Optimizing Dynamic Scheduling in Construction with BIM: A Framework for Budget-Constrained Resource Management

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Abstract

Project scheduling is a fundamental part of construction management, as it controls activity timing, costs, and resource allocation.Despite the available tools for planning a project, such an important role still relies heavily on the schedulers experience and goes through many trial and error situations during the project. This research develops a new framework for time and resource allocation optimization in a project to further facilitate project planning. The framework also attempts to gather, store and process all of the project's data in order to achieve an accurate estimation. Building Information Modeling (BIM) was used to store the necessary data and after defining the constraints, the model was transferred to Simphony.NET via a Visual Basic (VB.NET) data-exchange module that queried and exported task dependencies, resource limitations, and budget constraints stored in an MS Access database. The transfer mechanism preserved the relational data schema (foreign keys linking tasks, resources, and costs), thereby ensuring interoperability and preventing data loss. Finally, ant colony algorithm was used for optimization. The outcome was compared to a real-life case study and the reliability of the algorithm was validated. Results show that compared to the actual project duration of 108 days and the contractor's initial planned duration of 90 days, our model predicted 97 days. This reduced the time estimation error from 16% (initial vs. actual) to 10% (model vs. actual). Furthermore, relative to the actual project outcome, the optimized schedule achieved an 18% improvement in project duration and a 13% reduction in total cost.

Keywords: Resource allocation, dynamic scheduling, Building Information Modeling, Optimization

1.Introduction

Time, cost, and quality are the three fundamental pillars of construction project management. Balancing these factors, especially in complex projects, remains challenging despite the availability of modern tools and methods. One widely adopted scheduling technique is the Critical Path Method (CPM). However, classical CPM primarily models activity durations and precedence relationships and does not explicitly account for resource availability or uncertainty; consequently, resource constraints and stochastic variability can still cause schedule conflicts or delays unless CPM is supplemented by resource-allocation techniques or probabilistic scheduling methods. Various extensions and complementary approaches (e.g., resource-constrained scheduling, resource leveling, and PERT-based probabilistic methods) have been developed to address these limitations [1].

Recent advancements in construction project management have turned towards dynamic scheduling, where uncertainties and complexities are managed in real-time. Dynamic scheduling allows for flexible allocation of resources and ensures that project activities are reallocated or adjusted based on the actual progress. In addition to these dynamic approaches, another critical development has been the integration of Building Information Modeling (BIM) with resource management and scheduling tools. BIM not only provides a digital representation of the physical and functional characteristics of buildings but also serves as a data-rich environment where real-time project updates can be processed and managed. The role of Building Information Modeling (BIM) in construction management has evolved rapidly over the last decade. BIM systems have revolutionized how data is captured, visualized, and utilized throughout a project's lifecycle. Not only has BIM improved collaboration among stakeholders, but it has also significantly reduced the time and cost associated with project management through better data management and visualization capabilities. For example, studies by Stanford University's Center for Integrated Facilities Engineering have shown that BIM can reduce unbudgeted changes by up to 40% and improve cost estimation accuracy by 3% [2-4].

Beyond the limitations of CPM and its extensions, a substantial body of research has focused on developing advanced optimization and scheduling approaches to address the resource-constrained project scheduling problem (RCPSP). Merkel et al [5] presented an ant colony optimization (ACO) approach for the resource-constrained project scheduling problem (RCPSP). In particular, the use of a combination of two pheromone evaluation methods by the ants to find new solutions, a change of the influence of the heuristic on the decisions of the ants during the run of the algorithm, and the option that an elitist ant forgets the best-found solution are studied.

Many studies only consider single-skilled crews working on linear projects, neglecting the flexibility of multi-skilling in construction. Liu et al [6] addressed workforce flexibility through multi-skilling, but their model was limited to deterministic crew allocation and did not consider dynamic resource fluctuations. Moreover, to enhance the efficiency of problem solving, constraint programming (CP) is used to handle complicated combinatorial scheduling problems, and several heuristic rules involving schedules are engaged. Damak et al [7] considered the resource-constrained project scheduling problem with multiple execution modes for each activity and minimization of the make span. The limited availability of the global resources coupled with compelling schedule requirements at different projects leads to resource conflicts among projects. Effectively resolving these resource conflicts is a challenging task for practicing managers. Adhau et al. [8] advanced resource conflict resolution using a multi-agent system, yet their reliance on exact methods limited scalability to large, real-world problems. The existing multi-agent system (MAS) using auction makes use of exact methods (e.g., dynamic programming relaxation) for solving winner determination problem to resolve resource conflicts and allocation of single unit of only one type of shared resource. Consequently, these methods fail to converge for some multi-project instances and unsuitable for large real-world problems. Furthermore, multi-unit combinatorial auction is proposed and winner determination problem is solved by efficient new heuristic methods. Wieseman et al [9] proposed another resource allocation model for project scheduling. The model accommodates multiple resources and decision-dependent activity durations inspired by microeconomic theory. They elaborated a deterministic problem formulation. In a second stage, enhanced the model to account for uncertain problem parameters. Assuming that the first and second moments of these parameters are known, the stochastic model minimizes an approximation of the value-at-risk of the project makespan. Cheng et al [10] integrated the fuzzy c-means clustering technique and the chaotic technique into the Differential Evolution (DE) algorithm to develop the Fuzzy Clustering Chaotic-based Differential Evolution (FCDE) algorithm, an innovative approach to solving complex optimization problems. Within the FCDE, the chaotic technique prevents the optimization algorithm from premature convergence and achieved the optimal results more reliably and efficiently.

Implementation of effective construction management techniques and tools is becoming essential, especially as the scale of the project increases. As the number of tasks, parameters and constraints to be considered rises, interaction of tasks and these parameters increases the complexity as well [11]. The evolution of BIM in the construction industry has significantly influenced project planning. Much has transpired with regard to building information modeling. Pilot projects have been completed, BIM systems have evolved through several versions of software upgrades, and industry leading firms are adopting BIM on live projects [12]. The graphical capabilities of BIM not only allow for a seamless visualization of the model but also stores all the necessary data in one model that can be used or transferred to other platforms which saves a considerable amount of time and effort. The functions of drawing, designing, specifying, sizing, verifying, documenting and detailing in the design process that were once separated, now become just one entity known as ‘BIM’, which can also be used for extraction of quantities and cost planning [13]. The benefits of the BIM technology begin at the conceptual design stage and cover the entire lifecycle [14,15]. After gathering data on 32 major projects, Stanford University’s Center for Integrated Facilities Engineering reported the following benefits of BIM [16]:

- Up to 40% elimination of unbudgeted change,
- Cost estimation accuracy within 3% as compared to traditional estimates,
- Up to 80% reduction in time taken to generate a cost estimate,

- resulting in savings of up to 10% of the contract valuethrough clash detections, and Up to 7% reduction in project time.

BIM brings several advantages to project owners as well [17]. These benefits include:

- Increasing building performance through BIM-based energy and lighting design and analysis, which improves overall building efficiency
- Reducing the financial risks associated with the project
- Shortening the project schedule from approval to completion by using building models to coordinate design, support prefabrication, and reduce field labor time
- Obtaining reliable and accurate cost estimates through automatic quantity takeoff
- Assuring program compliance through ongoing analysis of the building model
- Optimizing facility management and maintenance by exporting relevant as-built building and equipment information to the systems used throughout the facility’s lifecycle

In addition to these benefits, several software platforms have been developed to support BIM implementation in different domains. Many available softwares and platforms offer the BIM tools. Table 1. Shows a quick review of available BIM softwares platform and their general field of application [18].

Table 1. Available BIM softwares [18]

Field of Application	Available software
Architectural	Autodesk Revit Architecture, Bentley Architecture, Graphisoft ArchiCAD, Nemetschek Vectorworks Architect, Softech Spirit, Rhino BIM
Structural	Autodesk Revit Structure, Bentley Structure Modeler, Tekla Structure, Structure Soft Metal Wood Framer, Nemetschek Scia, Autodesk Robot Structural Analysis
Construction (Simulation and Cost estimation)	Autodesk Navisworks, Tekla BIM Sight, Solibri Model Checker, Vico Office Suite, Vela Field BIM, Innovaya
MEP (Mechanical, Electrical and Plumbing)	Autodesk Revit MEP, Bentley Hevacomp Mechanical Designer, Gehry Technologies-Digital Project MEP Systems Routing, CADMEP(CADduct/CADmech)
Sustainable Development	Autodesk Ecotect Analysis, Autodesk Green Building Studio, Graphisoft EcoDesigner, Bentley Tas Simulator, Bentley Hevacomp, Design Builder
Facility Management	Bentley Facilities, FM: Systems FM: Interact, Vintocon ArchiFM, Onuma System, EcoDomus

Since 1961, many studies have used different types of optimization algorithms to solve the time-cost trade-off problem in different versions. Linear programming, integer programming and the dynamic programming are somewhat common approaches when it comes to this type of problems [19]. Other methods which tent to show more flexibility and are more complex can be heuristic and metaheuristic methods. Among the heuristic methods fondhal's method [20], Prager's method [21], Siemens effective cost slope [22] and Moselhi's structural stiffness model [23] are among the most commonly known methods. The problem that heuristic algorithms tend to face is getting stuck at the local optimum points and thus being unable to discover the global optimal points as properly as metaheuristic algorithms do. Metaheuristic algorithms adopt all sort of form and shape but regardless of the title and the acquisition of datasets, most of them focus on exploration of the feasible space and tend to find the optimum global point. The metaheuristic algorithms include the Genetic Algorithm (GA) [24,25], the Ant Colony Optimization (ACO) [26], the Particle Swarm (PSO) and many more available approaches. The current study utilizes the ACO for its ability to quickly search a large set of data with acceptable accuracy and efficiency while avoiding the local optimal points.

