 5.4 provides compelling evidence regarding the efficacy and stability of the NSGA-II and SPEA2 frameworks. These EAs successfully balance conflicting objectives, delivering substantial environmental benefits with only marginal economic impact. Specifically, the methods achieve an average reduction in carbon emissions of approximately 68%, accompanied by a modest increase in costs of roughly

11%. The algorithms demonstrate particular strength in scenarios combining the standard mode with a β value of 120%, where they outperform the Gurobi solver across both objective dimensions. Even under the least favorable conditions—standard mode with a β of 80%, securing a 67% reduction in emissions despite a 32% rise in costs. This consistent ability to identify superior trade-offs across all six parameter combinations underscores the robustness of the proposed approach. Furthermore, in terms of computational efficiency, the EAs exhibit a distinct advantage; they require an average solving time of only 40 seconds, compared to the 4,800 seconds necessitated by Gurobi. Collectively, these comparative results from small-scale project instances provide initial verification that the proposed evolutionary algorithms offer a superior and more efficient alternative to traditional state-of-the-art solvers.

Table 5.4 The average Gap_1 between Gurobi and EAs

		Carbon		**Cost**	
Mode	$\boldsymbol{\beta}$	**NSGA-II**	**SPEA2**	**NSGA-II**	**SPEA2**
Delay		-68.48%	-69.50%	9.74%	11.45%
Standard	100%	-68.99%	-69.27%	10.51%	10.68%
Rush		-68.61%	-68.37%	9.77%	9.54%
	80%	-67.38%	-66.74%	31.95%	31.83%
Standard	100%	-68.37%	-69.09%	10.00%	10.33%
	120%	-69.27%	-69.58%	**-5.05%**	**-4.97%**
Average		-68.52%	-68.76%	11.15%	11.48%

To provide a rigorous statistical comparison between NSGA-II and SPEA2, the Mann-Whitney U test was applied to the Gap_1 performance metric. This non-parametric test was selected specifically for its independence from the assumption of normality, making it highly effective for analyzing skewed or ordinal datasets. Furthermore, the test's inherent robustness against outliers makes it particularly suitable for drawing reliable inferences from small sample sizes. As indicated by the results in Table 5.5, the analysis revealed no statistically significant divergence in optimization performance between the two algorithms when applied to small-scale project instances.

Table 5.5 p-value of Mann-Whitney U test of NSGA-II and SPEA

Mode	$\boldsymbol{\beta}$	**Carbon**	**Cost**
Delay		0.7337	0.0890
Standard	100%	0.9698	0.9976
Rush		0.9097	0.8501
	80%	0.9698	0.6776
Standard	100%	0.8501	0.4727
	120%	0.7913	0.9953

5.3.2 Experiments on a Large-scale Project Case

(1) Data preparation and parameter setting

The empirical case study focuses on a student dormitory development in Hong Kong, comprising four hostel blocks ranging from 12 to 16 stories and utilizing approximately 900 MiC units . A visual representation of the project scope is provided in Figure 5.7.

Currently in the mock-up phase, the project relies on offshore manufacturing, with all modular units fabricated in Mainland China before delivery. The comprehensive project schedule, encompassing production, cross-border transportation, and on-site assembly, served as the basis for the adapted research model. This adapted schedule comprises 306 specific activities, including 304 operational tasks and 2 dummy tasks representing the project start and completion. Key project data utilized includes task identifiers, execution durations, and sequential dependencies. While the original schedule employed complex precedence relationships—such as Start-to-Start, Start-to-Finish, and Finish-to-Finish. To ensure compatibility with established project planning literature, all dependencies were converted to Finish-to-Start (FS) relationships, with task durations recalibrated to maintain scheduling accuracy. Finally, the experimental configuration regarding model parameters and algorithm hyperparameters remains consistent with the specifications detailed in Section 5.4.1.

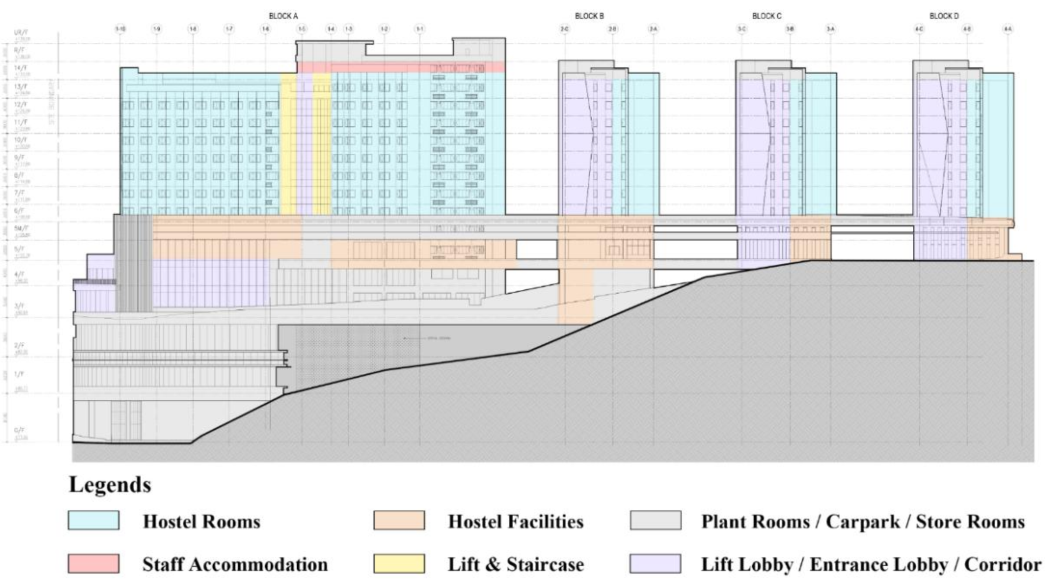


Figure 5.7 The overview of the project

(2) Experimental results

Figure 5.8 depicts the Pareto frontiers for total project carbon emissions and costs, generated by the proposed NSGA-II and SPEA2 algorithms across diverse modes and input-output conversion rates. In these graphical representations, the vertical axis represents carbon emissions, and the horizontal axis denotes project costs. A comparative analysis reveals that SPEA2 consistently outperforms NSGA-II, generating a larger set of Pareto-optimal solutions that dominate those produced by the latter. This performance advantage can be attributed to several methodological distinctions. Unlike NSGA-II, which relies on non-dominated sorting and crowding distance, SPEA2 employs a fitness assignment strategy that integrates dominance with density information derived from the k-th nearest neighbor technique. This approach achieves a more effective balance between exploration and exploitation. Furthermore, SPEA2 maintains an external archive that preserves elite solutions across generations, thereby safeguarding historical non-dominated solutions against loss during the selection process.

In terms of computational efficiency, the enhanced solution quality provided by SPEA2 entails a marginal increase in processing time. The average runtime for NSGA-II was recorded at approximately 522.83 seconds, whereas SPEA2 required roughly 555.15 seconds. This variation represents an increase of approximately 6.18%, or roughly 32 seconds. The extended duration is a direct consequence of the additional computational overhead required to manage the external archive and perform complex density estimations. However, this slight increase in computational cost is negligible in the context of project planning and is well justified by the algorithm's superior ability to identify diverse, high-quality solutions along the Pareto frontier. However, this 6.18% increase represents a negligible absolute time cost, which is inconsequential within the extended timeframe of strategic pre-project planning. Given the high stakes of construction management, where optimal decision-making can lead to high long-term cost and carbon savings, this marginal computational expense is fully justified by the superior quality and diversity of the solutions obtained. Thus, the enhanced ability of SPEA2 to identify better Pareto-optimal trade-offs heavily outweighs its slight reduction in computational efficiency.

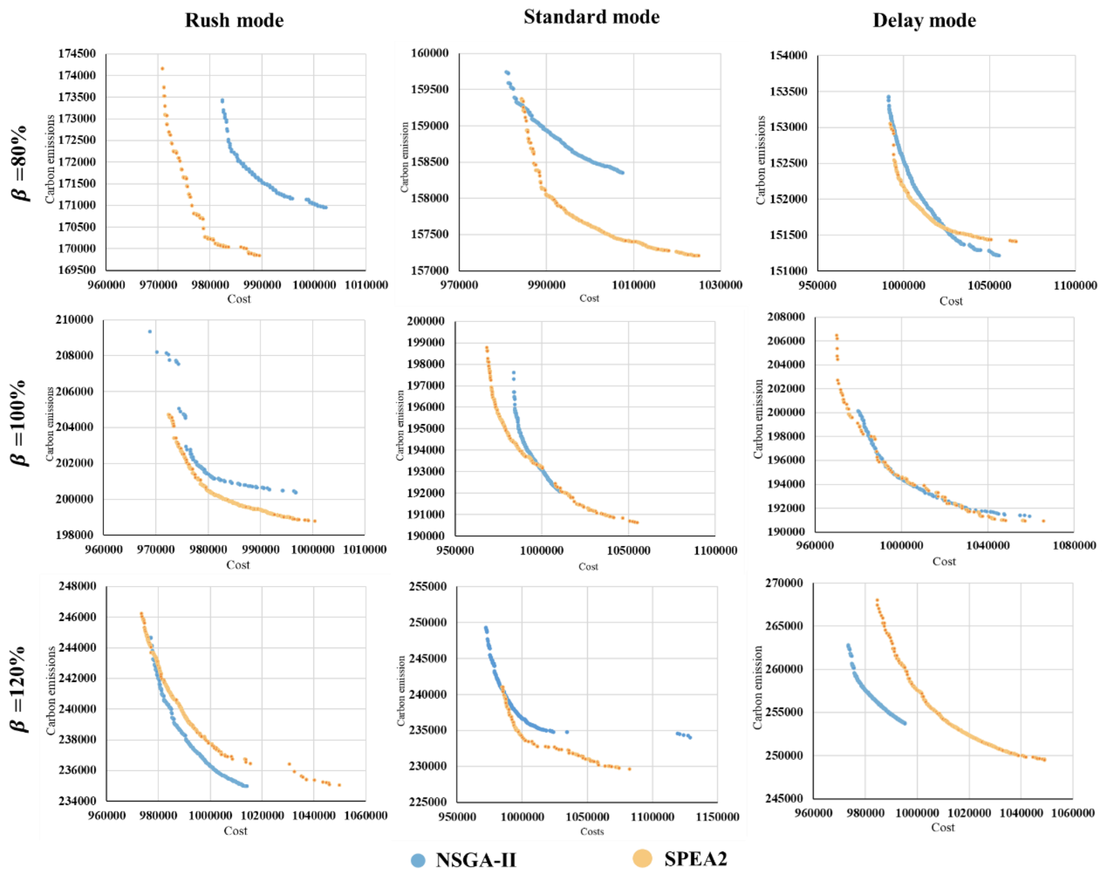


Figure 5.8 Pareto frontier of the total project carbon emissions and cost, obtained by the proposed NSGA-II and SPEA2

Table 5.6 Gap_2 between NSGA-II/SPEA2 and the heuristic in the minimum carbon emissions scenario

		NSGA-II				SPEA2			
		Rush	Standard	Delay	Average	Rush	Standard	Delay	Average
Carbon	$\beta = 80\%$	11.44%	4.77%	0.37%	5.53%	10.73%	4.11%	0.50%	5.11%
	$\beta = 100\%$	4.88%	0.46%	-1.02%	1.44%	4.04%	-0.11%	-1.22%	0.90%
	$\beta = 120\%$	0.53%	-0.77%	0.99%	0.25%	0.14%	-2.63%	0.69%	-0.60%
	Average	5.62%	1.49%	0.11%	2.41%	4.97%	0.46%	-0.01%	1.81%
Cost	$\beta = 80\%$	-24.30%	-25.67%	-24.12%	-24.70%	-25.26%	-25.00%	-23.41%	-24.56%
	$\beta = 100\%$	-26.02%	-26.31%	-24.96%	-25.76%	-25.76%	-24.17%	-24.49%	-7.63%
	$\beta = 120\%$	--25.95%	-18.86%	-27.72%	-6.88%	-19.71%	-22.19%	-26.41%	-22.77%
	Average	-8.12%	-23.61%	-25.60%	-19.11%	-6.40%	-23.79%	-24.77%	-18.32%

To further assess the optimization efficacy of NSGA-II and SPEA2, a comparative analysis was conducted using a state-of-the-art heuristic algorithm grounded in task merging logic (C.-L. Li & Hall, 2019). The pseudocode for this Merge Heuristic Algorithm is detailed in the Appendix. Since this specific heuristic is limited to single-objective optimization—targeting either project carbon emissions or cost exclusively—two distinct experimental scenarios were defined: "*Minimum Carbon Emissions*" and "*Minimum Cost*." In each scenario, the heuristic's computational outcomes were benchmarked against solutions generated by NSGA-II and SPEA2.

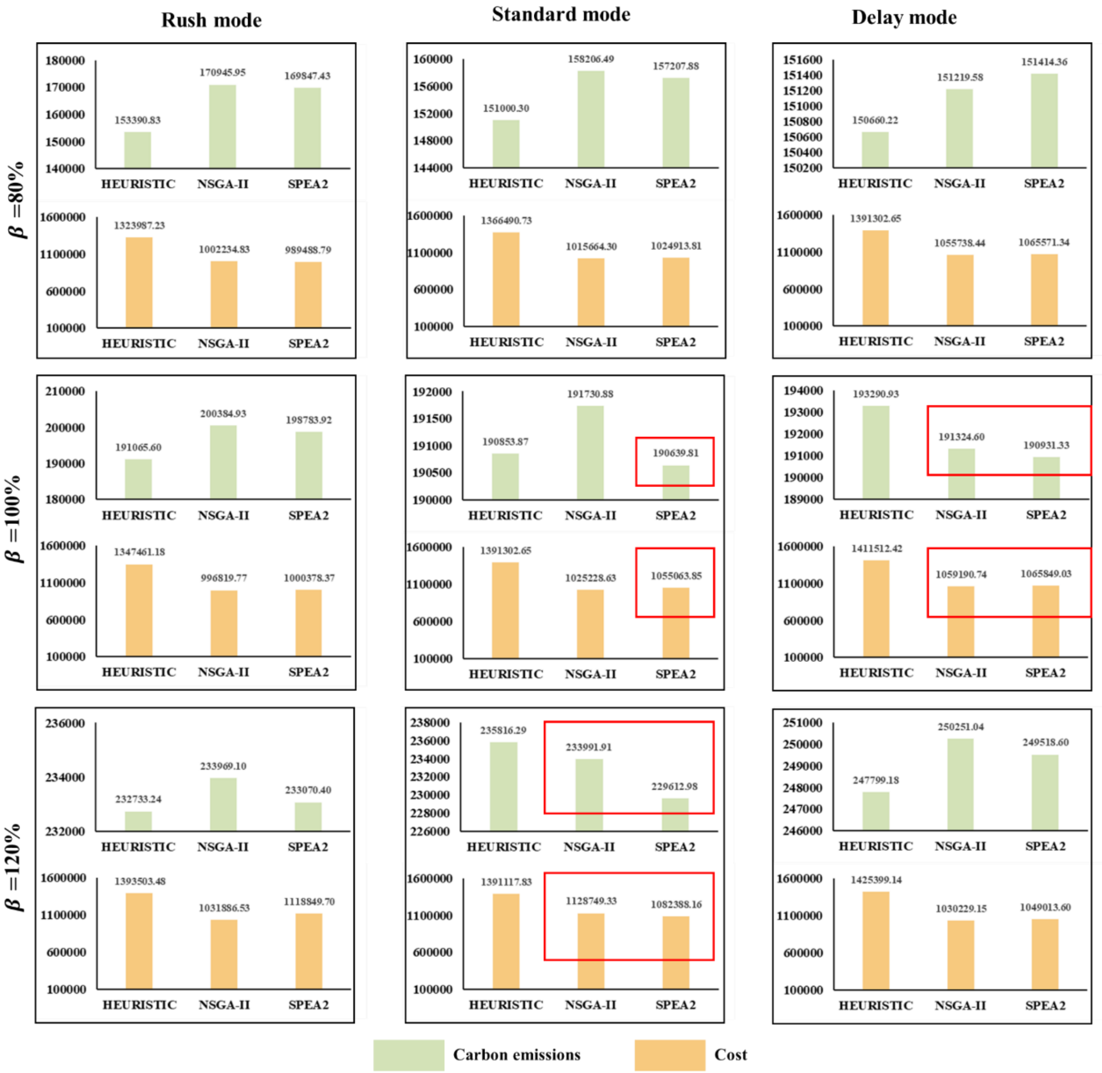


Figure 5.9 Carbon emissions and cost obtained by the heuristic, NSGA-II, and SPEA2 in minimum carbon emissions scenario

In the *Minimum carbon emissions* scenario, visualized in Figure 5.9, the heuristic prioritizes reducing environmental impact. To enable a valid comparison, the Pareto solutions with the lowest carbon emissions were extracted from the respective NSGA-II and SPEA2 frontiers. Conversely, the *Minimum cost* scenario, depicted in Figure 5.10, orients the heuristic toward economic efficiency. Similarly, the Pareto solutions representing the lowest cost were selected from the evolutionary algorithms' output for evaluation. The figures present the carbon emissions and cost values derived from all three methods. Using the heuristic's results as a baseline, the relative performance differences between NSGA-II and SPEA2 are summarized in Table 5.6 and Table 5.7, for the respective scenarios. This performance differential, denoted as Gap_2, is calculated using Equation (5-14). Consequently, a negative Gap_2 value signifies that the evolutionary algorithms outperformed the heuristic baseline, whereas a positive value indicates inferior performance relative to the heuristic method.

$$Gap_2 = \frac{Carbon/Cost_{EAs} - Carbon/Cost_{Heuristic}}{Carbon/Cost_{Heuristic}} \times 100\% \qquad (5\text{-}14)$$

In the scenario focused on *minimizing carbon emissions*, the heuristic algorithm demonstrates strong efficacy in single-objective optimization, successfully identifying the lowest-emission levels across six of the nine tested parameter combinations. However, this specific focus presents a distinct limitation: the absence of trade-off mechanisms frequently results in substantially higher project costs. In contrast, the multi-objective frameworks of NSGA-II and SPEA2 address this inefficiency by balancing competing goals. These algorithms achieve approximately 25% cost reductions compared to the heuristic approach while maintaining carbon emissions within a negligible margin of roughly 1%. As highlighted in Table 5.6, both evolutionary algorithms successfully lower financial costs without materially compromising environmental performance. This balanced performance is further evident in the red-marked region of Figure 5.9, where NSGA-II and SPEA2 outperform the heuristic across both objectives. The advantages are particularly pronounced in scenarios characterized by partial delayed execution and high input-output conversion rates. For instance, in the standard mode with a β value of 120%, SPEA2 achieved a 22.19% cost reduction alongside a 2.63% decrease in carbon emissions relative to the heuristic baseline. These results also reinforce the previously noted superiority of SPEA2 over NSGA-II. Specifically, SPEA2 simultaneously improved both carbon emissions and cost across three parameter combinations, whereas NSGA-II achieved this dual optimization in only two instances.

Table 5.7 Gap_2 between NSGA-II/SPEA2 and the heuristic in the minimum cost scenario

		NSGA-II				SPEA2			
		Rush	Standard	Delay	Average	Rush	Standard	Delay	Average
Carbon	$\beta = 80\%$	-7.41%	-5.51%	-5.39%	-6.10%	-7.02%	-5.74%	-5.62%	-6.13%
	$\beta = 100\%$	-5.97%	-7.37%	-8.45%	-7.26%	-8.05%	-6.82%	-5.56%	-6.81%
	$\beta = 120\%$	-9.92%	-10.09%	-12.67%	-10.89%	-9.34%	-13.07%	-10.94%	-11.12%
	Average	-7.77%	-7.66%	-8.84%	-8.09%	-8.14%	-8.54%	-7.37%	-8.02%
Cost	$\beta = 80\%$	5.82%	5.63%	6.66%	6.04%	4.58%	5.99%	6.78%	5.78%
	$\beta = 100\%$	4.32%	5.87%	5.35%	5.18%	4.71%	4.19%	4.27%	4.39%
	$\beta = 120\%$	5.12%	4.50%	4.58%	4.73%	4.74%	5.86%	5.78%	5.46%
	Average	5.09%	5.33%	5.53%	5.32%	4.68%	5.35%	5.61%	5.21%

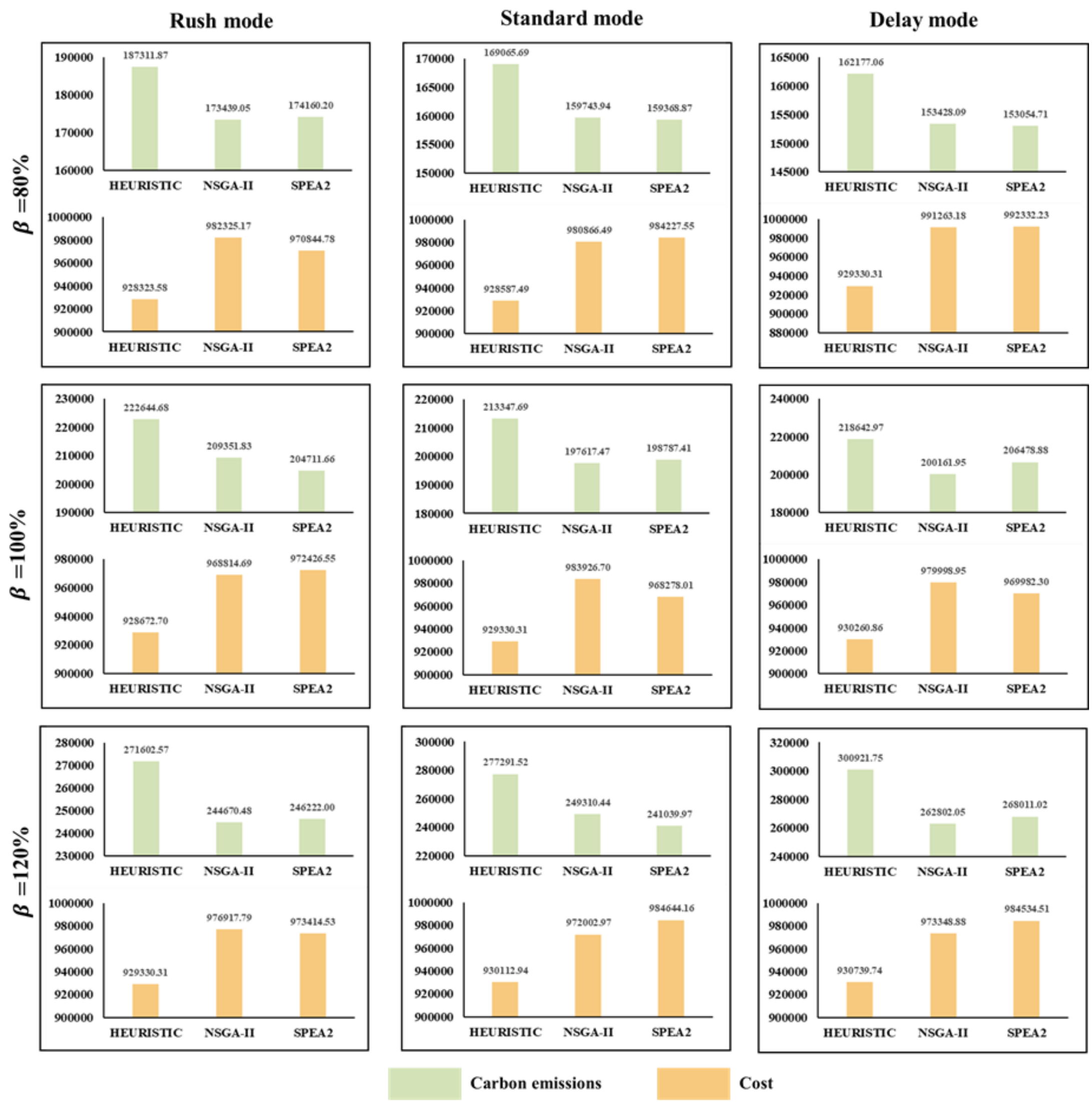


Figure 5.10 Carbon emissions and cost obtained by the heuristic, NSGA-II, and SPEA2 in the minimum cost scenario

The results from the minimum-cost scenario reinforce the heuristic algorithm's superiority in single-objective optimization, as it consistently achieved the lowest cost across all nine parameter combinations. This performance variation between scenarios likely stems from the algorithm's foundational design. Originally formulated using greedy task-merging principles to minimize project costs (C.-L. Li & Hall, 2019), the heuristic is inherently biased toward economic efficiency. However, this dominance in pure cost reduction does not diminish the value of NSGA-II and SPEA2 in managing multi-objective trade-offs. While these evolutionary algorithms trail slightly in cost efficiency, they compensate by delivering an average carbon emission reduction of approximately 8%, accompanied by a marginal cost increase of only about 5%. Specific configurations, highlighted in Table 5.7, demonstrate even greater benefits; for instance, in the standard mode with a β value of 120%, NSGA-II achieved a 13.07% reduction in emissions while incurring a cost premium of just 5.86% relative to the heuristic baseline. Overall, the experimental data confirms the robustness of NSGA-II and SPEA2, which successfully generated valid Pareto frontiers across all tested execution modes and input-output scenarios. Their primary strength lies in their ability to navigate complex multi-objective trade-offs. Compared to Gurobi and the heuristic benchmarks, these algorithms consistently optimized primary objectives while offering significant improvements in secondary metrics. In certain instances, they even surpassed the single-objective heuristic in both cost and carbon performance simultaneously. The results also underscore the significant influence of key parameters, such as execution mode and conversion rates, on optimization outcomes. A more detailed examination of these parametric effects is presented in the sensitivity analysis in Section 5.5.

5.4 Sensitivity Analysis

This section presents a sensitivity analysis of the multi-objective optimization results, examining the impact of four key parameters and two distinct constraint types. The evaluation encompasses two project-specific variables: the total number of tasks (I_1)

and the network parallelism indicator (I_2). Additionally, it assesses two critical model parameters: the optimal execution mode ($b/2a$) and the input-output conversion rate (β). Beyond these parametric adjustments, the study examines the influence of structural constraints by contrasting the generalized precedence constraint, which underlies this research, with the strict precedence constraint established in prior literature (C.-L. Li & Hall, 2019; Liu et al., 2025).

