



BIM-Integrated Metaheuristic Approach for Multi-Objective Optimization of Large-Scale Construction Projects

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ABSTRACT:

Building Information Modeling (BIM) has become an essential platform for managing construction information; however, its integration with intelligent optimization techniques for simultaneous project planning and structural design remains limited. This study proposes a comprehensive data-driven framework integrating BIM with Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to optimize construction planning, resource allocation, scheduling, and structural design in large-scale building projects. A six-story case-study building located in Sahand New Town, Tabriz, was modeled in Autodesk Revit, and project information including geometry, material quantities, costs, schedules, and resources was extracted directly from the BIM model. The extracted data were linked to multi-objective optimization models through Revit API, Dynamo, and Python-based computational tools. The optimization simultaneously minimized construction cost, project duration, structural weight, material consumption, and embodied carbon emissions while satisfying structural and constructability constraints. Results demonstrated that the proposed framework successfully generated feasible Pareto-optimal solutions and selected a balanced structural configuration with a total material cost of IRR 95142270000, structural steel weight of 56.34 tons, embodied carbon emissions of 135,504kgCO₂e, and a construction duration of 16.5 days. Compared with the baseline design, the optimized solution reduced structural cost by 3.04%, steel consumption by 3.52%, embodied carbon emissions by 2.74%, project duration by 10.81%, and execution risk by 10%, while increasing resource productivity by 12.82% without violating engineering constraints. The findings demonstrate that integrating BIM with metaheuristic optimization algorithms provides an effective intelligent decision-support framework capable of improving economic performance, construction efficiency, structural sustainability, and resource management in complex construction projects.

KEYWORDS:

Building information modeling, Genetic algorithm, Particle swarm optimization, Revit, Multi-Objective Optimization.

1. Introduction

Large-scale construction projects, due to their inherent complexity, resource constraints, and the

presence of conflicting objectives such as reducing time and cost while enhancing quality, safety, and sustainability, require advanced management and decision-making approaches. In recent years, Building Information Modeling (BIM) has emerged

as a modern technology that enables integrated data management and improves coordination among project stakeholders. At the same time, metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and NSGA-II (Non-dominated Sorting Genetic Algorithm II) have been widely applied in construction optimization due to their capability to solve complex and multi-objective problems. The integration of BIM capabilities with the computational power of these algorithms can provide an effective framework for the simultaneous optimization of key project performance indicators, including time, cost, quality, resource efficiency, and sustainability. Accordingly, this study aims to develop an integrated BIM–Metaheuristic framework to enhance planning and execution processes in construction projects and to provide intelligent decision-making solutions in complex construction environments.

Success in construction projects is no longer defined solely by completing a project within the predetermined time and budget. Rather, it encompasses a comprehensive set of performance criteria, including construction quality, resource productivity, safety, environmental sustainability, energy efficiency, and risk management. Consequently, identifying and prioritizing these performance criteria as the fundamental basis for project evaluation plays a critical role in the development of optimization models. A review of the existing literature indicates that most previous studies have focused on a limited number of performance indicators, while the integrated consideration of multiple project objectives has received comparatively little attention. This highlights both theoretical and practical gaps in the field of intelligent construction project management and underscores the need to formulate research questions and develop comprehensive decision-support frameworks. In this context, the identification of Key Performance Indicators (KPIs) as objective measures for evaluating the effectiveness of the proposed framework provides a robust basis for accurately assessing project performance improvements and systematically comparing alternative optimization strategies.

Xu and Wei (2015) developed a multi-objective optimization model integrating Building Information Modeling (BIM) with a (GA) to achieve an optimal balance among project time, cost, and quality. Project information was extracted directly from the BIM model, and integrated objective functions were formulated to support construction project management. The case study demonstrated that the proposed BIM–GA framework effectively generated optimal time-cost-quality trade-off solutions, thereby improving the efficiency and reliability of managerial decision-making.

Fardmoradinia and Khademi (2018) addressed the Resource-Constrained Project Scheduling Problem (RCPSP) using GA. The proposed approach was evaluated using standard PSPLIB benchmark instances and a real construction project comprising 29 activities and four limited resources, with the objective of minimizing project duration. The results showed that GA reduced the project completion time to 245 days, produced results comparable to those obtained using Microsoft Project, and demonstrated higher computational efficiency and suitability for large-scale and complex construction projects.

He et al. (2019) proposed a five-dimensional BIM-based framework integrated with GA for the simultaneous optimization of project time and cost. In their approach, GA was employed to generate Pareto-optimal solutions, while BIM was used to simulate construction processes and evaluate the constructability of alternative execution scenarios. The findings indicated that the integration of BIM and GA can accelerate decision-making related to scheduling and cost management while improving construction planning through dynamic and visual project simulation.

Hamidavi, Abrishami, and Hosseini (2020) proposed an intelligent BIM-based framework for the automated structural design of high-rise buildings. Their model automatically generated, updated, and optimized multiple structural alternatives by extracting information directly from architectural BIM models. The case study showed that the proposed approach significantly improved coordination between architects and structural engineers and enabled the generation of optimized structural designs with greater efficiency and reduced design time.

In 2021, several studies further expanded the application of BIM and evolutionary optimization in construction management. Nusen et al. (2021) investigated resource utilization optimization in large-scale building renovation projects using GA. They developed a model based on the resource fluctuation index M_x , which enabled multi-objective optimization of scheduling and resource allocation. Application of the model to a real project consisting of 251 activities showed that objective functions based on M_x and $M_x/1000M_x/1000M_x/1000$ were effective in reducing resource fluctuations and improving scheduling efficiency.

In another study, Nusen et al. (2021) employed BIM and a Multi-Objective Genetic Algorithm (MOGA) to optimize planning and scheduling in renovation projects. Using real project data, the proposed model simultaneously optimized cost, time, and resource allocation and generated 70 Pareto-optimal solutions after 500 generations. The findings confirmed that integrating BIM with multi-objective evolutionary algorithms can support

project decision-making, planning, and resource management.

Zhao and Chen (2021) also presented a multi-objective construction optimization framework integrating BIM and GA. Construction time, cost, quality, and safety were simultaneously optimized, while BIM capabilities such as virtual construction and clash detection were used to manage complex project conditions. Their results demonstrated that the proposed integration can improve project scheduling, enhance resource efficiency, and reduce construction costs.

Feng and Haihe (2022) proposed a BIM-based construction progress optimization system integrated with GA to simultaneously optimize time, cost, and quality. The study developed a two-stage approach comprising a time–cost trade-off model and a resource-leveling model under a fixed project duration. The results showed that the BIM–GA integration could determine optimal activity durations and start times for non-critical activities, reduce project costs, and improve resource balance.

Baghalzadeh Shishehgharkhaneh et al. (2022) investigated the simultaneous optimization of time, cost, quality, and risk in dam construction projects using BIM and several metaheuristic algorithms. Five algorithms, including GA, Simulated Annealing, Black Widow Optimization, Royal Battle Optimization, and Black Hole Mechanics, were evaluated using the Qucham Reservoir Dam as a case study. Although several algorithms performed satisfactorily under particular scenarios, GA consistently produced the most balanced results across the four optimization objectives.

Espoutin and Fardmoradina (2022) similarly investigated the simultaneous optimization of project time, cost, quality, and risk in the Qucham Reservoir Dam project. Six algorithms, including GA, Tabu Search, Simulated Annealing, Butterfly Optimization Algorithm, Cyclical Parthenogenesis Algorithm, and Harris Hawks Optimization, were evaluated based on project performance indicators. The results indicated that GA achieved the best quality-optimization performance and, together with Harris Hawks Optimization, generated the most efficient solutions for simultaneous multi-objective optimization.

Lao et al. (2023) proposed a BIM-based framework for optimizing prefabricated buildings with emphasis on constructability, cost efficiency, and standardization. Information on prefabricated components was extracted from the BIM model, while component dimensions and reinforcement layouts were optimized using the Optimality Criteria method and a hybrid NSGA-II–Great Deluge algorithm. The findings revealed an optimal trade-off between construction cost and standardization and showed that the proposed hybrid algorithm outperformed conventional optimization methods

in convergence rate, computational efficiency, and search performance.

Yu et al. (2023) integrated BIM with GA to develop a dynamic time–cost optimization model for large and deep excavation projects. BIM was used to extract project data, while time-dependent financial value and a reward–penalty mechanism for delays were incorporated into the optimization process. Compared with static methods, the proposed model reduced total project cost by 1.68% and improved project duration by 8.47%, confirming its effectiveness for managing time and cost in complex civil engineering projects.

Baghalzadeh Shishehgharkhaneh et al. (2023) examined the evolution and applications of blockchain technology in the construction industry through a systematic literature review and bibliometric analysis of 482 publications. The study identified major application areas, including supply-chain management, smart contracts, sustainability, BIM, the Internet of Things, and energy efficiency. The findings highlighted the potential of blockchain to improve transparency, data sharing, stakeholder collaboration, and overall project performance and identified circular economy, risk management, and infrastructure projects as promising areas for future research.

Luong et al. (2024) developed an integrated framework combining BIM, Building Energy Modeling, and the Jellyfish Search optimization algorithm to simultaneously optimize building energy consumption and installation costs. Using EnergyPlus and a real-world case study, the framework identified the optimal thermal insulation configuration, resulting in a 10.7% reduction in total construction cost and a decrease of 65 kWh/m²/year in Energy Use Intensity. The findings demonstrated the contribution of BIM-based multi-objective optimization to sustainable building design and performance improvement.

Wefki et al. (2024) proposed an integrated framework combining BIM, GA, 5D simulation, and Business Intelligence dashboards for generating and optimizing construction schedules. Scheduling data were automatically extracted from BIM and optimized through GA, after which the results were visualized using 5D simulation and managerial dashboards. The case study demonstrated improvements in project productivity, planning intelligence, and integration between project management and engineering functions.

Bakhshi et al. (2024) integrated Earned Value Management with hybrid artificial intelligence algorithms to predict project completion time and cost in dam construction projects. Several hybrid models, including LSSVM–PSO and LSSVM–GA, were developed and evaluated using real data from five dam projects. The results showed that the LSSVM–PSO model achieved the highest prediction accuracy for project completion time and outperformed the

probabilistic Kalman Filter, indicating its effectiveness for time and cost forecasting and control.

Padala (2025) proposed a BIM-based framework integrated with the NSGA-III multi-objective optimization algorithm to enhance sustainability in construction projects. The model simultaneously minimized embodied energy and construction cost and was evaluated using a commercial building case study. The results demonstrated reductions of 30% in embodied energy and 21% in construction costs, highlighting the framework's effectiveness as a decision-support tool for sustainable design and construction.

Zhang (2025) introduced an intelligent BIM-based framework for the multi-objective optimization of assembly processes in prefabricated buildings. The framework combined BIM semantic modeling, Multi-Objective Particle Swarm Optimization, and Deep Q-Network-based reinforcement learning to generate optimal execution plans with respect to project duration, construction cost, and resource conflicts. The proposed model outperformed conventional approaches, NSGA-II, and conventional MOPSO in convergence speed, solution diversity, and objective-space coverage.