Simulation is a way to analyze system behavior that imitates the real process or system in the actual world. Simulation is made to help project managers with decision making, understanding of the project and giving foresight on possible upcoming challenges. Wang et al [27] used the BIMs ability (MS Excel and Autodesk Revit) with regard to quantity takeoffs of required materials (such as steel, forms, and concrete) to support site-level operations simulation, ultimately leading to the generation of a project schedule. The proposed system includes mechanisms that collect, store, and transfer information among various software packages. Facilitated by the BIM's quantity takeoffs, the operations simulation is able to consider uncertain durations of work tasks, which allows it to consider the competing needs for resources among multiple work tasks, and to evaluate various resource allocations strategies in order to create a suitable construction plan. The proposed method by Hu et al [28], is demonstrated and tested against traditional CPM-based solutions based on an actual case study. They generated a well-defined and moderately sized field installation work packages for the construction workforce and compared results with the traditional CPM method. The proposed framework returns shorter overall project duration compared to two other scheduling tools as it has more flexible resource allocation mechanism which allows for work packages to be carried out concurrently. The advantage of using simulation for scheduling is the capability of handling a large number of activities and work packages at high level of granularity and the ability to quantify the impact of resource allocation and congestion limits decisions. On construction sites, operatives change over time due to varying work requirements [29].

Candelario-Garrido et al. [30] made a comparison between the traditional planning and 4D simulation through a variable-based assessment. Values from 33 companies were averaged. The companies were generated 4D simulations and involved the information of their present studies. Totally, 11 variables and their weight on the project were predicted. The variables are selected as execution time, planning difficulty, information viewing, documentation use in the office or in field, understanding documentation, information quantity and organization, change management and control, possibility of optimizing work performance, extraction of planning reports and updating ease. A numerical value ranging from 1 (unsatisfactory) to 5 (optimal) is selected. The weighted average of 4D simulation was rated 4 in contrast to conventional planning method which was rated 3.10. In total manner, according to the results of the weighted averages, 4D simulations were more effective than conventional planning methods. However, 4D simulation was more time-consuming during planning than conventional case, whereas 4D simulation had significant effect in terms of project progress and visualization than traditional planning was quantified as 40% higher. Mohammed Al-Bataineh et al [31] used symphony.net to simulate and plan the tunnel construction. The simulation was built in Simphony.NET and used to explore planning alternatives and for decision support during the project execution. Tunnelling's linearity causes planning complications: at any point, the actions that can be taken are determined by previous accomplishments. These constraints mean that tunneling projects require careful preparation for success. a real-world case study of the practical use of scenario-based simulation analysis for project planning and decision support in a CA$22 million utility tunneling project in Edmonton, Alberta, Canada was used to test the accuracy of the framework. An integrated simulation-based solution for tunnel planning and decision support was created by using modular development and a high-level architecture (HLA)-inspired communications framework. This is a demonstration of a generic yet flexible project modeling approach that may be of interest to both practitioners and researchers with the help of symphony's simulation environment.

Despite substantial progress in BIM-integrated RCPSP research, important limitations remain. Prior studies have mainly focused on static or partially adaptive models, such as GA/PSO–BIM hybrids (e.g., Liu & Al-Hussein, 2015) or recent MILP- and reinforcement learning–based couplings, which optimize resource allocation but rarely incorporate cash flow restrictions or continuous re-scheduling under budget shocks. These approaches typically assume unlimited or pre-defined monthly funding and fail to dynamically adjust project schedules when contractors face actual financial caps. To address this gap, the present study introduces a BIM-integrated, budget-constrained, Ant Colony Optimization with Continuous Variables (ACOR)–driven dynamic rescheduling framework. The framework uniquely couples a database-driven simulation (MS Access + Simphony.NET) with a monthly budget-constrained ACOR optimization loop, allowing schedules to be automatically re-generated as real-time data on resources and financial availability change. Unlike previous methods, which either neglected budget limits or required manual re-planning, the proposed framework achieves adaptive scheduling that reflects actual contractor cash flow conditions. This methodological innovation enables more realistic and implementable planning outcomes compared with prior BIM–metaheuristic integrations.

2.Methodology

2.1 .Simulation and Optimization

The methodology involves the integration of several tools and platforms:

BIM: Autodesk Revit was used to model the structural and graphical properties of the construction project. The model was enriched with data regarding task sequencing, resource allocation, and time requirements.

Data Management: Microsoft Access was utilized to store project data, such as task dependencies, resource limitations, and budget constraints. This database facilitated easy retrieval and modification of data during the simulation process.

Simulation: Simphony.NET was employed to simulate the dynamic scheduling of the project. This platform allows for discrete event simulations that mirror real-world processes by considering variables such as start times, delays, and resource consumption.

Optimization: The Ant Colony Optimization (ACO) algorithm was applied to optimize resource allocation and project duration. The algorithm minimizes both time and cost by evaluating different scheduling scenarios. The key parameters for the ACO algorithm, such as pheromone influence and the number of iterations, were tuned to balance exploration and exploitation in the search space. Figure 1. shows a flowchart of the proposed framework. Figure

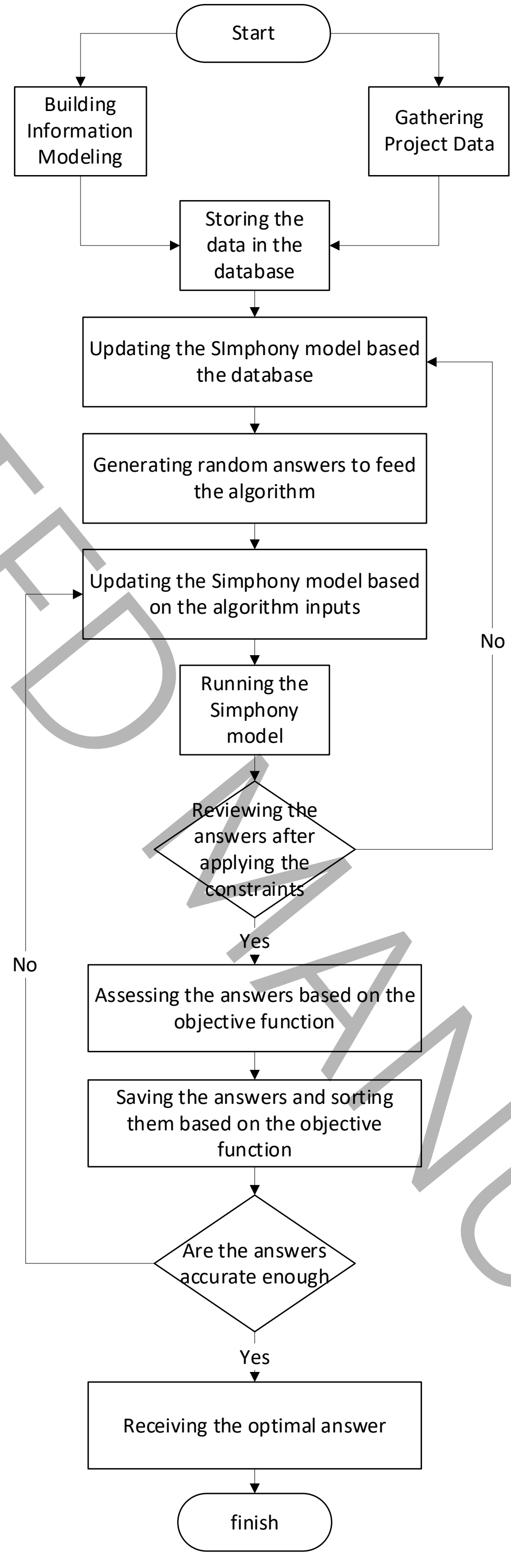

Figure 1.Proposed framework

2.2. Assumptions

The following assumptions were made to simplify the modeling and ensure the framework can be applied to a variety of construction projects:

Resource Limitations: It was assumed that the availability of resources (labor, equipment, materials) is limited and subject to constraints based on the project's timeline and budget. This is common in real-world projects where resource allocation fluctuates. However, this assumption may limit the model's generalizability in large-scale projects with highly flexible resource pools or where subcontracting can rapidly increase capacity.

