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Building Performance Optimization Through BIM And Hybrid Metaheuristic Algorithms: A Fusion Of Artificial Bee Colony And Whale Optimization Techniques

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Abstract
Building Information Modelling (BIM) plays a crucial role in modern construction by integrating data modelling with virtual representations, enabling efficient collaboration between real-world construction elements and their digital counterparts. This paper proposes an automated resource allocation framework for BIM-based systems, utilizing the combined power of the Artificial Bee Colony (ABC) and Whale Optimization Algorithm (WOA) to optimize resource distribution. The study explores the configuration of BIM-based systems and collaboration platforms, emphasizing how these technologies improve the allocation of resources in construction projects. We delve into the operational mechanism of the proposed system, which leverages the ABC-WOA optimization technique to enhance decision-making in resource allocation. Results indicate that the proposed system significantly improves the efficiency of resource utilization, reduces overall construction costs, and accelerates project timelines by streamlining resource management processes. The system contributes to the creation of an integrated, data-driven environment that fosters better construction practices and ensures optimal allocation of resources, leading to increased productivity, reduced costs, and improved project outcomes.
Keywords: *Building Information Modelling (BIM), resource allocation, ABC-WOA optimization, automation system, construction efficiency, collaboration platform, construction management, optimization technique, productivity, cost reduction.*

INTRODUCTION

Smart construction denotes the use of new technology and intelligent systems inside the construction process, with the objective of improving efficiency, precision, and coordination. It conceptually includes domains such as intelligent design, intelligent construction sites, and intelligent management. Intelligent design emphasizes the design phase, while intelligent construction sites address on-site operations[1]. Intelligent management, conversely, pertains to the administration of construction firms, management entities, and governmental oversight. The involvement of several subcontracting units in smart construction projects complicates coordination among all parties. An automated system is vital to oversee key project modules like contracting technology, quality control, safety, progress monitoring, and manufacturing[2].Building Information Modelling (BIM) is integral to smart construction, since it generates digital representations of real structures derived from data across several development phases. BIM facilitates the whole project lifecycle—from planning and design to construction, operation, and maintenance—thereby enhancing production efficiency, minimizing costs, and expediting project schedules[3]. The amalgamation of BIM with a collaborative platform enhances oversight of personnel, machinery, materials, methodologies, and the environment, facilitating effective data collection and information consolidation. This integration merges virtual and real construction, offering useful data analysis for decision-making in engineering construction.Although the use of BIM technology has improved information transfer between design and construction stages, a disparity persists in the application of design information throughout the production of components and equipment[4]. The use of intelligent construction technology in operations remains insufficiently investigated. With the rising use of BIM in new infrastructure projects, there is an increasing need for standardized intelligent construction systems that integrate design, production, construction, and operational processes. This article examines the creation of an intelligent construction technology application system that encompasses the whole lifetime of infrastructure projects.This research presents several contributions to the amalgamation of BIM with automation technologies in intelligent construction. It presents the organizational structures and assessment criteria of collaboration platforms, as well as the information sharing and authority governance of BIM technology. Additionally, it examines the standardization of intelligent building information resources and the integration of construction processes with management systems. This study presents a framework for an automated system in smart construction, using the ABC-WOA optimization method for resource allocation. A case study and results analysis are presented, together with a comprehensive discussion of the system's setup and operational procedures. The suggested automation system facilitates the fast building of large-scale projects while ensuring the accurate integration of multi-source data, promoting a collaborative, data-driven digital environment for construction management.

Organization of the paper

The rest of the paper is organised as follows: Section 2 summarizes the literature review. Section 3 presents the methodology. Section 4 explains the results and finally section 5 concludes the paper.