Bian (2025) developed a generic and reusable BIM-based framework employing NSGA-III for the multi-objective optimization of building components. By connecting IFC-based component data to an optimization engine, the framework simultaneously evaluated construction cost, embodied carbon, and project duration while automating the decision-making process. The case study generated diverse and interpretable Pareto-optimal solutions and improved cost, carbon emissions, and construction duration by optimizing prefabrication rates and substituting low-carbon materials.

Kaurav and Sharma (2025) proposed a hybrid decision-support framework integrating the Analytic Hierarchy Process and an opposition-based learning-enhanced NSGA-III algorithm to balance project time, cost, and quality. The Analytic Hierarchy Process was used to determine the relative importance of activities and quality indicators, while the optimization algorithm generated Pareto-optimal solutions. Comparisons with MOPSO, Multi-Objective Ant Colony Optimization, and LHS-NSGA-III showed that the proposed model achieved better convergence, solution diversity, and Pareto-front quality.

Shams and Marzouk (2026) developed a BIM-based framework for evaluating leading safety indicators and simultaneously optimizing project

time, cost, and safety. NSGA-II was used to generate optimal solutions, and safety-risk levels during project execution were visualized through a three-dimensional heat map. The results demonstrated that integrating BIM, time-cost-safety trade-off analysis, and multi-criteria decision-making tools can facilitate proactive risk management and improve construction decision-making.

Finally, Wang et al. (2026) compared five multi-objective metaheuristic algorithms AGE-MOEA, AGE-MOEA-II, NSGA-II, NSGA-III, and MOPSO for optimizing the layout of multiple tower cranes. The objectives were to minimize safety risks and maximize crane operational coverage. Although MOPSO exhibited faster computational performance, it produced lower-quality solutions than the other methods. In contrast, NSGA- and AGE-based evolutionary algorithms demonstrated stronger performance in generating balanced and efficient Pareto-optimal solutions.

Information Modeling (BIM) with metaheuristic algorithms has attracted increasing scholarly attention in recent years as an advanced approach to the management and optimization of construction projects. Existing studies have demonstrated the effectiveness of BIM-assisted optimization for improving individual project performance indicators, including structural design, activity scheduling, cost reduction, sustainability assessment, energy efficiency, and resource allocation. However, as summarized in Table (1), most previous research has focused on optimizing one or a limited number of project objectives, while comparatively few studies have proposed a comprehensive framework capable of simultaneously addressing multiple engineering, managerial, economic, and environmental aspects of construction projects. Furthermore, in many existing studies, BIM has primarily been utilized as a platform for three-dimensional modeling or geometric data extraction, whereas its potential to establish a bidirectional data flow between the BIM environment and intelligent optimization engines has not been fully exploited. Consequently, there remains a significant research gap in the development of an integrated decision-support framework that combines BIM-based information management with intelligent optimization techniques to simultaneously evaluate structural design, construction scheduling, resource allocation, project cost, embodied carbon emissions, execution risk, and Key Performance Indicators (KPIs) throughout the project lifecycle.

Table 1. Comparison of the Proposed BIM–Metaheuristic Framework with Recent Related Studies

Structural Design Optimization	Main Optimization Objectives	Optimization Method	BIM Integration	Study
Limited to sustainable building design variables	Construction cost and embodied energy	NSGA-III	Yes	Padala (2025)
Mainly focused on prefabricated assembly-process planning	Assembly duration, construction cost, and resource conflicts	MOPSO combined with DQN-based reinforcement learning	Yes, through semantic BIM modeling	Zhang (2025)
No	Schedule generation, project duration, and project cost	Genetic Algorithm	Yes	Wefki et al. (2024)
No	Operational energy consumption and installation cost	Jellyfish Search Optimization	Yes, integrated with BEM	Luong et al. (2024)
No	Dynamic time–cost optimization	Genetic Algorithm	Yes	Yu et al. (2023)
Yes, mainly for precast components and reinforcement layouts	Constructability, cost, and standardization	Hybrid NSGA-II–GD and Optimality Criteria	Yes	Lao et al. (2023)
No	Project duration and cost	Genetic Algorithm	Yes, 5D BIM	He et al. (2019)

To address this gap, the present study proposes an integrated BIM-based optimization framework that combines (GA) and (PSO) within a unified computational environment. In the proposed framework, project information including geometric, structural, scheduling, material, cost, and resource data is automatically extracted from BIM models and transferred to intelligent optimization modules through a structured data exchange process. GA is employed to optimize construction scheduling and resource allocation, whereas PSO is utilized to optimize structural design variables. The optimized results are subsequently fed back into the BIM environment, enabling continuous evaluation and visualization of project performance. Unlike previous studies, the proposed framework simultaneously considers project duration, cost, structural weight, material consumption, embodied carbon, execution risk, resource productivity, and KPI-based performance assessment within a single decision-support platform. Therefore, the principal contribution of this research lies not merely in applying GA or PSO independently, but in integrating their complementary capabilities with BIM to establish a comprehensive, bidirectional, and data-driven framework for intelligent decision-making throughout the entire construction project lifecycle.

The primary contribution of this research is the development of a unified BIM-driven optimization framework that integrates Building Information Modeling with (GA) and (PSO) to support multi-objective decision-making in construction projects. In contrast to previous studies that generally optimize a limited number of project parameters or address individual project phases separately, the proposed framework simultaneously considers construction cost, project duration, structural material consumption, embodied carbon emissions, resource productivity, and execution risk within a single integrated environment. This holistic integration enables more comprehensive

and practical project optimization while providing continuous feedback between the BIM model and the optimization engine.

2. Materials and Methods

2.1. Components of the Integrated BIM–Metaheuristic Framework

The development of the proposed framework requires the systematic identification and definition of its core components, including BIM-derived data, decision variables, objective functions, constraints, and optimization algorithms, in order to establish a robust foundation for multi-objective analysis and decision-making. The primary objective of this stage is to develop a coherent framework for data exchange, information analysis, and optimization within construction projects. Building Information Modeling (BIM) was selected as the core platform of the proposed framework because it provides an integrated digital environment capable of managing and coordinating heterogeneous project information throughout the entire project lifecycle. Unlike conventional project management tools that handle scheduling, cost estimation, and design separately, BIM enables the centralized integration of geometric, temporal, cost-related, resource, and technical information within a unified data environment. This capability makes BIM an appropriate foundation for supporting data-driven optimization and intelligent decision-making.

In the proposed framework, Building Information Modeling (BIM) serves as the central platform for project information management and integration, providing comprehensive access to geometric, temporal, cost-related, resource, technical, and performance data throughout the project lifecycle. These data can be extracted from three-dimensional (3D) models, construction scheduling (4D), cost estimation (5D),

sustainability analysis (6D), and facility management (7D) models, thereby creating a comprehensive digital representation of the project. The optimization component of the framework employs metaheuristic algorithms including the (GA), (PSO), (ACO), and (NSGA-II) as the intelligent decision-making engine. Using the information extracted from the BIM model, these algorithms analyze key project decision variables, including activity sequencing, resource allocation, construction scheduling, construction method selection, and equipment assignment. By exploring thousands of feasible alternatives, the algorithms search the solution space to identify optimal solutions under multiple competing objectives. The optimization process simultaneously considers conflicting project objectives, such as minimizing project duration, construction cost, energy consumption, and project risk while maximizing construction quality and resource productivity. Rather than producing a single solution, the framework generates a set of Pareto-optimal solutions, enabling project stakeholders to evaluate trade-offs among different performance criteria and select the most appropriate alternative according to project priorities. Within the proposed framework, BIM functions as both an intelligent project database and a digital simulation environment, whereas the metaheuristic algorithms perform the optimization and search for optimal decision alternatives. The optimization results are subsequently fed back into the BIM environment, where they can be visualized, analyzed, and compared through interactive project models. This bidirectional integration between BIM and metaheuristic optimization algorithms establishes a comprehensive data-driven decision-support framework that reduces uncertainty, enhances planning accuracy, improves resource utilization, and ultimately increases the overall performance of large-scale construction projects.

2.2. Modeling the Relationships Between BIM Data and Decision Variables (Resources, Scheduling, and Structural Design)

Following the definition of the components of the integrated framework, it is essential to accurately model the relationships between the data extracted from the BIM environment and the decision variables employed in the optimization

process. At this stage, the information available within the BIM model including the geometric properties of structural components, material quantities and volumes, construction activity sequences, activity durations, cost information, equipment specifications, and human resource data is considered the primary input to the optimization system. These data form the basis for defining the decision variables, which include resource allocation strategies, construction scheduling, selection of construction methods, workforce assignment, equipment allocation, and, where applicable, structural design alternatives. The relationships between BIM-derived data and the decision variables are modeled in such a way that any modification to the decision variables is directly reflected in key project performance indicators, including project duration, construction cost, quality, energy consumption, and sustainability. For example, increasing the number of construction crews may reduce the overall project duration but simultaneously increase labor costs and resource consumption. Similarly, selecting a lighter structural design alternative can reduce material costs and embodied carbon emissions, although it may also influence construction duration or structural performance. Consequently, the BIM model functions as a dynamic information repository that provides the data required to analyze these interdependencies and enables the evaluation of alternative project scenarios within the optimization environment. In the proposed framework, the relationships between BIM data and decision variables are formulated through mathematical objective functions, engineering constraints, and logical decision rules. These relationships enable the metaheuristic optimization algorithms to evaluate the impact of each decision on multiple project objectives and to identify the optimal combination of decision variables for obtaining Pareto-optimal solutions. Therefore, the integration of BIM and optimization models establishes a robust data-driven decision-support framework that facilitates intelligent decision-making, reduces uncertainty, and enhances the efficiency and performance of large-scale construction projects. Table 2 presents the relationships between the data extracted from BIM/Microsoft Project (MSP), the corresponding decision variables, and the optimization objectives for the individual building blocks of the Mehrsan project.