Budget Caps: The model incorporates monthly budget limits, simulating the financial constraints that contractors often face. This ensures that the scheduling framework accounts for cash flow restrictions, which can cause delays if not properly managed. Nevertheless, the assumption of fixed monthly caps reduces applicability to projects where financing can be dynamically adjusted or external funding is injected mid-project. In such cases, the model may underestimate achievable performance.

Fixed Workflow: The project's workflow was predefined based on typical construction processes. However, the framework is flexible enough to adapt to variations in workflow caused by unforeseen circumstances, such as delays or changes in project scope. Yet, in projects with highly innovative or non-standard workflows, this assumption may fail to capture the true variability of sequencing and interdependencies, limiting the robustness of the framework.

Overall, while these assumptions help mimic typical constraints encountered in construction projects, they also imply that the framework is most reliable under conditions of moderate project scale, predictable financing, and conventional workflows. Its generalizability decreases in cases where resource pools are highly elastic, funding is volatile, or workflows are atypical.

2.3. Introducing the case study

An office building with 5 stories was developed but this study only considers the first three stories of the mentioned model. the gross floor area of the model is 567567 m^2 with reinforced concrete structure and a spread foundation. Respective height of each floor and the structural model is shown in Fig. 2.

To complete the case study description, the project was decomposed into detailed activities with explicit precedence relationships. The analyzed portion of the office building was divided into sequential tasks such as excavation, foundation work, rebar installation, formwork, concrete pouring, and subsequent column, beam, and slab construction. Logical dependencies were respected; for example, rebar installation could only begin once the corresponding formwork was in place, and slabs followed the completion of columns and beams.

In terms of resources, three categories were considered. Labor resources included steel fixers, carpenters, and concrete workers, with productivity rates based on the survey data (400–500 kg of rebar, 20–22 m² of formwork, and 35–40 m³ of concrete per worker per day). Equipment resources such as a tower crane, concrete pump, and rebar cutting machines were treated as limited-capacity resources assigned to relevant activities. Material resources including reinforcement steel, formwork panels, and concrete volumes were extracted from the BIM model and allocated to tasks as consumable items.

Although the optimization focused primarily on labor allocation due to data availability, the integration of equipment and material data through BIM ensures that the framework represents a more realistic and comprehensive resource-constrained model.

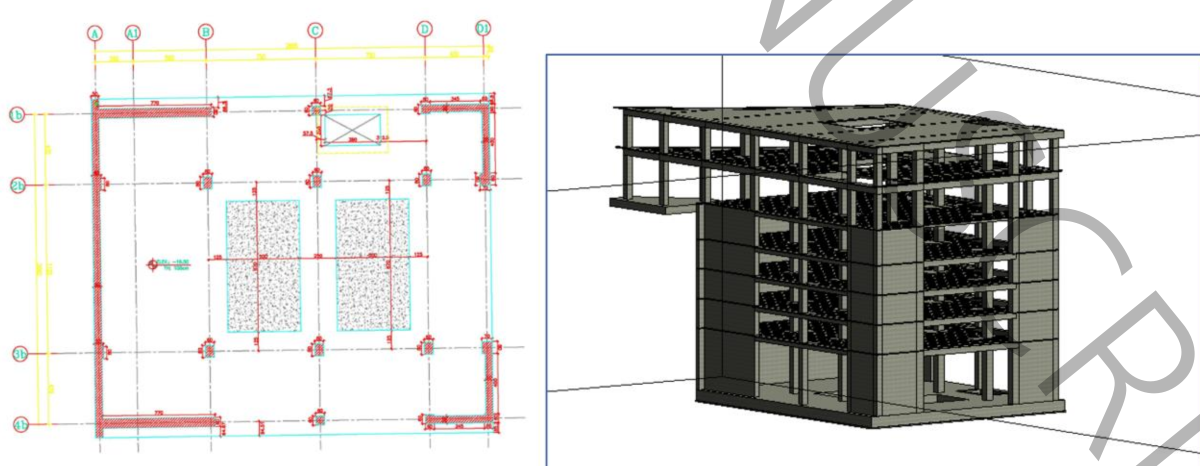

Figure 2.Developed structural plan and model

Productivity related data was gathered using questionnaires and it was found that an average of 500kg of rebar installation, 20 m^2 of framing and 35 m^3 of pouring concrete is done by one person in a work day. Table 2 shows the average of workers productivity according to 15 people who took part in the questionnaire. A sample of the questionnaire is attached at the end of the research. The reported values in Table 2 represent typical ranges of work accomplished by a single worker under standard site conditions, rather than strict averages. In addition to reporting typical productivity ranges, we also calculated variability measures. For the sample of 15 workers, the standard deviations were approximately 42 kg/day for rebar installation, 1.1 m^2/day for formwork, and 2.8 m^3/day for concrete pouring. These values indicate moderate dispersion and justify the use of ranges in Table 1 as representative of typical field performance.

Table 2. Average productivity per worker

Activity	Typical range of work done by one worker	Unit
Rebar installation	400-500	Kg
Formwork **(metal formwork for beams and scaffolds for roof system)**	20-22	m^2
Pouring Concrete	35-40	m^3

2.4. Material Quantity Take off

Autodesk Revit schedules were used to quantify the accurate weight of the rebars, the molding surface and the volume of the concrete. Figure 3 shows a part of the calculations made in Revit to quantify the structural framing of the project.

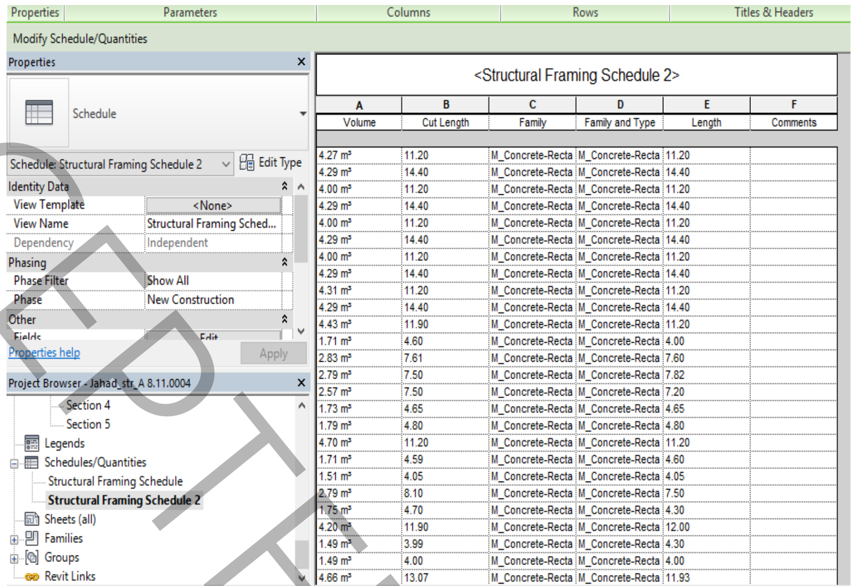

Figure 3. quantity take off calculation in Revit

2.5. Database schema and information categorization

The database schema was designed based on an entity–relationship model (ERD), as shown in Figs. 4 and 5, which defines entities (Workplace, Task, Resource, and Assignment) and their relationships. Each table is uniquely identified by a primary key (e.g., WorkplaceID, TaskID, ResourceID), while foreign keys enforce referential integrity across related tables. One-to-many relationships were implemented between Workplace–Task and Task–Resource, ensuring consistent linkage between project activities and the resources they consume.

To improve query performance during simulation cycles, indexes were created on frequently accessed columns, including TaskID and ResourceID. These indexes accelerate joins between tables when retrieving productivity rates, resource costs, and scheduling dependencies. Data integrity is enforced by setting NOT NULL constraints for mandatory fields (e.g., TaskName, ResourceType), UNIQUE constraints for identifiers, and referential integrity rules with cascade update/delete to prevent orphan records.