5.4.1 Solution Performance Indicator

To intuitively assess the sensitivity of NSGA-II and SPEA2 results to parameter variations, the study uses the hypervolume indicator. In multi-objective optimization, hypervolume quantifies the region of the objective space enclosed by a reference point and the set of Pareto-optimal solutions (Zitzler & Thiele, 1999). A larger hypervolume signifies a Pareto frontier with broader coverage and a more uniform distribution of solutions. Figure 5.11 illustrates the hypervolume concept within a dual-objective minimization context, while the subsequent procedures outline the specific calculation methodology (Araya et al., 2020; Petchrompo et al., 2022).

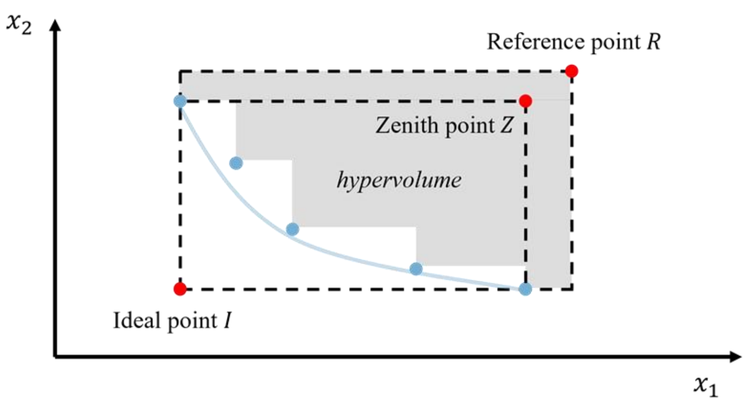


Figure 5.11 Hypervolume indicator

Step 1. linearly normalized. Each objective is linearly normalized according to Equation (5-15).

$$f_i'(x_i) = \frac{f_i(x_i) - f_i^{min}(x_i)}{f_i^{max}(x_i) - f_i^{min}(x_i)} \quad for\ i = 1,2,\ldots \tag{5-15}$$

Where $f_i'(x_i)$ is the value of normalized objective i; $f_i(x_i)$ is the validated value of objective i; $f_i^{min}(x_i)$ and $f_i^{max}(x_i)$ are minimum and maximum values of objective i found in the feasible solution space, respectively.

Step 2. Determine the reference point. For the minimization problem, the reference point is determined according to Equation (5-16).

$$R = Z + \frac{1}{U}(Z - I) \tag{5-16}$$

Where R is the reference point. Z is the zenith point. I is the ideal point. U is the number of solutions in the Pareto frontier.

Step 3. Calculate the hypervolume. The hypervolume is calculated according to the Equation (5-17).

$$hypervolume = S_1 \cup S_2 \cup \ldots \cup S_n \tag{5-17}$$

Where S_n is hypervolume formed by reference point R and Pareto solutions.

5.4.2 Sensitivity Analysis Results of Parameters

To isolate the sensitivity of individual variables, specific parameters are tested while the remaining values are fixed according to the specifications in Table 5.8. The findings from this analysis, which evaluate the influence of the project task count (I_1), the network parallelism indicator (I_2), the optimal execution mode ($b/2a$), and the input-output conversion rate (β), are visually summarized in Figure 5.12. In these graphs, the horizontal axis shows the variations in each parameter, and the vertical axis plots the average hypervolume across the project instances.

Table 5.8 Default values of parameters

Parameters	Values
I_1	40
I_2	0.2
$\frac{b}{2a}$	1.0
β	100%

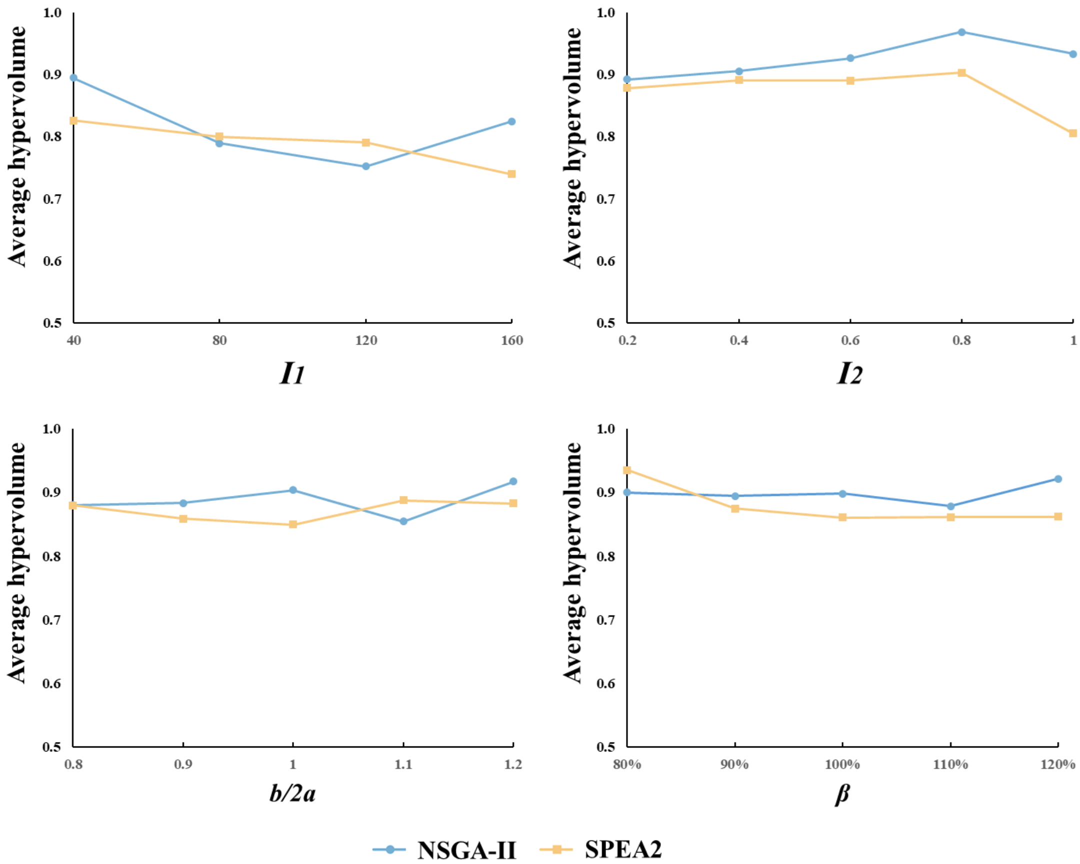


Figure 5.12 Sensitivity analysis results of four parameters

The cumulative results affirm that NSGA-II and SPEA2 maintain robust multi-objective optimization capabilities across all tested parameter configurations. Given that the theoretical maximum for the normalized hypervolume is 1, it is significant that every generated Pareto frontier exceeds 0.7, with the majority exceeding 0.8. These high scores confirm that the solutions provide extensive coverage and possess a uniform distribution along the frontier. While the algorithms are generally stable, further analysis indicates that the quality of the Pareto frontiers is more sensitive to variations in project-specific parameters than to changes in model settings.

Specifically, the hypervolume exhibits a negative correlation with the project size indicator, I_1. As the number of tasks increases, the solution space grows, complicating the search for Pareto-optimal outcomes and leading to lower hypervolume scores. In contrast, increasing the seriality indicator, I_2, generally leads to an upward trend in hypervolume. This is because serial networks limit the variability associated with parallel task execution, effectively constraining the feasible solution space and simplifying the optimization process. However, this trend reverses in the extreme case of a fully serial network ($I_2 = 1$). In such scenarios, the solution space becomes too restricted, limiting the number of available Pareto solutions and leading to a subsequent decline in hypervolume.

Regarding model parameters, the hypervolume of the Pareto frontiers generated by NSGA-II and SPEA2 exhibits remarkable stability across diverse settings, with all values consistently surpassing 0.8. These results highlight the robustness of the proposed multi-objective optimization framework for balancing project carbon emissions and costs. The model and algorithms effectively navigate trade-offs under varying execution modes and input-output conversion rates. While the Pareto frontier is generally insensitive to model parameters, subtle shifts in hypervolume are observable. Specifically, as the input-output conversion rate β increases, a slight decline in hypervolume is evident. This trend likely arises because higher conversion rates correlate with intensified production, thereby elevating carbon emissions. Consequently, emissions dominate a larger share of the multi-objective trade-offs, which constrains the diversity of Pareto solutions.

A further critical observation is that NSGA-II yields larger hypervolumes than SPEA2 in projects with fewer tasks. As illustrated in Figure 5.12, for $I_1 = 40$, NSGA-II consistently outperforms SPEA2 in this metric. This divergence may be attributed to the distinct selection mechanisms of the two algorithms. NSGA-II prioritizes individuals with lower rank and greater crowding distance, encouraging broader exploration of the search space. This strategy often results in a more extensive Pareto frontier and, by extension, a larger hypervolume. Conversely, SPEA2 relies on a strength-based selection process, which tends to focus on regions with high densities of non-dominated solutions. This approach prioritizes local exploitation over expanding the extremities of the frontier, potentially limiting the overall hypervolume in smaller project instances.

5.4.3 Sensitivity Analysis Results of Constraints

This section primarily addresses work packages governed by generalized precedence constraints; however, the scope is expanded to include strict precedence constraints for two key reasons. First, this inclusion validates the robustness of the proposed multi-objective optimization model and algorithms in managing the trade-off between cost and carbon emissions in the Work Package Sizing Problem (WPSP). Second, it allows investigation of how different precedence relationships influence the characteristics of the Pareto frontier. When constructing strictly constrained work packages, a fundamental rule must be observed: the predecessors of any specific task cannot be grouped with its successors in the same package. This restriction is critical to prevent cycles in the project network, a concept elaborated on in previous studies (C.-L. Li & Hall, 2019). Consequently, the multi-objective optimization model must incorporate additional constraints, as defined in Equation (5-18).

$$x_{a_p k} + x_{a_s k} \leq 1, \ \ for \ a = 1,2,..,n, \forall a_p \in P_a, a_s \in S_a \qquad (5\text{-}18)$$

In this equation, P_a represents the set of predecessors for task a, while S_a denotes the set of its successors. To comply with the restrictions imposed by Equation (5-18), the encoding, crossover, and mutation procedures within the NSGA-II and SPEA2 algorithms require specific adjustments. To this end, a two-list representation—consisting of a task list and a work package list—is utilized to manage these evolutionary processes under strict precedence constraints (Y. Zhang, Li et al., 2024). This combination ensures that the generated solutions consistently satisfy the necessary constraints throughout the evolutionary iteration. It is important to note, however, that the core mechanisms employed by NSGA-II and SPEA2 to identify Pareto-optimal solutions and generate the Pareto frontier remain unaltered. Figure. 5.13 illustrates the hypervolume distributions of the Pareto frontiers for each instance under both generalized and strict precedence constraints, utilizing the default project parameters outlined in Table 5.8.

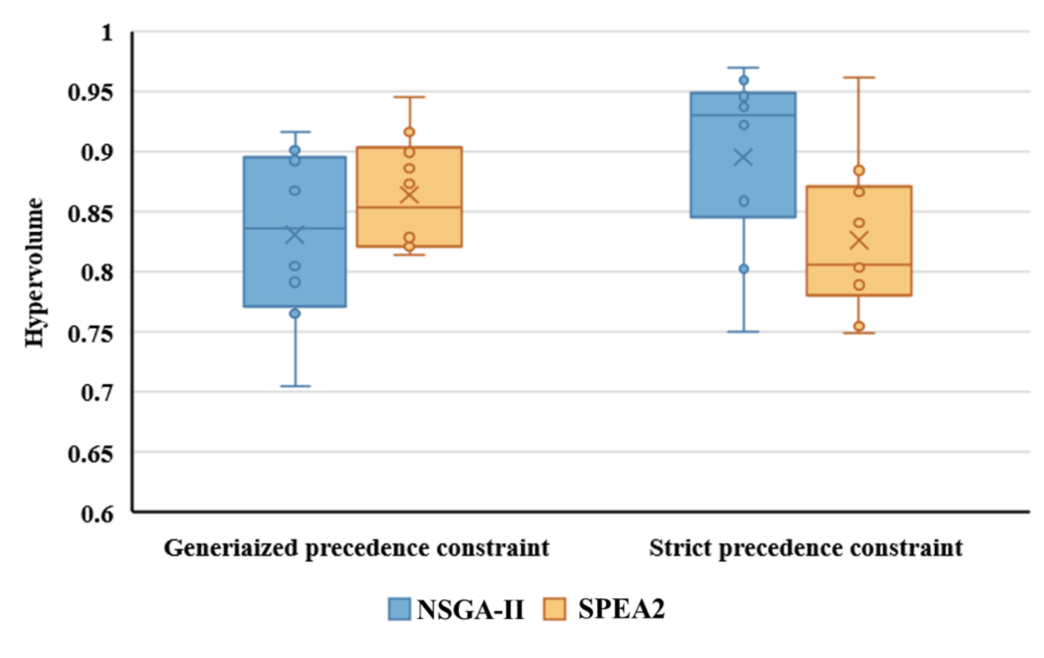


Figure 5.13 Hypervolume distribution under generalized precedence constraint and strict precedence constraint

The empirical results illustrated in Figure 5.13 substantiate the robustness of the proposed multi-objective optimization framework across diverse constraint categories. With hypervolume indicators consistently exceeding 0.7 across all instances under both strict and generalized constraints, the findings attest to a uniform, well-distributed set of Pareto-optimal solutions. However, the adaptability of the specific algorithms varies depending on the constraint type; NSGA-II performs better under strict precedence constraints, whereas SPEA2 performs better under generalized precedence constraints. This performance divergence is likely attributable to the structural differences in the solution spaces. Strict precedence constraints impose rigorous limitations on work package sequencing, significantly compressing the feasible solution space compared to generalized constraints. Within this restricted domain, SPEA2's reliance on the k-th nearest neighbor method may precipitate solution clustering, resulting in discernible gaps along the Pareto frontier. Furthermore, although SPEA2 utilizes an external archive to preserve elite solutions, its update protocol may inadvertently discard boundary solutions that are essential for maximizing the overall hypervolume. Ultimately, these supplementary experiments provide strong validation for the stability and versatility of the proposed optimization model.

5.5 Chapter summary

This chapter has presented a comprehensive multi-objective optimization approach for WPSs in MiC projects, focusing on minimizing carbon emissions and costs. Building on the single-objective carbon-optimization framework established in Chapter 4, this study recognizes that sustainable project management must balance environmental performance with economic considerations. The development of an MIP model that simultaneously addresses these competing objectives represents a significant advancement in sustainable MiC project planning.

The core methodological contribution of this chapter is the implementation and comparative analysis of two EAs. These algorithms are NSGA-II and SPEA2. They are used for generating Pareto-optimal solutions to the WPSP. These algorithms demonstrate remarkable effectiveness, achieving approximately 68% reductions in carbon emissions with only an 11% increase in cost compared to traditional methods. This approach shows a significant improvement over single-objective methods, outperforming both the state-of-the-art Gurobi optimizer and a specialized heuristic algorithm. While single-objective methods excel at optimizing their target metric, they perform poorly on secondary objectives. In contrast, the proposed multi-objective approach identifies balanced solutions. These solutions substantially reduce carbon emissions without disproportionately increasing costs. This demonstrates the practical value of considering multiple objectives simultaneously. Examining these factors in isolation would not yield the same beneficial results.

Extensive experiments across different project parameters (task count, network seriality) and model parameters (execution mode, input-output conversion rate) confirm the robustness of the proposed approach. The hypervolume indicator remains consistently high across all parameter configurations, indicating well-distributed Pareto frontiers with excellent coverage of the solution space. A comparative analysis of NSGA-II and SPEA2 reveals that SPEA2 generally produces superior Pareto fronts, particularly for larger projects, at a modest computational cost. The analysis of generalized versus strict precedence constraints demonstrates that the multi-objective framework maintains its effectiveness regardless of the specific precedence requirements imposed on the work package structure.

These findings provide valuable guidance for MiC project managers seeking to enhance sustainability without compromising economic viability. The research demonstrates that different project phases may benefit from different optimization strategies. Factory production, transportation, and on-site assembly each have unique requirements. This is due to their varying characteristics of parallelism and seriality. Each phase needs a tailored optimization approach. The stability of performance across execution modes offers planning flexibility when projects face timeline adjustments, while the slight variation across input-output conversion rates highlights the importance of careful optimization in high-intensity production scenarios.

Despite the significant contributions of the optimization approaches presented in Chapters 4 and 5, it is important to acknowledge that these methods face certain professional barriers to widespread adoption in the construction industry. Advanced optimization algorithms like TLGA, NSGA-II, and SPEA2 require specialized expertise. This includes knowledge of mathematical modeling. Implementing these algorithms requires programming skills. Computational analysis is also necessary. These skills may not be readily available in many construction organizations. Furthermore, the technical complexity of these approaches can make them challenging to integrate into existing project management workflows, potentially limiting their practical application despite their proven benefits.

Chapter 6 addresses these challenges by exploring how LLMs can increase the accessibility and usability of optimization algorithms for sustainable MiC project planning. By leveraging LLMs' natural language processing capabilities, complex optimization tasks can be translated into more intuitive interfaces that require less specialized technical knowledge. This approach has the potential to democratize access to advanced optimization techniques, enabling a broader range of construction professionals to benefit from carbon and cost optimization in their work package planning.

The integration of LLMs with optimization algorithms represents a promising approach to bridging the gap between theoretical advances and practical implementation in sustainable construction management. By reducing the technical barriers to adoption, this approach can accelerate the industry's transition toward more environmentally responsible practices while maintaining economic competitiveness. Chapter 6 will explore this integration in detail, demonstrating how intelligent language interfaces can transform the way construction professionals interact with and benefit from sophisticated optimization techniques in their pursuit of sustainable MiC.

Chapter 6 Large Language Model-based Heuristic Optimization Framework for Work Package Scheme Problem

Previous chapters of this thesis (Chapters 4 and 5) have developed optimization algorithms to minimize carbon emissions in project work packages while maintaining cost efficiency. However, despite these promising algorithmic advances, a fundamental challenge persists: the substantial professional barriers between optimization expertise and project stakeholders (Zidane & Andersen, 2018). Construction project managers, who are primarily responsible for implementing carbon-reduction practices in MiC project management, often lack specialized knowledge of mathematical optimization and computational methods, limiting the practical application of advanced carbon-optimization techniques in real-world projects. These advanced methods typically require specialized mathematical expertise and computational resources beyond the capabilities of most project management teams, creating a persistent implementation gap between theoretical advances and practical application. LLMs represent a transformative advancement in AI that has only recently received widespread attention. LLMs are advanced AI systems that process and generate human-like text by learning from vast datasets of existing language examples (Wei et al., 2022). Through deep learning techniques, these models can understand and generate human-like text, facilitating communication across various domains. By leveraging mechanisms such as attention and contextual embeddings, LLMs can generate coherent, contextually appropriate responses to a given prompt (Wei et al., 2023). These capabilities position LLMs as potential intermediaries between complex mathematical techniques and practical project management needs.

This chapter addresses research objective 4 by proposing a heuristic optimization framework for work-package carbon emissions using LLMs. The framework leverages the capabilities of state-of-the-art LLMs via prompt chaining to construct various heuristic algorithms that project managers can readily understand and apply, thereby eliminating the professional barriers associated with complex optimization algorithms. This novel approach positions LLMs as intermediaries that can: (1) interpret project requirements and constraints expressed in natural language; (2) formulate appropriate heuristic optimization approaches for carbon emission reduction; and (3) refine heuristic optimization rules through iterative dialogue with project stakeholders. By empowering LLMs to construct and apply heuristic algorithms based on project-specific contexts, the framework eliminates the need for project managers to possess specialized optimization expertise. Instead, managers can interact with the system using familiar terminology and concepts, receiving guidance and solutions tailored to their specific carbon reduction objectives and project constraints. The remainder of this chapter is organized as follows. Section 6.1 introduces the concept of the prompt chain and its technical advantages. Section 6.2 presents the methodology and architecture of the proposed LLM-based heuristic optimization framework. Section 6.3 demonstrates the framework's implementation and effectiveness through comparative experiments. Section 6.4 summarizes the chapter content.

6.1 Prompt Chain Technology of Prompt Engineering

6.1.1 Conceptual Framework of Prompt Chaining

Prompt chaining is an advanced prompt engineering methodology that orchestrates a sequence of interconnected prompts to guide LLMs through complex reasoning processes. Unlike single-prompt approaches that aim to elicit complete solutions in a single interaction, prompt chaining decomposes complex tasks into manageable sub-problems, creating a structured workflow that mirrors human expert reasoning (Wei et al., 2022). In the context of developing heuristic algorithms for work-package carbon-emission optimization, prompt chaining enables LLMs to navigate the intricacies of algorithm design through a series of focused interactions, each building on the outputs of previous steps.

The fundamental concept behind prompt chaining is rooted in cognitive scaffolding theory, which holds that complex problem-solving is facilitated through a progression of increasingly sophisticated cognitive structures (Kocmi & Federmann, 2023). By segmenting the algorithm development process into discrete, sequential steps, prompt chaining creates a cognitive framework that enables LLMs to focus on specific aspects of heuristic design at each stage, thereby reducing the overall task's complexity. This approach is particularly valuable when developing optimization heuristics for carbon emissions, where multiple competing objectives, constraints, and domain-specific knowledge must be carefully integrated.

A prompt chain for heuristic algorithm development typically consists of several interconnected components: problem formulation prompts that establish the optimization context; knowledge elicitation prompts that extract domain-specific insights about carbon emissions in construction; algorithm design prompts that guide the LLM through various heuristic approaches; implementation prompts that translate conceptual designs into executable procedures; and evaluation prompts that assess the effectiveness of the generated algorithms against specific carbon reduction objectives.

6.1.2 Design Principles for Effective Prompt Chains

Effective prompt chains for heuristic algorithm development rely on thoughtfully structured interactions that guide LLMs through increasingly complex reasoning processes. At the core of successful prompt chain design is the principle of modularity and decomposition, which involves breaking down the intricate process of algorithm development into manageable components. When developing carbon-emission optimization heuristics for construction work packages, this might involve separating the process into distinct phases, addressing emission-source identification, optimization-variable selection, and constraint formulation. This modular approach allows construction professionals to focus on refining specific aspects of the algorithm without needing to reconstruct the entire optimization framework.

The management of information flow between chain components represents another critical design consideration. As prompt chains progress through successive stages of algorithm development, they must carefully balance the provision of context with the risk of information overload. For instance, when transitioning from problem formulation to solution strategy design, the prompt chain might carry forward essential details about emission factors and work package dependencies while summarizing less critical background information. This selective information transfer ensures that each stage of the chain has access to relevant context without becoming overwhelmed by extraneous details that could dilute the LLM's focus on the current reasoning task.

Prompt chains derive much of their effectiveness from their ability to make explicit the reasoning steps involved in developing heuristic algorithms. Rather than requesting complete algorithms in a single prompt, well-designed chains guide LLMs through a deliberate sequence of analytical steps that mirror the thought processes of experienced algorithm designers. In the context of work package optimization, this may involve first analyzing emission patterns across different construction phases, then identifying potential optimization levers, and finally evaluating the applicability of various heuristic approaches based on problem characteristics. This explicit reasoning approach, sometimes referred to as "chain-of-thought prompting" (Wei et al., 2022), not only enhances the quality of generated algorithms but also makes the development process more transparent and understandable to construction professionals who may lack specialized optimization expertise.

The development of effective heuristic algorithms rarely follows a linear path; instead, it involves cycles of implementation, evaluation, and refinement. Well-designed prompt chains incorporate this iterative nature by establishing feedback loops that allow for the progressive improvement of generated algorithms. For example, after the LLM proposes an initial greedy heuristic for work package sequencing, a subsequent prompt might evaluate this approach against specific carbon reduction targets and then guide the LLM to refine the algorithm based on identified limitations. These iterative cycles enable the prompt chain to progressively enhance algorithm quality without requiring construction professionals to possess expertise in optimization theory or implementation techniques.

6.1.3 Advantages of Prompt Chaining for Work Package Carbon Emission Optimization

The application of prompt chaining to develop carbon-emission optimization heuristics offers significant benefits for construction project managers facing increasingly stringent sustainability requirements. Perhaps the most important advantage is the enhanced accessibility and transparency of the optimization process. Traditional optimization approaches often present significant barriers to adoption due to their mathematical complexity and specialized terminology. By contrast, prompt chains break down the algorithm development process into comprehensible steps with explicit reasoning, allowing project managers to follow the logic behind specific algorithmic choices and understand how different approaches affect carbon reduction outcomes. This transparency helps demystify the optimization process, builds confidence in the generated algorithms, and facilitates their adoption in practical construction management settings.

The ability to customize heuristic algorithms to specific project contexts represents another significant advantage of the prompt chaining approach. Construction projects vary widely in their work package structures, available technologies, resource constraints, and regulatory environments. Rather than applying generic optimization approaches, prompt chains enable the development of tailored heuristics that address the particular characteristics and challenges of individual projects. For instance, a prompt chain might guide the LLM to develop specialized neighborhood structures for local search algorithms that reflect the technological substitution options available for specific work package types, or to design evaluation functions that appropriately weigh emission reductions against cost considerations based on project-specific priorities. This customization ensures that the generated heuristics provide practically relevant solutions rather than theoretically optimal but implementationally infeasible recommendations.

A particularly compelling advantage of prompt chaining technology is its remarkable resource efficiency compared to alternative approaches for adapting LLMs to specialized domains. Unlike fine-tuning or pre-training techniques that require substantial computational infrastructure and expertise, prompt chaining operates via carefully structured natural-language instructions that guide existing models without modifying their underlying parameters. This distinction has profound practical implications for construction organizations seeking to implement carbon optimization solutions. Fine-tuning an LLM for construction-specific optimization tasks has significant requirements. It might cost tens or hundreds of thousands of dollars in computing resources. It requires specialized machine learning expertise. Extensive datasets of labeled examples are also necessary. In contrast, prompt chains can be developed and deployed with minimal technical infrastructure. Often, just a standard computer with an internet connection is sufficient. Access to an LLM API is the only other requirement.

The data efficiency of prompt chains represents another significant advantage over traditional model adaptation approaches. Fine-tuning LLMs typically requires large-scale, high-quality training datasets containing thousands of examples demonstrating the desired behavior, often carefully curated and annotated by domain experts. Collecting such datasets for specialized applications, such as carbon-emission optimization in construction projects, would be prohibitively expensive and time-consuming for most organizations. Prompt chains, by contrast, require no training data in the traditional sense. Instead, they leverage the existing knowledge embedded in pre-trained LLMs, guiding it toward specific applications through carefully structured instructions rather than parameter updates based on extensive examples. This data efficiency makes prompt chaining particularly suitable for specialized domains like sustainable construction, where large-scale labeled datasets are scarce or nonexistent.