Table 2. Summary of the Relationships between BIM/MSP-Extracted Data, Decision Variables, Project Execution Duration, and Optimization Objectives for the Mehrsan Project Building Blocks

Optimization Objectives	Decision Variables	Data Extracted from BIM/MSP	Block Duration (Days)	Block
Minimize project duration, minimize cost, maximize resource productivity	Activity scheduling, workforce allocation, material procurement planning	Material quantities, construction activities, project duration, resource allocation	513	A1
Minimize cost, reduce delays, improve quality	Number of construction crews, material ordering schedule, construction method	Structural work quantities, material procurement schedule, activity sequence	489	A2
Minimize project duration, improve quality, reduce rework	Equipment allocation and workforce assignment	Concrete and reinforcement quantities, structural and architectural construction duration	321	A3
Minimize project duration, reduce execution conflicts	Activity overlap strategy, resource allocation	Construction and MEP activities, required resources	345	A4
Minimize project duration, cost, and delay risk	Material procurement timing, number of construction crews, activity sequencing	Block execution duration, material procurement time, construction operations, finishing activities	369	A5
Minimize cost and project duration	Structural execution and procurement planning	Construction material quantities, foundation and structural operations	465	B1
Minimize cost and improve quality	Resource allocation and activity scheduling	Structural, architectural, and MEP activities	441	B2
Minimize project duration and maximize resource productivity	Number of construction teams, procurement scheduling	Construction execution data, resource consumption, activity durations	417	B3
Minimize project duration, reduce project risk, and improve quality	Equipment mobilization schedule, sequencing of finishing operations	Building finishing information, façade, MEP systems, and equipment	393	B4
Minimize project duration, project cost, and carbon emissions while maximizing quality and resource productivity	Resource allocation, activity scheduling, construction methods, and material procurement scheduling	Geometric, scheduling, cost, workforce, equipment, and material data extracted from BIM and Microsoft Project (MSP)	1.017	Entire Project

2.3. Development of a Data-Driven Framework for Integrating BIM and Intelligent Optimization Algorithms

The primary objective of the first subsystem is to establish a data-driven workflow that connects information extracted from the BIM model such as Autodesk Revit models or Industry Foundation Classes (IFC) files to an intelligent optimization engine. At this stage, BIM data, including the geometric properties of building components, material quantities, work volumes, construction schedules, execution costs, human resources, equipment, and structural design information, are extracted and transformed into a computationally compatible format suitable for processing by metaheuristic optimization algorithms. This data exchange can be achieved through the Revit API, IFC exports, Excel/CSV files, or an intermediate database. Subsequently, the raw BIM data are cleaned, classified, and standardized before being converted into decision variables and input parameters for the optimization model. The information exchange between BIM and the optimization engine follows a bidirectional workflow. In the first stage, project information, including geometric properties, material quantities, construction schedules, resource data, and cost information, is extracted from the BIM model and

transformed into optimization variables. The optimization algorithms subsequently evaluate numerous feasible alternatives and identify Pareto-optimal solutions according to the predefined objective functions and constraints. Finally, the optimized decision variables including updated construction schedules, resource allocations, structural member dimensions, and material quantities are transferred back to the BIM environment. This feedback process enables the BIM model to be automatically updated and provides project stakeholders with a digital representation of the optimized project configuration for visualization, performance assessment, and informed decision-making.

This enables optimization algorithms such as the (GA), (PSO), (NSGA-II), and (MOPSO) to evaluate alternative scenarios for project planning, resource allocation, construction scheduling, and construction method selection. Consequently, this subsystem serves as the interface between the Building Information Model and the computational optimization engine, ensuring that decision-making in construction projects is based on accurate, structured, traceable, and data-driven information. Fig. 1 illustrates a representative floor plan of the project developed in the Autodesk Revit environment, which served as the primary source for extracting geometric information, material quantities, and construction activity data. Fig. 2 and

Fig. 3 present the parking-level plans modeled in Revit, from which information related to the foundation system, structural columns, and construction constraints was extracted for use in the optimization framework.



Fig. 1. Typical Floor Plan of the Mehrsan Project Developed in the Autodesk Revit Environment



Fig. 2. Ground Floor Parking Plan of the Mehrsan Project in the Autodesk Revit Environment

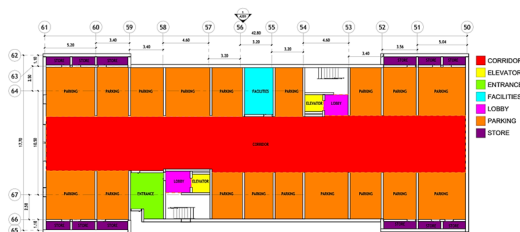


Fig. 3. Basement Level -1 Parking Plan of the Mehrsan Project in the Autodesk Revit Environment

In the proposed framework, the optimization process simultaneously considers multiple performance indicators, including construction cost, structural weight, material consumption, project duration, and embodied carbon emissions. The required data for these indicators are extracted directly from the BIM model, standardized, and subsequently transferred to the optimization

algorithms. During each optimization iteration, the candidate solutions are evaluated against all objective functions while satisfying structural and constructability constraints. This integrated workflow enables the generation of Pareto-optimal solutions that support informed decision-making throughout the project lifecycle.

2.4. Extraction of Required Project Data (Cost, Time, Materials, and Resources)

One of the most critical stages in developing the proposed data-driven framework integrating Building Information Modeling (BIM) and intelligent optimization algorithms is the extraction of project data from the Building Information Model. During this stage, all information required for project analysis, simulation, and optimization is identified and extracted from BIM platforms such as Autodesk Revit or from standardized Industry Foundation Classes (IFC) files. These data include project costs, scheduling information, material quantities, human resources, equipment, and the technical specifications of building components, which collectively constitute the primary input to the optimization engine. From the cost perspective, information such as material costs, labor costs, equipment costs, transportation costs, and construction execution costs is extracted to enable the economic evaluation of alternative project scenarios. Regarding project scheduling, data related to activity durations, precedence relationships, the critical path, and the overall project schedule are obtained from the BIM-based 4D model. Furthermore, material-related information including material types, required quantities, weights, volumes, and technical properties of individual building components is extracted for use in cost estimation, energy consumption analysis, and embodied carbon assessment. In addition, resource-related data, including workforce size, labor skills, construction equipment, machinery, and project execution capacities, are collected to support resource planning and optimization. Following extraction, all project data are stored, structured, and standardized within a centralized database to ensure their compatibility with intelligent optimization algorithms. This data management process enables the optimization engine to evaluate multiple project scenarios using actual BIM-derived information and to identify the optimal combination of resource allocation, construction scheduling, and execution strategies required to achieve the project's objectives. The BIM-extracted project data used in the proposed optimization framework are presented in Table 3.

Table 3. Data Extracted from the Building Information Model (BIM)

Information Extracted from the BIM Model	Data Category
Member length, width, and height; component area and volume; number of stories; dimensions of beams, columns, slabs, shear walls, and foundations	Geometric Information
Concrete volume, reinforcement weight, steel grade, concrete compressive strength, material specifications, and material quantities for each structural element	Structural Material Data
Structural element type, element ID, design specifications, design strengths, concrete class, and reinforcement detailing	Component Technical Specifications
Activity durations, start and finish dates, predecessor relationships, construction sequence, critical path, and project progress percentage	Scheduling Information (4D BIM)
Concrete cost, reinforcement cost, formwork cost, labor cost, equipment cost, transportation cost, and total cost of each activity	Cost Information (5D BIM)
Number of construction crews, number of skilled and semi-skilled workers, workforce specialties, working hours, and labor productivity	Human Resources
Equipment type, machinery capacity, operating hours, utilization rate, and rental or depreciation cost	Equipment and Machinery
Component locations, work zones, access routes, construction constraints, equipment layout, and material storage locations	Project Spatial Information
Quality control specifications, concrete test results, construction quality indicators, and technical and code compliance requirements	Quality Data
Energy consumption, material CO ₂ emission factors, construction waste generation, and sustainability indicators	Environmental Data
High-risk work zones, required safety equipment, construction constraints, and HSE (Health, Safety, and Environment) requirements	Safety Data
Cumulative project cost, physical progress, resource productivity, schedule and cost variances, and project performance indices (SPI and CPI)	Project Performance Indicators (KPIs)

2.5. Implementation of the Genetic Algorithm for Resource Planning Optimization

Following the extraction of project data from the BIM environment, the (GA) is employed as the intelligent search engine for optimizing project resource planning. The primary objective of this stage is to determine the optimal allocation of human resources, equipment, machinery, and construction materials to project activities while simultaneously achieving multiple objectives, including minimizing project duration and cost, maximizing resource utilization, and reducing

construction risks. In the proposed approach, each candidate solution is represented as a chromosome, whose genes encode the allocation of resources to individual project activities. The BIM-derived data including work quantities, activity durations, equipment capacities, workforce availability, and construction constraints serve as the input parameters for the optimization process. Subsequently, an initial population of candidate solutions is generated, and the quality of each solution is evaluated using a fitness function. This function is typically formulated based on key project performance criteria, including total project duration, construction cost, resource utilization efficiency, the number of execution conflicts, and the overall project risk level. Through the application of the genetic operators of selection, crossover, and mutation, successive generations of candidate solutions are produced, allowing the search process to progressively converge toward superior solutions. The evolutionary process continues until a predefined stopping criterion such as reaching a maximum number of generations or the absence of further improvement in solution quality is satisfied. At the end of the optimization process, the Genetic Algorithm identifies the optimal resource allocation scenario, which may include the optimal workforce size, equipment utilization schedule, resource distribution among project activities, and the overall construction execution plan. These optimization results are then transferred back to the BIM environment, where the optimized schedule and cost plan are visualized through 4D and 5D BIM models. Consequently, an intelligent, data-driven framework is established for resource planning, project decision-making, and construction management.

Fig. 4 illustrates the integrated workflow between Building Information Modeling (BIM) and the (GA) for resource planning optimization in construction projects. In the first stage, project information including building geometry, material quantities, construction activities, project costs, human resources, equipment, and construction constraints is extracted from the BIM environment (Autodesk Revit or IFC files) and stored in a standardized project database. The extracted information is subsequently transformed into decision variables and input parameters for the Genetic Algorithm. During the optimization stage, an initial population of candidate solutions is generated and iteratively evolved through the genetic operators of selection, crossover, and mutation. Each candidate solution is evaluated using a fitness function based on project duration, construction cost, resource utilization, and execution risk. The evolutionary process continues until the predefined stopping criterion is achieved, after which the optimal solution is identified. The optimization outputs including the optimized construction schedule, optimal resource allocation,

reduced project cost, and improved project performance are then transferred back to the BIM environment and visualized through 4D and 5D BIM models to support project managers in decision-making. In addition, the algorithm convergence curve illustrates the evolutionary search process and demonstrates the progressive convergence toward the optimal solution across successive generations.