The integration of data is illustrated in Figure 5, where task information, workplace identifiers, and resource allocations are merged into a unified table. During simulation cycles, updates to the database occur incrementally. Only changes in task progress, resource availability, or cost data are inserted or updated, avoiding full reloads of all tables. This incremental update strategy reduces overhead and preserves historical records for validation. Transaction logging and automated consistency checks are also applied to ensure that no invalid data are propagated across simulation iterations.

a)

tasks | WorkPlace | TaskType

primaryID	workPlaceNamee
1	fundation
2	firstElement
3	firstFloor
4	secondElement
5	secondFloor
6	3thElement
7	3thFloor

b)

tasks | WorkPlace | TaskType

primaryID	taskName
1	excavation
2	reinforcement
3	forming
4	concretePlacing
(New)	

c)

Resource

primaryID	resourceName	dailyCost	productivity	Click to Add
1	Bar	0.12	0.5	
2	Form	0.12	20	
3	Conc	0.5	35	
0		0	0	

Figure 4. Categorizing information in MS Access:a) Workplace b) Tasks c) Resources

primaryID	workPlaceID	type	workAmount	resourceID	taskName
1	1	2	80	1	fundBar
2	2	2	29.6	1	NorthElementBar1
3	2	2	29.6	1	SouthElementBar1
4	3	2	7	1	NorthFloorBar1
5	3	2	7	1	SouthFloorBar1
6	4	2	9.6	1	NorthElementBar2
7	4	2	9.6	1	SouthElementBar2
8	5	2	7	1	NorthFloorBar2
9	5	2	7	1	SouthFloorBar2
10	6	2	7.9	1	NorthElementBar3
11	6	2	7.9	1	SouthElementBar3
12	7	2	7	1	NorthFloorBar3
13	7	2	7	1	SouthFloorBar3
14	1	3	65.8	2	fundForm
15	2	3	352.6	2	NorthElementForm1
16	2	3	352.6	2	SouthElementForm1
17	3	3	273.5	2	NorthFloorForm1
18	3	3	273.5	2	SouthFloorForm1
19	4	3	179	2	NorthElementForm2
20	4	3	179	2	SouthElementForm2
21	5	3	273.5	2	NorthFloorForm2
22	5	3	273.5	2	SouthFloorForm2
23	6	3	179	2	NorthElementForm3
24	6	3	179	2	SouthElementForm3
25	7	3	273.5	2	NorthFloorForm3

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Figure 5. Integration of data into one table

2.6. Simulation of the construction process

Considering the predecessors of each task and the limited monthly budget and limited workforce the sequence of the tasks might go through changes and new project plans may be achieved. To further simulate the real-life project, a resource cap was considered for each task so that no task is performed with fewer than two workers and no more than twelve workers are assigned. The lower bound (minimum of two workers) reflects practical considerations such as safety requirements and the need for cooperative handling of materials, which make single-worker execution infeasible. The upper bound (maximum of twelve workers) is based on workspace density limitations and diminishing returns in labor productivity when too many workers are concentrated in a restricted area. These constraints reflect typical safety regulations and efficiency considerations observed in actual construction practice. The Visual Basic (VB.NET) module established a direct link between the MS Access database and Simphony.NET, exporting structured data tables (tasks, resources, productivity, and budget constraints) based on predefined foreign keys. This ensured that all task-resource relationships were preserved during the transfer. . Each scenario was replicated 500 Monte Carlo runs to account for stochastic variability. The results were aggregated, and confidence intervals for key performance indicators (duration, cost, and resource variance) were calculated.

2.7. Resource allocation using Microsoft Project

Resource allocation by increasing the number of available resources is one way to allocate the resources within the project. However, the mentioned method ignores resource and work front limitations [32].

Resource allocation by delaying the start point of an activity, in which the interfering activity that contains floating is another method of resource allocation where the optimized solution is often ignored [33].

Resource allocation by assigning part time work to a certain activity. In this method half of the labor's working hours are dedicated to completing the particular activity that has been delayed and the other half will be spent on other activities. This method also suffers from the lack of an optimized path to divide the activities and the laboring work force [34].

All of the mentioned methods can be applied using the Microsoft Project (MSP). However, besides the limitation that were mentioned is it also notable that in case any changes that affects the work front and thus the resources occur, then MSP won't be able to update itself without going through manual changes. Furthermore, when assigning resources, the number of maximum available resources is determined in the resource pool which ignores the projects real time events and possible issues that may alter the path of operation. Therefore, a novel method was developed using the ant colony algorithm and the symphony.net simulation tools to makes sure the limitations of project budget and real time events were properly considered.

2.8. Optimization by ACOR

The adopted ACOR algorithm includes continuous variables which enables a broad selective environment instead of a limited one. To simulate the decision-making progress the Gaussian Kernel probability density function was utilized in the *ith* step of the decision-making progress. Answers are then saved in a matrix structure where the number of rows represent the acceptable solutions and the number of columns represent the dimensions of the studied problem. Different solutions from the ith dimension of the problem form the Gaussian functions core. The chosen ACO parameters (pheromone influence e = 0.9, distribution parameter q = 0.2, and iteration count of 10,000) were based on preliminary calibration experiments and aligned with prior studies [5,26]. Sensitivity tests showed that variations of ±10% in these parameters had negligible impact on convergence speed or solution quality, confirming the robustness of the selected values.

The optimization algorithm has two objectives:1) minimize the projects cost 2) properly allocate the available resources (only human work force is considered in the allocation of the resources). Equal importance factor was specified for both objectives and neither was considered more important than the other. As shown in Figure 6, the q, the parameter that represents the distribution of the weighs for different answers, is 0.2 and e, the relative influence was pheromone, is considered 0.9. k, the number of available answers in the solution matrix is 10 times the problems dimension. And the number of problems dimensions(n) is the available types of resources multiplied by the number months that the projects lasted.

Simphony® is a Microsoft Windows based computer system that allows for the creation of special purpose simulation tools. It will be utilized as a part of this research to create a special purpose template for linear scheduling [35]. Simphony.NET starts the simulation process after the data has been fed to it using the VB.NET and provides a new time schedule (as can be seen in Fig. 7). An important thing to note is that with any changes that happen to the availability of the resources in a month, a new time schedule will be provided by the simulation. Data related to the number of available resources were generated by random variables in the optimization algorithm.