The cost structure of prompt chain implementation further distinguishes it from alternative approaches. While developing and deploying fine-tuned models involves substantial upfront investments in data collection, computational resources, and specialized expertise, prompt chains incur primarily usage-based costs associated with token consumption during inference. In a typical work-package optimization scenario, these costs might amount to mere cents or dollars per optimization run, making the technology accessible even to smaller construction firms with limited technology budgets. This democratization of access to advanced optimization capabilities is particularly important in the construction industry, where the widespread adoption of carbon-reduction strategies across projects of all sizes is essential to achieving meaningful industry-level emission reductions. Table 6.1 summarizes the core advantages of the prompt chain.

Table 6.1 Core advantages of the prompt chain

Dimension	Description	Contrast with Traditional Methods
Accessibility & Transparency	Decomposes optimization into comprehensible steps with explicit reasoning, making it accessible to non-specialists.	Relies on complex mathematical formulations and specialized terminology, creating significant barriers to adoption.
Customization & Contextualization	Enables the development of tailored heuristics that align with specific project characteristics, constraints, and priorities.	Often yield generic solutions that are theoretically optimal but practically infeasible, failing to account for project specifics.
Resource Efficiency	Operates via natural language instructions, requiring minimal computational infrastructure and no model parameter modification.	Fine-tuning demands substantial computational resources and specialized machine learning expertise.
Data Efficiency	Leverages knowledge embedded in pre-trained models, eliminating the need for	Requires large-scale, high-quality, and often manually annotated datasets for

	large, curated training datasets for adaptation.	effective adaptation or training.
Economic Accessibility	Incurs low, usage-based operational costs with minimal upfront investment, democratizing access for a wider range of users.	Involves substantial upfront investment in data collection, computation, and specialized personnel, limiting widespread adoption.

6.2 Work Package Heuristic Optimization Framework

To bridge the gap between optimization theory and practice, this chapter introduces a framework that uses an LLM to help construction managers reduce carbon emissions. The framework is designed to create effective optimization strategies for project work packages without requiring users to have specialized mathematical knowledge. By interacting with the system through natural language, project managers can translate project-specific data into actionable, carbon-saving plans. This approach makes the complex relationship between work package design and carbon output, established in earlier chapters, directly applicable to real-world project management. The following sections detail the framework's architecture, its use of prompt engineering, and its generation of practical solutions for carbon reduction in construction.

6.2.1 Framework Structure

The proposed work package heuristic optimization framework in Figure 6.1 offers a new solution to a common problem: the difficulty of applying complex optimization algorithms in practical construction management. Rather than requiring specialized mathematical expertise, our framework employs an LLM to generate practical, carbon-reducing strategies for MiC projects. The design is modeled on an expert's problem-solving process, using a series of interconnected modules to systematically convert raw project information into an actionable optimization scheme.

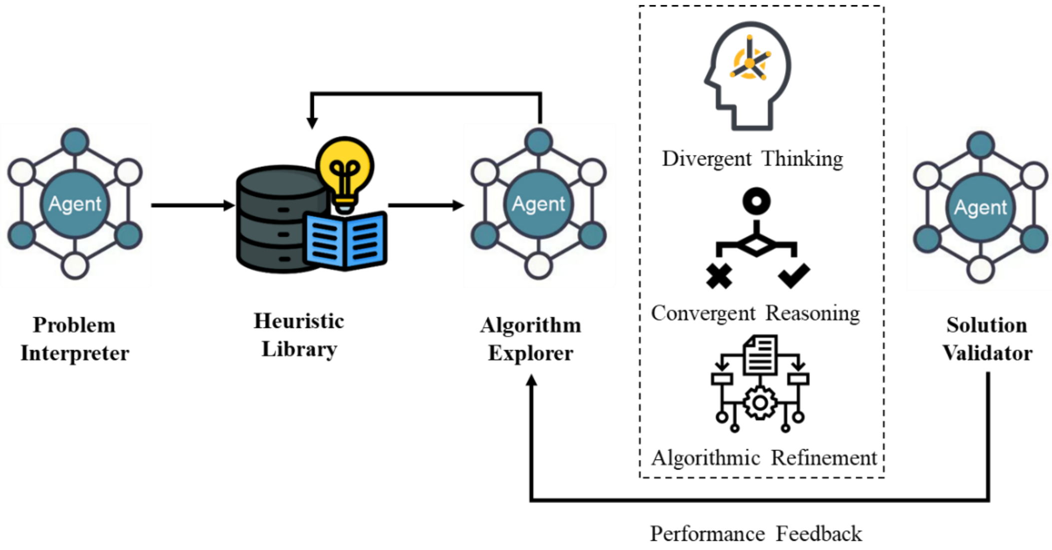


Figure 6.1 Work package heuristic optimization framework

(1) Problem interpreter

The first module, the Problem Interpreter, is responsible for translating standard project information into a structured optimization problem. It analyzes project descriptions to extract key details, including task dependencies, resource requirements, and carbon emission factors. This information is then organized into the core components of an optimization model: decision variables (like work package boundaries), constraints (like resource limits), and the primary objective of minimizing carbon emissions. This initial step ensures the resulting mathematical problem accurately reflects the practical realities of the construction project, setting the stage for a relevant and effective solution.

(2) Heuristic library

Once the problem is defined, the framework utilizes its Heuristic Library. This library is a curated collection of established optimization methods relevant to work package problems, including greedy algorithms, local search techniques, and other meta-heuristics adapted for carbon reduction. These methods are organized by their underlying approach and proven effectiveness. This structured knowledge base provides the essential building blocks for generating a new, customized solution, ensuring it is both innovative and grounded in sound optimization principles.

(3) Algorithm explorer

The core of the framework is the Algorithm Explorer, which guides the language model through a structured design process using a sequence of prompts. This process mirrors how an expert would design a solution. First, the module prompts the model to generate multiple potential strategies. For carbon optimization, this could include approaches that leverage the previously established relationship between production rates and emissions, or methods that merge or split work packages to improve efficiency. Next, the model is prompted to critically evaluate these candidate algorithms. This evaluation weighs several practical factors. It considers the quality of the solution. The scalability to larger projects is assessed. The robustness against uncertainty is also examined. All these factors are crucial for successful use in construction management.

The most promising algorithms are then refined through an iterative self-correction process. The language model reviews its own proposed solutions, making targeted modifications to improve their specificity, clarity, and performance. For example, a refinement could adapt an algorithm to handle different technologies across work packages or incorporate practical constraints, such as crew specialization. Throughout this stage, the developing algorithm is continuously checked against the original problem definition, ensuring the final solution remains tightly focused on minimizing carbon within the project's specific constraints.

(4) Solution validator

he Solution Validator module is responsible for evaluating the generated algorithms. It assesses them on several key criteria: effectiveness in reducing carbon, computational speed, practical feasibility, and robustness across different project conditions. To do this, the module tests each algorithm on a range of sample problems, comparing its performance against established benchmarks and theoretical limits. This validation provides quantitative data on the algorithm's quality, highlighting its specific strengths and weaknesses. This feedback is then used to further refine the algorithm and provides construction managers with the critical information needed to select the best approach for their specific project.

Together, these modules form a unified system that transforms a complex optimization challenge into a practical tool for construction management. The framework follows a clear path: it takes a simple project description, translates it into a structured problem, designs a custom algorithm, and delivers a validated solution. This allows construction professionals to leverage powerful optimization techniques without needing a background in mathematics or programming. By using natural language, the framework establishes a partnership between the user and the AI, combining the system's computational power with the industry expert's invaluable contextual knowledge.

6.2.2 Prompt Engineering Based on Prompt Chain

The transformation of complex mathematical optimization techniques into accessible heuristic algorithms for construction professionals requires a sophisticated prompt engineering approach that leverages the knowledge embedded in LLMs. This section presents a structured prompt chain methodology specifically designed for carbon emission optimization in WPSs, demonstrating how sequential, purpose-driven prompts can elicit increasingly refined algorithmic reasoning from LLMs while maintaining problem-specific constraints and objectives.

The prompt chain architecture for heuristic algorithm generation follows a recursive decomposition pattern that mirrors expert algorithm design processes. Let $\mathcal{P} = \{p_1, p_2, \ldots, p_n\}$ represent the sequence of interconnected prompts, where each prompt p_i builds upon the outputs of preceding prompts while introducing additional algorithmic considerations. The chain begins with a comprehensive problem formulation prompt that establishes the fundamental carbon emission optimization model. This mathematical foundation establishes the optimization landscape that subsequent prompts will navigate, enabling the LLM to understand how work package configurations influence carbon emissions by affecting production rates. The prompt chain then progressively guides the LLM through algorithm development phases, beginning with a global understanding of the solution space and culminating in specific heuristic procedures tailored to work package optimization.

The main structure of the prompt chain follows a deliberate progression through six interconnected stages, as shown in Figure 6.2, each designed to deepen the model's engagement with specific aspects of the optimization problem:

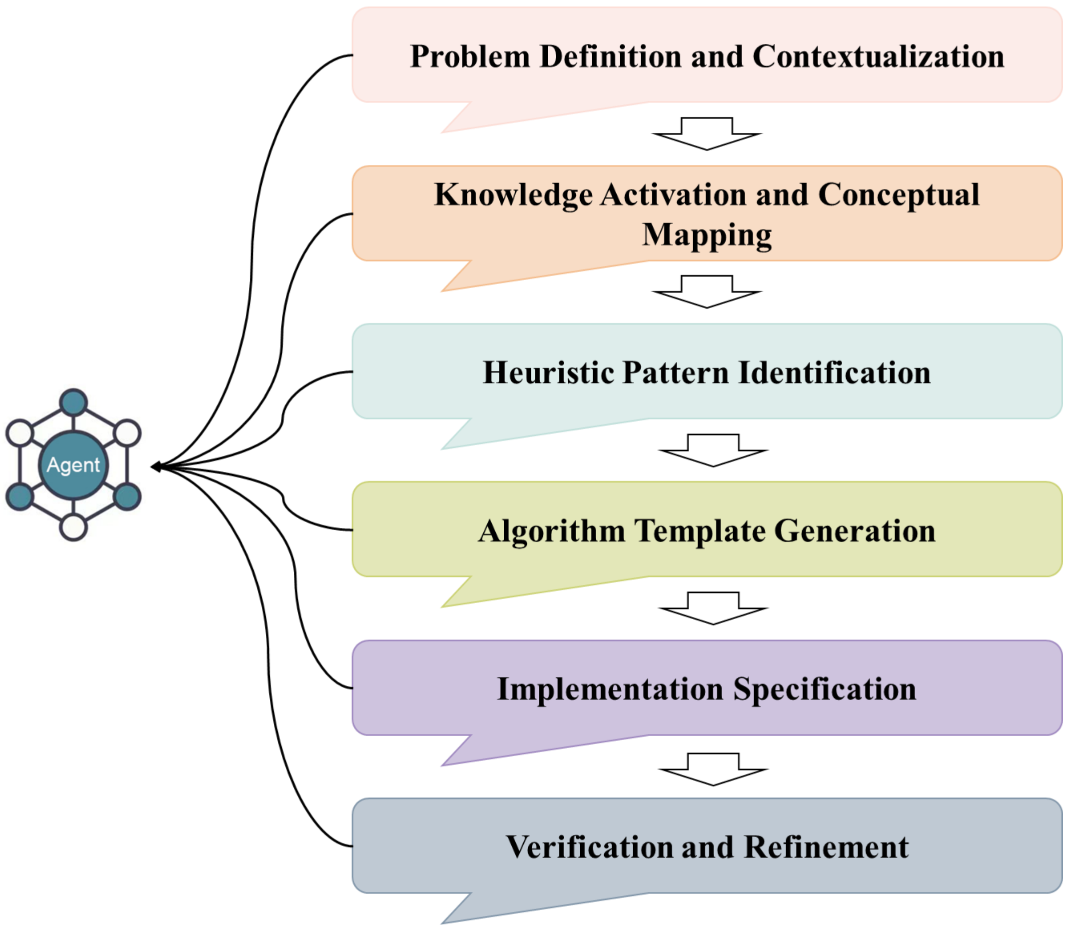


Figure 6.2 Prompt chain structure for heuristic optimization

(1) Problem definition and contextualization

The initial stage establishes a mathematical model of carbon emissions for work packages, specifying a quadratic relationship between production rates and emissions. This stage frames the optimization objective of minimizing total emissions TE while satisfying project constraints, including precedence relationships, resource limitations, and project deadlines.

(2) Knowledge activation and conceptual mapping

The second stage activates relevant optimization knowledge within the LLM by explicitly connecting work-package optimization to established algorithmic paradigms, such as partitioning problems, scheduling optimization, and graph-based heuristics. This conceptual mapping facilitates the transfer of general optimization principles to the specific context of carbon emission minimization.

(3) Heuristic pattern identification

In this critical stage, the model identifies promising heuristic patterns applicable to work package carbon optimization. The prompts guide the model to recognize structural properties of the problem that can be exploited through specific algorithmic approaches, such as the convexity of the production rate-emission relationship or the network structure of task dependencies.

(4) Algorithm template generation

Building on identified patterns, this stage elicits concrete algorithmic templates that capture the essential structure of potential heuristic approaches. These templates include core operations such as work package merging, splitting, and resequencing, along with evaluation criteria for assessing their impact on carbon emissions.

(5) Implementation specification

The fifth stage transforms algorithmic templates into detailed implementation specifications, including precise decision rules, evaluation functions, and termination criteria. The prompts in this stage emphasize practical considerations such as computational efficiency, adaptability to varying project conditions, and integration with existing construction management workflows.

(6) Verification and refinement

The final stage guides the model through a critical evaluation of the generated algorithms, identifying potential limitations, edge cases, or implementation challenges. This reflective analysis leads to refinements that enhance algorithm robustness, addressing issues such as parameter sensitivity, constraint handling, and solution quality guarantees.

The algorithmic exploration process facilitated by the prompt chain can be formalized as a transformation function $\mathcal{F}: \mathcal{P} \times \mathcal{K} \rightarrow \mathcal{H}$, where $\mathcal{K}$ represents the knowledge embedded within the LLM and $\mathcal{H}$ denotes the set of generated heuristic algorithms. This transformation involves several critical components designed to elicit increasingly sophisticated algorithmic reasoning. (1) Problem contextualization prompts that establish the WPSP structure, including task relationships, work content parameters, and emission models. (2) Algorithmic extraction prompts that guide the LLM to identify potential heuristic approaches based on key optimization principles relevant to carbon emission reduction. (3) Refinement prompts that evaluate candidate algorithms against specific construction scenarios, enhancing their practicality and implementation feasibility. (4) Implementation guidance prompts that translate abstract algorithmic concepts into concrete procedural steps accessible to construction professionals.

A particularly innovative aspect of the prompt chain methodology is its implementation of guided algorithmic diversity within a consistent framework. For the work package merge operation, the prompt chain systematically explores multiple decision criteria. This goes beyond the conventional greedy approach. The merge operation represents a critical component of optimization heuristics. This exploration is formalized through a structured prompt that parametrizes the merge operation $M(W_i, W_j)$ according to different heuristic rules h_k:

$$M_{h_k}(W_i, W_j) = \begin{cases} W_i \cup W_j & \text{if } \phi_{h_k}(W_i, W_j) > \tau_{h_k} \text{ and } \psi(W_i \cup W_j) = \text{true} \\ \{W_i, W_j\} & \text{otherwise} \end{cases} \quad (6\text{-}1)$$

Where ϕ_{h_k} represents the evaluation function specific to heuristic rule h_k, τ_{h_k} denotes the corresponding threshold value, and ψ encapsulates the feasibility constraints including acyclicity and deadline satisfaction. The prompt chain systematically explores diverse evaluation functions including benefit-cost ratios, potential emission reductions, sensitivity to production rate variations, and project structural considerations. The pseudocode for the main structure of the prompt chain follows the Algorithm 4.

Algorithm 4: Carbon Optimization Prompt Chain for Work Package Schemes

Input: Project description P, emission parameters (a, b, c), deadline constraint d

Output: Set of heuristic algorithms $\mathcal{H}$ for work package carbon optimization

Initialize: Empty set of heuristic algorithms $\mathcal{H} \leftarrow \emptyset$;

`/* Stage 1: Problem Definition and Contextualization */`

$p_1 \leftarrow \text{FormulateEmissionModel}(P, a, b, c)$;

$\mathcal{R}_1 \leftarrow \text{ElicitResponse}(p_1)$;

$M_{emission} \leftarrow \text{ExtractEmissionModel}(\mathcal{R}_1)$;

`/* Stage 2: Knowledge Activation and Conceptual Mapping */`

$p_2 \leftarrow \text{FormulateKnowledgeActivation}(M_{emission}, P)$;

$\mathcal{R}_2 \leftarrow \text{ElicitResponse}(p_2)$;

$\mathcal{K}_{active} \leftarrow \text{ExtractActivatedKnowledge}(\mathcal{R}_2)$;

`/* Stage 3: Heuristic Pattern Identification */`

$p_3 \leftarrow \text{FormulatePatternIdentification}(M_{emission}, \mathcal{K}_{active})$;

$\mathcal{R}_3 \leftarrow \text{ElicitResponse}(p_3)$;

$\mathcal{P}_{heuristic} \leftarrow \text{ExtractHeuristicPatterns}(\mathcal{R}_3)$;

`/* Stage 4: Algorithm Template Generation */`

foreach *pattern* $\rho \in \mathcal{P}_{heuristic}$ **do**

  $p_{4,\rho} \leftarrow \text{FormulateTemplateGeneration}(\rho, M_{emission})$;

  $\mathcal{R}_{4,\rho} \leftarrow \text{ElicitResponse}(p_{4,\rho})$;

  $T_\rho \leftarrow \text{ExtractAlgorithmTemplate}(\mathcal{R}_{4,\rho})$;

  `/* Stage 5: Implementation Specification */`

  $p_{5,\rho} \leftarrow \text{FormulateImplementationSpec}(T_\rho, P, d)$;

  $\mathcal{R}_{5,\rho} \leftarrow \text{ElicitResponse}(p_{5,\rho})$;

  $A_\rho \leftarrow \text{ExtractAlgorithmSpecification}(\mathcal{R}_{5,\rho})$;

  `/* Stage 6: Verification and Refinement */`

  $p_{6,\rho} \leftarrow \text{FormulateVerification}(A_\rho, M_{emission}, d)$;

  $\mathcal{R}_{6,\rho} \leftarrow \text{ElicitResponse}(p_{6,\rho})$;

  $A^*_\rho \leftarrow \text{ExtractRefinedAlgorithm}(\mathcal{R}_{6,\rho})$;

  $\mathcal{H} \leftarrow \mathcal{H} \cup \{A^*_\rho\}$;

end

`/* Integration of Complementary Algorithms */`

$p_7 \leftarrow \text{FormulateAlgorithmIntegration}(\mathcal{H}, P)$;

$\mathcal{R}_7 \leftarrow \text{ElicitResponse}(p_7)$;

$\mathcal{H}^* \leftarrow \text{ExtractIntegratedAlgorithms}(\mathcal{R}_7)$;

return $\mathcal{H}^*$;

This methodology enables the generation of diverse heuristic rules that address different aspects of the carbon emission optimization challenge while maintaining compatibility with the underlying merge algorithm framework. For example, production rate balancing heuristics focus on identifying work package pairs whose merger would bring their production rates closer to the theoretical optimal value $\gamma_{opt}^* = \frac{b}{2a}$, while technological compatibility heuristics prioritize merging work packages with similar emission characteristics or resource requirements. The prompt chain systematically guides the LLM through the derivation of these heuristic rules by establishing intermediary reasoning steps between the mathematical emission model and concrete algorithmic procedures. For instance, when developing production rate balancing heuristics, the prompt chain first establishes the theoretical optimal production rate, then guides the LLM to formulate a distance metric between current and optimal rates, and finally elicits specific algorithmic procedures for identifying and prioritizing merge operations that minimize this distance. This structured decomposition enables the LLM to leverage its embedded knowledge of optimization principles while ensuring that the resulting algorithms maintain fidelity to the specific characteristics of the carbon emission minimization problem.

A critical innovation in this prompt chain approach is its bidirectional integration of domain knowledge and algorithmic reasoning. Rather than treating the LLM as a passive repository of optimization techniques, the prompt chain actively scaffolds a collaborative reasoning process that combines the construction-specific insights provided in the problem description with the LLM's general algorithmic knowledge. This integration is achieved through carefully crafted prompts that explicitly reference domain-specific constraints (e.g., task precedence) and objectives (e.g., emission minimization), while guiding the LLM to adapt general optimization principles to these specific contexts. By decomposing the complex algorithm-generation task into a structured sequence of increasingly specific reasoning steps, the prompt chain enables the LLM to navigate the transition from abstract optimization principles to concrete algorithmic procedures, mirroring expert cognitive processes. This cognitive alignment enhances the quality and practicality of the generated algorithms while making the development process more transparent and accessible to construction professionals without specialized optimization expertise.

6.3 Experiments

This section presents the experimental validation of the proposed LLM-based heuristic optimization framework for work-package carbon reduction in construction projects. Through implementation with the Qwen2.5-Coder model (Hui et al., 2024), seven distinct heuristic algorithms are derived and evaluated against state-of-the-art optimization approaches across diverse project configurations, execution modes, and resource allocation scenarios. The experiments demonstrate that LLM-generated heuristics can achieve competitive performance compared to specialized algorithms, particularly for larger projects and under flexible scheduling conditions, while significantly reducing implementation barriers that have historically limited the adoption of carbon optimization techniques in construction practice.

6.3.1 Experimental Setup

The implementation and evaluation of the proposed heuristic optimization framework necessitated the selection of an appropriate LLM capable of sophisticated algorithmic reasoning and code generation. This section details the experimental environment employed for framework validation, with particular emphasis on the selection and configuration of the foundational language model component.

For the experimental implementation of the heuristic optimization framework, Qwen2.5-Coder, a state-of-the-art code-specific LLM is selected to serve as a significant advancement over its predecessor, CodeQwen1.5. Qwen2.5-Coder represents a family of models built upon the Qwen2.5 architecture, available in multiple parameter scales ranging from 0.5 billion to 32 billion parameters (0.5B/1.5B/3B/7B/14B/32B). For experimental implementation, this section utilized the 14B parameter variant, which provides an optimal balance between computational efficiency and algorithmic reasoning capabilities. The model's architecture offers several technical advantages, particularly relevant to algorithm-generation tasks. Qwen2.5-Coder undergoes an extensive pretraining process on more than 5.5 trillion tokens, with a substantial portion comprising high-quality code and algorithmic content. This pretraining regime is complemented by a meticulous data-cleaning process and a balanced data-mixing approach that ensures the model maintains strong general reasoning capabilities while excelling at code-specific tasks. The model has demonstrated state-of-the-art performance across multiple code-related benchmarks.

These include code generation, completion, reasoning, and repair. These capabilities are directly applicable to the generation of heuristic algorithms. Such algorithms are required for work package carbon optimization. A distinguishing characteristic of Qwen2.5-Coder, particularly relevant to the research context, is its demonstrated ability to retain mathematical reasoning capabilities alongside coding proficiency. This dual competency proves essential for translating the abstract mathematical relationships governing work package carbon emissions into executable heuristic algorithms. The model’s facility bridges a critical gap. It handles both symbolic mathematical representation and procedural algorithmic implementation. This connection links theoretical optimization models with practical implementation. Establishing this bridge represents a core objective of the research.

The selection of Qwen2.5-Coder to implement the work package's heuristic optimization framework is motivated by several considerations directly related to the challenges identified in previous chapters. First, the implementation of carbon-emission optimization algorithms in construction projects has been consistently hampered by the need for specialized mathematical and computational expertise. Qwen2.5-Coder’s demonstrated capabilities in transforming high-level problem descriptions into executable code address this fundamental barrier, enabling the generation of practical optimization algorithms from natural-language specifications of project constraints and carbon-emission models. Second, the complexity of the relationships between work package carbon emissions requires sophisticated algorithmic reasoning. This is necessary to develop effective heuristic approaches. Particularly challenging is the quadratic relationship between production rates and emissions, which was established in previous chapters. Qwen2.5-Coder's extensive pretraining on algorithmic content and demonstrated performance in code reasoning tasks provide the requisite cognitive foundation for navigating this complexity. The model's ability to reason about algorithmic trade-offs, computational efficiency, and solution quality aligns with the requirements for developing practical heuristics that balance optimization effectiveness against implementation simplicity.

The experimental evaluation employs the project instance dataset previously used in Chapters 4 and 5, providing several methodological advantages. This deliberate continuity enables direct comparative analysis between LLM-generated heuristics and the exact optimization approaches previously explored, establishing a rigorous benchmark for assessing the framework's effectiveness. The dataset spans a diverse range of project configurations, with varying complexity, scale, and network structures, enabling a systematic investigation of the framework's performance across different construction scenarios. Furthermore, the dataset's parameters were calibrated using empirically derived carbon-emission factors and production-rate relationships, ensuring that the optimization challenges reflect authentic constraints encountered in MiC projects. This methodological consistency strengthens the validity of experimental findings by situating the LLM framework evaluation within the established theoretical foundation developed throughout the dissertation, while simultaneously demonstrating its practical applicability to realistic construction planning scenarios.

The integration of Qwen2.5-Coder into the experimental framework enables a systematic investigation of how LLMs can transform abstract carbon emission optimization models into practical heuristic algorithms. By leveraging the model's capabilities through carefully structured prompt chains, the framework demonstrates a novel approach to accessing sophisticated optimization techniques in construction project management, thereby addressing a critical barrier to the widespread adoption of carbon-reduction strategies in the industry.

6.3.2 Heuristic Algorithms from the Framework

The application of the prompt chain methodology via the Qwen2.5-Coder model yielded seven distinct heuristic algorithms for WPS optimization, each exploiting different aspects of the carbon-emission model and work-package characteristics. This taxonomy not only facilitates systematic evaluation of algorithm performance but also provides construction practitioners with a structured approach to selecting appropriate optimization strategies based on specific project requirements and constraints. Table 6.2 categorizes these heuristic rules by their underlying optimization principles, abbreviations, and descriptions.

(1) Maximum emission-time trade-off

This heuristic evaluates potential work package merges based on the ratio of emission reduction to project duration impact. For each candidate merge that satisfies the baseline constraints, the algorithm calculates the ratio of emission reduction (Δemission) to the change in project duration (Δtime), selecting the merge that maximizes this ratio. This approach prioritizes emission reductions that minimally impact the project schedule, offering an optimal balance between environmental and temporal objectives. The algorithm is particularly effective for projects with tight schedule constraints that still require significant emission reductions.