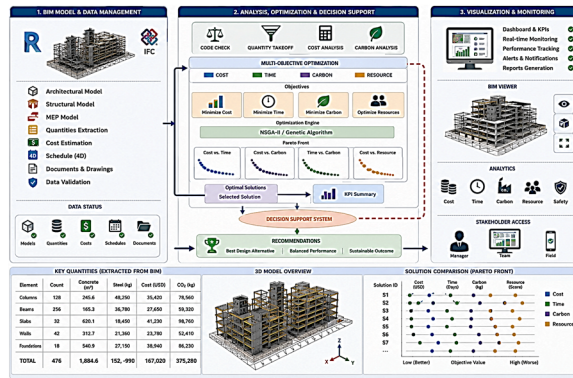


Fig. 5. Integrated BIM-Genetic Algorithm Framework for Data Extraction, Resource Planning Optimization, and Feedback of Optimized Results to the BIM Environment

2.6. Implementation of (PSO) for Structural Design Optimization

At this stage, the (PSO) algorithm is employed to achieve the optimal structural design of the building. The primary objective of the algorithm is to identify the optimal combination of structural design variables including member dimensions, beam and column cross-sections, slab thickness, material properties, and geometric parameters while simultaneously satisfying design code requirements and engineering constraints and minimizing structural weight, construction cost, material consumption, and environmental impacts. In the PSO framework, each particle represents a candidate structural design composed of a set of structural design variables. The optimization process begins by generating an initial swarm of candidate structural designs. Each particle possesses a position and velocity within the design search space, and its position is iteratively updated according to two fundamental concepts: the particle's Personal Best (Pbest) solution and the swarm's Global Best (Gbest) solution. The performance of each candidate design is evaluated using an objective function that may include minimizing structural weight, total construction cost, steel and concrete consumption, structural displacements, energy consumption, and embodied carbon emissions. Simultaneously, structural design constraints including member strength, stress limitations, allowable deflection, structural stability, and compliance with relevant design codes

are incorporated into the evaluation process. Within the proposed integrated BIM framework, the geometric information and structural properties of building components are extracted directly from the BIM model and transferred to the PSO optimization engine. By exploring thousands of alternative combinations of design variables, the algorithm gradually converges toward the most promising regions of the search space and ultimately identifies the optimal structural design or a set of Pareto-optimal design alternatives. The optimization outputs may include optimized member dimensions, reduced structural weight, lower material costs, improved seismic performance, and enhanced project sustainability. These optimized results are subsequently transferred back to the BIM environment and visualized within the three-dimensional model, enabling engineers to compare alternative design solutions and support informed engineering decision-making. Fig. 5 illustrates the integrated workflow between Building Information Modeling (BIM) and the Particle (PSO) algorithm for the optimal structural design of a six-story reinforced concrete building. In the first stage, geometric information, structural member properties, material characteristics, loading conditions, and the lateral load-resisting system are extracted from the BIM model developed in Autodesk Revit or imported through an IFC file. Subsequently, the principal design variables including beam and column dimensions, slab thickness, concrete compressive strength, reinforcement ratio, and the type of lateral structural system are defined and transferred to the PSO optimization engine. The PSO algorithm explores the structural design space by iteratively updating particle positions based on the concepts of Personal Best (Pbest) and Global Best (Gbest). Candidate solutions are evaluated using a multi-objective optimization framework aimed at minimizing construction cost, structural weight, material consumption, project duration, and embodied carbon emissions. At the same time, structural code requirements including flexural, shear, and axial resistance, inter-story drift limitations, deflection limits, and reinforcement detailing requirements are verified to ensure the feasibility of each design alternative. After convergence of the optimization process, the optimal structural design is selected, providing improvements such as reduced structural weight, lower construction cost, decreased material consumption, and enhanced structural performance. The optimized solution is then transferred back to the BIM environment, where it is visualized through 3D, 4D, and 5D BIM models to facilitate engineering analysis, comparison of alternative design scenarios, construction planning, and decision support for project managers. Furthermore, the lower section of Fig. 5 demonstrates the direct relationship between the

optimized structural model and the architectural and structural floor plans of the case-study project, highlighting that the entire optimization process is performed using actual project data extracted directly from the BIM model rather than hypothetical or synthetic datasets.

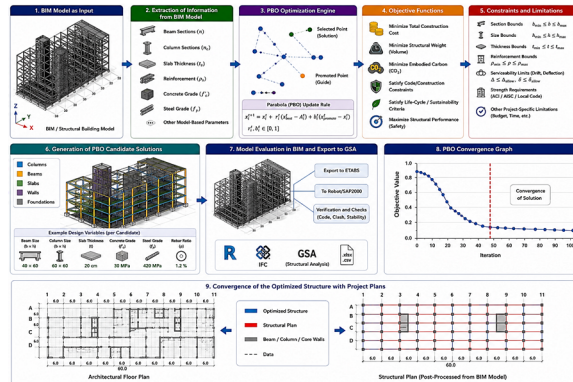


Fig. 5. Integrated BIM-Particle Swarm Optimization Framework for Structural Design Optimization and Performance Improvement in Construction Projects

2.7. Definition of Objective Functions and Constraints for the Optimal Design of a Six-Story Reinforced Concrete Building

In this study, the case-study project is a six-story reinforced concrete building, and the objective of the optimization process is to obtain a structural design that is safe, economical, constructible, and sustainable. To achieve this objective, the principal design variables include beam and column dimensions, slab thickness, concrete compressive strength, reinforcement ratio, the type of lateral load-resisting system, and the allocation of construction resources. The optimization model is formulated to satisfy the requirements of reinforced concrete design and seismic design codes while simultaneously minimizing total construction cost, structural weight, material consumption, project duration, and embodied carbon emissions, without compromising structural quality or constructability. Fig. 6 presents the three-dimensional structural model of the case-study project developed in the Autodesk Revit environment. The geometric and engineering information associated with structural beams, columns, slabs, reinforced concrete cores, and the lateral load-resisting system was extracted directly from this BIM model and employed as the primary input for the optimization process. Furthermore, the dimensions of structural members, concrete volumes, steel quantities, and other geometric characteristics required for the formulation of the objective functions and the evaluation of structural design constraints were obtained directly from the BIM model. This data-driven integration ensures that the optimization process is performed using accurate project-specific information, thereby improving the reliability,

practicality, and engineering applicability of the optimized structural solutions.

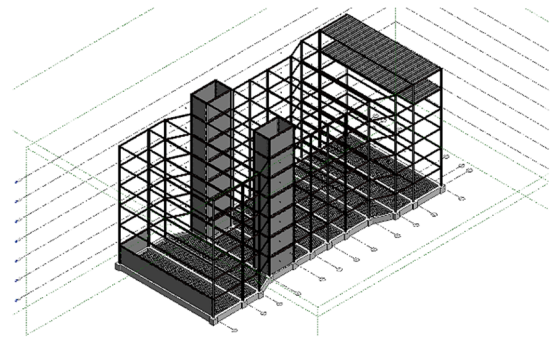


Fig. 6. Three-Dimensional Structural Model of the Six-Story Reinforced Concrete Building Developed in the BIM (Autodesk Revit) Environment and Used as the Basis for Extracting Structural Design Variables and Engineering Constraints

The primary objective functions considered in this study include minimizing the total cost of the reinforced concrete structural frame, minimizing structural weight, minimizing concrete and reinforcing steel consumption, minimizing the construction duration of the structural frame, and minimizing the embodied carbon emissions associated with material consumption. The total structural cost is calculated as the sum of the costs of concrete, reinforcing steel, formwork, labor, construction equipment, and transportation. Similarly, the total structural weight is determined from the combined weight of beams, columns, slabs, and, where applicable, reinforced concrete shear walls. Furthermore, embodied carbon emissions are estimated based on the volume of concrete, the weight of reinforcing steel, and the corresponding emission factors associated with each construction material. For the six-story building considered in this study, both member strength verification and inter-story lateral displacement control are critical design requirements. However, owing to the building's moderate height, the sensitivity to inter-story drift is less significant than that observed in high-rise structures. The optimization problem is subject to a comprehensive set of structural and construction constraints, including flexural, shear, and axial strength requirements, inter-story drift limitations, beam and slab deflection limits, minimum and maximum reinforcement ratios, beam and column dimensional limits, architectural requirements, foundation capacity constraints, and construction feasibility requirements. Within the proposed optimization framework, every candidate structural design is first evaluated against all engineering and code-based constraints. Only solutions satisfying these constraints are admitted to the objective function evaluation stage. Consequently, the optimization model generates a set of feasible Pareto-optimal solutions that provide an appropriate balance among construction cost, project duration, structural safety, material

consumption, and sustainability. The mathematical formulation of the objective functions is presented in Equation (1).

$$\begin{aligned} \text{Min } C_{\text{total}} &= C_c + C_s + C_f + C_l + C_m + C_t \\ \text{Min } W_{\text{total}} &= W_{\text{beam}} + W_{\text{column}} + W_{\text{slab}} + W_{\text{shearwall}} \\ \text{Min } M &= V_c + W_s \\ \text{Min } CO_2 &= EFC \times V_c + EFS \times W_s \\ \text{Min } T &= \sum_{i=1}^n t_i \end{aligned} \quad (1)$$

where:

C_{total} = total structural cost;

C_c = concrete cost;

C_s = structural steel cost;

C_f = formwork cost;

C_l = labor cost;

C_e = equipment cost;

C_t = transportation cost.

The principal structural and construction constraints considered in the optimization model are defined in Equation (2).

$$\begin{aligned} M_u &\leq \phi M_n \\ V_u &\leq \phi V_n \\ P_u &\leq \phi P_n \\ \Delta_{\text{story}} &\leq \Delta_{\text{allowable}} \\ \text{Deflection} &\leq \text{Deflection}_{\text{allowable}} \\ \rho_{\text{min}} &\leq \rho \leq \rho_{\text{max}} \\ b_{\text{min}} &\leq b \leq b_{\text{max}} \\ h_{\text{min}} &\leq h \leq h_{\text{max}} \end{aligned} \quad (2)$$

Where:

M_u = Factored bending moment (design bending moment) acting on the structural member (kN·m)

ϕM_n = Design flexural strength of the member, where M_n is the nominal flexural capacity and ϕ is the strength reduction factor (kN·m)

V_u = Factored shear force acting on the structural member (kN)

ϕV_n = Design shear strength of the member, where V_n is the nominal shear capacity and ϕ is the strength reduction factor (kN)

P_u = Factored axial load acting on the structural member (kN)

ϕP_n = Design axial load capacity of the member, where P_n is the nominal axial capacity and ϕ is the strength reduction factor (kN)

Δ_{story} = Calculated inter-story drift (mm)

$\Delta_{\text{allowable}}$ = Maximum allowable inter-story drift specified by the design code (mm)

Deflection = Calculated structural deflection under the specified loading condition (mm)

Deflection_{allowable} = Maximum allowable structural deflection according to the applicable design code (mm)

ρ = Reinforcement ratio of the reinforced concrete member

ρ_{min} = Minimum reinforcement ratio required by the design code

ρ_{max} = Maximum reinforcement ratio permitted by the design code

b = Width of the structural member cross-section (mm)

b_{min} = Minimum allowable cross-sectional width (mm)

b_{max} = Maximum allowable cross-sectional width (mm)

h = Depth (height) of the structural member cross-section (mm)

h_{min} = Minimum allowable cross-sectional depth (mm)

h_{max} = Maximum allowable cross-sectional depth (mm)

ϕ = Strength reduction factor specified by the applicable structural design code (dimensionless)

M_n , V_n and P_n = Nominal flexural, shear, and axial capacities of the structural member, respectively.

The decision variables considered in the proposed optimization model are presented in Table 4.