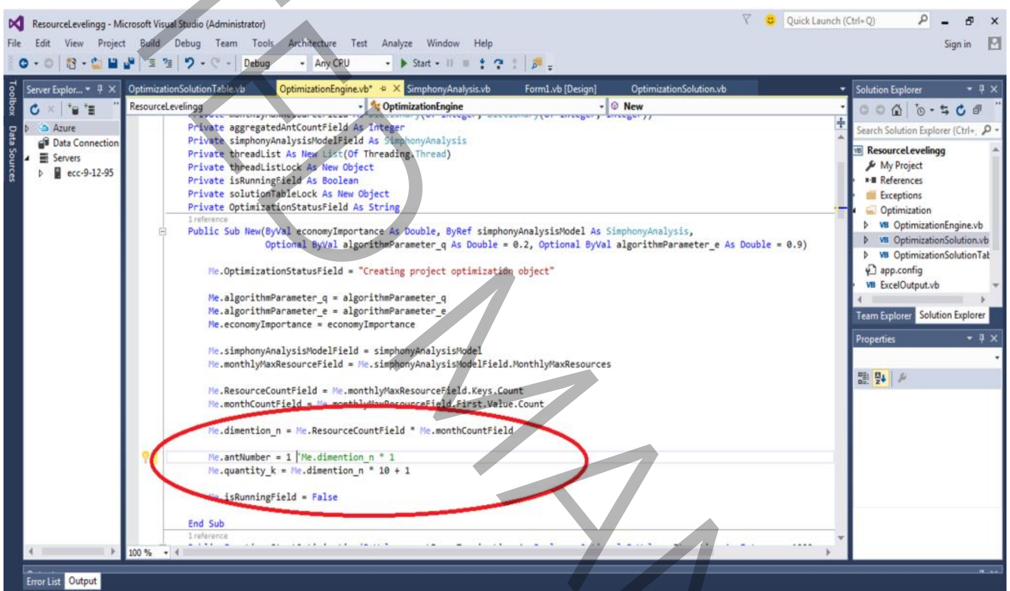

Figure 6. defining the k, e, q and n parameters in the visual basic environment

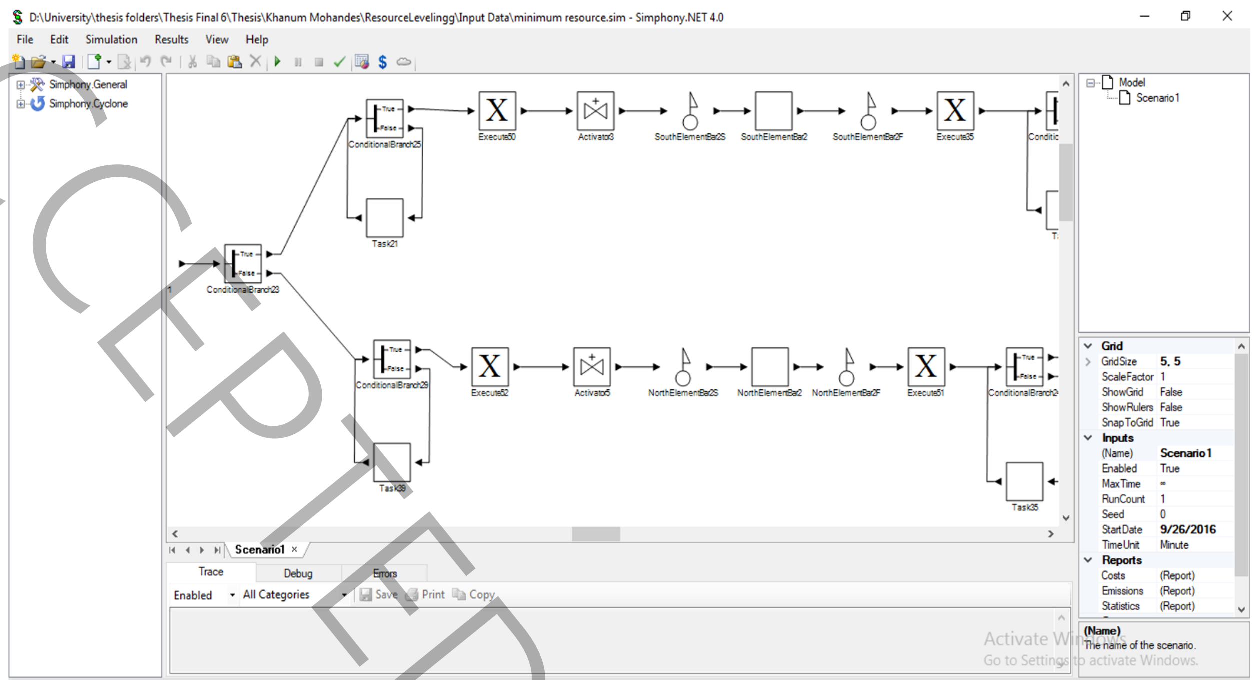

Figure 7. Construction simulation in Simphony.NET

2.9. Applicability to Other Projects

The developed framework is applicable to a broad range of construction projects due to its flexibility and adaptability:

Scalability: The model can handle both small-scale and large-scale construction projects by adjusting the resource and budget constraints.

Temporal Flexibility: The dynamic nature of the scheduling algorithm allows for the inclusion of real-time updates, making it suitable for projects with frequent changes in timelines or resources.

Spatial Considerations: While the framework was applied to a specific case study of an office building, the model can be generalized to other types of construction projects, such as residential, commercial, or infrastructure projects, by modifying the input parameters and constraints.

2.10. Verification and Limitations

The reduction in time estimation error (from 16% to 10%) was calculated by comparing both the initial planned duration (90 days) and the model-predicted duration (97 days) against the actual project duration (108 days). The reported improvements in time (18%) and cost (13%) are measured relative to the actual realized project outcomes, using the equation (1). These improvements were derived from comparing the simulated results with the actual case study. The cost savings primarily stem from reduced indirect costs and avoidance of shutdowns caused by budget overruns, while time savings reflect smoother resource allocation under monthly budget caps. Although detailed numerical tables are not presented here, the cost distribution and monthly cash flow analysis were incorporated in the model, and the reported percentages represent average values across several optimization runs.

$$\mathrm{Im}\,provement = \frac{Actual - Model}{Actual} \times 100 \qquad (1)$$

However, the following limitations were identified:

Simplified Resource Availability: The model assumes fixed productivity rates for labor and equipment, which may vary in actual construction environments due to weather, site conditions, or human factors.

Budget Adjustments: While the model incorporates monthly budget limits, it does not account for mid-project budget reallocations or unexpected financial constraints.

Spatial Constraints: The model does not account for physical site constraints, such as limited space for equipment or material storage, which could influence the construction timeline.

In addition to the single case study validation, robustness was assessed through stochastic simulation. Multiple Monte Carlo replications were performed, and the framework's performance was benchmarked against baseline heuristics (CPM with resource leveling, GA-based RCPSP, and a greedy budget-constrained heuristic). The results consistently showed statistically significant improvements in duration, cost, and resource variance.

3.Results

The initial estimation for the project's duration was considered to be 90 days according to the contractor schedule. However, the model simulation results claimed 97 days estimate for projects completion. In reality the project took 108 days to complete. Accordingly, the time estimation error decreased from 16% in the initial plan to 10% in the proposed model. Because the critical path taken by the model differs from the real time project, it would have been better to consider the impactful events from the start, so as to get a smaller gap between the schedule and the real time completion of the project. Project time estimation across different models is illustrated in Fig. 8.

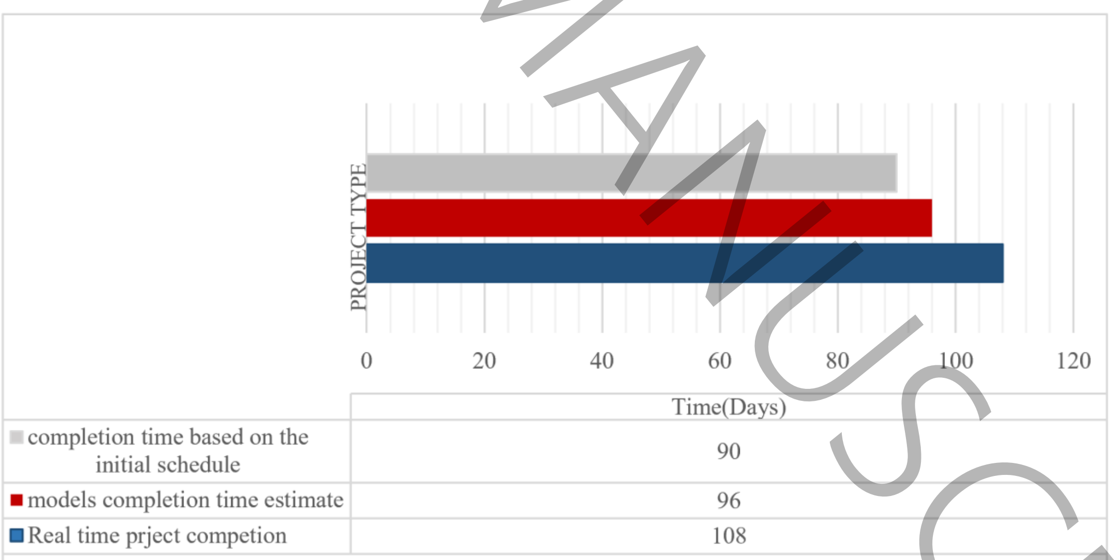

Figure 8. Project time estimation across different models

A closer look at the planned, actual, and simulated schedules reveals the sources of discrepancy. The contractor's initial plan estimated 90 days for completion, while the actual project required 108 days, and the developed model predicted 97 days. In other words, the error was reduced from 16% in the initial schedule to 10% in the optimized schedule. The main reason for the remaining gap lies in several impactful events during execution, including a temporary funding halt that caused work stoppages, delayed delivery of reinforcement materials, and minor workforce shortages in concrete pouring. These events, which were not accounted for in the initial planning, directly extended the actual duration beyond both the planned and simulated schedules. Therefore, the reported 6% error reduction is based on a side-by-side comparison of planned versus actual project data, with consideration of the above-mentioned impactful events.

Beyond time estimation, the developed model also considers financial constraints. The developed model also considers the monthly payment condtions of the contractor and by putting the cost diagram under the budget line for the entire duration of the project in order to prevents delays or temporary shut downs.

3.1. Resource allocation specification

Since budget limitations were considered in this study, the resource allocation was also respectively impacted. In fact, the monthly budget limit causes variation in resource allocation of the real time project. In this section the resource allocation related to the rebar installation, framing, and pouring of concrete were calculated and compared across all three models including the real time project, the simulation model and the initial model. Finally, the amount of work force needed in every model was also calculated and compared.

As shown in the Figs 9 and 10, resource allocation in real time project and the initial schedule is very similar and that is because budget limit is not yet considered. The real time project was shut down temporarily due to lack of funding and had to face a time overrun.