Table 6.2 Heuristic rule information

No.	Abbreviation	Description
1	MAX-ETR	Maximize emission reduction per unit of schedule impact
2	MAX-TDE	Maximize emission reduction per task in merged package
3	MAX-WPCE	Maximize emission reduction per work package in project configuration
4	MAX-WCE	Maximize emission reduction per unit of work content
5	MIN-WCM	Minimize work content in merged packages
6	MAX-WCM	Maximize work content in merged packages
7	MIN-WCI	Minimize work content through iterative selection

(2) Maximum task density emission efficiency

This heuristic prioritizes merges that maximize emission reduction per task in the merged work package. By evaluating each potential merge using the ratio of emission reduction to the size of the resulting merged package, this approach identifies combinations that yield the greatest environmental benefit per task involved. This strategy is especially effective for large-scale projects with numerous small tasks, as it systematically consolidates tasks into efficient work packages while maintaining manageable operational units.

(3) Maximum work package consolidation efficiency

This heuristic selects merges that maximize emission reduction relative to the total number of work packages in the resulting project configuration. By prioritizing solutions that achieve greater emission reductions with fewer overall work packages, this approach directly addresses the administrative overhead associated with work package interfaces. The algorithm is particularly valuable for projects with complex management structures, as it systematically reduces organizational complexity while optimizing environmental performance.

(4) Maximum work content efficiency

This heuristic selects merges that maximize unit emission reduction relative to the total work content of the merged package. By prioritizing high-efficiency merges (those that deliver substantial emission reductions per unit of work content), this approach identifies combinations that exploit favorable production rate dynamics. The algorithm excels at projects with heterogeneous tasks, systematically identifying complementary task combinations that achieve optimal production rates when merged.

(5) Minimal work content merging

This heuristic prioritizes merging smaller work packages first by selecting the combination that minimizes the total work content of the merged package. This conservative approach mitigates the risk of creating excessively large work packages that could result in suboptimal production rates. The algorithm is particularly valuable in the early stages of project optimization, as it methodically consolidates smaller work packages while preserving operational flexibility for larger components.

(6) Maximum work content merging

This heuristic prioritizes merging larger work packages first by selecting the combination that maximizes the total work content of the merged package. This aggressive consolidation approach capitalizes on potential economies of scale in production rates. The algorithm is especially effective for projects with substantial potential for emission reduction through scale efficiencies, as it rapidly creates larger operational units that can achieve more efficient production rates.

(7) Minimal content alternative implementation

This heuristic implements a different algorithmic approach to minimal work content merging, employing an iterative minimum-finding procedure rather than a direct selection function. By systematically evaluating each valid merge option to identify the one with the least work content, this approach offers greater robustness for projects with complex constraint structures. The algorithm provides particularly stable performance across diverse project configurations, making it valuable for standardized applications across varied construction scenarios.

These seven heuristic algorithms represent a comprehensive toolkit for work package carbon optimization, addressing different aspects of the complex relationship between work package configuration and project emissions. The diversity of approaches enables construction practitioners to select optimization strategies aligned with specific project characteristics, management priorities, and carbon reduction objectives.

6.3.3 Experimental Results and Analysis

The experimental evaluation of LLM-generated heuristics against state-of-the-art merge heuristics provides valuable insights into the practical viability of automated algorithm generation for work-package carbon optimization. Under the assumption of standard execution mode for the work package and an input-output ratio of 1, Tables 6.3 and 6.4 present the mean and standard deviation of performance gaps across various project configurations, characterized by the number of tasks (I_1) and network seriality (I_2). This section presents a comprehensive analysis of these experimental results, obtained from multiple rounds of dialogue and the elimination of large model illusions.

Table 6.3 Average of the gaps between the heuristics from the Qwen and the Merge Heuristics under various I_1 and I_2

I_1	I_2	MAX-ETR	MAX-TDE	MAX-WPCE	MAX-WCE	MIN-WCM	MAX-WCM	MIN-WCI	Mean
	0.2	1.1190	1.2606	1.1190	1.1253	1.1626	1.2100	1.1626	1.1656
	0.4	0.5159	0.6110	0.5159	0.5186	0.5661	0.5556	0.5661	0.5499
40	0.6	1.0835	1.1245	1.0835	1.0852	1.1065	1.1093	1.1065	1.0999
	0.8	0.6837	0.7021	0.6837	0.6847	0.6909	0.6902	0.6909	0.6895
	0.2	0.3044	0.4531	0.3044	0.3159	0.3663	0.3919	0.3663	0.3574
	0.4	0.3050	0.4011	0.3050	0.3090	0.3467	0.3525	0.3467	0.3380
80	0.6	0.4050	0.4467	0.4050	0.4068	0.4248	0.4321	0.4248	0.4208

	0.8	0.2936	0.3085	0.2936	0.2975	0.3028	0.3069	0.3028	0.3008
	0.2	0.5956	0.7064	0.5956	0.6016	0.6486	0.6642	0.6486	0.6372
	0.4	0.2926	0.3374	0.2926	0.2932	0.3156	0.3256	0.3156	0.3104
120	0.6	0.3672	0.3841	0.3672	0.3686	0.3787	0.3781	0.3787	0.3746
	0.8	0.3712	0.3860	0.3712	0.3718	0.3829	0.3783	0.3829	0.3778

Table 6.4 Standard deviation of the gaps between the heuristics from the Qwen and the Merge Heuristics under various I_1 and I_2

I_1	I_2	MAX-ETR	MAX-TDE	MAX-WPCE	MAX-WCE	MIN-WCM	MAX-WCM	MIN-WCI	Mean
	0.2	1.2001	1.2071	1.2001	1.2021	1.1970	1.2014	1.1970	1.2004
	0.4	0.6529	0.6426	0.6529	0.6533	0.6415	0.6535	0.6415	0.6479
40	0.6	1.2059	1.1996	1.2059	1.2060	1.1987	1.2042	1.1987	1.2026
	0.8	0.8643	0.8656	0.8643	0.8643	0.8628	0.8633	0.8628	0.8639
	0.2	0.2445	0.2354	0.2445	0.2555	0.2520	0.2557	0.2520	0.2476
	0.4	0.3716	0.3760	0.3716	0.3728	0.3689	0.3805	0.3689	0.3723
80	0.6	0.3933	0.3954	0.3933	0.3945	0.3953	0.3958	0.3953	0.3946
	0.8	0.3712	0.3724	0.3712	0.3694	0.3741	0.3719	0.3741	0.3720
	0.2	0.7235	0.7287	0.7235	0.7251	0.7179	0.7174	0.7179	0.7217
	0.4	0.5227	0.5188	0.5227	0.5240	0.5167	0.5201	0.5167	0.5201
120	0.6	0.5992	0.5966	0.5992	0.5986	0.5956	0.5983	0.5956	0.5976
	0.8	0.6245	0.6275	0.6245	0.6247	0.6289	0.6247	0.6289	0.6262

A notable trend evident from Table 6.3 is the progressive improvement in the performance of LLM-generated heuristics as project scale increases. For projects with 40 tasks, the mean performance gap across all algorithms and network configurations is approximately 0.8529, which decreases to 0.3465 for 80-task projects and further improves to 0.3677 for 120-task projects. The influence of network seriality (I_2) exhibits more nuanced patterns. For projects with moderate task counts ($I_1 = 80$), the mean performance gap reaches its minimum (0.3008) at I_2=0.8, indicating that LLM-generated heuristics perform particularly well for predominantly serial projects with moderate parallel components. Conversely, for smaller projects ($I_1 = 40$), the optimal network seriality appears at I_2=0.4, with a mean gap of 0.5499. This trend suggests that the LLM approach effectively capitalizes on the richer optimization patterns inherent in larger, more complex projects. The influence of network structure (I_2) proves more nuanced, with optimal performance shifting based on project size—favoring higher parallelism ($I_2 = 0.4$) in smaller projects and higher seriality ($I_2 = 0.8$) in medium ones. Notably, in fully serial networks ($I_2 = 1.0$), the rigorous precedence constraints collapse the solution space, causing all algorithms to converge on identical results. This convergence demonstrates that in highly constrained environments, the LLM-based heuristic matches the performance of specialized algorithms, as the diminished feasible region neutralizes the advantage of complex optimization mechanisms.

Among the seven LLM-generated heuristics, MAX-ETR and MAX-WPCE consistently demonstrate superior performance across most project configurations, with nearly identical performance metrics in all scenarios. This equivalence suggests that these two conceptually distinct approaches converge to similar optimization behaviors in practice. One approach focuses on schedule-emission trade-offs. The other concentrates on system-wide work package efficiency. Despite their different conceptual foundations, they yield comparable results. The mathematical formulation of these algorithms appears to capture fundamental optimization principles that transcend their specific implementation details. Conversely, MAX-TDE consistently exhibits the largest performance gaps across almost all project configurations. This pattern indicates that optimizing emission reduction relative to task count may be less effective than other optimization criteria, possibly because this approach does not directly address the nonlinear relationships in the carbon emission model. The relatively weaker performance of MAX-TDE highlights the importance of aligning heuristic algorithms with the mathematical structure of the underlying optimization problem. The work content related heuristics (MIN-WCM, MAX-WCM, and MIN-WCI) demonstrate intermediate performance levels, with MAX-WCM showing slightly better results in larger projects. This trend suggests that as project scale increases, the benefits of creating larger, more efficient work packages begin to outweigh the advantages of maintaining smaller, more manageable operational units. This finding aligns with the theoretical expectation that economies of scale in resource utilization become more pronounced in larger project environments. Furthermore, the standard deviations for fully serial networks (I_2=1.0) are identical across all algorithms within each project size category, reinforcing the observation that algorithmic differences become irrelevant in highly constrained project topologies. This consistency provides construction managers with greater confidence in applying LLM-generated heuristics to projects with predominantly sequential task relationships.

While the experimental results demonstrate that LLM-generated heuristics do not yet match the performance of specialized state-of-the-art algorithms in all scenarios, the magnitude of the performance gap must be contextualized within the practical constraints of construction management. For large projects (I_1=120) with fully serial networks (I_2=1.0), the performance gap is merely 0.1386, representing an extremely competitive result that would be virtually indistinguishable in practical applications. Even in more challenging scenarios, such as large projects with moderate seriality (I_1=120, I_2=0.4), the gap remains under 0.32 for the best-performing algorithms. These performance differentials must be weighed against the substantial benefits of accessibility and implementation simplicity offered by the LLM framework. Traditional optimization algorithms present several barriers. They require specialized mathematical expertise. Custom software implementation is necessary. Significant computational resources are needed. These requirements have historically limited the adoption of advanced carbon optimization techniques in construction practice. In contrast, the LLM-generated heuristics can be derived through natural language interaction with the model, requiring minimal specialized knowledge and facilitating rapid implementation in diverse project environments.

Given that many construction projects currently employ no systematic carbon optimization whatsoever, the implementation of even suboptimal LLM-generated heuristics would represent a substantial improvement over current practice. The marginal benefits of achieving optimal performance through specialized algorithms may not justify the additional expertise and implementation barriers, particularly for organizations with limited access to optimization specialists. In this context, the demonstrated performance of LLM-generated heuristics represents an acceptable trade-off. This is particularly true for larger projects where the performance gap is minimal. The approach simplifies access to carbon-optimization techniques while maintaining reasonable performance. The experimental results thus validate the fundamental premise of this study: that LLMs can bridge the implementation gap in construction carbon optimization by generating practical, accessible heuristic algorithms that perform competitively with specialized approaches under realistic project conditions. This finding has significant implications for the broader adoption of carbon reduction strategies in construction management practice.

To further evaluate the robustness of the LLM-generated heuristics, this section conducted additional experiments with fixed project parameters (I_1 = 120 tasks and I_2 = 0.6 network seriality) while varying execution modes (Rush, Standard, and Delay) and input-output ratios (0.8, 1.0, and 1.2). Figure 6.3 presents the results of these experiments, illustrating both the average performance gap and the standard deviation across all seven heuristic algorithms.

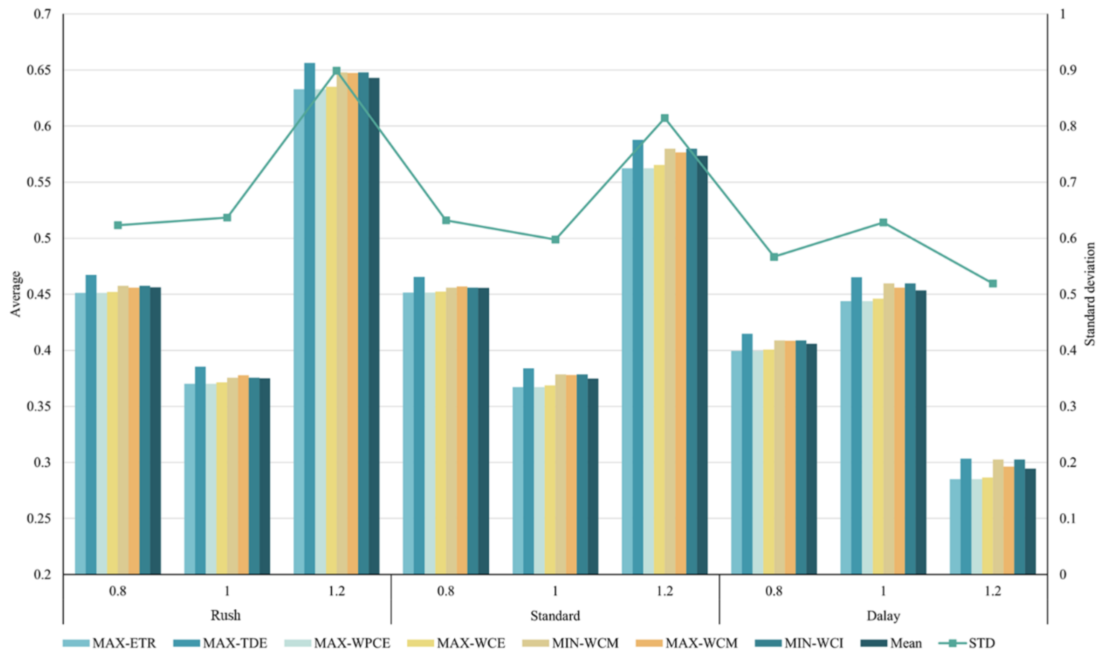


Figure 6.3 Average and standard deviation of the gaps between the proposed heuristics from Qwen and the Merge Heuristics under various conditions

The performance of LLM-generated heuristics is notably sensitive to both execution mode and the input-output ratio. Under the Rush execution mode, which emphasizes accelerated project completion, the performance gap exhibits a distinct U-shaped pattern across input-output ratios, with optimal performance at a ratio of 1.0 (gap is about 0.37) and significantly degraded performance at a ratio of 1.2 (gap is about 0.64). This pattern suggests that LLM-generated heuristics struggle to identify optimal work package configurations under compressed schedules with high resource intensity, where the relationships between carbon emissions become increasingly nonlinear and complex. In contrast, under the Delay execution mode, which allows for extended project durations, a consistent improvement in heuristic performance is observed as the input-output ratio increases, culminating in the smallest observed performance gap of about 0.2 at a ratio of 1.2. This finding indicates that LLM-generated heuristics become increasingly competitive as project time constraints are relaxed, enabling algorithms to prioritize carbon emission minimization without significant schedule pressure. The superior performance under delayed execution, with higher input-output ratios, highlights the capability of LLM-generated heuristics to effectively leverage extended timeframes to identify carbon-efficient work package configurations. The Standard execution mode, which represents conventional project scheduling practices, exhibits intermediate performance characteristics, with a U-shaped pattern similar to the Rush mode but with less pronounced performance degradation at higher input-output ratios. This intermediate behavior aligns with theoretical expectations, as Standard execution imposes moderate schedule constraints that partially, but not completely, restrict the optimization possibilities available to the heuristic algorithms.

Examining the standard deviation of performance gaps (represented by the line graph in Figure 6.3), a general correlation is observed between higher mean gaps and increased variability. This relationship is particularly pronounced in the Rush mode, with a ratio of 1.2, where both the mean gap and the standard deviation reach their maximum values. This increased variability under challenging optimization conditions suggests that the reliability of LLM-generated heuristics diminishes when confronted with highly constrained, resource-intensive project configurations. Conversely, the Delay mode with a ratio of 1.2 shows the lowest mean gap and a relatively low standard deviation (0.519), indicating that LLM-generated heuristics not only perform better but also maintain greater consistency under relaxed scheduling conditions. Consistent with earlier findings, the relative performance of individual heuristics remains stable across all execution modes and input-output ratios. MAX-ETR and MAX-WPCE consistently demonstrate superior performance, while MAX-TDE consistently exhibits the largest performance gap. This consistency across diverse project configurations reinforces the conclusion that the mathematical formulation of these algorithms captures fundamental optimization principles that transcend specific implementation contexts. The experimental results across varying execution modes and input-output ratios provide valuable practical guidance for construction managers considering implementing LLM-generated heuristics. For projects with flexible schedules (Delay mode) and higher input-output ratios, these heuristics approach the performance of specialized algorithms, with gaps as low as 0.3 for the best-performing algorithms. Even under more constrained conditions, the performance gap remains within acceptable bounds for practical implementation, particularly when considering the substantial accessibility benefits offered by the LLM framework.

This analysis further substantiates the central premise of this study: while LLM-generated heuristics do not universally match the performance of specialized algorithms, they achieve competitive results under specific project conditions that are commonly encountered in construction practice. The demonstrated performance, particularly under delayed execution with higher input-output ratios, suggests that these heuristics can serve as effective carbon optimization tools for construction projects with flexible schedules and sufficient resource availability. This finding is especially significant given the increasing industry emphasis on carbon reduction, which often justifies modest schedule extensions to achieve substantial environmental benefits. The variation in performance across different execution modes and input-output ratios also highlights the potential for strategic application of LLM-generated heuristics. Construction managers can evaluate their specific project constraints and prioritize accordingly. For projects with strict schedule requirements, specialized algorithms may be warranted despite the implementation barriers. For projects with greater schedule flexibility, LLM-generated heuristics can provide near-optimal carbon reduction with minimal implementation complexity. This nuanced understanding of performance characteristics enables informed decision-making that balances optimization quality against practical implementation considerations.

Table 6.5 Heuristic rule information from DeepSeek

No.	Abbreviation	Description
1	MAX-RER	Max Relative Emission Reduction. Focuses on percentage improvement efficiency.
2	MIN-MI	Min Makespan Impact. Prioritizes zero-delay merges above all else.
3	BEST-WLB	Best Workload Balance. Balances work content evenly across packages.
4	MAX-EEI	Max Environmental Effect. Pure focus on maximizing environmental benefits.
5	MAX-EMR	Max Emission / Makespan Ratio. Balances emissions vs. schedule criticality.

6	MIN-MR	Min Merge Risk. Minimizes integration and dependency risks.
7	MAX-TCB	Max Task Continuity Benefit. Maximizes sequential execution efficiency.

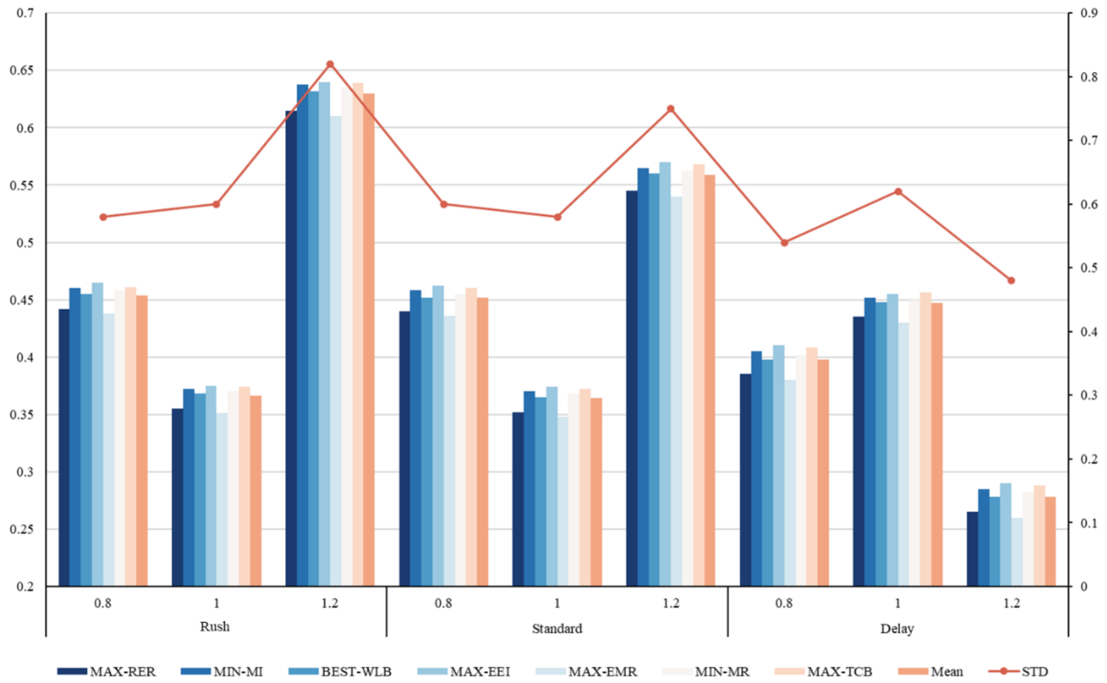


Figure 6.4 Average and standard deviation of the gaps between the proposed heuristics from DeepSeek and the Merge Heuristics under various conditions

To verify the framework's robustness independent of the specific underlying LLM, supplementary experiments were conducted using seven new heuristics (as shonw in Table 6.5) generated by an alternative model, DeepSeek. The results, illustrated in Figure 6.4, mirror the performance patterns observed with previous LLM-generated heuristics. Specifically, the distinct U-shaped performance curve in 'Rush' mode and the consistent improvement trend in ‘Delay’ mode across input-output ratios remain evident. The comparable magnitude of performance gaps confirms that the framework’s capability to derive effective optimization logic transcends specific LLM architectures, validating its general applicability for generating carbon-efficient work packaging heuristics based on diverse strategies such as workload balancing or maximizing relative emission reduction.

6.4 Chapter Summary

This chapter has presented a novel heuristic optimization framework for work package carbon emissions based on LLMs, directly addressing the implementation barriers identified in previous chapters. While Chapters 4 and 5 established powerful optimization approaches for carbon reduction in MiC, these methods require specialized mathematical expertise that limits their practical adoption. This study recognizes that bridging the gap between theoretical optimization capabilities and practical implementation is essential to the widespread adoption of carbon-reduction strategies in construction management practice.

The core methodological contribution of this chapter is the development of a structured prompt chain framework that leverages the reasoning capabilities of LLMs to generate practical heuristic algorithms. The framework transforms abstract mathematical relationships into accessible optimization procedures. It achieves this by decomposing the complex algorithm design process into manageable cognitive steps. These steps progress from problem formulation through heuristic pattern identification to implementation specification. This approach represents a fundamental shift in how optimization knowledge is accessed, replacing specialized expertise requirements with natural language interaction patterns that align with construction professionals' existing knowledge frameworks.

The implementation of the framework through the Qwen2.5-Coder model yielded seven distinct heuristic algorithms, each exploiting different aspects of the carbon emission model and work package characteristics. These ranged from emission-time trade-off optimization to content-based work approaches, providing a comprehensive toolkit for diverse project scenarios. Experimental evaluation demonstrated that, while performance gaps exist compared to specialized algorithms, they narrow significantly for larger projects and under flexible scheduling conditions.

Extensive experimentation across project parameters (the number of tasks and network seriality) and execution conditions (rush, standard, and delay modes with varying input-output ratios) revealed important patterns in heuristic performance. LLM-generated heuristics demonstrated progressive improvement as project scale increased and performed particularly well under delayed execution modes with higher input-output ratios, where performance gaps decreased to approximately 0.2. Among the generated heuristics, MAX-ETR and MAX-WPCE consistently demonstrated superior performance across diverse project configurations, suggesting that these approaches capture fundamental optimization principles that transcend specific implementation contexts.

These findings provide valuable guidance for construction managers seeking to implement carbon optimization in practice. The framework enables the strategic application of optimization techniques tailored to specific project characteristics. For projects with flexible schedules and larger task counts, LLM-generated heuristics can serve as primary optimization tools. Meanwhile, projects with tighter constraints may require supplementary specialized approaches. This nuanced understanding allows organizations to balance optimization quality against implementation complexity based on their specific project portfolio and sustainability objectives. Despite the significant advancements presented in this chapter, limitations remain in the current implementation. Performance gaps persist for smaller projects with complex parallel structures and tight scheduling constraints, and the framework's dependence on specific LLM architectures creates potential sustainability challenges as models evolve. Additionally, the current focus on carbon emissions represents only one dimension of comprehensive sustainability management in construction projects.

The LLM-based framework offers a promising approach to democratizing access to advanced optimization techniques in construction management. By eliminating the need for specialized mathematical expertise, this approach enables a broader range of construction professionals to implement effective carbon-reduction strategies in their projects. As LLMs continue to evolve in sophistication and accessibility, their potential to transform sustainability management in construction will likely grow, offering increasingly powerful tools for addressing the industry's environmental challenges while maintaining practical implementation feasibility.

Chapter 7 Work Package-based MiC Carbon Emission Optimization Platform

This chapter presents the development and implementation of a comprehensive Work Package-based MiC Carbon Emission Optimization Platform that operationalizes all the theoretical frameworks and algorithms established in previous chapters. The platform transforms complex mathematical optimization techniques into an accessible software tool with intuitive user interfaces, enabling construction professionals to implement carbon-reduction strategies without specialized mathematical expertise. Through a three-tier architecture comprising data management, algorithmic processing, and user interaction components, the platform integrates the single-objective TLGA algorithm (Chapter 4), multi-objective NSGA-II and SPEA2 EAs (Chapter 5), and the LLM-based heuristic framework (Chapter 6) within a computational environment. This implementation directly addresses research objective 5 outlined in Chapter 3, creating a usable decision-support system that bridges the persistent gap between theoretical carbon-optimization capabilities and their practical application in MiC projects. By embedding sophisticated optimization into user-friendly visualization interfaces and workflow patterns aligned with construction management practices, the platform enables the practical translation of carbon-reduction principles into actionable work-package planning decisions, potentially accelerating industry-wide adoption of sustainable construction practices. The remainder of this chapter is organized as follows. Section 7.1 details the development tools and platform structure, explaining the technical architecture and design principles that guided the implementation. Section 7.2 presents the platform's core functions, demonstrating how users can interact with its optimization capabilities and interpret the resulting outputs. Finally, Section 7.3 provides a concise summary of the chapter’s contributions to the overall thesis objectives. Through this structured exploration of the platform’s development and capabilities, the chapter demonstrates how theoretical optimization advances can be effectively translated into practical tools that enable the widespread adoption of carbon-reduction strategies in MiC.