Table 4. Decision Variables Used in the Proposed Optimization Model

Decision Variable	Proposed Range	Description
Beam Width (b)	25–45 cm	Cross-sectional width of reinforced concrete beams considered during structural optimization.
Beam Depth (h)	40–70 cm	Cross-sectional depth of reinforced concrete beams, optimized to satisfy strength, stiffness, and serviceability requirements.
Column Dimensions	40 × 40 cm to 80 × 80 cm	Cross-sectional dimensions of reinforced concrete columns selected to satisfy axial load and structural performance requirements.
Slab Thickness	12–25 cm	Thickness of reinforced concrete floor slabs considered for structural safety, serviceability, and material optimization.
Concrete Compressive Strength (f'_c)	25–40 MPa	Characteristic compressive strength of concrete used as a design variable affecting structural capacity, material consumption, and embodied carbon emissions.
Lateral Load-Resisting System	Reinforced Concrete Moment-Resisting Frame, Shear Wall, or Dual System	Alternative structural systems considered to resist lateral loads such as wind and earthquake actions.
Reinforcement Ratio (ρ)	Code-specified minimum and maximum limits; typically 0.8–4.0%	Ratio of reinforcing steel area to concrete cross-sectional area, constrained according to the requirements of the applicable design code.
Number of Construction Crews	1–4 crews	Number of labor crews assigned to construction activities for optimizing project duration and resource allocation.
Equipment Type and Capacity	Tower crane or light mobile crane, concrete pump, concrete vibrator, and modular formwork system	Construction equipment selected according to the workload, construction sequence, and operational requirements of each floor.

The symbols used in the above equations are defined in Table 5.

Table 5. Definition of Symbols Used in the Objective Functions and Constraint Equations

Symbol	Concept
C_{total}	Total structural cost
C_c	Concrete cost
C_s	Reinforcing steel cost
C_f	Formwork cost
C_l	Labor cost
C_m	Equipment cost
C_t	Transportation cost
W_{total}	Total structural weight
V_c	Volume of concrete
W_s	Weight of reinforcing steel
EF_c	Concrete CO ₂ emission factor
EF_s	Steel CO ₂ emission factor
T	Total structural construction duration
M_u, V_u, P_u	Design bending moment, shear force, and axial load demand
$\phi M_n, \phi V_n, \phi P_n$	Design flexural, shear, and axial load capacity
ρ	Reinforcement ratio
Δ_{story}	Inter-story drift

2.8. Selection of Software Tools

The selection of appropriate software tools plays a crucial role in implementing the proposed data-driven framework based on Building Information Modeling (BIM) and intelligent optimization algorithms. Since the proposed model requires data extraction from the BIM environment, information processing, execution of optimization algorithms, and the feedback of optimized results into the building model, the use of a complementary set of software platforms and programming languages is essential. Autodesk Revit is employed as the primary BIM platform for developing and managing the three-dimensional building model, project scheduling information, material quantities, and the technical specifications of structural components. Revit API and Dynamo provide the capability to automate data extraction, establish connections with project databases, and transfer information to computational environments. For the analysis and optimization stage, Python is considered a suitable programming environment due to its powerful scientific and optimization libraries, including NumPy, Pandas, SciPy, DEAP, PyGAD, and pymoo. These libraries enable the implementation of metaheuristic algorithms such as the (GA), (PSO), (NSGA-II), and Multi-Objective Particle Swarm Optimization (MOPSO). Within this framework, data extracted from Revit or IFC models are first transferred to Python or MATLAB through Dynamo, Revit API, or CSV/Excel files. Intelligent optimization algorithms then analyze alternative scenarios related to resource allocation, scheduling, cost estimation, and structural design and identify the best solutions based on the defined objective functions and constraints. Finally, the optimized

outputs can be transferred back to the BIM environment and visualized as a three-dimensional model, a 4D construction schedule, a 5D cost estimation model, or a decision-support dashboard.

3. Results and Discussion

To evaluate the effectiveness of the proposed BIM-Genetic Algorithm framework, a six-story reinforced concrete building (Mehrsan Project) located in Sahand New Town, Tabriz, Iran, was selected as the case study. Initially, the required project information was extracted from the BIM model, including the characteristics of structural components, concrete volume, steel weight, construction activity durations, project costs, and resource requirements. The extracted data are presented in Table 6 and served as the primary input to the optimization model, forming the basis of the project database. The extracted data indicate that the structural system consists of a steel frame combined with cast-in-place reinforced concrete slabs. On average, 30 structural steel beams were identified on each of the first six floors, whereas the number of beams decreases to 10 members on the seventh floor. This reduction results from the smaller roof floor area and the elimination of several structural bays. Furthermore, the sixth floor contains the largest number of structural columns (20 columns), while only eight columns are present on the seventh floor. This configuration reflects the gradual transfer of gravity loads and the reduction of the structural footprint at higher elevations, which is fully consistent with the structural layout developed in the Revit model. According to the BIM-extracted data, the total volume of cast-in-place concrete slabs is 104,234m³, indicating that concrete is used exclusively for the floor slabs, whereas the primary load-bearing members including beams and columns are fabricated from ASTM A992 structural steel. The steel volume associated with the typical beams on each floor is approximately 0.532m³, corresponding to a weight of about 4,180kg. In contrast, the primary columns on the sixth-floor weigh approximately 18,466kg, representing the largest contribution to the total structural steel consumption. From an economic perspective, the steel cost for the typical beam system on each floor is approximately IRR 5956470000, while the steel columns on the sixth floor account for IRR 26313960000. In addition, the construction cost of the first-floor concrete slab is estimated at IRR 14853300000, demonstrating the significant contribution of concrete work to the project's direct construction costs. These findings indicate that structural steel represents the dominant cost component of the structural system, suggesting that optimizing steel member sections can produce the greatest reduction in the overall project cost. From an environmental perspective,

the embodied carbon emissions associated with the first-floor concrete slab are estimated at 31,270.11kg CO₂e, whereas the sixth-floor steel columns generate approximately 34,162.04kg CO₂e, representing the highest carbon footprint among all structural components. These results indicate that heavy steel members contribute substantially not only to construction costs but also to the project's embodied carbon emissions. Consequently, reducing structural steel weight has the potential to simultaneously decrease both project costs and environmental impacts. The structural quantities extracted from the BIM model further reveal that the concrete slabs constitute the heaviest structural component, with an estimated total weight of 250.161 tons. By comparison, the typical beam system on each floor weighs only 4.18 tons, while the primary steel columns on the sixth floor weigh 18.466 tons. This comparison demonstrates that although steel dominates both construction cost and embodied carbon emissions, the concrete slabs account for the largest proportion of the overall structural weight. Therefore, optimizing slab thickness could play a significant role in reducing the building's dead load and improving structural efficiency. Overall, the results presented in Table 6 demonstrate that the BIM model successfully extracted both quantitative and qualitative structural information with a high degree of accuracy, providing a comprehensive project database for subsequent optimization. This capability eliminates the need for manual quantity takeoff, accelerates the preparation of optimization input data, and significantly reduces human errors. Furthermore, it establishes a reliable data foundation for implementing intelligent optimization techniques, such as the (GA) and (PSO), in structural design and construction project management. The use of actual project data extracted directly from the Revit model also enhances the reliability of the optimization results and ensures that the proposed framework more closely represents real-world construction conditions.

Following data extraction from the BIM model, the decision variables including structural member dimensions, the number of construction crews, equipment allocation strategies, activity sequencing, and other controllable design parameters were defined. These variables, presented in Table 6, played a fundamental role in the optimization process by enabling the generation and evaluation of alternative design and construction scenarios. As shown in the table, the case-study building consists of six stories, 190 structural steel beams, 128 steel columns, and six reinforced concrete slabs, forming a steel frame structural system with cast-in-place concrete slabs. The total concrete volume of the slabs is 104.23m³, while the total structural steel weight is 56,343.5kg, indicating that steel weight and concrete volume

constitute the principal quantitative inputs for estimating structural cost, total weight, and embodied carbon emissions. In addition, the decision variables include beam and column dimensions, slab thickness, and construction crew allocation, providing the flexibility required to generate multiple design and execution alternatives. The (GA) was configured with a population size of 90 chromosomes, 120 generations, a crossover rate of 0.82, and a mutation rate of 0.08, enabling an efficient exploration of the solution space while reducing the likelihood of premature convergence. The optimization objectives were formulated to minimize total project cost, construction duration, structural weight, and embodied CO₂ emissions. Consequently, the proposed framework represents a BIM-based multi-objective optimization model that simultaneously evaluates the economic, scheduling, structural, and environmental aspects of construction projects.

The performance of each candidate solution was subsequently evaluated using a comprehensive set of objective functions aimed at minimizing total project cost, construction duration, material consumption, and embodied carbon emissions while maximizing resource utilization efficiency. These objective functions are summarized in Table 7. The optimization results indicate that the Steel Frame with Concrete Slab structural system was identified as the optimal design alternative. By satisfying all structural and construction constraints, this system achieved an effective balance between economic efficiency, structural performance, and environmental sustainability. Material-related results indicate a total concrete volume of 104.23m³ and a total structural steel weight of 56,343.50kg (56.34 tons). These quantities were extracted directly from the Revit/IFC structural model and served as the basis for calculating structural weight, construction cost, and embodied carbon emissions. The total structural weight was estimated at 306.50 tons, demonstrating that the majority of the structural mass is associated with the reinforced concrete slabs and primary steel members. From an economic perspective, the total structural material cost was calculated as IRR 95142270000, obtained from the combined cost of concrete and structural steel (Cc+Cs), and selected as the optimal value of the cost objective function. Environmentally, the total embodied carbon emissions were estimated at 135,504.48kg CO₂e, confirming that the proposed optimization framework explicitly incorporates environmental considerations alongside economic objectives during the decision-making process.

The BIM-derived model further revealed that the structural system comprises 190 steel beams, 128 steel columns, and six reinforced concrete slabs, all of which were extracted automatically from the Revit/IFC model without manual data entry.

Furthermore, both the beams and columns are specified as ASTM A992 structural steel, demonstrating the capability of the proposed framework to automatically retrieve geometric information and material properties directly from the BIM environment and incorporate them into the optimization process. The best-performing design alternative was classified as Feasible, indicating that all geometric constraints, material specifications, and BIM-defined design requirements were successfully satisfied and that the optimized solution is fully constructible. Overall, the results presented in Table 8 demonstrate that the integration of BIM and the Genetic Algorithm successfully produced a practical and optimized design solution for the Mehrsan project using actual project data. In addition to reducing construction cost and embodied carbon emissions, the proposed framework enables intelligent material management and simultaneous evaluation of economic, technical, and environmental performance indicators. These findings highlight the considerable potential of the proposed BIM-based optimization framework for the development of intelligent decision-support systems for structural design and construction project management.

To ensure the constructability and safety of the proposed design alternatives, a comprehensive set of structural and construction constraints—including flexural strength, shear strength, column axial capacity, inter-story drift limits, deflection limits, and permissible reinforcement ratios—was incorporated into the optimization process, as summarized in Table 9. This table presents the structural and execution constraints adopted in the BIM/IFC-based optimization framework for the Mehrsan project and illustrates how actual information extracted from the Building Information Model was translated into a series of design, construction, and analytical constraints. The first group of constraints is associated with the structural member types, namely ASTM A992 steel beams and columns. These constraints ensure that the optimization process selects only permissible steel sections while maintaining adequate axial capacity and structural stability. Similarly, slab-related constraints define the allowable slab thickness and concrete volume to preserve diaphragm action and floor stiffness. This demonstrates that the BIM model directly defines the feasible design space by restricting the range of admissible structural configurations.