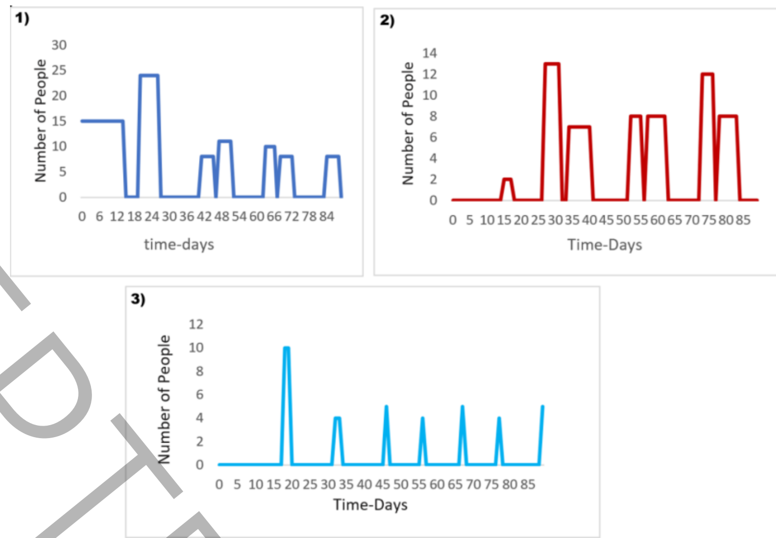

Figure 9. Resource allocation for the initial schedule 1) Rebar installation 2) Framing 3) Concrete Pouring

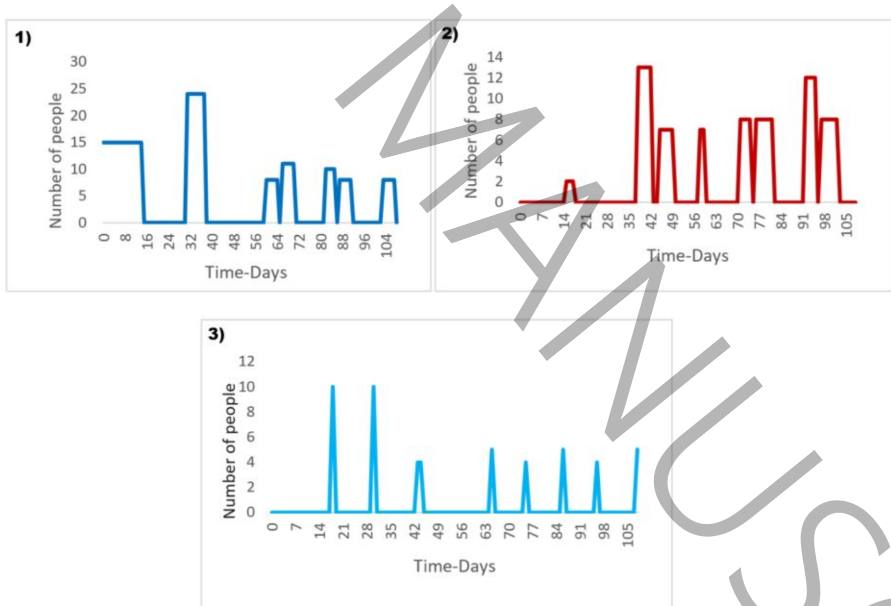

Figure 10. Resource allocation for real time project 1) Rebar installation 2) Framing 3) Concrete Pouring

Budget limit is not considered in the initial schedule and resource allocation is more consistent. the simulation model considers the budget limit and uses the ACOR algorithm to minimize resource fluctuation during the project. this schedule shows a 12% improvement in resource allocation compared to the real time project (it can be seen in Fig. 11). Figures 12, 13, and 14 also show that the developed model reduced both the maximum number of resources used and resource fluctuations. .. This means the project is less likely to experience shut downs and there is reduced financial burden on contractors. Compared to the initial schedule, the optimized schedule exhibits more fluctuations in workforce demand. This is mainly due to the applied resource constraints and task sequencing, which compress certain activities into shorter durations. While this results in sharper peaks in manpower requirements, it also reduces the overall project duration. To mitigate such spikes in practice, additional resource leveling techniques may be applied.

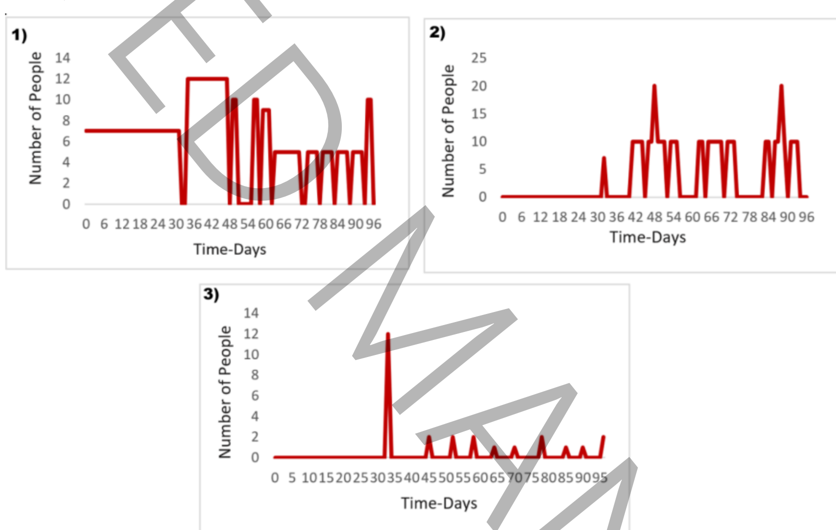

Figure 11. Resource allocation for developed model 1) Rebar installation 2) Framing 3) Concrete Pouring