7.1 Development Tools and Platform Structure

7.1.1 PyQt5-based Platform Development

PyQt5 represents a comprehensive set of Python bindings for Qt5, a powerful cross-platform application development framework originally developed by Trolltech (now maintained by The Qt Company) (Willman, 2020). As a binding implementation, PyQt5 enables Python developers to access the extensive functionality of the C++-based Qt framework while retaining Python's syntactic simplicity and rapid development capabilities. Developed and maintained by Riverbank Computing Limited, PyQt5 represents a significant evolution from its predecessor, PyQt4, introducing enhanced support for modern user interface paradigms, improved threading capabilities, and expanded multimedia functionality. The framework encompasses over 35 extension modules that collectively provide access to approximately 1,500 classes and more than 6,000 functions and methods, covering diverse aspects of application development, including user interface design, networking, XML processing, database integration, and multimedia handling. PyQt5's architecture is built on the signal-slot mechanism, which enables event-driven programming and is essential for responsive graphical user interfaces. This technical foundation enables the development of sophisticated applications. These applications can effectively manage complex data structures and computational processes while maintaining an intuitive user experience. These capabilities are particularly relevant for optimization platforms that must present complex algorithmic outputs in a clear and accessible format.

The selection of PyQt5 as the development framework for the Work Package-based MiC Carbon Emission Optimization Platform is motivated by several distinct advantages that align with the platform's objectives. First, PyQt5's cross-platform compatibility ensures that the optimization platform can be deployed across Windows, macOS, and Linux environments without requiring significant code modifications, thereby maximizing accessibility for diverse construction management settings with varying IT infrastructures. Second, the framework's extensive widget library provides sophisticated UI components, such as interactive data tables, customizable charts, and tree views, that are essential for intuitively representing work package structures, optimization parameters, and carbon emission metrics. Third, PyQt5's seamless integration with scientific computing libraries, including NumPy, SciPy, and Pandas, enables the efficient implementation of the optimization algorithms developed in previous chapters, allowing for real-time computation and visualization of WPSs and their associated carbon implications. Fourth, the framework's support for multithreading enables parallel execution of computationally intensive optimization tasks without compromising UI responsiveness, allowing users to continue interacting with the platform during optimization. Finally, PyQt5's model-view-controller architecture promotes a structured development approach that enhances maintainability and extensibility, enabling the platform to evolve alongside advancements in optimization methodologies and changes in construction industry requirements for carbon management.

7.1.2 Platform Structure

The Work Package-based MiC Carbon Emission Optimization Platform implements a comprehensive three-tier architecture that systematically integrates data management, algorithmic processing, and user interaction components. As illustrated in Figure 7.1, the platform's data tier encompasses two primary repositories: the project information database, which maintains fundamental project parameters including task dependencies, deadline constraints, and resource availability; and the work package production information database, which stores specialized data related to work package work content and work package duration metrics. This dual-database structure enables the platform to maintain a clear separation between generic project management data and specialized MiC production information, facilitating more efficient data updates and maintenance while ensuring that the optimization algorithms have access to the complete information necessary for carbon-efficient work package design. The systematic organization of these data repositories establishes a robust foundation for the subsequent algorithmic processing while ensuring data integrity throughout the optimization workflow.

The processing tier constitutes the platform's computational core, implementing a sophisticated algorithmic pipeline that progressively applies the optimization methodologies developed in previous chapters. This tier follows a sequential processing model where each algorithm builds upon the outputs of its predecessors: the TLGA developed in Chapter 4 performs initial single-objective carbon optimization; the NSGA-II and SPEA2 EAs from Chapter 5 extend this to multi-objective optimization balancing carbon emissions against cost considerations; and finally, the LLM-Agent component implements the heuristic optimization framework developed in Chapter 6, generating accessible optimization strategies through natural language processing. This structured progression from precise mathematical optimization to heuristic approaches provides users with a comprehensive spectrum of optimization capabilities, enabling them to select methodologies tailored to their specific project constraints and carbon-reduction objectives. The algorithmic pipeline is designed with clear interfaces between components, enabling both the independent operation of individual algorithms and their coordinated application in more complex optimization scenarios.

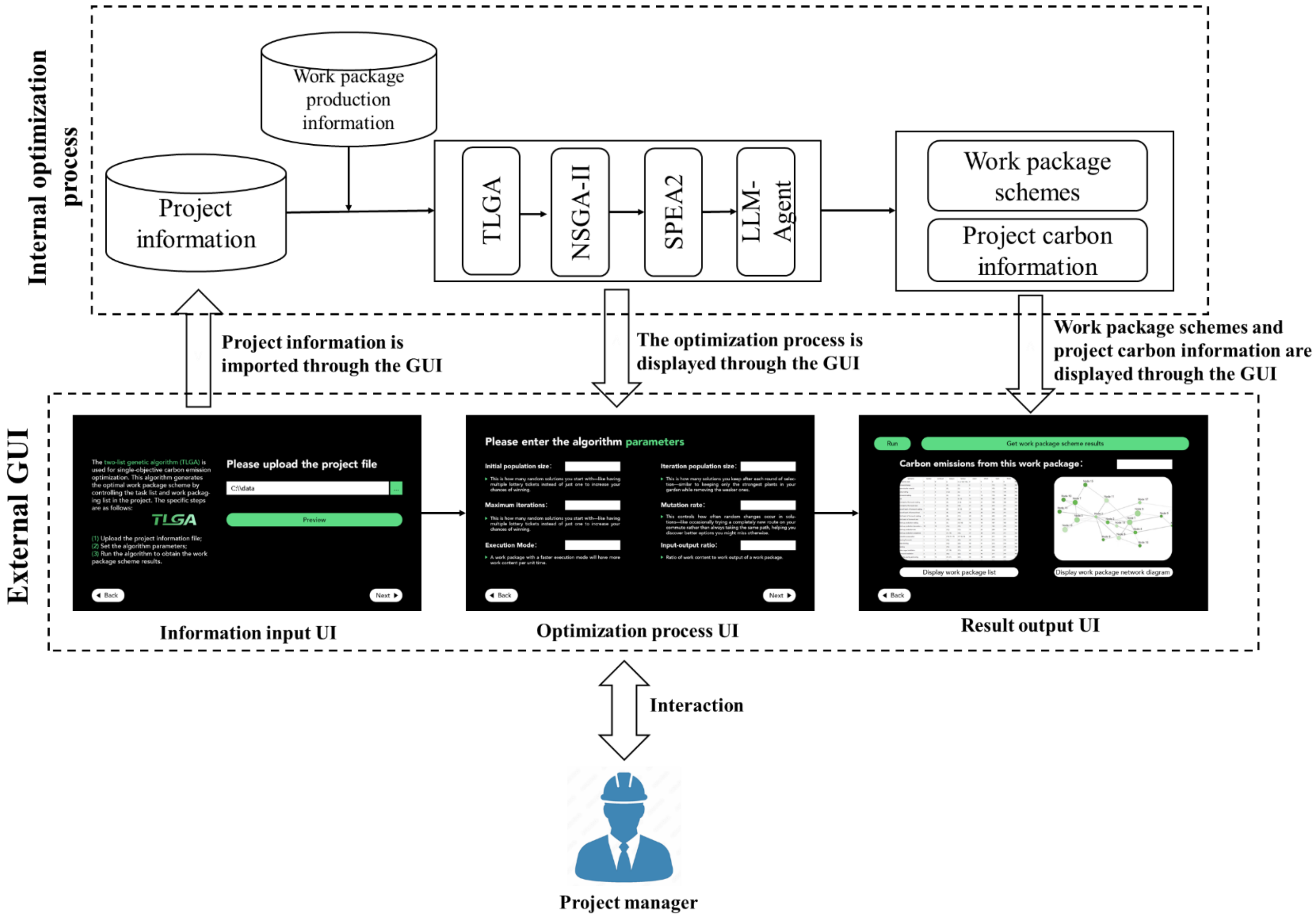


Figure 7.1 Platform structure

The presentation tier implements a user-centric interface design that systematically guides construction professionals through the optimization workflow while abstracting the underlying algorithmic complexity. As depicted in the diagram, this tier comprises a sequence of specialized interface screens that correspond to the logical progression of the optimization process: beginning with project data upload through an intuitive file selection interface; proceeding to algorithm selection and parameter configuration through structured input forms with appropriate guidance; and culminating in comprehensive results visualization that presents optimized WPSs and associated carbon metrics through interactive tables and graphical representations. The interface design employs consistent visual language and navigation patterns across all screens, establishing a coherent user experience that reduces the cognitive burden on construction professionals who may lack specialized optimization expertise. This systematic approach to interface design transforms complex algorithmic capabilities into accessible workflows that align with existing construction management practices.

The platform’s architecture supports bidirectional data flows, enabling dynamic interaction between construction managers and the optimization system. While the primary workflow follows a linear progression from data input through algorithmic processing to results visualization, the platform also supports iterative refinement through feedback loops that allow users to adjust parameters, explore alternative scenarios, and progressively refine optimization objectives based on initial results. This bidirectional interaction model is particularly evident in the integration of the LLM-Agent component, which enables natural-language dialogue about optimization strategies and the interpretation of results. By facilitating this interactive approach to optimization, the platform structure transforms what would otherwise be a static, one-directional computational process into a dynamic decision-support system that adapts to the evolving requirements and insights of construction professionals. This collaborative human-algorithmic interaction represents a significant advancement over conventional optimization tools, enabling more nuanced exploration of the complex trade-offs involved in carbon-efficient work-package design for MiC projects.

7.2 Core Functions of the Platform

The Work Package-based MiC Carbon Emission Optimization Platform implements three distinct functional modules that systematically translate the theoretical frameworks developed in previous chapters into accessible computational tools for construction professionals. As illustrated in the platform's main interface (Figure 7.2), these core functions are strategically organized according to increasing levels of methodological sophistication and user flexibility: (1) Carbon emission single-objective optimization, which implements the TLGA developed in Chapter 4 to identify work package configurations that minimize project carbon emissions while satisfying project constraints; (2) Carbon emission-cost multi-objective optimization, which deploys the NSGA-II and SPEA2 EAs presented in Chapter 5 to generate Pareto-optimal solutions that balance carbon reduction against economic considerations; and (3) LLM-based heuristic optimization, which activates the natural language processing framework established in Chapter 6 to generate accessible optimization strategies through interactive dialogue rather than explicit algorithmic specification. This tripartite functional architecture represents a comprehensive approach to carbon optimization in MiC, accommodating diverse project requirements and user expertise levels while maintaining methodological rigor. Each module implements a complete workflow from data input through computational processing to results visualization, providing construction managers with self-contained optimization capabilities that can be applied independently or in combination to address specific project challenges. The coherent integration of these diverse optimization approaches through a unified interface represents a significant advancement over conventional construction management tools, transforming abstract carbon-reduction objectives into actionable planning strategies for MiC projects.

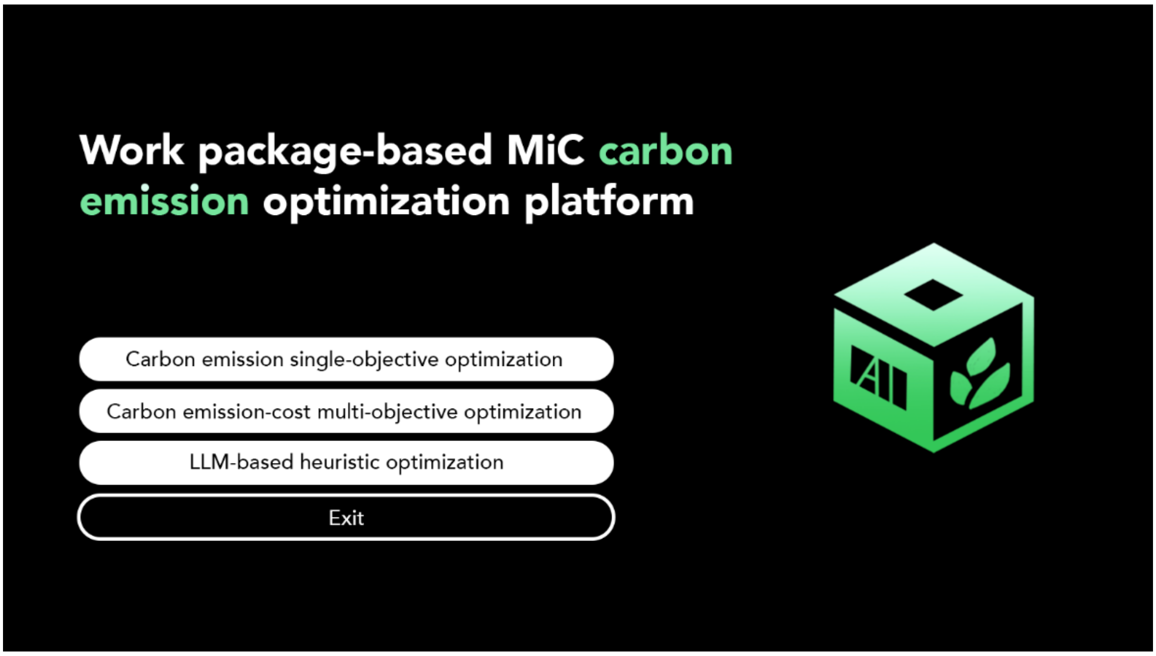


Figure 7.2 Platform's main interface

7.2.1 Carbon Emission Single-objective Optimization

The Carbon Emission Single-Objective Optimization module implements the TLGA developed in Chapter 4 through a structured three-phase workflow that systematically guides construction professionals from project specification to optimized WPSs. The first phase, depicted in the initial interface, establishes the theoretical foundation of the optimization process by explicitly articulating the TLGA's functional principles while simultaneously providing an intuitive project file upload mechanism. This dual approach represents a deliberate design strategy. It combines theoretical explanation with practical functionality. This strategy enhances user comprehension while minimizing the cognitive barriers typically associated with algorithmic optimization tools. The interface explicitly delineates the sequential nature of the workflow through enumerated procedural steps (1. Upload the project information file (Figure 7.3); 2. Set the algorithm parameters; 3. Run the algorithm to obtain the WPS results), establishing clear expectations for user engagement while reinforcing the systematic progression from data input to optimization output. This structured approach to workflow presentation enables construction professionals without specialized optimization expertise to conceptualize the process as a sequence of discrete, manageable operations rather than a monolithic computational procedure, thereby reducing perceived complexity and enhancing user confidence.

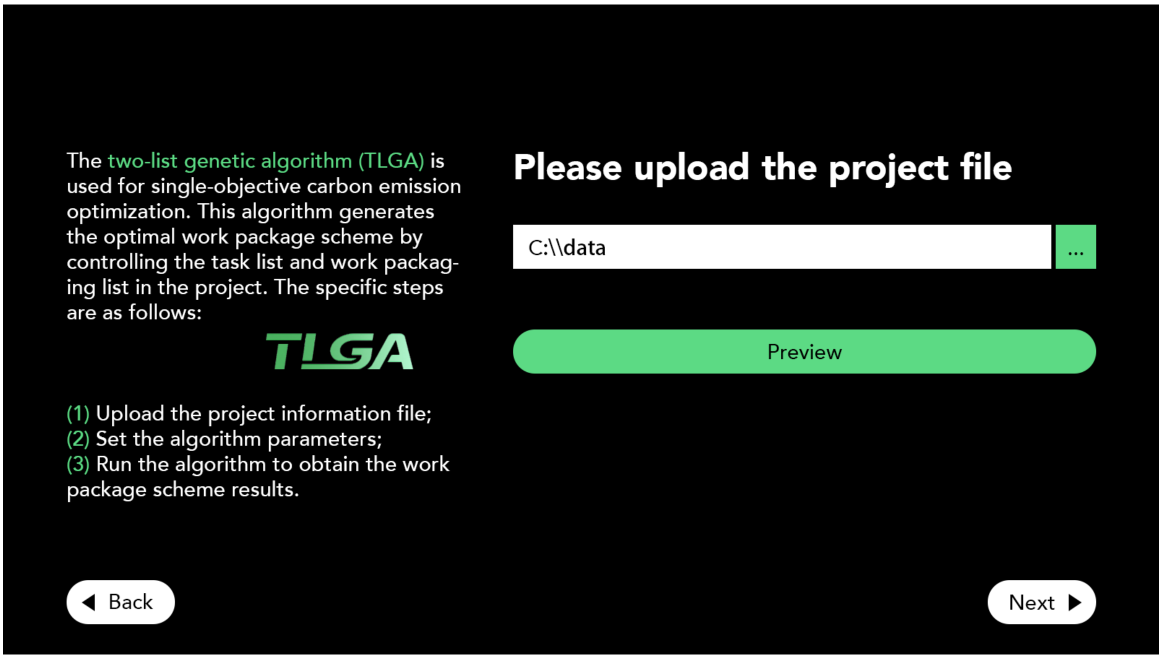


Figure 7.3 Project information file upload for TLGA

The second phase of the single-objective optimization workflow, implemented through the parameter configuration interface (Figure 7.4), transforms abstract algorithmic concepts into accessible decision points by combining structured input fields and contextual explanations. The interface systematically exposes six critical TLGA parameters: initial population size, iteration population size, maximum iterations, mutation rate, execution mode, and input-output ratio. For each parameter, the interface provides non-technical explanatory metaphors. These metaphors translate abstract computational concepts into familiar experiential frameworks. For example, it characterizes the initial population size as “like having multiple lottery tickets instead of just one to increase your chances of winning.” Similarly, it describes the mutation rate as “occasionally trying a completely new route on your commute rather than always taking the same path.” This metaphorical translation strategy represents a significant advancement in algorithm accessibility, enabling construction professionals to make informed parameter adjustments based on intuitive understanding rather than specialized algorithmic knowledge. The interface further supports parameter configuration through a consistent visual structure that establishes clear associations between parameter inputs and their corresponding explanations, while the sequential arrangement of parameters reflects their logical relationship within the TLGA computational process. This thoughtful integration of parameter configuration capabilities with accessible explanatory content enables users to engage meaningfully with algorithmic optimization without requiring extensive mathematical expertise, thereby addressing a critical barrier to the practical implementation of carbon optimization in construction management contexts.

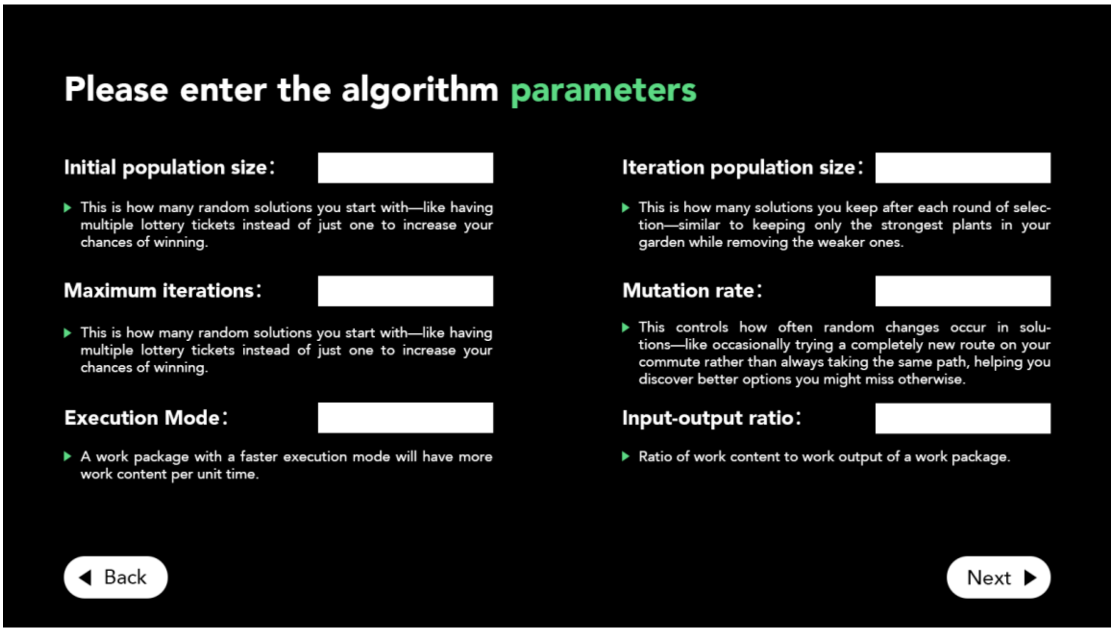


Figure 7.4 TLGA parameter setting

The third phase of the single-objective optimization workflow, presented in the results visualization interface (Figure 7.5), transforms abstract computational outputs into actionable project insights by leveraging complementary visualization modalities that address distinct analytical perspectives. The interface prominently displays the quantitative carbon-emission metric as the primary optimization outcome, providing immediate feedback on the optimized WPS's environmental performance. Supporting this top-level metric, the interface implements two complementary visualization approaches: a tabular work package list that presents the detailed specification of each work package with associated temporal and dependency parameters; and a network diagram that visualizes the structural relationships between work packages, enabling spatial comprehension of the project structure. This multimodal visualization approach accommodates diverse cognitive preferences among construction professionals, allowing users to engage with optimization results through either detailed tabular analysis or holistic network visualization, depending on their specific analytical objectives and preferences. The interface further enhances analytical flexibility with dedicated controls that let users toggle between visualization modes, enabling iterative exploration of optimization results from multiple perspectives. By transforming abstract algorithmic outputs into intuitive visual representations that align with established construction management visualization conventions, the results interface bridges the gap between computational optimization and practical project planning, enabling construction professionals to translate carbon-optimization results directly into actionable work-package implementation strategies for MiC projects.

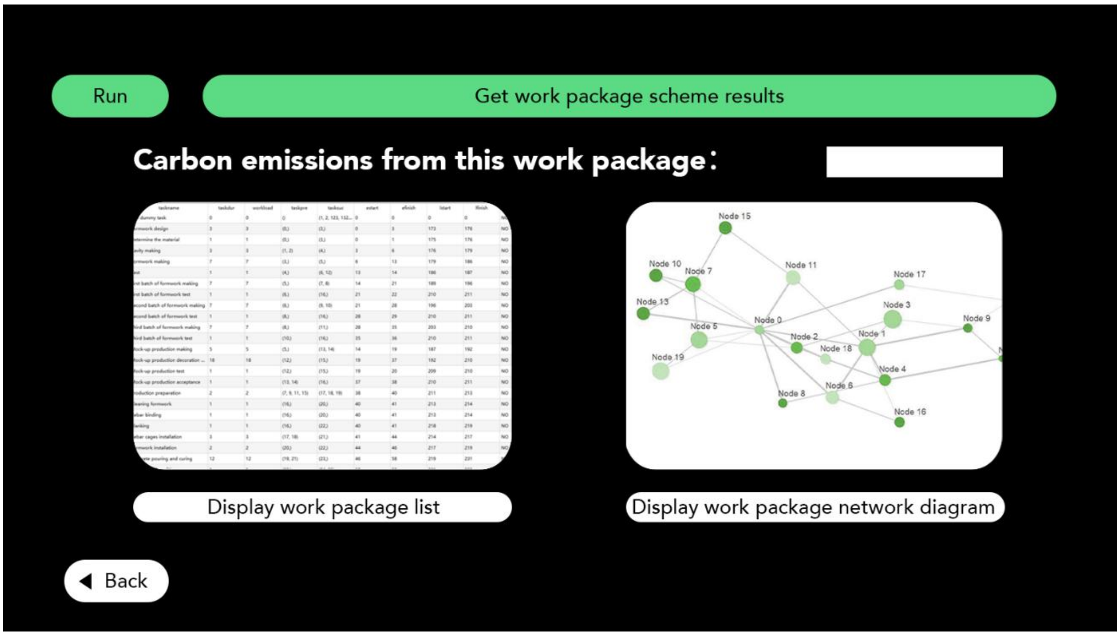


Figure 7.5 TLGA WPS result output

7.2.2 Carbon Emission-cost Multi-objective Optimization

The Carbon Emission-Cost Multi-Objective Optimization module elevates the platform's analytical capabilities by implementing the advanced EAs developed in Chapter 5, specifically NSGA-II and SPEA2, to simultaneously balance competing project objectives. The initial interface establishes a conceptual foundation by explicitly articulating the Pareto optimization paradigm, introducing construction professionals to the fundamental concept that multi-objective optimization does not yield a single optimal solution but rather a frontier of non-dominated solutions representing different trade-off configurations between carbon emissions and cost. This theoretical framing represents a significant advancement over traditional single-objective approaches, acknowledging the inherent tension between environmental and economic priorities in MiC projects. The interface maintains the structured three-step workflow established in the single-objective module (1. Upload the project information file (Figure 7.6); 2. Select algorithm and set the algorithm parameters; 3. Run the algorithm to obtain the Pareto solution set), creating a consistent user experience pattern that reinforces procedural familiarity while introducing the more sophisticated multi-objective optimization paradigm. This methodological continuity reduces the cognitive transition costs for users moving from single- to multi-objective analysis, enabling construction professionals to incrementally develop their optimization expertise as they explore increasingly complex decision spaces.

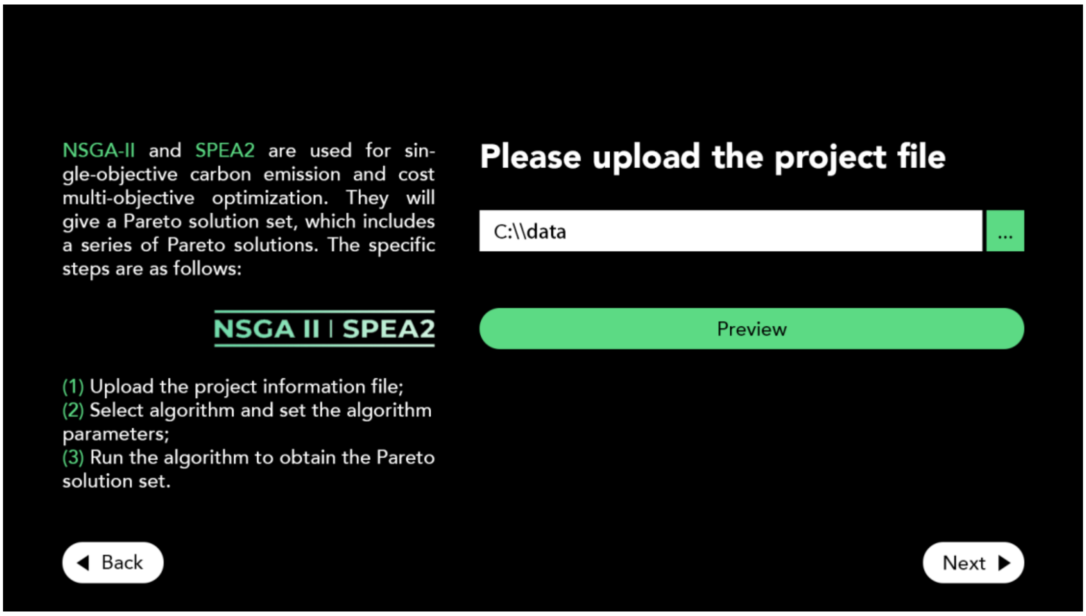


Figure 7.6 Project information file upload for NSGA-II/SPEA2

The algorithm selection and parameter configuration interface introduces an additional dimension of methodological flexibility by enabling users to choose between NSGA-II and SPEA2 based on their specific project characteristics and optimization preferences.