The second group of constraints concerns the fixed number of structural members, consisting of 190 beams, 128 columns, and six concrete slabs. These quantities are treated as fixed constraints because the overall structural geometry is extracted directly from the IFC model and remains unchanged throughout the optimization process. Consequently, only sectional properties and construction-related

variables are optimized. This strategy reduces the computational complexity of the optimization problem while enabling the algorithm to focus on the most influential decision variables, such as member dimensions and material consumption. Furthermore, material-related constraints are simultaneously incorporated as both objective functions and hard constraints. Specifically, the total structural steel weight (56,343.5kg) and concrete volume (104.23m³) are minimized while ensuring that all structural capacity requirements remain satisfied. This formulation establishes a constrained multi-objective optimization problem. Another important category of constraints comprises the structural performance requirements, including flexural capacity, shear capacity, axial capacity, inter-story drift, and deflection limits. Finally, constructability constraints address geometric clashes, compatibility with the architectural layout, and practical construction feasibility. These constraints establish a direct connection between the digital BIM model and real-world construction practice, ensuring that the optimized solutions are not merely theoretical but are fully constructible.

The implementation of the Genetic Algorithm (GA) demonstrated its capability to generate and evaluate numerous alternative design scenarios during successive generations. A representative subset of these solutions is presented in Table 10. The results indicate that the Standard design option was identified as the reference optimal solution with a fitness value of 1000, representing the baseline solution within the design space. The remaining alternatives introduce modifications to structural member sections and material consumption, resulting in different overall performance characteristics. The Light Steel scenario reduces the structural steel weight to 54.90 tons, leading to a corresponding reduction in embodied carbon emissions (132,840kg CO₂e); however, this improvement is accompanied by an increase in the risk index (0.70). This finding suggests that excessive reduction of structural member sizes may negatively affect structural safety and stability. Conversely, the Minimum Weight scenario achieves the lowest steel consumption (52.95tons) and the lowest embodied carbon emissions (129,233kg CO₂e), but exhibits the highest risk index (0.85), indicating a significant reduction in structural capacity. These results reveal a clear trade-off between environmental and economic objectives on one hand and structural safety on the other. Intermediate solutions, including the Optimized Beam, Optimized Column, and Hybrid Option scenarios, demonstrate the ability of the Genetic Algorithm to identify balanced design alternatives in which localized modifications to beam or column dimensions progressively improve the objective function without compromising the overall structural performance. Overall, the results presented in Table 10 indicate

that the proposed GA successfully generated a set of Pareto-feasible solutions that effectively balance the four principal optimization objectives: structural cost, structural weight, embodied carbon emissions, and structural risk. These findings demonstrate the capability of the integrated BIM-GA framework to provide multiple high-quality design alternatives for engineering decision-making in the Mehrsan project.

Among the generated design alternatives, the Standard configuration was ultimately selected as the optimal solution, and its optimization history is presented in Table 11. This table illustrates the convergence behavior of the Genetic Algorithm throughout the optimization process. The fitness value decreased from 1195.40 in the first generation to 1000.00 by Generation 31, after which it remained unchanged until Generation 120, indicating that the algorithm converged to a stable solution after approximately 31 generations. Simultaneously, the total structural steel weight was reduced from 58.40 tons to 56.34 tons, while embodied carbon emissions decreased from 139,315kg CO₂e to 135,504kg CO₂e. The concrete volume remained constant at 104.23 m³ throughout the optimization because the concrete slabs were modeled as fixed components within the BIM environment. The progression of the best-performing solution from Robust Design in the initial generation to Balanced Design, and finally to the Standard configuration indicates that the algorithm initially explored conservative structural alternatives before gradually converging toward a more balanced solution characterized by reduced steel consumption and lower embodied carbon emissions. Overall, the results presented in Table 11 demonstrate that the Genetic Algorithm successfully reduced structural weight, embodied carbon emissions, and the objective function value while maintaining the feasibility of all candidate solutions. Consequently, the Standard configuration was identified as the most robust and balanced optimization outcome for the Mehrsan project.

Table 12 presents the optimized construction schedule and resource allocation generated by the (GA) for the Mehrsan project. The results demonstrate that, by utilizing data extracted from the BIM model and applying the Genetic Algorithm, the sequence of construction activities was optimized to preserve logical activity dependencies while simultaneously minimizing project duration, construction cost, and embodied carbon emissions. According to the optimized schedule, construction begins with the installation of the first-floor steel beams, followed by the execution of the concrete slab. Subsequently, the installation of beams and columns on the upper floors proceeds in a continuous sequence, resulting in the completion of the entire structural construction process within 16.5 days.

The optimization results indicate that four construction crews were assigned to most steel beam installation activities, reflecting the need for rapid execution and increased labor resources during these operations. In contrast, the installation of steel columns on the sixth and seventh floors required only three and two crews, respectively, corresponding to the reduced construction volume and the smaller number of structural members on the upper levels. This resource allocation demonstrates the capability of the Genetic Algorithm to achieve an effective balance between available construction capacity and workload distribution.

From a scheduling perspective, the construction of the first-floor concrete slab represents the longest activity, requiring 4.0 days, whereas the installation of steel beams on most floors requires only 1.5 days. Due to the reduced number of structural members on the seventh floor, beam installation is completed within 0.75 days. These findings indicate that concrete slab construction which includes formwork installation, reinforcement placement, and concrete casting is the most time-consuming structural activity within the project.

From an economic standpoint, the highest construction cost is associated with the installation of the sixth-floor steel columns, amounting to IRR 26314005000, primarily because of their larger dimensions and greater structural weight. The first-floor concrete slab represents the second-largest cost component, estimated at IRR 14853300000, while the installation of steel beams on the intermediate floors exhibits a relatively constant cost of approximately IRR 595647000 per floor. The lowest construction cost is observed for the seventh-floor steel beams (IRR 961305000), reflecting the reduced number of members and the smaller construction volume at this level.

From an environmental perspective, the sixth-floor steel columns generate the highest embodied carbon emissions (34,162.04kg CO₂e), followed by the first-floor concrete slab (31,270.11kg CO₂e). In comparison, the seventh-floor steel beams produce only 1,248.02kg CO₂e, indicating the substantial reduction in steel consumption at the roof level. These findings demonstrate that heavy steel members are the primary contributors to the project's embodied carbon emissions and suggest that optimizing their cross-sectional dimensions can significantly improve the environmental sustainability of the structural system.

Overall, the results presented in Table 13 confirm that the proposed BIM-GA framework successfully generated a practical and implementable construction schedule for the Mehrsan project, in which activity sequencing, resource allocation, construction cost, and embodied carbon emissions were optimized simultaneously. In addition to reducing the overall

structural construction duration, the optimized schedule enables more efficient utilization of construction crews, lowers direct construction costs, and mitigates environmental impacts. Consequently, it can serve as an effective decision-support tool for project managers during both the planning and construction control phases.

Table 13 evaluates the overall performance of the proposed BIM–Genetic Algorithm framework using a set of Key Performance Indicators (KPIs) for the Mehrsan project. The results demonstrate that the optimization model achieved simultaneous improvements in economic performance, construction scheduling, environmental sustainability, and resource productivity without violating any structural design constraints. From an economic perspective, the total structural material cost was reduced from IRR 98120775000 to IRR 95142270000, corresponding to an improvement of 3.04%. This reduction is primarily attributed to the optimization of steel member sections and the associated decrease in total structural weight achieved by the selected Genetic Algorithm solution. Similarly, the total structural steel weight decreased from 58.40 tons to 56.34 tons, representing a 3.52% reduction in steel consumption.

From a scheduling perspective, the duration of structural construction activities decreased from 18.50 days to 16.50 days, corresponding to a 10.81% improvement in project execution time. This result indicates that the optimized resource allocation and the controlled overlapping of construction activities within the Genetic Algorithm framework played a significant role in shortening the project schedule while maintaining construction feasibility.

From an environmental perspective, embodied carbon emissions were reduced from 139,315 kg CO₂e to 135,504 kg CO₂e, representing a 2.74% improvement in environmental performance. This reduction is directly attributable to the decrease in structural steel consumption and the optimization of the structural design. In contrast, the concrete slab volume (104.23 m³) remained unchanged in both the initial and optimized solutions because this component was defined as a fixed geometric element within the BIM model and was therefore excluded from the optimization process. Similarly, the numbers of structural beams (190), columns (128), and concrete slabs (6) remained constant throughout the optimization, indicating that the optimization was performed at the level of member cross-sections and construction resource allocation rather than by modifying the structural topology.

With respect to resource utilization, Resource Productivity increased from 78% to 88%, corresponding to a 12.82% improvement in the efficient use of labor and construction equipment. This result demonstrates that the Genetic Algorithm successfully optimized the allocation of

construction crews, thereby reducing idle time and minimizing resource conflicts during project execution. Furthermore, the Execution Risk Index decreased from 0.70 to 0.63, representing a 10% improvement in construction safety and execution reliability. This reduction indicates that the optimized solution is not only more cost-effective but also operationally more stable, reliable, and practical from a construction management perspective.

Finally, the Constraint Compliance Status remained "Acceptable" for both the baseline and optimized solutions, confirming that none of the structural, construction, or BIM-related constraints were violated during the optimization process. Overall, the KPI results presented in Table 12 demonstrate that the proposed BIM-Genetic Algorithm framework effectively improves project performance across multiple dimensions including cost, schedule, environmental sustainability, and resource efficiency while fully satisfying all structural and constructability requirements. These findings confirm the robustness of the proposed framework as a practical multi-objective decision-support tool for BIM-based structural design and construction project management.

From a project management perspective, the proposed framework provides practical decision-support capabilities beyond numerical optimization. By generating multiple feasible optimization scenarios and evaluating them simultaneously based on cost, construction duration, structural performance, resource utilization, and environmental impact, the framework enables project managers to compare alternative execution strategies according to project priorities. Depending on whether the primary objective is minimizing cost, reducing project duration, improving sustainability, or increasing resource productivity, decision-makers can select the most appropriate solution from the generated Pareto-optimal alternatives. Therefore, the proposed BIM-integrated framework functions not only as an optimization tool but also as an intelligent decision-support system for planning and managing complex construction projects.

Beyond the numerical improvements reported in Table 13, the optimization results have important practical implications for construction project management. Although the percentage improvements may appear moderate, their cumulative impact can become significant in medium- and large-scale projects. Based on the differences between the baseline and optimized values reported in Table 13, the proposed framework achieved an estimated direct saving of IRR 297850500 in structural material cost, corresponding to a 3.04% reduction in project expenditure. It also reduced steel consumption by 2.06 tons, equivalent to a 3.52% decrease, and lowered embodied carbon emissions by

approximately 3.81 tons of CO₂e. Furthermore, the 10.81% reduction in structural construction duration shortened the project period by approximately two days, potentially enabling earlier project delivery, lower indirect costs, and improved schedule performance. The increase in resource productivity and the reduction in execution risk further indicate that the proposed framework improves not only economic and environmental performance but also construction efficiency and operational reliability. Collectively, these findings demonstrate that even relatively moderate percentage improvements can generate tangible technical, economic, environmental, and managerial benefits, confirming the practical value of the proposed BIM-based optimization framework for real-world engineering decision-making.