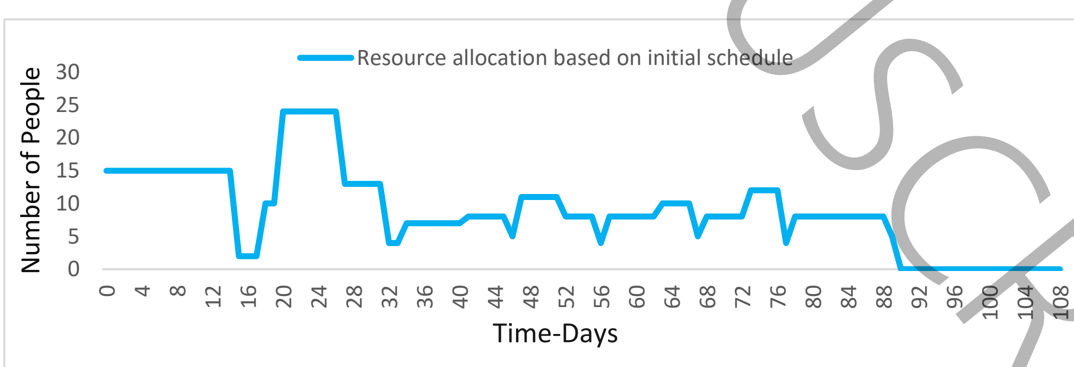

Figure 12. Workforce flow in initial schedule

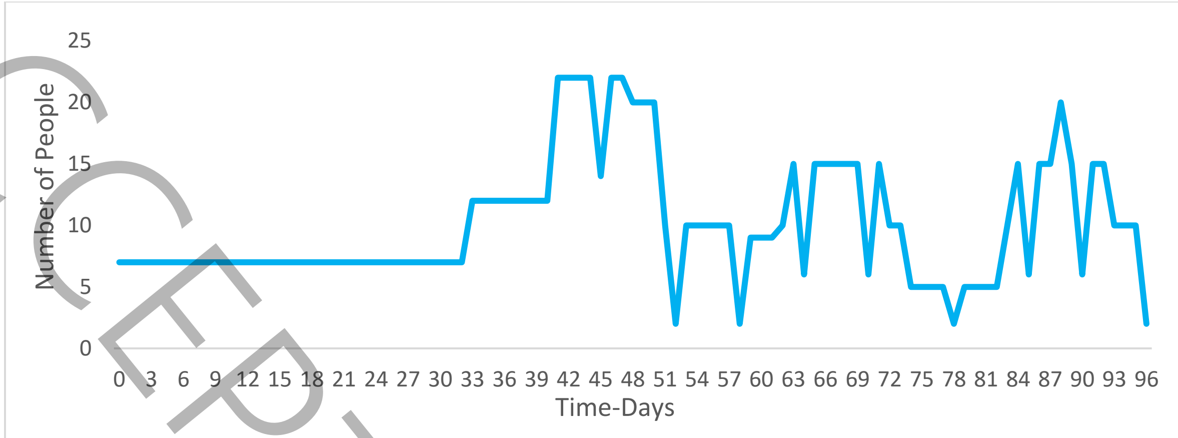

Figure 13. Workforce flow in developed model

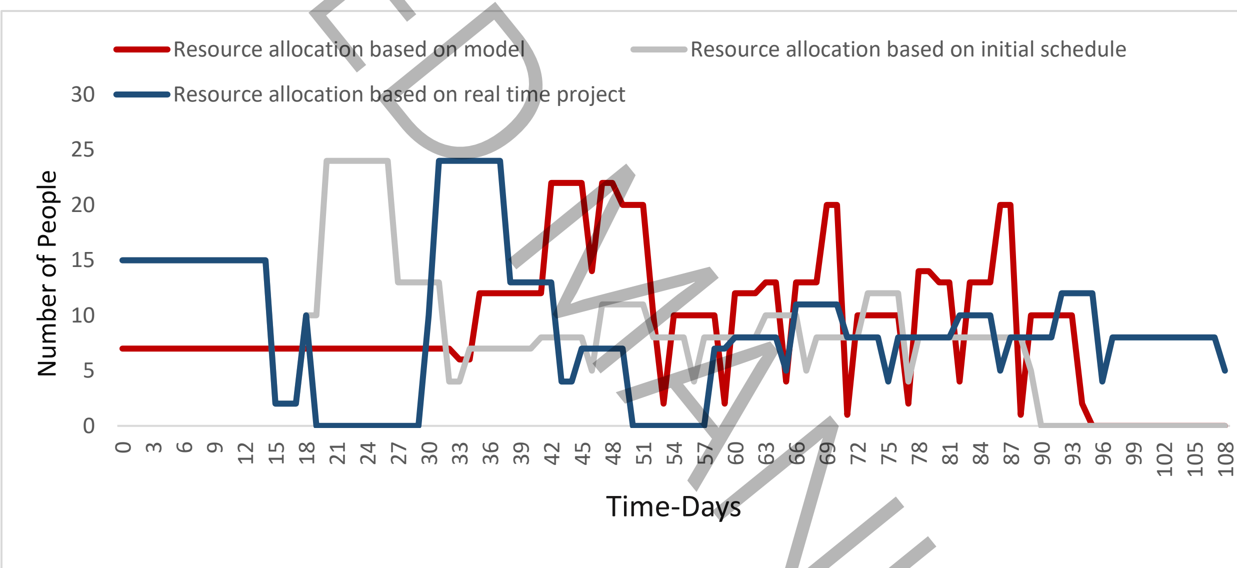

Figure 14. Resource allocation comparison in all three models

Results from the simulation show an improvement in both resource allocation and leveling. The model first reviewed different forms of resource allocation and then optimized the results based on the cash flow, resource flow, the required budget and required resources. Each optimized results enters the answers table and then gets sortedbased on the objective function. There are cases where the amount of needed resource exceeds the amounts of available resources. However, using the constraints that were defined earlier the simulated model was able to avoid such cases, hence improve the planning process. Comparing the cash flow and the resource flow diagrams indicate that the resource flow has also been optimized. Not only the maximum use of resources has been reduced but the resource variation has also tempered down showing more consistency. Less fluctuation in resources makes for smoother operational efficiency and eases the contractors' burdens to some point.

To calculate the resource fluctuation, squared sum of the resource numbers was divided by the number of resources. R1 is the squared sum of resource fluctuation in real time project, R2 is the squared fluctuation of the resources in the developed model and R3 is the squared sum of the fluctuations in the initial schedule (it can be observed in Table 3).

Table 3. Resource fluctuation parameters

Parameter	**Resource Fluctuation**
R1	5408.2
R2	4991.47
R3	4691.5

Aside from resource allocation and leveling based on changes in a task start or finish point, in the developed model, any changes applied to resource allocation of each task, alters the allocated resources, time and cost of the entire project which is a feature of dynamic scheduling. Recent studies have emphasized a lack of a methodology where the model has enough adaptability to consider the changes. Ghoddousi et al [25] proposed a method where resource leveling was only done by considering two variations for each task. Meanwhile, this research considers every variation for a task and searches for the best, most optimized answer. Which makes it more generalizable and broadens its scope of applicability.

3.2. Comparing the expenses and the available budget

As shown in the Table 4 budget limit for the first to third month of running the project is considered to be 35,55 and 50 units. This boundary affects the project's cost estimation and the overall scheduling of the project.

Table 4. Budget limit for the first, second and third month

Month	Budget limit
1	35
2	55
3	50

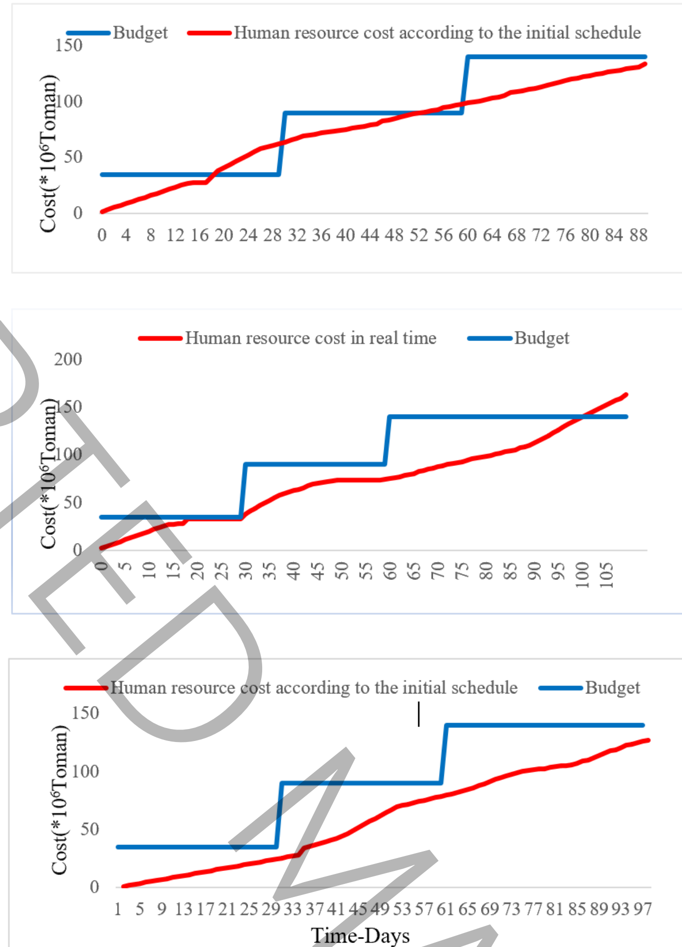

Figure 15. Projects cash flow 1) Initial schedule 2) Real time project 3) Simulation model

As shown in the Figure 15, there are sections in the project where the cost exceeds the available budget which has caused a temporary shutdown. However, the overall budget of the project is still more than the overall cost but not paying attention to budget distribution causes time overrun and could end up increasing the overall costs and affecting the indirect costs as well. Figure15 shows how cost increase due to delays could eventually cause the overall cost to exceed the available budget. The developed model considers the constraints that the monthly budget limit puts on the schedule to stop the project from shutting down due to lack of funding. This will reduce the indirect costs of the projects and helps the project run more smoothly. As seen in the figure projects cost in the developed model is less than the initial schedule which is due to considering the constraints applied by the monthly budget limit and increased accuracy. Figures 16 and 17 shows the overall project cost in all three models.