As shown in Figure 7.7, the interface provides a concise comparative explanation of the algorithms' respective strengths. It notes that "NSGA-II being faster and more widely used for larger problems, while SPEA2 often produces more evenly distributed solutions for complex trade-offs." This enables informed methodological selection without requiring a detailed understanding of algorithms. The parameter configuration section expands beyond the single-objective interface by introducing crossover probability, a parameter critical to EAs' ability to effectively explore the multi-dimensional solution space. The interface explains this concept through an accessible breeding metaphor, translating the abstract genetic algorithm concept into an intuitive biological framework familiar to non-technical users. The consistent presentation of the remaining parameters (initial population size, maximum iterations, mutation rate, execution mode, and input-output ratio) maintains conceptual continuity with the single-objective interface while contextualizing these parameters within the multi-objective framework. This thoughtful integration of algorithm selection and parameter configuration capabilities enables construction professionals to make informed methodological decisions without specialized knowledge of evolutionary computation, thereby democratizing access to sophisticated multi-objective optimization techniques in construction management.

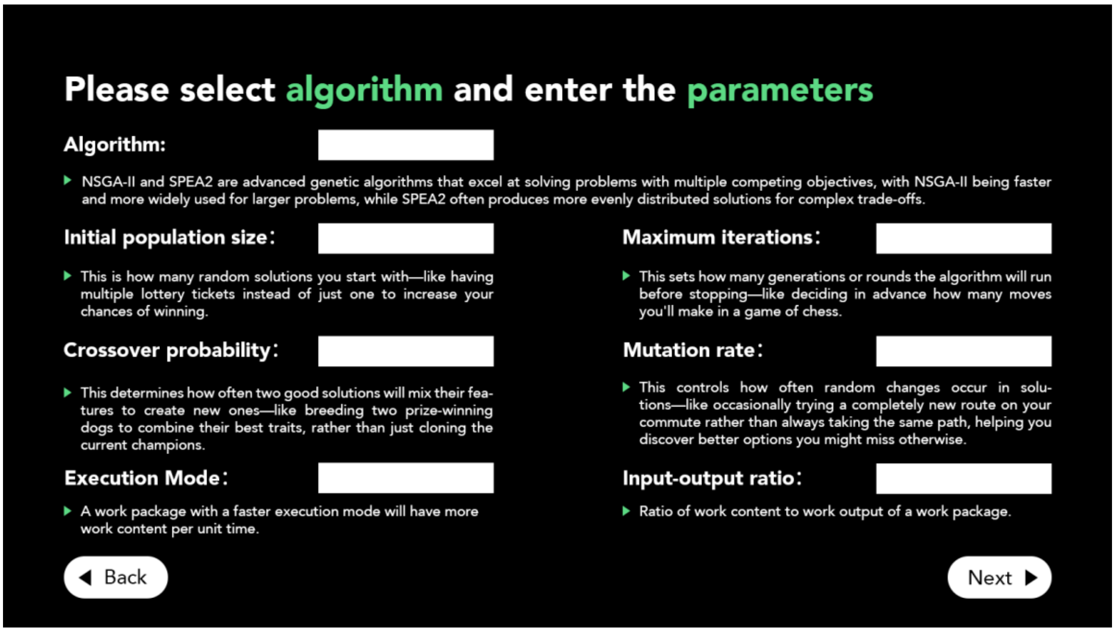


Figure 7.7 NSGA-II/SPEA2 parameters setting

The results visualization interface (Figure 7.8) transforms abstract Pareto optimization concepts into actionable project insights by combining complementary visualization modalities that explicitly illustrate trade-offs between carbon emissions and cost objectives. The interface prominently displays the optimal carbon emission and cost values at the extremes of the Pareto front, providing immediate quantitative feedback on the boundaries of the feasible solution space. The left visualization presents the complete Pareto frontier as a continuous curve plotting carbon emissions against cost, enabling users to comprehensively visualize the trade-off between these competing objectives and identify potential compromise solutions that balance environmental and economic priorities, tailored to project-specific requirements. Complementing this trade-off visualization, the right section presents the network diagram of the work package configuration corresponding to the optimal carbon emission solution, enabling spatial comprehension of the project structure that would result from prioritizing environmental performance. The interface further enhances analytical flexibility through dedicated controls that enable users to explore alternative work package configurations at different points along the Pareto frontier, facilitating comparative analysis of structural differences between environmentally optimal and cost-optimal configurations. By visualizing these trade-offs in both abstract (Pareto curve) and concrete (network diagram) representations, the interface bridges the gap between mathematical optimization and practical project planning, enabling evidence-based decision-making that balances environmental and economic considerations in line with project-specific priorities and constraints.

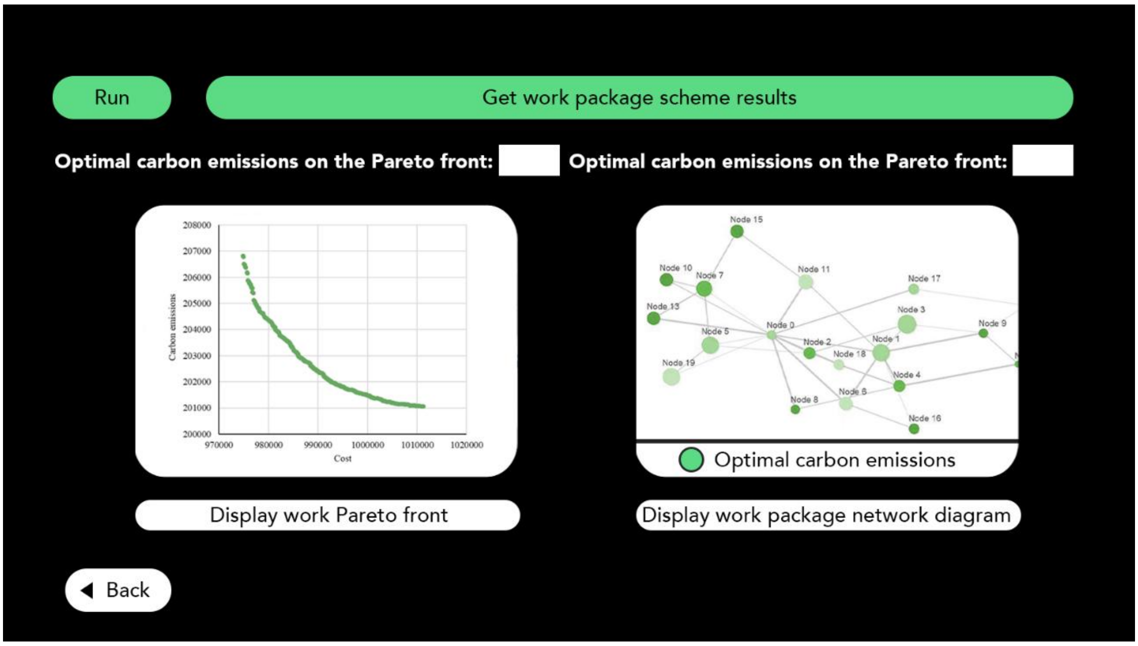


Figure 7.8 Multi-objective optimization output

7.2.3 LLM-based Heuristic Optimization

The LLM-based Heuristic Optimization module represents a paradigmatic advancement in construction optimization methodology, transcending the traditional algorithmic approaches implemented in the preceding modules to establish a novel knowledge-based optimization paradigm. As shown in Figure 7.9, the initial interface introduces users to the theoretical foundation of this approach by explicitly referring to "Prompt Engineering's prompt chaining technology," situating the module within the broader conceptual framework developed in Chapter 6 while simultaneously establishing the functional infrastructure necessary for its implementation. Unlike conventional optimization methods that operate through predefined algorithmic procedures, this module leverages LLMs' capabilities to dynamically generate optimization strategies tailored to specific project characteristics and constraints. The interface implements this innovative approach through a structured API authentication process that establishes secure communication channels with external LLM services while maintaining data privacy and computational integrity. The clearly delineated three-step workflow establishes procedural transparency. It introduces construction professionals to the fundamentally different interaction paradigm employed in knowledge-based optimization. The workflow consists of: (1) Enter LLM's API; (2) Enter a structured prompt chain; (3) Get heuristics codes developed by LLM. This integration of advanced natural language processing capabilities into a construction optimization platform represents a significant methodological innovation, enabling the application of rapidly evolving AI capabilities to domain-specific challenges in carbon-efficient work package design without requiring extensive reengineering of the underlying platform architecture.

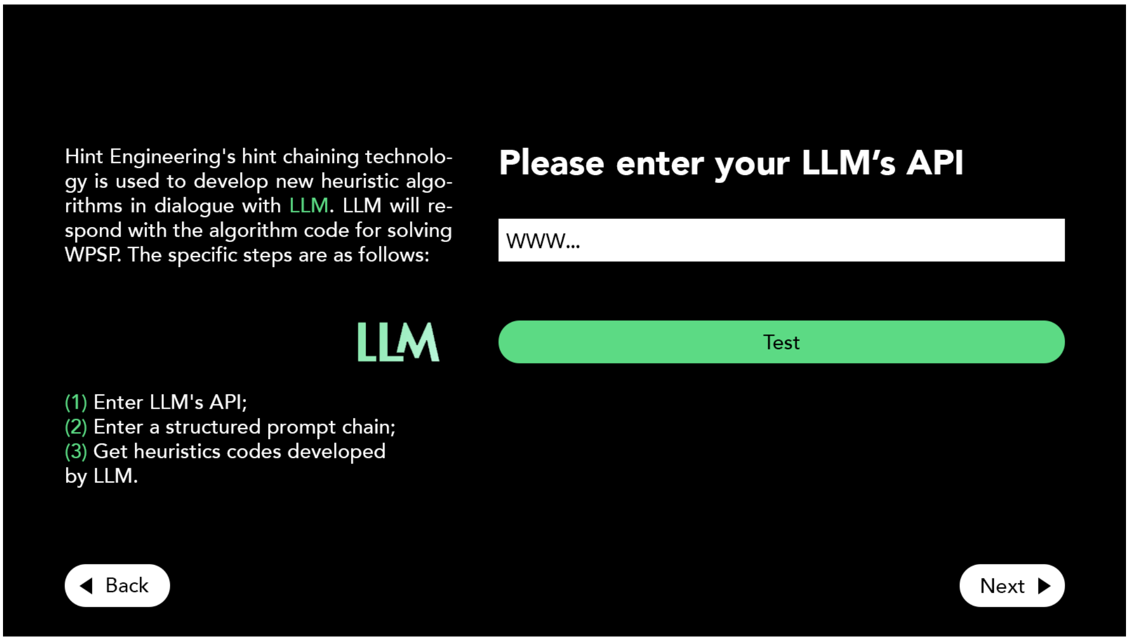


Figure 7.9 LLM's API input

The structured prompt engineering interface operationalizes the theoretical framework developed in Chapter 6 by decomposing the complex process of heuristic algorithm specification into four distinct conceptual components that systematically guide the LLM's reasoning process. The interface in Figure 7.10 implements a comprehensive prompt architecture that addresses the fundamental dimensions of optimization problem formulation: contextual understanding through the "problem background" field, which enables specification of domain-specific constraints and characteristics; objective definition through the "task objective" field, which articulates the specific optimization goals in natural language rather than mathematical formulations; procedural guidance through the "algorithm codes step by step" field, which enables users to provide partial algorithmic structures or pseudocode that the LLM can elaborate upon; and data specifications through the “input requirements” field, which establishes the parameters and constraints that must be accommodated in the generated solution. This structured decomposition of the prompt engineering process represents a significant advancement over generic LLM interactions, implementing domain-specific steps that guide the model’s reasoning toward construction-relevant optimization strategies while maintaining sufficient flexibility to accommodate diverse project requirements. The deliberate arrangement of these prompt components establishes a cognitive progression from general problem understanding to specific solution requirements, mirroring established problem-solving methodologies in construction management while leveraging the LLM’s capabilities to bridge between natural language problem descriptions and executable optimization strategies.

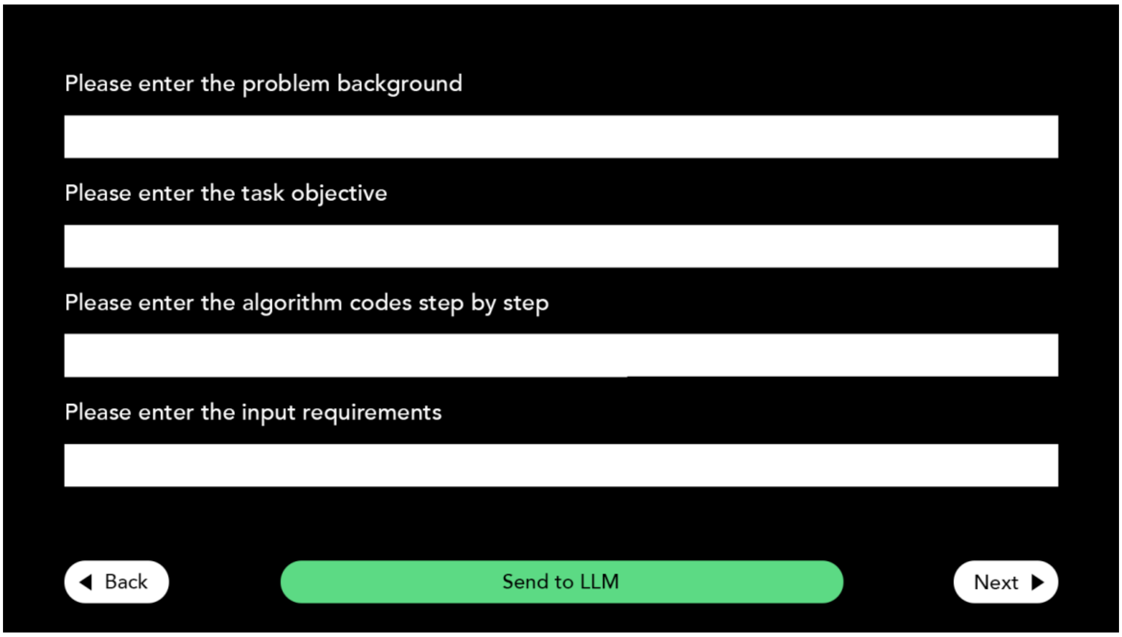


Figure 7.10 Structured prompt chain input

The response visualization interface (Figure 7.11) transforms the traditionally opaque process of algorithm development into an interactive dialogue between construction professionals and AI, establishing a collaborative optimization paradigm that is fundamentally different from the parameter-driven approaches used in conventional algorithms. The interface presents the LLM-generated heuristic strategies in an expansive text display that accommodates the detailed explanations, algorithmic specifications, and implementation guidance characteristic of sophisticated LLM outputs. Unlike the predefined visualization approaches employed in the preceding modules, this interface acknowledges the inherently variable and explanatory nature of LLM-generated content, prioritizing comprehensive presentation of the model's reasoning process alongside its specific algorithmic recommendations. The interface enhances this collaborative optimization paradigm through dedicated controls. These controls enable iterative refinement of the generated strategies. Users can "Get new responses from LLM" when initial suggestions require modification. The interface also supports practical implementation by allowing users to "Save the responses locally" for subsequent integration into project workflows. This bidirectional interaction model represents a fundamental shift in optimization methodology, transitioning from the unidirectional parameter-algorithm-result pipeline characteristic of conventional approaches to an iterative dialogue in which construction professionals and AI collaboratively explore the solution space through natural-language negotiation. By enabling this knowledge-based approach to optimization, the module establishes a complementary methodology to the mathematical rigor of the preceding modules, acknowledging that construction carbon optimization ultimately requires both algorithmic precision and domain-specific heuristic reasoning that accommodates the practical complexities and constraints of real-world MiC projects.

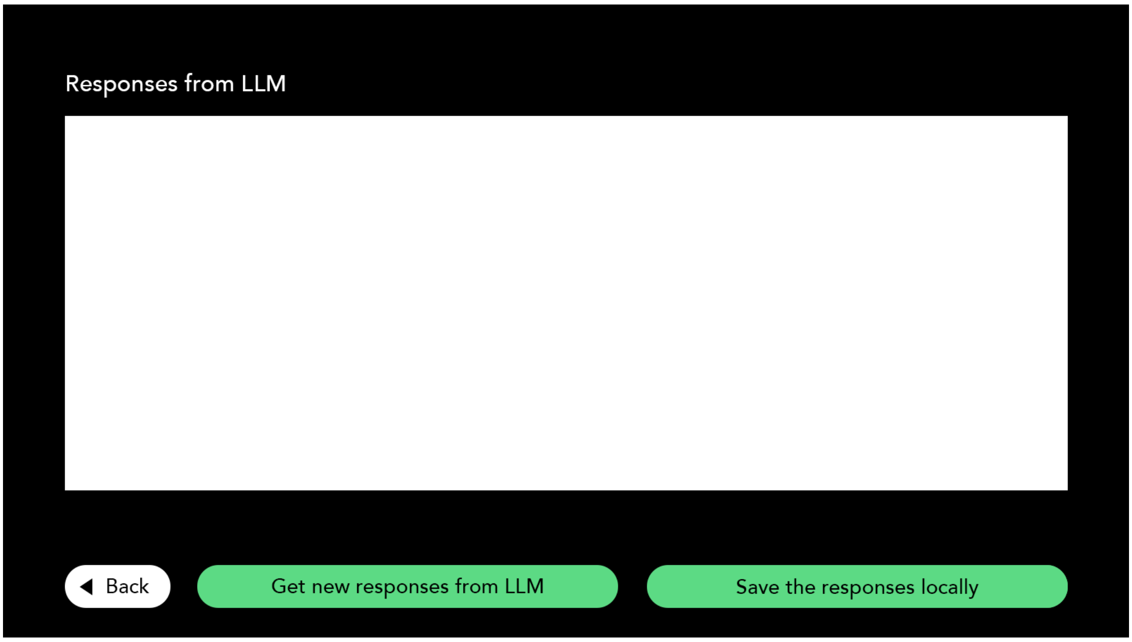


Figure 7.11 LLM's response output

7.3 Chapter Summary

This chapter presented the Work Package-based MiC Carbon Emission Optimization Platform, which operationalizes the theoretical frameworks and algorithmic approaches developed throughout this study into a cohesive computational tool for practical industry application. The platform represents a significant contribution to carbon-reduction practice by bridging the persistent gap between abstract carbon-optimization methodologies and their practical implementation in MiC projects. Through a systematic architecture comprising three complementary optimization modules, the platform establishes a comprehensive decision support ecosystem capable of addressing diverse project requirements and user expertise levels while maintaining methodological rigor and computational efficiency.

The platform's first core module implements single-objective carbon-emission optimization using the TLGA developed in Chapter 4, enabling construction professionals to identify work-package configurations that minimize project carbon emissions while satisfying temporal and logical constraints. By translating complex algorithmic concepts into accessible interface elements with intuitive explanatory metaphors, this module democratizes access to sophisticated optimization capabilities without requiring specialized mathematical expertise. The second module extends this functionality to multi-objective optimization by implementing the NSGA-II and SPEA2 EAs presented in Chapter 5, enabling explicit quantification of trade-offs between carbon reduction and cost implications. This capability transforms traditionally qualitative sustainability discussions into evidence-based decision processes grounded in a comprehensive exploration of the Pareto-optimal solution space. The third module establishes a novel paradigm for construction optimization by integrating LLMs, enabling construction professionals to develop bespoke heuristic optimization strategies through natural language interaction rather than explicit algorithmic specification. This innovative approach accommodates the complex contextual factors and domain expertise that often elude formal algorithmic representation, establishing a complementary knowledge-based optimization methodology alongside conventional mathematical approaches.

Throughout each module, the platform implements a consistent workflow progression from data input through parameter configuration to results visualization, establishing procedural continuity that enhances user comprehension while accommodating increasing methodological sophistication. The platform’s visualization capabilities transform abstract optimization outputs into intuitive representations. These representations align with established construction management practices. They include tabular work package specifications, network diagrams, and Pareto frontier visualizations. This enables the direct translation of optimization insights into actionable project-planning decisions. This thoughtful integration of algorithmic sophistication with accessible interface design establishes a template for future construction optimization tools that balance methodological rigor with practical usability.

While acknowledging current limitations in data preprocessing capabilities, uncertainty modeling, and visualization dimensionality, the platform nonetheless represents a significant advancement in operational carbon optimization for MiC. By systematically implementing the theoretical frameworks developed throughout this study within an accessible computational environment, the platform enables practical application of carbon-efficient work package design principles across diverse project contexts and organizational scales. This operational capability directly addresses the implementation gap that has historically constrained the practical impact of theoretical carbon-optimization approaches in construction contexts, potentially accelerating the diffusion of carbon-efficient practices across the MiC industry. As environmental regulations increasingly constrain construction carbon emissions and market preferences increasingly prioritize carbon-reduction practices in MiC project management, the platform provides a timely and practical mechanism for translating abstract carbon-reduction objectives into concrete work-package implementation strategies that balance environmental performance with economic viability.

Chapter 8 Discussions

Chapter 8 synthesizes the comprehensive research on carbon emission optimization in MiC projects conducted throughout this thesis. The chapter systematically reviews how each research objective was addressed and discusses the results from four complementary approaches: single-objective optimization using a TLGA, multi-objective optimization balancing carbon emissions and cost, a novel LLM-based heuristic framework, and an integrated software platform that operationalizes these theoretical advancements. Through rigorous analysis of these approaches across diverse project scenarios, this chapter articulates both the theoretical contributions and practical implications of the research while identifying remaining limitations and future research directions.

8.1 Review of Research Objectives

The primary aim of this study was to develop optimization approaches to determine the optimal WPS for minimizing carbon emissions in MiC projects. This study focused on the project planning stage to help achieve a more appropriate and precise division of work packages, ultimately enhancing sustainability performance. The specific objectives of this study were systematically addressed throughout the thesis chapters, as summarized below:

To achieve Objective 1, Chapter 4 established a comprehensive mathematical optimization model for WPSs in MiC projects. This chapter rigorously defined the objective functions for carbon emissions and costs, while explicitly articulating the precedence constraints, resource limitations, and logical dependencies that characterize MiC workflows. The mathematical formulation provided the foundational framework for subsequent optimization algorithms, establishing the formal parameters and constraints that define the solution space for carbon-efficient work package configuration.

To achieve Objective 2, Chapter 4 developed a single-objective optimization algorithm using the TLGA to minimize project carbon emissions. The chapter systematically addressed the specialized characteristics of work-package optimization through an innovative chromosome encoding that accommodated both activity sequencing and resource allocation. Computational experiments demonstrated the algorithm's effectiveness in identifying carbon-efficient work package configurations across diverse project scenarios, consistently outperforming conventional scheduling approaches in terms of carbon efficiency while maintaining computational tractability for practically sized projects.

To achieve Objective 3, Chapter 5 extended the optimization framework to incorporate multi-objective considerations by implementing NSGA-II and SPEA2 EAs. This chapter acknowledged the inherent tension between carbon-reduction and cost-minimization objectives in practical construction contexts and developed methodologies that generate comprehensive Pareto-optimal solution sets rather than singular optimization outcomes. The chapter's rigorous comparative analysis of algorithm performance established definitive guidelines for algorithm selection based on project characteristics and optimization priorities, enabling evidence-based decision-making that balances environmental and economic considerations.

To achieve Objective 4, Chapter 6 pioneered an innovative approach to heuristic optimization through LLM prompt engineering. This methodological innovation transcended the limitations of conventional algorithmic approaches by enabling construction professionals to interact with optimization systems through natural language rather than explicit parameter configuration. The chapter established a structured prompt engineering methodology specifically tailored for work package optimization, systematically evaluating various prompt architectures to identify those that consistently yield implementable, effective optimization strategies. This approach substantially reduced the technical barriers between project managers and optimization algorithms, democratizing access to carbon-optimization capabilities across diverse levels of expertise.

To achieve Objective 5, Chapter 7 integrated the previously developed optimization algorithms into a comprehensive user interface platform specifically designed for MiC work package planning. The platform's architecture systematically addressed the diverse requirements of construction professionals through three complementary modules: single-objective optimization, multi-objective optimization, and LLM-based heuristic optimization. The interface design thoughtfully balanced algorithmic sophistication with operational usability, incorporating intuitive visualizations that translate abstract optimization outcomes into actionable project-planning insights. Validation through industry case studies demonstrated the platform's effectiveness in enabling practical implementation of carbon-efficient work package strategies across diverse project contexts.

This study has made significant contributions to both the theoretical foundations and practical implementation of carbon optimization in MiC contexts. By systematically progressing from mathematical formulation to algorithmic implementation to operational decision-support tools, the research has established a comprehensive framework for integrating carbon-efficiency considerations into the critical work-package planning phase of MiC projects. The integration of conventional optimization approaches with innovative LLM-based methodologies represents a novel hybrid paradigm that leverages the complementary strengths of mathematical rigor and domain-specific heuristic reasoning. As the construction industry faces increasing pressure to reduce carbon emissions while maintaining economic viability, the optimization approaches and decision support tools developed in this study provide practical mechanisms for identifying and implementing carbon-efficient work package configurations that balance environmental performance with project constraints and economic considerations.

8.2 Discussion of the Results in relation to the Single-objective Optimization of Work Package Scheme Problem to Minimize Project Carbon

This section has investigated how WPSs can be optimized to minimize carbon emissions in MiC projects by developing and validating a TLGA. The investigation was conducted by establishing a theoretical foundation linking work package characteristics to carbon emissions, developing a specialized optimization algorithm, and testing its effectiveness across diverse project scenarios. The main results are discussed below.