In addition to its demonstrated practical benefits, the proposed framework is not inherently

limited to the case study examined in this research. Since the optimization workflow is driven by project-specific BIM data, objective functions, decision variables, and engineering constraints, it can potentially be adapted to other construction projects by replacing the corresponding BIM model and defining appropriate project inputs. Accordingly, the same general workflow may be applied to residential, commercial, industrial, and infrastructure projects, provided that their specific scheduling, structural, resource, cost, and environmental requirements are incorporated into the optimization model. This adaptability indicates that the proposed methodology has the potential to serve as a transferable decision-support framework across different construction contexts. Nevertheless, its performance in other project types should be further evaluated through additional case studies.

Table 6. Ata Extracted from the IFC/Revit-Based Building Information Model (BIM) of the Mehrsan Project Structural Model

Base_Weight_ton	Base_CO2_kg	Steel_Cost_IRR	Concrete_Cost_IRR	Steel_kg	Steel_volume_m3	Concrete_m3	Material	Activity	IFC_Element_Count	Floor	Activity_ID
4.18	7732.97	5,956,470,000	0	4180.0	0.532	0.0	Steel	Beams	30	L1	L1-BEA
250.161	31270.11	0	14,853,300,000	0.0	0	104.234	Concrete, Cast-in-Place gray	Slabs	29	L1	L1-SLA
4.18	7732.97	5,956,470,000	0	4180.0	0.532	0.0	Steel	Beams	30	L2	L2-BEA
4.18	7732.97	5,956,470,000	0	4180.0	0.532	0.0	Steel	Beams	30	L3	L3-BEA
4.18	7732.97	5,956,470,000	0	4180.0	0.532	0.0	Steel	Beams	30	L4	L4-BEA
4.18	7732.97	5,956,470,000	0	4180.0	0.532	0.0	Steel	Beams	30	L5	L5-BEA
18.466	34162.04	26,314,005,000	0	18466.0	2.352	0.0	Steel ASTM A992	Columns	20	L6	L6-COL
4.18	7732.97	5,956,470,000	0	4180.0	0.532	0.0	Steel	Beams	30	L6	L6-BEA
8.618	15942.43	12,279,975,000	0	8617.5	1.098	0.0	Steel ASTM A992	Columns	8	L7	L7-COL
0.675	1248.02	961,305,000	0	674.6	0.086	0.0	Steel	Beams	10	L7	L7-BEA

Table 7. Cost Parameters, Carbon Emission Factors, and Genetic Algorithm Settings Used in the Optimization Model

Unit	Value	Parameter
Story	6	Number of Stories
No.	190	Total Structural Beams
No.	128	Total Structural Columns
No.	6	Concrete Slabs
-	ASTM A992 Steel Beam	Beam Type
-	ASTM A992 Steel Column	Column Type
m ³	104.23	Total Concrete Volume (Slabs)
kg	29,260	Total Beam Steel Weight
kg	27,083.5	Total Column Steel Weight
kg	56,343.5	Total Structural Steel Weight
-	Steel Frame with Concrete Slabs	Structural System
-	Beam dimensions, column dimensions, slab thickness, crew allocation	Design Variables
Chromosomes	90	GA Population Size
Iterations	120	Number of Generations
Ratio	0.82	Crossover Rate
Ratio	0.08	Mutation Rate
-	Minimize Total Project Cost	Objective Function 1
-	Minimize Project Duration	Objective Function 2
-	Minimize Structural Weight	Objective Function 3
-	Minimize CO ₂ Emissions	Objective Function 4

Table 8. Best BIM–Genetic Algorithm Optimization Scenario for the Six-Story Mehrsan Building

Status	Result	Formula / Rule	Definition	Objective / Constraint	Optimized Value	Metric
Feasible	Standard	BIM-based selection	Best feasible structural option	Design Option	Steel Frame + Concrete Slab	Selected Structural System
Minimized	104.23 m ³	Vc	Minimize concrete consumption	Material	104.23	Total Concrete Volume
Minimized	56.34 ton	Ws	Minimize steel consumption	Material	56,343.50	Total Steel Weight
Minimized	306.50 ton	Ws + concrete weight	Minimize structural weight	Weight	306.50	Structural Weight
Minimized	95142270000 IRR	Cc + Cs	Minimize total material cost	Cost	63,428.18	Total Cost
Minimized	135,504.48 kgCO ₂ e	EFc × Vc + EFs × Ws	Minimize embodied carbon	CO ₂	135,504.48	Total CO ₂ Emission
Fixed	190 members	IFC Beam Count	Extracted from Revit/IFC model	BIM Constraint	190	Beam Quantity
Fixed	128 members	IFC Column Count	Extracted from Revit/IFC model	BIM Constraint	128	Column Quantity
Fixed	6 slabs	IFC Slab Count	Extracted from Revit/IFC model	BIM Constraint	6	Slab Quantity
OK	ASTM A992	IFC Material/Profile	Structural member type	Design Constraint	ASTM A992 Steel Beam	Beam Type
OK	ASTM A992	IFC Material/Profile	Structural member type	Design Constraint	ASTM A992 Steel Column	Column Type
OK	Feasible	BIM/IFC Review	Check based on BIM-extracted geometry and material data	Constraint Status	Feasible	Structural Feasibility
Status	Result	Formula / Rule	Definition	Objective / Constraint	Optimized Value	Metric

Table 9. Structural and Construction Constraints of the BIM-Based Optimization Model

Status	Optimization Treatment	Decision Variable	Constraint / Rule	BIM/IFC-Based Project Data	Constraint Type
Checked	Select lighter or stronger steel profiles	Beam section size	Beam sections must remain within allowable steel profiles	ASTM A992 Steel Beams	Beam Type Constraint
Checked	Select feasible column profile	Column section size	Column sections must satisfy axial and stability requirements	ASTM A992 Steel Columns	Column Type Constraint
Checked	Optimize concrete volume	Slab thickness	Slab thickness and concrete volume must remain within design limits	Concrete slabs	Slab Constraint
Fixed	Fixed geometry, variable section	Beam layout / profile	Beam layout should not conflict with architectural grid	190 beams extracted from IFC	Beam Quantity Constraint
Fixed	Fixed location, variable section	Column profile	Column locations must comply with architectural and structural grids	128 columns extracted from IFC	Column Quantity Constraint
Fixed	Variable within allowable range	Slab thickness / volume	Slabs must cover all structural floors	6 concrete slabs extracted from IFC	Slab Quantity Constraint
Minimized	Objective + constraint	Beam/column profiles	Steel weight should be minimized without violating capacity	56,343.5 kg total structural steel	Steel Weight Constraint
Minimized	Objective + constraint	Slab thickness	Concrete use should be minimized while maintaining slab performance	104.23 m ³ concrete slab volume	Concrete Volume Constraint
Required	Must be checked in ETABS/SAP/Robot	Beam section	$M_u \leq \phi M_n$	Requires structural analysis output	Flexural Capacity
Required	Must be checked in ETABS/SAP/Robot	Beam/column section	$V_u \leq \phi V_n$	Requires structural analysis output	Shear Capacity
Required	Must be checked in ETABS/SAP/Robot	Column section	$P_u \leq \phi P_n$	Requires structural analysis output	Axial Capacity
Required	Must be checked in ETABS/SAP/Robot	Structural system / member stiffness	$\Delta_{story} \leq \Delta_{allowable}$	Requires lateral analysis output	Inter-story Drift
Required	Must be checked in ETABS/SAP/Robot	Beam/slab stiffness	Deflection $\leq$ Deflection allowable	Requires analysis output	Deflection Limit
Checked	Clash control in BIM	Section size / execution method	No clash with architectural spaces, stairs, elevator core and slabs	Based on BIM geometry	Constructability

Table 10. Top Design Scenarios Generated by the Genetic Algorithm and Their Multi-Objective Evaluation Results

Status	Risk Index	CO ₂ Emissions (kgCO ₂ e)	Concrete Volume (m ³)	Structural Steel Weight (ton)	Fitness Score	Design Option	Rank
Feasible	0.63	135,504	104.23	56.34	1000.00	Standard	1
Feasible	0.70	132,840	104.23	54.90	1012.35	Light Steel	2
Feasible	0.66	133,395	104.23	55.20	1021.18	Optimized Beam	3
Feasible	0.65	134,598	104.23	55.85	1035.72	Optimized Column	4
Feasible	0.78	130,805	104.23	53.80	1048.91	Reduced Sections	5
Feasible	0.68	134,136	104.23	55.60	1056.43	Hybrid Option	6
Feasible	0.85	129,233	104.23	52.95	1064.27	Minimum Weight	7
Feasible	0.73	131,361	104.23	54.10	1073.44	Cost-Oriented	8

Table 11. Convergence History of the Best Genetic Algorithm Solution over Successive Generations

Feasible	Best Option	Risk Index	CO ₂ (kgCO ₂ e)	Concrete Volume (m ³)	Steel Weight (ton)	Best Fitness	Generation
Yes	Robust Design	0.55	139,315	104.23	58.40	1195.40	1
Yes	Balanced Design	0.58	137,095	104.23	57.20	1148.25	6
Yes	Balanced Design	0.60	136,540	104.23	56.90	1116.80	11
Yes	Standard	0.61	136,170	104.23	56.70	1089.35	16
Yes	Standard	0.62	135,800	104.23	56.50	1062.10	21
Yes	Standard	0.63	135,615	104.23	56.40	1035.75	26
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	31
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	36
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	41
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	46
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	51
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	56
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	61
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	66
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	71
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	76
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	81
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	86
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	91
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	96
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	101
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	106
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	111
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	116
Yes	Standard	0.63	135,504	104.23	56.34	1000.00	120

Table 12. Optimized Construction Schedule and Resource Allocation Generated by the Genetic Algorithm for the Mehrsan Project

CO ₂ _kgCO ₂ e	Cost IRR	Duration_days	Finish_Day	Start_Day	Optimized_Crews	Activity	Floor	Activity_ID
7,732.97	5956470000	1.50	1.50	0.00	4	Steel Beams	L1	L1-BEA
31,270.11	14853300000	4.00	5.50	1.50	4	Concrete Slabs	L1	L1-SLA
7,732.97	5956470000	1.50	7.00	5.50	4	Steel Beams	L2	L2-BEA
7,732.97	5956470000	1.50	8.50	7.00	4	Steel Beams	L3	L3-BEA
7,732.97	5956470000	1.50	10.00	8.50	4	Steel Beams	L4	L4-BEA
7,732.97	5956470000	1.50	11.50	10.00	4	Steel Beams	L5	L5-BEA
34,162.04	26314005000	1.75	13.25	11.50	3	Steel Columns	L6	L6-COL
7,732.97	5956470000	1.50	14.75	13.25	4	Steel Beams	L6	L6-BEA
15,942.43	12279975000	1.00	15.75	14.75	2	Steel Columns	L7	L7-COL
1,248.02	961305000	0.75	16.50	15.75	2	Steel Beams	L7	L7-BEA

Table 13. Evaluation of the Key Performance Indicators (KPIs) of the Proposed BIM–Genetic Algorithm Framework

Improvement	Optimized Value	Initial Value	Key Performance Indicator (KPI)
3.04%	95142270000	98120775000	Structural Material Cost (IRR)
10.81%	16.50	18.50	Structural Execution Duration (days)
2.74%	135,504	139,315	CO ₂ Emissions (kg CO ₂ e)
0.00%	104.23	104.23	Concrete Slab Volume (m ³)
3.52%	56,343.5	58,400	Structural Steel Weight (kg)
3.52%	56.34	58.40	Structural Steel Weight (ton)
Fixed	190	190	Number of Structural Beams
Fixed	128	128	Number of Structural Columns
Fixed	6	6	Number of Concrete Slabs
12.82%	88	78	Resource Productivity (%)
10.00%	0.63	0.70	Execution Risk Index
—	Acceptable	Acceptable	Constraint Compliance Status

4. Conclusion

This study developed and validated an integrated data-driven framework that combines Building Information Modeling (BIM) with two metaheuristic optimization techniques, namely the (GA) and (PSO), to simultaneously optimize construction planning, resource allocation, scheduling, and structural design. Unlike many previous studies that focused on only one or two project objectives, the proposed framework provides a unified optimization environment in which economic, structural, environmental, and managerial objectives are considered concurrently using actual BIM-derived project information.