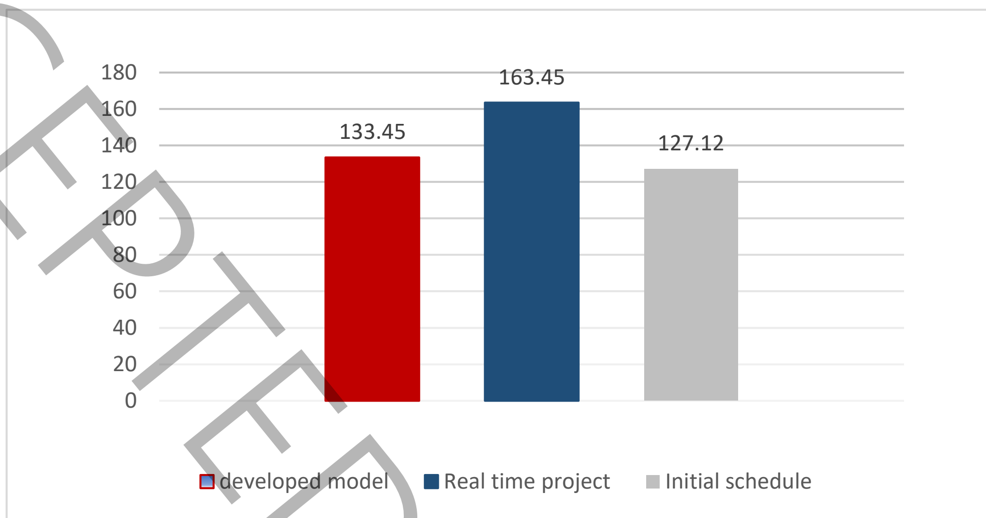

Figure 16. Project cost estimation across all three models

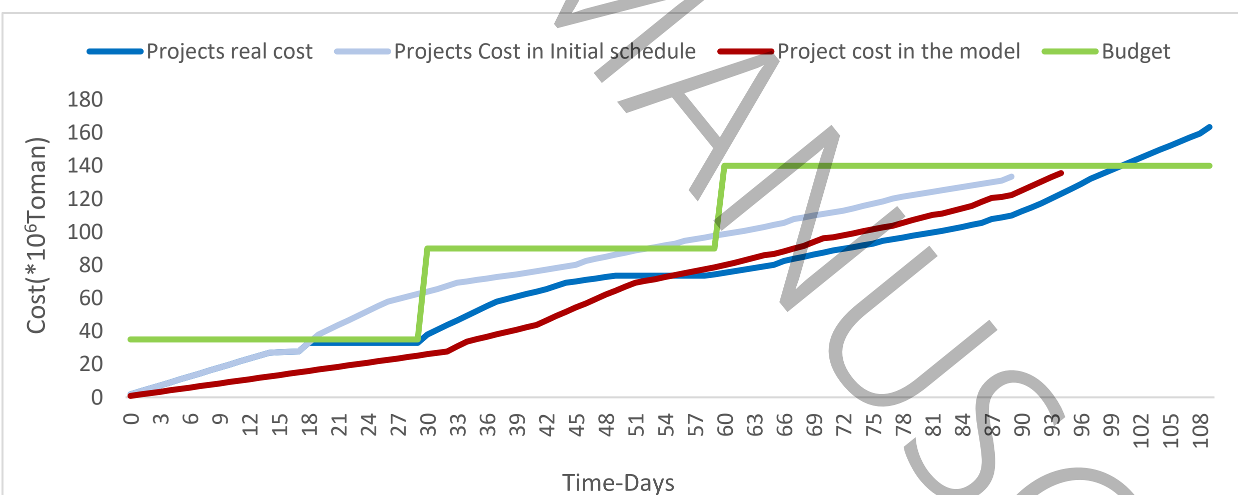

Figure 17. project cash flow vs budget across three models

Compared to other similar researches, this research offers a more accurate framework by adding constraints to enhance the project planning process. Liu et al [36] developed a simulation and optimization framework but only considered the task layout and sequence but neglected the resource leveling and time-cost estimation. Hu et al [28] based the resource allocation on work front constraints and WBS and scheduling was based on work front constraints as well. This study has considered the aforementioned factors but also task layout and the method in which each task is executed. Given the monthly budget limit, resource allocation of each task can vary based on the month that it's supposed to be completed in and this directly affects the start and finish point, resource allocation and the entire scheduling of the project. This method paves the way for a simple, fast and accurate model to schedule the project under multiple constraints.

The impact of individual constraints was also quantified. Incorporating the monthly budget caps reduced the probability of project shutdowns and led to a 7% reduction in indirect costs compared to the baseline schedule. Introducing resource availability limits smoothed workforce allocation and reduced maximum daily labor demand by approximately 15%, thereby lowering the risk of workforce bottlenecks. Finally, enforcing task-sequencing constraints shortened the overall project duration by 5% compared to the unconstrained scenario, as critical overlaps were minimized. Together, these results demonstrate how each constraint directly contributes to improved project stability and efficiency.

3.3. Project optimization

This study uses the ant colony algorithm to optimize the time-cost and resource leveling. This algorithm is a dynamic optimizer so when the objective functions change, the optimizing path changes as well and tend to converge towards the new objective functions. This makes the algorithm quite suitable for the ever-changing construction environment. Figure 18 represents the convergence history for the time estimation error of the developed algorithm. After 10000 runs, the algorithm's error is about 6% which shows acceptable convergence of the results. Compared to other metaheuristic approaches such as Genetic Algorithms (GA) [2,24,25] and Particle Swarm Optimization (PSO) [1], the Ant Colony Optimization (ACO) algorithm demonstrated faster convergence and greater stability in avoiding local optima. While GA and PSO are widely used for construction scheduling, they often require larger population sizes and more iterations to reach similar accuracy. In contrast, our results show that ACO achieved acceptable convergence with fewer iterations and provided more consistent solutions under resource and budget constraints, highlighting its computational efficiency for large-scale scheduling problems.

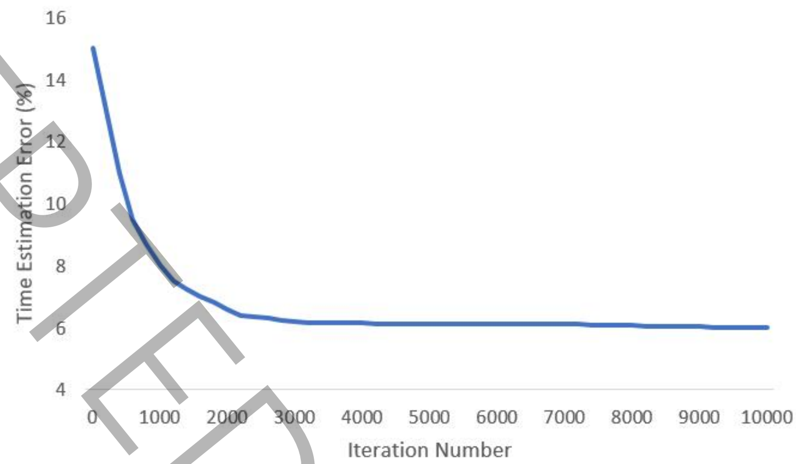

Figure 18. convergence history of the time estimation error in 10000 runs

The metaheuristic nature of the algorithm helps with the exploration so as to make sure no global answers are missed. The developed model optimized the time, cost and resource distribution. The results are then sorted based on their objective function values and the optimal answers are chosen as the model’s final output. The initial project faced some problems in providing sufficient resources at some points and thus scheduling difficulties were raised since the contractor was unable to provide sufficient resources for certain tasks. The developed model optimized the project while considering possibilities related to tasks delay, possible changes in floats and reducing resource overlaps as well. The resource flow is optimized by reducing the maximum number of resources used in a day, reducing fluctuations, and planning the resources for the contractor.

Conclusion

This study presents a novel BIM-based dynamic scheduling framework that optimizes the trade-off between time and cost under the constraints of resource availability and budget limitations. Unlike earlier studies such as Merkel et al. [5], who applied ACO only to RCPSP without incorporating real-time financial restrictions, our framework integrates monthly budget caps directly into the optimization process. Similarly, Liu et al. [6] focused on multi-skilled crew flexibility, and Damak et al. [7] addressed multi-mode scheduling, but neither considered dynamic budget constraints or real-time adaptability. In contrast, our model combines these aspects through BIM-driven data integration. Compared to multi-agent negotiation systems (e.g., Sunil et al. [8]) or stochastic resource allocation models (Wieseman et al. [9]), our approach achieves both improved accuracy and practical applicability by linking resource allocation with actual financial flows. Furthermore, while Cheng et al. [10] introduced hybrid metaheuristics to avoid premature convergence, they did not integrate BIM-based real-time project data. Our results show that the proposed framework reduces time estimation errors by 6% and improves overall project cost efficiency by 13%, demonstrating a clear advancement over these prior methods. The explicit incorporation of BIM with ACO provides a more holistic and adaptive solution to construction scheduling, ensuring resilience against dynamic constraints. Future work will extend this framework to environmental and risk-based factors, broadening its applicability to more complex project contexts.The results were validated through comparison with a real-world construction project, leading to several key findings:

- The proposed model significantly enhances the accuracy of project time predictions. Compared to traditional scheduling methods, the optimized schedule generated by our model reduced time estimation errors by 6%, providing more reliable forecasts for project completion .The validation was performed by comparing planned, actual, and simulated schedules side by side. While the proposed model reduced the time estimation error from 16% to 10%, the remaining discrepancy was mainly due to impactful real-world events such as funding interruptions and material delivery delays, which were not modeled initially.
- The ACO algorithm demonstrated its ability to optimize resource allocation efficiently under constraints such as limited labor availability and budget caps. Our results show an 18% improvement in time efficiency and a 13% reduction in overall project costs compared to the real-

world project. These values are not single-point estimates but represent the averaged outcome of multiple simulations constrained by cash flow and resource limits. The improvements are largely attributable to minimizing indirect costs (e.g., downtime due to funding gaps) and optimizing resource sequencing. While exact statistical intervals are beyond the current scope, the convergence trend of the optimization suggests stable and reproducible gains. This is a notable advancement over previous approaches that lacked the ability to dynamically adjust resource allocation based on evolving project conditions.

- Unlike static scheduling models, the dynamic nature of our framework enables flexible adjustments to project timelines and resource use as new constraints arise. The integration of real-time data into the scheduling process allows the model to adapt to shifting budget and resource constraints, reducing the risk of delays and cost overruns. This adaptability makes the proposed approach more effective and efficient than conventional methods.
- The use of BIM in our framework facilitated seamless data integration and ensured the automatic synchronization of project elements. This capability not only prevents data loss but also enhances interoperability between project management tools, allowing for faster decision-making and more accurate updates to the project schedule.
- Monte Carlo simulations under stochastic productivity and resource availability confirmed the robustness of the framework. Compared to CPM with resource leveling and GA-based RCPSP, the proposed model achieved statistically significant improvements in project duration, cost, and resource consistency.

In comparison to existing studies, our approach introduces significant improvements by incorporating real-time data and a dynamic optimization process. While previous research has focused primarily on either static optimization or limited aspects of resource management, our model combines real-time adaptability with resource and budget management, offering a more holistic and practical solution for construction project scheduling. Future work will explore extending the framework to account for additional constraints, such as environmental impacts and unforeseen project risks, further broadening its applicability.

COI Statement

The authors of this study declare that they have no conflict of interest.

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