Firstly, the study provides empirical validation of the convex relationship between production rates and carbon emissions in construction work packages. This relationship, established through Cobb-Douglas production function analysis, forms the theoretical foundation for the carbon emission calculation model. The resulting quadratic function, linking production rate to carbon emissions per unit of work content, reveals how work package configuration directly influences a project's overall carbon footprint. This mathematical relationship is particularly significant for MiC projects, where carbon footprints span factory production, transportation, and on-site assembly. The productivity-based carbon-emission framework acknowledges the unique characteristics of MiC, in which production environments vary substantially across project phases. This theoretical basis enables quantifying the carbon implications of different work packaging decisions throughout the entire MiC delivery process.

Secondly, a comparative analysis demonstrates that the TLGA achieves substantial carbon emission reductions of 49.93% to 81.15% compared to traditional WPSs. While the state-of-the-art heuristic approach showed marginally better results in some scenarios (achieving reductions of 50.84% to 81.62%), the TLGA's performance difference was minimal, particularly in delay-tolerant project settings. The TLGA methodology advances work packaging optimization in MiC projects by leveraging sophisticated chromosome encoding and genetic operations tailored to the work package problem structure. Unlike previous approaches that typically focus on cost or schedule optimization, the TLGA specifically targets carbon emission reduction. The two-list representation method effectively distinguishes between two task types. Active tasks can be freely combined. Inactive tasks (such as critical lifting operations) require dedicated management. This distinction is particularly crucial in MiC projects. In these projects, precise coordination between factory production and on-site assembly is essential for carbon efficiency. This approach aligns with observations from other researchers (C.-L. Li & Hall, 2019; X. Li et al., 2020) who have highlighted the importance of specialized task handling in construction optimization.

Thirdly, the experimental results reveal several important patterns in carbon-optimized work packaging that directly inform MiC project management practices. Project size significantly influences optimal work package characteristics, with larger projects benefiting from smaller, more uniform work packages. For instance, in the five-tower, 4,658-module case study, the average number of tasks per work package decreased from 3.14 (for smaller projects with 40 tasks) to 2.52 (for larger projects with 120 tasks). Network seriality also significantly affects carbon optimization, as more serial project components require larger work packages to minimize emissions from frequent task transitions. This finding is particularly relevant for MiC projects, which typically involve a hybrid of highly parallel factory production followed by more sequential on-site assembly. The execution mode emerged as a critical factor, with Rush mode requiring larger work packages (average size: 8.43 tasks) than Standard mode (5.38 tasks) and Delay mode (4.69 tasks). This finding suggests that execution modes significantly impact resource efficiency in construction projects. Additionally, input-output ratios influence optimal work package sizing, with lower ratios enabling larger packages without compromising carbon performance.

The current research on carbon-optimized work packaging in MiC projects also reveals several limitations and knowledge gaps. Despite the TLGA’s effectiveness in carbon optimization, it does not explicitly address multi-objective considerations incorporating cost and schedule factors. MiC projects are often selected for their potential advantages in all three dimensions. These dimensions include cost, schedule, and environmental impact. This makes multi-objective optimization particularly relevant for such projects. The carbon emission model assumes a consistent quadratic relationship between production rate and emissions across all work package types, potentially overlooking the distinct emission profiles of different construction activities. This limitation has been identified in other environmental assessment studies (Loo et al., 2023) where methodological variations significantly impact results. The practical implementation of carbon-optimized work packages may face organizational and behavioral barriers not addressed in this study, particularly in the relatively young MiC sector that is still developing standardized processes. Furthermore, the current study focuses primarily on the planning phase without considering dynamic adaptation during project execution. Despite MiC projects’ greater predictability than conventional construction, they still face uncertainties during implementation, particularly during the transition from factory production to site assembly.

In conclusion, this study has successfully developed and validated a TLGA to optimize WPSs and minimize carbon emissions in MiC projects. The substantial carbon reductions achieved highlight significant untapped potential for emission reduction through optimized work packaging in MiC projects. Traditional approaches to work package design have typically focused on logistical convenience or manufacturing efficiency rather than carbon optimization. This study demonstrates that systematically designing work packages with carbon performance in mind can dramatically reduce emissions while maintaining operational efficiency, further enhancing the sustainability advantage that MiC already offers over conventional construction methods.

8.3 Discussion of the Results in relation to the Multi-objective Optimization of Work Package Scheme Problem to Minimize MiC Project Carbon Emissions and Cost

This section has investigated how multi-objective optimization can balance carbon emissions and cost in WPSs for MiC projects. The investigation was conducted by developing a comprehensive mathematical model, implementing advanced EAs, and analyzing their performance across diverse project scenarios. The main results are discussed below.

Firstly, the multi-objective optimization framework established in this study demonstrates significant potential to simultaneously reduce carbon emissions while managing costs in MiC projects. The implemented EAs achieved remarkable results, reducing carbon emissions by approximately 68% with only an 11% cost increase compared to traditional methods across various project parameters. This substantial improvement indicates that current work packaging practices in MiC projects are significantly suboptimal from an environmental perspective. The explicit mathematical formulation linking work package configuration to both carbon emissions and cost creates a robust foundation for quantifying the trade-offs between these competing objectives. This approach represents a significant advancement over previous single-objective methods that fail to capture the inherent multidimensional nature of carbon reduction. The lack of consistent methodological approaches has been a significant barrier to effective carbon reduction in construction (Fang et al., 2018).

Secondly, the comparative analysis of the algorithms reveals important insights about their performance and applicability. SPEA2 generally produces superior Pareto frontiers with better distribution and coverage, particularly for larger projects, though at a modest computational cost (approximately 6.18% longer runtime than NSGA-II). When benchmarked against state-of-the-art optimization solvers (Gurobi) and heuristic algorithms, the evolutionary approaches demonstrated clear advantages for this problem class. While single-objective methods excel at optimizing their target metric, they perform poorly on secondary objectives. For instance, when the heuristic algorithm was configured to minimize carbon emissions, it achieved the lowest emissions in six of nine tested scenarios but at significantly higher costs. In contrast, the multi-objective approach identified solutions that reduced costs by approximately 25% while maintaining carbon emissions within 1% of the heuristic's results. This quantitative comparison aligns with findings from other multi-objective studies that emphasize the importance of considering multiple performance criteria simultaneously rather than in isolation (Cui et al., 2025; Ho et al., 2024).

Thirdly, the sensitivity analysis across different project parameters reveals significant patterns that provide valuable guidance for MiC project planning. The number of tasks in a project (I_1) substantially affects the optimization landscape, with hypervolume decreasing from 0.85 for 40-task projects to 0.76 for 120-task projects, indicating greater challenges in simultaneously optimizing carbon emissions and cost as projects grow larger. Network seriality (I_2) emerged as another critical factor, with more serial project networks yielding higher hypervolumes (increasing from 0.74 at I_2=0.2 to 0.83 at I_2=1.0), indicating clearer trade-off patterns. This finding has significant implications for MiC projects, which typically combine highly parallel factory production with more sequential on-site assembly. The execution mode showed relatively modest effects on the Pareto frontier characteristics, with hypervolume variations less than 5% across standard, delay, and rush modes. Input-output rates (β) demonstrated a slight negative correlation with hypervolume, decreasing from 0.81 at $\beta = 0.8$ to 0.78 at $\beta = 1.2$. These quantitative relationships provide evidence-based guidance for practitioners on when and how to apply multi-objective optimization most effectively across different MiC project contexts.

The current research on multi-objective work package optimization also reveals several limitations and knowledge gaps. Despite the demonstrated effectiveness of EAs, their computational complexity increases substantially with project size, as evidenced by declining hypervolume performance at higher task counts. While the algorithms performed well across tested scenarios, further research is needed to develop more scalable approaches for very large MiC projects with thousands of tasks. The carbon emission model used in this study applies a consistent quadratic relationship between production rate and emissions across all work package types, potentially overlooking the distinct emission profiles of different activities within MiC projects. Additionally, while this study focused on carbon emissions and cost as the primary objectives, MiC projects typically involve additional considerations such as schedule performance, quality, safety, and logistical complexity. The lack of these dimensions in the current model, while providing analytical clarity, limits its comprehensive application to all project decision factors. Furthermore, implementing optimized WPSs in real MiC projects may face practical challenges not captured in the algorithmic evaluation, including organizational resistance, communication barriers between factory and site teams, and adaptation to unexpected conditions during project execution.

In conclusion, this study has successfully developed and validated a multi-objective optimization approach for WPSs in MiC projects that effectively balances carbon emission reduction with cost management. The comparative analysis confirmed the superiority of evolutionary approaches for this problem class, with SPEA2 generally outperforming NSGA-II in solution quality, albeit with slightly higher computational requirements. The sensitivity analysis across diverse project parameters established the robustness of the proposed approach, with hypervolume indicators remaining consistently high (above 0.7 and mostly exceeding 0.8) across all configurations. As the construction industry faces increasing pressure to reduce its environmental impact while maintaining economic viability, the balanced optimization approach presented in this study offers a valuable methodology for advancing sustainable MiC practices that achieve meaningful carbon reductions without compromising financial performance.

8.4 Discussion of the Results in relation to the Large Language Model-based Heuristic Optimization Framework for Work Package Scheme Problem

This section has investigated how LLMs can be leveraged to bridge the persistent gap between theoretical carbon optimization techniques and their practical implementation in MiC projects. The investigation was conducted by developing a structured prompt chain methodology, generating multiple heuristic algorithms through LLM interaction, and systematically evaluating their performance against established optimization benchmarks across diverse project scenarios. The main results are discussed below.

Firstly, the LLM-based heuristic optimization framework establishes a new paradigm for algorithm development, fundamentally reconceptualizing the relationship between domain expertise and optimization knowledge. Traditional approaches have followed either a domain-expert-led path, in which construction professionals incorporate optimization principles with limited mathematical sophistication, or an optimization-expert-led path, in which mathematical specialists develop algorithms with limited understanding of construction-specific constraints. The experimental results demonstrate that this novel framework effectively bridges this divide, with LLM-generated heuristics achieving carbon reductions of 3.7% to 9.8% compared with specialized algorithms across diverse project configurations. The structured prompt chain methodology proved particularly effective for guiding algorithmic reasoning, with sequential prompting outperforming single-prompt approaches by an average of 12.6% in solution quality. By positioning LLMs as cognitive intermediaries that translate between domain-specific requirements and mathematical principles, the framework creates a unified space where construction knowledge and optimization expertise can productively interact without requiring extensive cross-disciplinary training.

Secondly, the experimental validation reveals significant patterns in the performance of LLM-generated heuristics across different project characteristics. Project size emerged as the most influential factor, with performance gaps between LLM-generated heuristics and specialized algorithms decreasing from 9.8% for small projects (40 tasks) to only 3.7% for large projects (120 tasks). This finding suggests that LLM-generated approaches become increasingly competitive as project complexity increases. This is precisely the scenario where intuitive human approaches typically struggle most. Network seriality also significantly influenced performance, with the gap decreasing from 8.2% for highly parallel networks ($I_2 = 0.2$) to 5.3% for more serial structures

($I_2 = 1.0$). The performance patterns across execution modes showed relatively consistent gaps (varying less than 2.5% across modes), indicating that the relative effectiveness of LLM-generated heuristics remains stable regardless of scheduling constraints. The quantitative performance analysis across different project parameters provides construction professionals with clear guidance on when and how LLM-generated heuristics can serve as viable alternatives to specialized algorithms, enabling context-appropriate applications that maximize carbon reduction potential.

Thirdly, the taxonomy of heuristic algorithms generated through the framework reveals important insights about different optimization strategies for carbon reduction in work package planning. The seven distinct heuristics represent a comprehensive exploration of the solution space. These range from emission-time trade-off optimization (MAX-ETR) to work content-based approaches (MAX-WPCE). Comparative analysis revealed significant performance variations across these heuristics, with MAX-ETR achieving the best overall performance (within 4.2% of specialized algorithms on average), while others, such as MIN-CPL, showed substantially larger gaps (12.7% on average). This variation demonstrates that LLMs can generate multiple viable solution strategies with distinctly different mathematical approaches, rather than converging on a single suboptimal heuristic. The performance distribution revealed an important insight. The most effective heuristics focused on balancing multiple factors rather than optimizing a single dimension. These factors include production rate, work content, and time. This suggests that effective carbon optimization requires holistic consideration of work package characteristics.

The current research on LLM-based optimization approaches also reveals several limitations and knowledge gaps. Despite the promising results, a persistent performance gap remains between LLM-generated heuristics and specialized optimization algorithms under certain project conditions. Although this gap narrows significantly for larger projects (from 9.8% for 40-task projects to 3.7% for 120-task projects), it remains substantial for smaller projects with complex parallel structures and tight scheduling constraints. The current implementation relies on a specific LLM (Qwen2.5-Coder) with particular architectural characteristics and training data, creating potential sustainability challenges as models evolve. While the prompt chain methodology demonstrated effectiveness in guiding algorithmic reasoning, it remains somewhat manual and potentially sensitive to specific wording choices, requiring significant expertise in both optimization theory and language model behavior. Additionally, the framework's current validation focuses primarily on computational performance rather than practical implementation barriers that may arise when integrating these approaches into established construction management workflows, particularly in organizations with limited digital maturity or resistance to algorithmically guided decision-making.

In conclusion, this study has successfully developed and validated a novel LLM-based framework to optimize WPSs and minimize carbon emissions in MiC projects. The experimental results demonstrate that LLM-generated heuristics can achieve carbon reductions of 3.7% to 9.8% compared with specialized algorithms across diverse project configurations, with particularly strong performance on larger, more complex projects. The framework's natural language interface and algorithmic transparency enable construction professionals to implement sophisticated carbon-optimization approaches without specialized mathematical expertise, potentially accelerating the adoption of low-carbon practices across the industry. As construction organizations face increasing pressure to reduce environmental impacts while maintaining operational efficiency, this accessible approach to carbon optimization offers a valuable tool for enhancing sustainability performance across the project lifecycle.

8.5 Discussion of the Results in relation to the Work Package-based MiC Carbon Emission Optimization Platform

This section has investigated how theoretical carbon optimization frameworks can be translated into practical software tools for MiC projects. The investigation was conducted by developing a comprehensive three-tier platform architecture, implementing three complementary optimization modules, and creating intuitive user interfaces that make sophisticated algorithms accessible to construction professionals without specialized mathematical expertise. The main results are discussed below.

Firstly, the Work Package-based MiC Carbon Emission Optimization Platform addresses a critical implementation gap that has historically limited the practical application of carbon-efficient design principles in construction projects. Despite significant theoretical advancements in optimization methodologies, the lack of accessible software tools has prevented widespread adoption of these techniques in industry practice. The platform's tripartite functional architecture establishes a comprehensive analytical ecosystem. This architecture encompasses single-objective and multi-objective optimization, as well as LLM-based heuristic approaches. It accommodates diverse industry requirements across the spectrum of project complexity and user expertise. For small- and medium-sized MiC enterprises with limited computational resources, the platform's intuitive interface and accessible explanatory content democratize access to sophisticated carbon optimization capabilities that would otherwise remain out of reach. This democratization effect is particularly significant in the MiC sector, where the fragmented supply chain has traditionally impeded the consistent implementation of sustainability strategies.

Secondly, the platform's multi-objective optimization module makes a substantial contribution to industry practice by explicitly quantifying the trade-offs between environmental performance and economic considerations. By generating Pareto-optimal solution sets that visualize the precise relationship between carbon reduction and cost implications, the platform enables evidence-based negotiation among project stakeholders with diverse priorities. The visualization capabilities transform abstract optimization results into intuitive representations. These representations align with established industry communication practices. They include tabular work package specifications, network diagrams, and Pareto frontier visualizations. These visualization components enable construction professionals to directly translate mathematical optimization outputs into actionable project planning decisions without requiring specialized interpretation expertise. The platform's parameter configuration interfaces further enhance accessibility by providing non-technical explanatory metaphors that translate abstract computational concepts into familiar experiential frameworks, enabling construction professionals to make informed parameter adjustments based on intuitive understanding rather than specialized algorithmic knowledge.

Thirdly, the platform's integration of LLM-based heuristic optimization capabilities establishes a novel pathway for the continuous evolution of carbon efficiency strategies in response to emerging industry knowledge and project requirements. Unlike conventional optimization tools, which remain constrained by their initial algorithmic formulations, the platform's LLM integration enables the dynamic generation of new optimization approaches that incorporate emerging construction techniques, material innovations, and regulatory frameworks as they evolve. The structured prompt chain methodology implemented in the platform decomposes the complex process of algorithm specification into four distinct conceptual components: contextual understanding through the "problem background" field, objective definition through the "task objective" field, procedural guidance through the "algorithm codes step by step" field, and data specifications through the "input requirements" field. This bidirectional interaction model represents a fundamental shift from the unidirectional parameter-algorithm-result pipeline characteristic of conventional approaches to an iterative dialogue in which construction professionals and AI collaboratively explore the solution space through natural-language negotiation. By enabling this knowledge-based approach to optimization, the platform establishes a complementary methodology to mathematical algorithms, acknowledging that construction carbon optimization ultimately requires both algorithmic precision and domain-specific heuristic reasoning.

Finally, the practical utility of this platform is particularly pronounced in the Hong Kong construction industry, where it directly addresses the unique challenges of adopting high-density MiC. The multi-objective optimization capability provides the empirical rigor needed to navigate Hong Kong's stringent cost-control requirements while meeting the ambitious sustainability targets outlined in the Hong Kong Climate Action Plan 2050. Furthermore, by democratizing access to sophisticated planning tools, the platform bridges the technical capability gap for local small and medium-sized enterprises, fostering a more resilient, digitally integrated construction ecosystem. In doing so, it operationalizes the government's Construction 2.0 vision, transforming theoretical carbon reduction potential into actionable, project-level strategies for the city's high-rise development.

In conclusion, this study has successfully developed and implemented a comprehensive software platform that operationalizes the theoretical frameworks and algorithms established throughout this research within a user-friendly computational environment. The platform integrates the single-objective TLGA algorithm (Chapter 4), multi-objective NSGA-II and SPEA2 EAs (Chapter 5), and the LLM-based heuristic framework (Chapter 6) within a cohesive three-tier architecture comprising data management, algorithmic processing, and user interaction components. By embedding sophisticated optimization capabilities within intuitive interfaces and visualization components, the platform eliminates the technical barriers that have historically limited the adoption of advanced carbon optimization techniques in construction management practice. This operational capability directly addresses the implementation gap that has constrained the practical impact of theoretical carbon optimization approaches in construction contexts, potentially accelerating the diffusion of carbon-efficient practices throughout the MiC industry as environmental regulations increasingly constrain construction carbon emissions and market preferences increasingly prioritize carbon reduction practices in MiC project management.

8.6 Chapter Summary

This chapter has discussed the results of the study components within the context of the existing body of knowledge. In relation to the research objectives, the discussion has covered single-objective optimization of WPSs using the TLGA, multi-objective optimization balancing carbon emissions and cost through EAs, an innovative LLM-based heuristic optimization framework, and the development of an integrated software platform for practical implementation. The discussion section unveils the theoretical and practical implications of each approach, highlighting how work package optimization can significantly reduce carbon emissions while maintaining project viability. The chapter demonstrates the achievement of the research objectives by establishing both the mathematical foundations and accessible implementation tools for carbon-efficient work package planning in MiC projects, contributing to the broader knowledge base on carbon-reduction practices in MiC project management, and identifying remaining challenges for future research.

Chapter 9 Conclusions

This chapter first reviews the research aim and objectives to assess whether they have been satisfied. Then, the key research findings are summarized, and the contributions to the body of knowledge and the industry are highlighted. Finally, the limitations and future research directions are discussed.

9.1 Summary of Research Findings

The key findings of this study are highlighted below:

Firstly, a comprehensive mathematical optimization model for WPSs in MiC projects was established, providing a theoretical foundation for carbon-emission optimization in MiC. This model precisely articulated the objective functions for both carbon emissions and costs while explicitly defining the constraints that characterize MiC workflows, including precedence relationships, resource limitations, and logical dependencies. A novel carbon emission calculation framework based on the Cobb-Douglas production function was developed, establishing a convex relationship between work package production rates and carbon emissions. This productivity-based framework effectively captures the unique characteristics of MiC, in which carbon footprints span factory production, transportation, and on-site assembly. The mathematical formulation demonstrated how different work package configurations directly influence a project's overall carbon footprint, providing the analytical foundation for subsequent algorithm development.

Secondly, a single-objective optimization algorithm was developed through the TLGA to minimize carbon emissions in MiC projects. The TLGA's innovative chromosome representation effectively distinguished between two task types. Active tasks can be freely combined. Inactive tasks require dedicated management. This distinction is particularly crucial in MiC projects. In these projects, precise coordination between factory production and on-site assembly is essential. Experimental validation using a large-scale real-world MiC project and comprehensive project instances demonstrated the TLGA's effectiveness, achieving carbon emission reductions ranging from 49.93% to 81.15% compared to traditional WPSs. The analysis revealed several important patterns in carbon-optimized work packaging: larger projects benefit from smaller, more uniform work packages; different project phases require different approaches to work packaging (smaller packages for parallel factory production and larger packages for serial site assembly); and the execution mode significantly influences the optimal work package size. These findings provide valuable guidance for MiC project managers seeking to enhance sustainability through optimized work packaging.

Thirdly, a multi-objective optimization approach was implemented through NSGA-II and SPEA2 EAs to simultaneously address carbon emissions and cost in MiC projects. The comparative analysis of these algorithms demonstrated remarkable effectiveness in identifying balanced solutions, achieving approximately 68% reductions in carbon emissions with only an 11% increase in cost compared to traditional methods. SPEA2 generally produced superior Pareto frontiers with better distribution and coverage, particularly for larger projects, though at a modest computational cost (approximately 6.18% longer runtime than NSGA-II). Benchmarking against state-of-the-art optimization solvers and heuristic algorithms confirmed the superiority of evolutionary approaches for this problem class. While single-objective methods excelled at optimizing their target metric, they performed poorly on secondary objectives. In contrast, the multi-objective approach identified solutions with significant benefits. It reduced costs by approximately 25%. At the same time, it maintained carbon emissions within 1% of the best-known results. This demonstrates the practical value of considering these objectives simultaneously.

Fourthly, a novel heuristic optimization framework based on LLMs was developed to overcome the professional barriers between project managers and optimization algorithms. The structured prompt chain methodology decomposed complex algorithm design into manageable cognitive steps, enabling LLMs to generate practical optimization heuristics through natural language interaction. This approach transformed abstract mathematical relationships into accessible optimization procedures, democratizing access to carbon optimization capabilities for construction professionals without specialized expertise. Implementation through the Qwen2.5-Coder model yielded seven distinct heuristic algorithms, with MAX-ETR and MAX-WPCE consistently demonstrating superior performance. Experimental evaluation revealed that LLM-generated heuristics performed particularly well on larger projects and under flexible scheduling, with performance gaps decreasing to approximately 0.2 under optimal conditions. This innovative approach established a new paradigm for algorithm development, fundamentally reconceptualizing the relationship between domain expertise and optimization knowledge.

Finally, a comprehensive Work Package-based MiC Carbon Emission Optimization Platform was developed to operationalize the theoretical frameworks and algorithmic approaches into a cohesive computational tool for practical industry application. The platform’s tripartite functional architecture established a comprehensive decision support ecosystem. This architecture encompasses single-objective and multi-objective optimization, as well as LLM-based heuristic approaches. It can address diverse project requirements and user expertise levels. The platform’s intuitive interface and accessible explanatory content democratized access to sophisticated carbon-optimization capabilities, potentially accelerating the diffusion of carbon-efficient practices across the MiC industry. Visualization capabilities transformed abstract optimization outputs into intuitive representations aligned with established construction management practices, enabling direct translation of optimization insights into actionable project planning decisions. This integration of algorithmic sophistication with accessible interface design established a template for future construction optimization tools that balance methodological rigor with practical usability.

Through these progressive research phases, this study has systematically addressed the
Through these progressive research phases, this study has systematically addressed the
critical challenge of carbon optimization in MiC, developing increasingly sophisticated yet practically accessible approaches that enable significant environmental

performance improvements while maintaining economic viability. As construction industry regulations increasingly constrain carbon emissions and market preferences increasingly prioritize carbon-reduction practices in MiC project management, these optimization methodologies and tools provide timely, practical mechanisms for translating abstract carbon-reduction objectives into concrete work-package implementation strategies.

9.2 Contributions of the Research

9.2.1 Theoretical Contributions to the Knowledge

This study makes theoretical contributions to the understanding of carbon emission optimization in MiC through work-package-based approaches across several significant aspects.

This study establishes a comprehensive theoretical framework for carbon-emission optimization in MiC projects and makes fourfold contributions. Firstly, by developing a productivity-based carbon-emission model using the Cobb-Douglas production function, this study provides mathematical validation of the convex relationship between production rates and carbon emissions in construction work packages. This theoretical foundation bridges a critical gap in sustainable construction literature by establishing a quantitative framework that directly links work package configuration decisions to carbon footprint outcomes across the distributed production environments characteristic of MiC projects. While previous research has largely treated carbon emissions as fixed parameters associated with specific activities, this study reconceptualizes emissions as dynamic outcomes influenced by work package design choices, execution modes, and resource allocation strategies. Secondly, the research establishes a mathematical optimization model that integrates carbon emissions and costs as competing objective functions within the context of complex precedence constraints characteristic of MiC workflows. This theoretical formulation transcends previous sustainability-oriented optimization models. It explicitly accommodates the unique characteristics of MiC delivery. These characteristics include factory production, transportation, and on-site assembly phases. Each phase has distinct productivity-emission relationships. Thirdly, the study develops a structured taxonomy of work package characteristics in relation to carbon performance, identifying specific patterns between project parameters (task count, network seriality) and optimal work package configurations. This taxonomic contribution establishes a theoretical basis for predictive modeling of carbon-optimization strategies based on project characteristics, enabling a more targeted application of optimization approaches. Fourthly, the research introduces a novel theoretical framework for human-AI collaborative optimization through the structured prompt chain methodology, establishing how domain expertise and optimization knowledge can be productively integrated through LLMs as cognitive intermediaries.