The proposed framework enables the direct extraction of geometric, material, scheduling, and resource information from Autodesk Revit/IFC models and transforms these data into optimization variables without manual intervention. This automated data exchange significantly reduces manual quantity takeoff, minimizes human errors, improves data consistency, and establishes a reliable digital workflow between BIM and intelligent optimization algorithms. The bidirectional integration further allows optimized solutions to be transferred back into the BIM environment, supporting visualization through 3D, 4D, and 5D BIM models and facilitating engineering decision-making throughout the project lifecycle.

The case study demonstrated the practical applicability of the proposed framework for a six-story building project. The optimization process successfully generated multiple feasible Pareto solutions while satisfying all structural and constructability constraints. Compared with the baseline design, the selected optimal solution reduced structural material cost by 3.04%, structural steel consumption by 3.52%, embodied carbon emissions by 2.74%, project execution duration by 10.81%, and execution risk by 10%, while increasing resource productivity by 12.82%. These improvements confirm that integrating BIM with intelligent optimization algorithms can simultaneously enhance construction efficiency, structural performance, sustainability, and project management without compromising engineering safety or constructability.

From a structural engineering perspective, the study demonstrated that optimizing steel member sections has a substantially greater influence on reducing construction cost and embodied carbon emissions than modifying concrete quantities, whereas slab optimization primarily affects the total structural weight. Furthermore, incorporating engineering design constraints including strength requirements, inter-story drift, deflection limits, reinforcement ratios, and constructability conditions ensures that all optimized alternatives

remain fully compliant with structural design codes and practical construction requirements. Consequently, the generated solutions are directly applicable to real construction projects rather than representing purely theoretical optimization outcomes.

Another significant contribution of this research is the establishment of a comprehensive BIM-centered decision-support framework capable of integrating design optimization, construction planning, resource management, sustainability assessment, and project performance evaluation within a single computational platform. The proposed methodology demonstrates that BIM should not be regarded merely as a digital modeling tool but as an intelligent information infrastructure capable of supporting advanced optimization and data-driven decision-making across the entire construction lifecycle.

spite these contributions, several limitations should be acknowledged. The proposed framework was validated using a single mid-rise building project, and therefore its generalizability to high-rise buildings, infrastructure projects, or modular construction requires further investigation. In addition, although the optimization considered major structural, economic, and environmental objectives, uncertainties associated with material price fluctuations, labor productivity, weather conditions, and supply-chain disruptions were not explicitly incorporated into the optimization model. Furthermore, structural analyses relied on BIM-derived parameters, while direct coupling with advanced structural analysis software such as ETABS or SAP2000 was not implemented within the optimization loop.

From a practical perspective, the findings demonstrate that the proposed BIM-based optimization framework can support construction managers in achieving more balanced economic, environmental, and operational outcomes. The reductions in structural material cost, steel consumption, embodied carbon emissions, construction duration, and execution risk, together with the improvement in resource productivity, indicate that the framework can contribute to more efficient planning and resource management. By integrating the optimization outputs into the BIM environment, project stakeholders can compare alternative solutions, visualize their consequences, and select the most appropriate scenario according to project priorities. Therefore, the proposed framework can serve as a practical decision-support approach for improving project delivery performance and promoting more sustainable construction practices.

Future research should focus on extending the proposed framework by integrating digital twins, real-time IoT sensor data, cloud-based BIM platforms, reinforcement learning, and advanced

multi-objective evolutionary algorithms such as NSGA-III and MOEA/D. Future studies may also incorporate life-cycle assessment (LCA), life-cycle costing (LCC), operational energy performance, resilience analysis, and uncertainty-based optimization to support sustainable and adaptive construction management. Moreover, developing fully automated interoperability between BIM platforms and structural analysis software through open standards such as IFC and APIs could further enhance the practical implementation of intelligent optimization systems in engineering practice.

Overall, the findings demonstrate that the integration of BIM with metaheuristic optimization algorithms constitutes a robust and practical decision-support framework for modern construction management. By simultaneously improving project cost, construction duration, resource utilization, structural efficiency, and environmental sustainability while maintaining full compliance with engineering constraints, the proposed methodology provides a promising foundation for the next generation of intelligent BIM-enabled construction planning and structural design system.

References

- Baghalzadeh Shishehgharkhaneh M, Moradinia SF, Keivani A, Azizi M, "Application of classic and novel metaheuristic algorithms in a BIM-based resource Tradeoff in dam projects", *Smart Cities*, 2022, 5 (4), 1441-1464. <https://doi.org/10.3390/smartcities5040074>
- Bakhshi R, Fard Moradi Nia S, Jani R, Vafaeipour R, "Applying project management knowledge and hybrid algorithm in predicting the time and cost of completing dam projects", *Water Resources Engineering*, 17 (61), 65-85. 2024. <https://doi.org/10.30495/WEJ.2024.31317.2374>
- Espoutin B, Moradinia SF, "Optimization of Quantitative and Qualitative Indicators of Construction Projects with a Project Management Knowledge Approach (Case study: Qucham Reservoir Dam)", *Amirkabir Journal of Civil Engineering*, 2022, 53 (11), 5033-5052. <https://doi.org/10.22060/CEEJ.2020.18694.6929>
- Fard Moradi Nia S, Khademi A, "Optimization of project scheduling under resource constraints using a genetic algorithm", *Asas Scientific Research Quarterly*, 2018, 20 (50), 58-73. https://www.isceiran.org/article_66800_en.html
- Feng X, Hye J, "Multi-objective optimization of construction progress based on BIM and genetic algorithm", *International Conference on Multi-modal Information Analytics*, Springer, Cham, 2022, 995-1002. https://doi.org/10.1007/978-3-031-05237-8_123
- Hamidavi T, Abrishami S, Hosseini MR, "Towards intelligent structural design of buildings: A BIM-based solution", *Journal of Building Engineering*, 2020, 32, 101685. <https://doi.org/10.1016/j.jobbe.2020.101685>
- He W, Shi Y, Kong D, "Construction of a 5D duration and cost optimization model based on genetic algorithm and BIM", *Journal of Engineering, Design and Technology*, 2019, 17 (5), 929-942. <https://doi.org/10.1108/JEDT-12-2018-0214>
- Kaurav M, Sharma M, "Tri-objective optimization of time, cost, and quality in construction management using analytic hierarchy process and OBL-enhanced NSGA-III", *Asian Journal of Civil Engineering*, 2025, 1-19. <https://doi.org/10.1007/s42107-025-01552-z>
- Lao WL, Li M, Wong BCL, Gan VJ, Cheng JC, "BIM-based constructability-aware precast building optimization using optimality criteria and combined non-dominated sorting genetic II and great deluge algorithm (NSGA-II-GD)", *Automation in Construction*, 2023, 155, 105065. <https://doi.org/10.1016/j.autcon.2023.105065>
- Luong DL, Truong NS, Ngo NT, Nguyen NQ, "Developing the hybrid BIM-BEM and jellyfish search optimization system for optimizing energy consumption and building installation costs", *Scientific Reports*, 2024, 14 (1), 17186. <https://doi.org/10.1038/s41598-024-68021-6>
- Nusen P, Boonyung W, Nusen S, Panuwatwanich K, Champrasert P, Kaewmoracharoen M, "Construction planning and scheduling of a renovation project using BIM-based multi-objective genetic algorithm", *Applied Sciences*, 2021, 11 (11), 4716. <https://doi.org/10.3390/app11114716>
- Nusen P, Piyawongwisal P, Nusen S, Kaewmoracharoen M, "Resource utilization optimization using genetic algorithm based on variation of resource fluctuation moment for extra-large building renovation", *Proceedings of the 2021 6th International Conference on Intelligent Information Technology*, 2021, 14-21. <https://doi.org/10.1145/3460179.3460183>
- Padala SP, "A BIM-integrated multi objective optimization model for sustainable building construction management", *Construction Innovation*, 2025, 25 (6), 1727-1751. <https://doi.org/10.1108/CI-09-2023-0223>
- Shams A, Marzouk M, "Leveraging BIM and time-cost-safety trade-off analysis for optimized decisions in construction projects", *Engineering, Construction and Architectural Management*, 2026, 33 (7), 5180-5209. <https://doi.org/10.1108/ECAM-11-2024-1588>
- Wang Y, Zhao W, Cui W, Zhou G, "Comparison of five meta-heuristic algorithms in layout optimization of multiple tower cranes", *Engineering*,

- Construction and Architectural Management, 2026, 33 (7), 5849-5873.
<https://doi.org/10.1108/ECAM-12-2024-1774>
- Wefki H, Elnahla M, Elbeltagi E, "BIM-based schedule generation and optimization using genetic algorithms", Automation in Construction, 2024, 164, 105476.
<https://doi.org/10.1016/j.autcon.2024.105476>
- Yu Y, Han J, Gu H, Yang Y, "Dynamic optimization of construction time-cost for deep and large foundation pit based on BIM technology and genetic algorithm", Applied Sciences, 2023, 13 (19), 10716.
<https://doi.org/10.3390/app131910716>
- Zhang Y, "Development of an integrated intelligent BIM-based model for multi-objective optimization in engineering assembly processes", PLoS One, 2025, 20 (11), e0333354.
<https://doi.org/10.1371/journal.pone.0333354>
- Zhao D, Chen X, "Multi Objective Optimization Design of Building Construction Period based on BIM and Genetic Algorithm", Journal of Physics: Conference Series, 2021, 1992 (2), 022184.
<https://doi.org/10.1088/1742-6596/1992/2/022184>