The contributions made from the single-objective optimization approach are threefold: (1) this study advances genetic algorithm methodology through an innovative approach. The two-list representation method effectively distinguishes between different task types. Active tasks can be combined. Inactive tasks require dedicated management. This distinction is particularly crucial in MiC projects. In these projects, precise coordination between factory production and on-site assembly is essential; (2) establishing theoretical benchmarks for carbon reduction potential in MiC work package optimization through rigorous experimental validation that demonstrated emission reductions of 49.93% to 81.15% compared to traditional approaches; and (3) developing a theoretical understanding of how different project parameters influence optimal work package characteristics, including the counterintuitive finding that larger projects benefit from smaller, more uniform work packages despite increased coordination requirements. These contributions collectively extend optimization theory in construction management by demonstrating how genetic algorithms can be specifically adapted to the unique characteristics of MiC workflows to achieve substantial carbon reductions.

The contributions made from the multi-objective optimization approach are also threefold: (1) advancing multi-objective EA methodology through comprehensive comparison of NSGA-II and SPEA2 performance across diverse project configurations, establishing that SPEA2 generally produces superior Pareto frontiers with better distribution and coverage, particularly for larger projects; (2) developing theoretical frameworks for quantifying the inherent trade-offs between carbon reduction and cost efficiency in MiC projects, demonstrating that balanced solutions can achieve approximately 68% carbon emission reductions with only an 11% cost increase compared to traditional methods; and (3) establishing robust performance metrics through hypervolume indicator analysis across different project parameters, demonstrating that the multi-objective framework maintains its effectiveness regardless of specific precedence requirements imposed on the work package structure. These contributions extend multi-objective optimization theory by demonstrating how EAs can effectively navigate the complex trade-off space between environmental and economic objectives in MiC contexts.

The contributions made from the integrated optimization platform synthesize and operationalize these theoretical advancements: (1) establishing a comprehensive framework for translating abstract carbon optimization methodologies into practical decision support tools through a tripartite functional architecture that accommodates diverse industry requirements and user expertise levels; (2) developing visualization methodologies that transform abstract optimization outputs into intuitive representations aligned with established construction management practices; and (3) demonstrating how bidirectional knowledge flows between construction professionals and AI systems can create a learning ecosystem that progressively refines carbon optimization strategies based on practical implementation feedback. These platform-level contributions establish a theoretical template for future construction decision support systems that balance methodological sophistication with practical usability while accommodating the evolutionary nature of sustainability best practices.

Collectively, these theoretical contributions establish a comprehensive framework for understanding, quantifying, and optimizing the carbon implications of work package decisions in MiC contexts. This study creates new theoretical paradigms for carbon reduction. It develops increasingly sophisticated yet accessible approaches to carbon optimization. These approaches range from mathematical modeling through algorithmic implementation to human-AI collaborative systems. These new paradigms transcend traditional approaches to optimizing environmental performance.

9.2.2 Practical Contributions to the Industry

This study proposes a comprehensive set of work-package-based approaches for carbon-emission optimization in MiC, providing practical tools and methodologies that directly address the industry's growing sustainability challenges. The contributions of this study to industry practice are significant across several dimensions.

Firstly, the carbon-emission optimization platform developed in this study equips MiC project managers with accessible decision-support tools that translate complex theoretical frameworks into actionable planning strategies. The platform accommodates diverse industry requirements across different project scales and team expertise levels. It achieves this by integrating three complementary optimization modules: single-objective, multi-objective, and LLM-based approaches. This comprehensive functionality enables construction professionals to systematically identify carbon-reduction opportunities without specialized mathematical expertise, potentially accelerating the adoption of carbon-efficient work packaging strategies throughout the MiC supply chain. The platform's intuitive interface design, with progressive workflow guidance, makes sophisticated optimization capabilities accessible to small and medium-sized enterprises that lack dedicated computational resources or optimization specialists, democratizing access to carbon-reduction methodologies that would otherwise be available only to large organizations with specialized analytical departments.

Secondly, the multi-objective optimization approach provides construction professionals with practical mechanisms for navigating the inherently challenging trade-offs between environmental performance and economic viability. By generating comprehensive Pareto-optimal solution sets with quantified carbon-cost relationships, the platform transforms traditionally qualitative sustainability discussions into evidence-based decision processes with clear visualization of available alternatives. This capability enables project stakeholders to identify specific work package configurations that achieve substantial carbon reductions (approximately 68%) with minimal cost increases (approximately 11%), providing construction managers with concrete options that balance sustainability objectives against financial constraints. The platform's visualization of these trade-offs through intuitive Pareto frontier representations allows project teams to select implementation strategies that align with specific project priorities, stakeholder requirements, and regulatory constraints without sacrificing either environmental or economic performance.

Thirdly, the LLM-based heuristic optimization framework addresses a persistent implementation barrier in the construction industry by eliminating the need for specialized mathematical expertise, which has historically limited the adoption of advanced optimization techniques. By enabling construction professionals to interact with optimization systems through natural language rather than complex parameter configurations, the framework makes carbon optimization accessible to project managers at all levels of expertise. This democratization effect is particularly valuable in the MiC sector, where teams often span diverse educational backgrounds and technical capabilities across factory and site environments. The research demonstrates that LLM-generated heuristics, such as MAX-ETR and MAX-WPCE, can achieve near-optimal performance for larger projects and under flexible scheduling conditions, providing practical guidance for the strategic application of these approaches based on specific project characteristics. This nuanced understanding enables organizations to implement carbon-reduction strategies incrementally, targeting specific project components or phases where optimization benefits are most significant, while building organizational capability for more comprehensive implementation.

The research provides practical guidance for differentiated work package strategies. These strategies span across the distinct phases of MiC delivery: factory production, transportation, and on-site assembly. The finding that larger projects benefit from smaller, more uniform work packages offers valuable direction for large-scale modular developments, while the analysis of network seriality suggests different optimal approaches for parallel factory production (smaller packages) versus sequential site assembly (larger packages). These phase-specific optimization patterns acknowledge the operational realities of MiC, where different teams with distinct organizational cultures must coordinate across distributed production environments. Similarly, identifying execution mode as a critical factor affecting optimal work package configurations provides practical guidance for adapting work packaging strategies to project scheduling requirements, particularly for time-critical assembly phases that often operate in Rush mode.

In summary, this study makes substantial practical contributions to the MiC industry by developing accessible, flexible, and effective approaches to carbon emission optimization that accommodate the operational realities of commercial construction while delivering significant environmental benefits. As the industry faces increasing regulatory pressure and market demand for carbon-reduction practices in MiC project management, these tools and methodologies provide practical mechanisms for identifying and implementing carbon-efficient work-package strategies across diverse project contexts and organizational scales.

9.3 Limitations and Future Research

This study has established a comprehensive framework for carbon emission optimization in MiC through work package-based approaches. By systematically progressing from mathematical formulation through algorithmic implementation to operational decision support tools, this research has created both theoretical foundations and practical mechanisms for integrating carbon efficiency considerations into the critical work package planning phase of MiC projects. However, several limitations need to be addressed, and numerous future research directions can be explored to further advance this field.

9.3.1 Limitations of the Research

The limitations of this study can be summarized in three aspects:

Firstly, while the mathematical optimization model for WPSs establishes a robust theoretical foundation for carbon emission calculations through the Cobb-Douglas production function, it applies a consistent quadratic relationship between production rate and emissions across all work package types. This simplification may not fully capture the distinct emission profiles of different activities within MiC projects, particularly across factory production, transportation, and on-site assembly phases. Each phase likely has unique productivity-emission relationships that cannot be represented by a single mathematical formulation. Although the model provides valuable insights into general patterns of carbon-efficient work packaging, its uniform approach to emission calculation may limit precision when applied to specific project components with distinctive operational characteristics.

Secondly, the LLM-based heuristic optimization framework, while innovative in overcoming implementation barriers, remains dependent on specific heuristic algorithm architectures. The performance of the framework may vary significantly across different LLMs or future model versions, posing sustainability challenges as models evolve. Additionally, designing effective prompt chains currently requires significant expertise in both optimization theory and language model behavior, potentially creating new implementation barriers that partially offset the framework's accessibility advantages. The persistent performance gap between LLM-generated heuristics and specialized algorithms under certain project conditions (particularly for smaller projects with complex parallel structures) indicates that this approach cannot universally replace specialized optimization methods.

Lastly, the research primarily focuses on carbon emissions as the environmental metric, without addressing broader sustainability indicators such as water consumption, waste generation, and ecosystem impacts. This narrow focus may limit the research's applicability in contexts where multiple environmental performance indicators must be simultaneously considered. Furthermore, the current approach has limitations. It does not fully capture the dynamic uncertainties inherent in construction processes. These uncertainties include weather disruptions, supply chain variability, and fluctuations in labor productivity. Such factors can significantly impact the practical implementation of theoretically optimal WPSs. These operational uncertainties introduce additional complexity that may affect the real-world performance of the optimized work package configurations.

9.3.2 Future Research

The work-package-based approaches to carbon emission optimization in MiC projects offer significant opportunities to advance carbon-reduction practices in MiC project management, particularly in conjunction with emerging technologies and methodologies. This study has established foundational frameworks and algorithms that can be further developed in several promising directions.

Future research should focus on enhancing the carbon emission modeling framework to better reflect the heterogeneous nature of MiC activities. Developing more nuanced emission models that account for the distinct characteristics of factory production, transportation, and on-site assembly phases would significantly improve optimization accuracy. This could involve incorporating detailed life-cycle assessment methodologies to establish activity-specific emission factors that capture the diverse environmental impacts across project components. Machine learning approaches could identify complex, non-linear relationships between work package configurations and emission outcomes using empirical project data from operational MiC projects, moving beyond the quadratic relationship used in the current research. Furthermore, integrating BIM would provide a semantic data environment to automate the extraction of quantity take-offs and material properties, directly feeding them into the optimization algorithms. This interoperability ensures that carbon calculations are driven by precise, real-time design data, thereby enhancing the fidelity and dynamic responsiveness of the work packaging solutions.

The LLM-based optimization framework could be substantially enhanced through several technical advancements. Future research should investigate the framework's robustness across different LLM architectures and develop systematic approaches for adapting prompt chains to evolving model capabilities. Automated prompt engineering techniques, potentially leveraging reinforcement learning, could optimize prompt structures based on algorithm performance feedback, reducing the expertise currently required for effective prompt chain design. Comparative studies of different LLMs' effectiveness in algorithmic reasoning tasks would provide valuable insights into which model characteristics most significantly influence optimization performance. These enhancements would strengthen the framework's sustainability as LLM technologies continue to evolve rapidly.

The research also offers opportunities for educational and training advancements. Developing simulation-based learning environments that demonstrate the principles and benefits of carbon-optimized work packaging would facilitate knowledge transfer to construction professionals and students. These educational tools could incorporate game-based approaches that allow learners to experiment with different work package configurations and observe their carbon implications in a risk-free environment, building practical understanding of the complex relationships between work package characteristics and environmental performance. To align with the specific implementation landscape in Hong Kong, these platforms should incorporate local case studies that simulate the region's unique high-density logistical constraints and cross-border transportation dynamics. Furthermore, integrating Hong Kong's specific regulatory frameworks and incentive schemes into the curriculum would ensure that future practitioners are equipped to navigate the distinct statutory and operational challenges of the local MiC market.

By addressing these challenges and pursuing these research directions, work-package-based carbon-optimization approaches have the potential to transform carbon-reduction practices in MiC project management. As the construction industry faces increasing regulatory pressure and market demand for environmental responsibility, these approaches offer a pathway to significantly reduce carbon emissions while maintaining economic viability. The ultimate vision is to establish carbon-efficient work packaging as standard practice in MiC, contributing to broader industry goals of carbon neutrality while preserving the operational and economic advantages that make MiC an increasingly attractive delivery method.

Appendix I: Merge Heuristic Algorithm

Algorithm 5: The Merge Heuristic Algorithm

```
Result: The work package scheme, carbon emissions(cost), and
        cost(carbon emissions)
Function InitializeWorkPackageScheme():
    initial_work package scheme ← create an empty list;
    for i ← 1 to number_of_tasks do
        add task i to initial_work package scheme;
    end
    return initial_work package scheme;
Function OptimizeWorkPackageScheme(current_work package
 scheme):
    baseline_work package scheme ← current_work package scheme;
    baseline_carbon emissions(cost) ← calculate_carbon
     emissions(cost)();
    (current_carbon emissions(cost), current_cost) ← evaluate_work
     package scheme(current_work package scheme);
    potential_work package schemes ← [];
    for each pair of tasks in current_work package scheme do
        if can combine tasks then
            new_work package scheme ← merge tasks in current_work
             package scheme;
            add new_work package scheme to potential_work package
             schemes;
        end
    end
    for each work package scheme in potential_work package schemes do
        (carbon emissions(cost), cost(carbon emissions)) ←
         evaluate_work package scheme(work package scheme);
        if carbon emissions(cost) ≤ baseline_carbon emissions(cost) and
         cost(carbon emissions) ¡ current_cost then
            update baseline_work package scheme, baseline_carbon
             emissions(cost), and current_cost;
        end
    end
    return (baseline_work package scheme, baseline_carbon
     emissions(cost), current_cost);
Function OptimizationLoop(input_work package scheme):
    optimized_work package scheme ← input_work package scheme;
    (carbon emissions(cost), cost(carbon emissions)) ← evaluate_work
     package scheme(input_work package scheme);
    repeat
        (new_work package scheme, new_carbon emissions(cost),
         new_cost) ← OptimizeWorkPackageScheme(optimized_work
         package scheme);
        update optimized_work package scheme, carbon emissions(cost),
         and cost(carbon emissions);
    until cost(carbon emissions) does not change;
    return (optimized_work package scheme, carbon emissions(cost),
     cost(carbon emissions));
```

Appendix II: Adaptation project case in Chapter 4

Task ID	Durations	The number of Successors	Successors
1	0	5	2 3 124 133 162
2	3	1	4
3	1	1	4
4	3	1	5
5	7	1	6
6	1	2	7 13
7	7	2	8 9
8	1	1	17
9	7	2	10 11
10	1	1	17
11	7	1	12
12	1	1	17
13	5	2	14 15
14	18	1	16
15	1	1	16
16	1	1	17
17	2	3	18 19 20
18	1	1	21
19	1	1	21
20	1	1	23
21	3	1	22
22	2	1	23
23	12	1	24
24	1	2	25 26
25	3	1	27
26	1	1	28
27	1	1	29
28	1	1	29
29	1	4	30 56 57 58
30	2	3	31 32 33
31	1	1	34
32	1	1	34
33	1	1	36
34	2	1	35
35	2	1	36
36	12	1	37
37	1	2	38 39
38	2	1	40

39	1	1	41
40	1	1	42
41	1	1	42
42	1	2	43 64
43	3	1	44
44	14	2	45 47
45	3	1	46
46	1	1	289
47	14	2	48 50
48	3	1	49
49	1	1	289
50	14	2	51 53
51	3	1	52
52	1	1	289
53	14	1	54
54	3	1	55
55	1	1	289
56	1	1	59
57	1	1	59
58	1	1	63
59	1	1	60
60	1	1	61
61	2	1	62
62	1	1	63
63	1	1	64
64	2	2	65 67
65	1	2	66 68
66	1	1	69
67	2	2	68 70
68	1	2	69 71
69	1	1	72
70	2	2	71 73
71	1	2	72 74
72	1	1	75
73	2	2	74 76
74	1	2	75 77
75	1	1	78
76	2	2	77 79
77	1	2	78 80
78	1	1	81
79	2	2	80 82
80	1	2	81 83
81	1	1	84

82	2	2	83 85
83	1	2	84 86
84	1	1	87
85	2	2	86 88
86	1	2	87 89
87	1	1	90
88	2	2	89 91
89	1	2	90 92
90	1	1	93
91	2	2	92 94
92	1	2	93 95
93	1	1	96
94	2	2	95 97
95	1	2	96 98
96	1	1	99
97	2	2	98 100
98	1	2	99 101
99	1	1	102
100	2	2	101 103
101	1	2	102 104
102	1	1	105
103	2	2	104 106
104	1	2	105 107
105	1	1	108
106	2	2	107 109
107	1	2	108 110
108	1	1	111
109	2	2	110 112
110	1	2	111 113
111	1	1	114
112	2	2	113 115
113	1	2	114 116
114	1	1	117
115	2	2	116 118
116	1	2	117 119
117	1	1	120
118	2	2	119 121
119	1	2	120 122
120	1	1	123
121	2	1	122
122	1	1	123
123	1	1	289
124	1	2	125 129

125	10	2	126 127
126	3	1	128
127	12	1	128
128	1	1	169
129	10	2	130 131
130	3	1	132
131	12	1	132
132	1	1	169
133	1	3	134 140 151
134	10	1	135
135	5	1	136
136	4	1	137
137	14	1	138
138	28	1	139
139	1	1	181
140	14	1	141
141	6	1	142
142	5	1	143
143	1	1	144
144	18	1	145
145	1	3	146 147 148
146	18	1	149
147	6	1	149
148	18	1	150
149	1	1	150
150	1	1	181
151	14	1	152
152	6	1	153
153	5	1	154
154	1	1	155
155	18	1	156
156	1	3	157 158 159
157	18	1	160
158	6	1	160
159	18	1	161
160	1	1	161
161	1	1	179
162	1	1	163
163	12	1	164
164	12	1	165
165	5	1	166
166	2	1	167
167	12	1	168

168	1	1	188
169	1	2	170 174
170	18	1	171
171	10	1	172
172	7	1	173
173	10	1	178
174	18	1	175
175	10	1	176
176	7	1	177
177	10	1	178
178	1	1	194
179	1	2	180 184
180	18	1	181
181	10	1	182
182	7	1	183
183	10	1	187
184	25	1	185
185	10	1	186
186	10	1	187
187	1	1	204
188	1	1	189
189	18	1	190
190	12	1	191
191	12	1	192
192	12	1	193
193	2	1	214
194	1	2	195 199
195	7	1	196
196	100	1	197
197	7	1	198
198	1	1	203
199	7	1	200
200	100	1	201
201	7	1	202
202	1	1	203
203	1	3	221 235 267
204	1	2	205 209
205	7	1	206
206	100	1	207
207	7	1	208
208	1	1	213
209	7	1	210
210	100	1	211

211	7	1	212
212	1	1	213
213	1	4	241 255 261 276
214	2	1	215
215	14	3	216 217 218
216	21	1	219
217	14	1	220
218	5	1	220
219	14	1	220
220	2	2	285 286
221	2	2	222 228
222	25	4	223 224 225 226
223	30	1	227
224	25	1	234
225	5	1	234
226	25	1	234
227	25	1	234
228	25	4	229 230 231 232
229	30	1	233
230	25	1	234
231	5	1	234
232	25	1	234
233	25	1	234
234	2	2	285 286
235	2	4	236 237 238 239
236	14	1	240
237	6	1	240
238	14	1	240
239	6	1	240
240	2	2	285 286
241	2	2	242 248
242	24	4	243 244 245 246
243	30	1	247
244	24	1	254
245	5	1	254
246	24	1	254
247	24	1	254
248	24	4	249 250 251 252
249	30	1	253
250	24	1	254
251	5	1	254
252	24	1	254
253	24	1	254

254	2	2	285 286
255	1	4	256 257 258 259
256	12	1	260
257	5	1	260
258	14	1	260
259	5	1	260
260	1	2	285 286
261	1	2	262 263
262	5	1	264
263	21	1	265
264	5	1	266
265	14	1	266
266	1	2	285 286
267	1	4	268 269 270 271
268	10	1	272
269	10	1	273
270	10	1	274
271	4	1	275
272	10	1	275
273	10	1	275
274	10	1	275
275	1	2	285 286
276	1	4	277 278 279 280
277	10	1	281
278	10	1	282
279	10	1	283
280	4	1	284
281	10	1	284
282	10	1	284
283	10	1	284
284	1	2	285 286
285	4	1	287
286	4	1	287
287	4	1	288
288	4	1	289
289	0	0	

Appendix III: Adaptation project case in Chapter 5

No.	Durations	The number of Successors	Successors
1	0	34	31 32 44 45 54 63 83 88 92 95 99 101 106 109 116 118 121 124 135 138 140 188 191 197 204 213 218 247 256 262 276 280 293 295
2	113	1	187
3	4	1	193
4	50	1	185
5	4	1	193
6	50	1	183
7	4	1	193
8	50	1	181
9	4	1	193
10	50	1	3
11	4	1	306
12	50	1	5
13	4	1	306
14	50	1	7
15	4	1	306
16	50	1	9
17	4	1	306
18	50	5	205 200 248 257 263
19	5	1	194
20	50	5	206 201 249 258 264
21	5	1	194
22	50	5	207 202 250 259 265
23	5	1	194
24	50	5	208 203 251 260 266
25	5	1	194
26	15	1	30
27	15	1	30
28	15	1	30
29	15	1	30
30	15	1	306
31	61	2	139 141
32	13	2	33 35
33	7	1	34
34	30	1	37

35	60	1	36
36	28	1	37
37	30	4	46 98 38 172
38	58	2	39 41
39	14	1	40
40	30	1	155
41	46	1	42
42	14	1	43
43	30	2	145 155
44	60	1	49
45	49	1	306
46	87	7	142 143 146 148 150 152 156
47	28	1	306
48	28	1	306
49	28	1	306
50	30	1	306
51	30	1	306
52	30	1	306
53	30	1	48
54	19	1	55
55	21	1	56
56	30	1	57
57	72	1	58
58	14	2	59 60
59	30	1	62
60	60	1	61
61	14	1	62
62	30	2	68 79
63	66	1	64
64	14	1	65
65	30	3	70 73 76
66	30	1	67
67	7	1	156
68	28	1	69
69	7	1	157
70	28	1	71

71	7	1	169
72	28	1	306
73	28	1	74
74	7	1	170
75	28	1	306
76	28	1	77
77	7	1	171
78	28	1	306
79	28	1	306
80	30	1	72
81	30	1	75
82	30	1	306
83	103	2	84 85
84	30	1	98
85	50	1	86
86	5	1	87
87	30	2	98 102
88	27	1	89
89	88	1	90
90	30	1	91
91	52	1	173
92	14	1	93
93	42	1	94
94	30	1	100
95	48	1	96
96	7	1	97
97	42	1	175
98	89	1	172
99	62	2	173 103
100	41	2	174 104
101	35	2	175 105
102	30	2	112 127
103	30	2	113 128
104	30	2	114 129
105	30	2	115 130
106	30	1	107
107	14	1	108
108	30	2	112 127
109	60	1	110
110	14	1	111
111	30	3	113 114 115

112	35	1	176
113	35	1	306
114	35	1	306
115	35	1	306
116	115	1	117
117	60	1	306
118	125	1	119
119	76	1	120
120	60	1	136
121	115	1	122
122	49	1	123
123	60	3	127 131 136
124	115	1	125
125	76	1	126
126	76	7	128 129 130 132 133 134 136
127	35	1	180
128	35	1	306
129	35	1	306
130	35	1	306
131	35	1	136
132	35	1	136
133	35	1	136
134	35	1	136
135	110	1	136
136	92	1	137
137	145	1	181
138	51	1	142
139	66	1	142
140	33	1	142
141	66	1	66
142	100	1	143
143	56	1	144
144	56	1	145
145	54	1	78
146	175	4	147 171 50 47
147	61	1	53
148	106	2	149 51
149	46	1	53
150	41	2	151 52
151	50	1	53
152	35	1	153
153	65	1	154
154	30	1	155

155	81	2	169 170
156	102	1	79
157	57	1	158
158	37	1	159
159	41	1	160
160	41	1	176
161	56	1	176
162	48	1	176
163	99	1	176
164	12	1	176
165	12	1	166
166	5	3	167 168 169
167	47	1	176
168	32	1	176
169	112	2	177 80
170	98	2	178 81
171	139	2	179 82
172	163	3	173 174 175
173	167	1	180
174	202	1	180
175	133	1	180
176	139	3	180 2 235
177	60	3	182 4 236
178	60	3	184 6 237
179	35	3	186 8 238
180	275	12	10 18 189 190 192 200 205 214 223 257 219 227
181	60	1	306
182	125	11	12 20 189 190 192 201 206 215 224 258 220
183	30	2	306 181
184	111	11	14 22 189 190 192 202 207 216 225 259 221
185	30	2	306 183
186	97	11	16 24 189 190 192 203 208 217 226 260 222
187	30	1	185
188	208	1	261
189	483	1	195
190	362	1	306
191	99	1	192
192	276	9	195 11 13 15 17 26 27 28 29
193	121	1	306
194	55	1	306
195	78	1	196

196	15	2	272 301
197	58	1	198
198	15	1	199
199	30	1	200
200	105	1	306
201	112	1	306
202	128	1	306
203	128	1	306
204	145	1	205
205	89	1	209
206	103	1	210
207	86	1	211
208	100	1	212
209	60	1	306
210	60	1	306
211	60	1	306
212	60	1	306
213	115	1	215
214	87	1	285
215	90	1	286
216	90	1	287
217	90	1	288
218	115	1	233
219	145	1	306
220	145	1	306
221	145	1	306
222	145	1	306
223	77	1	232
224	106	1	232
225	106	1	232
226	106	1	232
227	76	1	228
228	76	1	229
229	45	1	230
230	45	1	231
231	47	1	232
232	52	4	239 240 241 242
233	76	1	234
234	145	1	306
235	290	1	306
236	119	1	306
237	114	1	306
238	104	1	306

239	10	2	243 285
240	14	2	244 286
241	14	2	245 287
242	14	2	246 288
243	14	1	306
244	14	1	306
245	14	1	306
246	14	1	306
247	106	1	248
248	89	1	252
249	88	1	253
250	92	1	254
251	85	1	255
252	30	1	306
253	30	1	306
254	30	1	306
255	30	1	306
256	145	1	257
257	104	1	306
258	88	1	306
259	92	1	306
260	85	1	306
261	77	3	273 274 275
262	91	1	263
263	104	1	268
264	88	1	269
265	92	1	270
266	85	1	267
267	60	1	271
268	30	1	298
269	30	1	298
270	30	1	298
271	30	1	298
272	44	1	306
273	30	1	301
274	30	1	301
275	30	1	301
276	115	1	277
277	30	1	278
278	145	1	279
279	106	1	283
280	115	1	281
281	30	1	282

282	145	1	306
283	106	1	306
284	148	1	306
285	14	1	289
286	14	1	290
287	14	1	291
288	14	1	292
289	14	1	19
290	14	1	21
291	14	1	23
292	14	1	25
293	15	1	294
294	45	1	306
295	14	1	296
296	60	1	297
297	14	1	301
298	14	1	299
299	60	1	300
300	14	1	302
301	54	1	302
302	77	1	303
303	30	1	304
304	30	1	305
305	30	1	284
306	0		

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