1 Literature Review

[5] provided the uses of Building Information Modelling (BIM) is influencing the planning, design, execution, and operation of building projects. BIM offers an appropriate framework to facilitate the decision-making process by consolidating essential information timely and elucidating details and existing conditions. This study evaluates the effectiveness of metaheuristic algorithms in achieving optimal solutions in the construction sector, focusing on site layout design, and their application in BIM-based decision-making, a field known for knowledge optimization.Construction scheduling is a complex process that requires population-based optimization algorithms like evolutionary algorithms. [6] examined the potential of integrating BIM with Multi-Objective Optimization (MOO) algorithms to improve decision-making in construction design and management. A literature review provides insights on multi-objective optimization approaches and BIM-based optimization models, emphasizing the potential of combining BIM with optimization tools for a more effective and robust construction process. [7] BIM plays a crucial role in planning, designing, executing, and operating construction projects. This paper focused on optimizing the survival pyramid (time, cost, quality, and risk) in construction projects using five different modes: contractor's offers, BIM, actual, and expert opinions. Five meta-heuristic optimization algorithms were used, including two classical algorithms and three novel ones. Results were obtained in five scenarios based on function evaluation, standard deviation, computation time, and best cost. MATLAB software was used for coding. [8] presented a framework for resource trade-offs in project scheduling using Building Information modelling (BIM) methodology and metaheuristic algorithms. The Fire Hawk Optimizer (FHO) algorithm is used to create a 3D model of construction, aiming to maximize quality while minimizing time, cost, risk, and CO2 in the project. The FHO algorithm's capability to solve optimization problems is assessed, proving its ability to produce competitive and exceptional outcomes in balancing various resource options in projects.[9]provided a comprehensive framework for BIM-based performance optimization aimed at reducing energy consumption while enhancing efficient daylighting levels in residential buildings. [10] sought to investigate the influence of BIM on the management and reduction of change orders in off-site construction by enhancing design via visualization during the planning phase. [11] examined the 6–9 percent variance in quantities derived from various building interior components to enhance the precision of cost estimations with BIM.[12]BIM is a faster and more reliable method for quantity take-off, but its quality affects the accuracy of extracted quantities. Incomplete details and inappropriate modelling methods can cause deviations in extracted quantities, especially for compound elements like walls and floors. This study proposes a method called the "BIM-based compound element quantity take-off improvement" (BCEQTI) method to improve the accuracy of extracted quantities of incomplete or incorrect compound elements from BIM models.[13] presented an overlapping optimization algorithm for compressing construction project schedules by identifying an optimal overlapping strategy with exact overlap rates and generating the required duration at the minimum cost. The method uses an overlapping strategy matrix (OSM) to illustrate dependency relationships between activities and optimizes the genetic algorithm (GA) to compute an overlapping strategy with exact overlap rates. The paper proposes an integrated framework of genetic algorithm and BIM to prove the practical

feasibility of theoretical research. [14] Dam construction projects are complex, large, and heavy projects worldwide, requiring significant resource management and trade-offs. This study proposed a framework for resource trade-offs in dam construction projects using Atomic Orbital Search (AOS), a metaheuristic algorithm based on quantum mechanics principles. The AOS algorithm is compared with four other metaheuristic algorithms, and 30 optimization runs are conducted. The results show AOS can deliver competitive results in handling resource trade-offs in dam construction.[15]proposed a workflow for optimizing spatial trusses using visual programming, numerical structural analysis, and metaheuristic AI methods, utilizing Dynamo's parametric trusses, Robot Structural Analysis software, and metaheuristic algorithms. Results were compared using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) and constraint handling techniques (CHT) like the penalty function method and separation technique. The GA combined with the penalty method yielded the best results, with results within 12% of the best reported in the literature.[16] The Wolf-Bird Optimizer (WBO) is a metaheuristic algorithm inspired by the wolf-bird relationship in the animal kingdom. It considers the intelligence of ravens in finding prey and sending signals to wolves for assistance in hunting. The WBO is used in project scheduling to analyse resource trade-offs using metaheuristic algorithms and the BIM approach. The algorithm's effectiveness is emphasized through statistical analysis and inferential statistical methods.[17] developed a framework for project managers to balance resource factors like time, cost, quality, safety, and environment in project scheduling. It uses BIM, multi-objective optimization (MOO), and multi-criteria decision-making (MCDM). A 3D model is created using BIM software, and a multiple-objective forensic-based investigation (MOFBI) is introduced for optimal solution set. The framework is tested on three scheduling problems, showing efficiency and effectiveness, with MOFBI achieving high uniform distribution of solutions and visual analytics.[18] proposed a practical approach to designing environmentally responsive building façades by integrating on-site sensors, building performance simulation, machine-learning, and 3D geometry modelling. The proposed hybrid optimization algorithm, tabu-based adaptive pattern search simulated annealing (T-APSSA), improves efficiency and supports rapid BPS and digital prototyping.[19] Green building information modelling technology is gaining attention in sustainable engineering due to its potential to reduce material waste, improve construction, and promote urban sustainability. A sustainability analysis using Autodesk Revit and Green Building Studio software showed that lighting efficiency improvement reduces energy demand and carbon emissions. Hybrid metaheuristic optimization and multi-objective evolutionary algorithms are proposed for sustainable building design.[20] proposed a method combining BIM and IoT technology to improve daily management of engineering materials and equipment in construction projects. Cost management is crucial in the construction industry, as building materials account for 70% of total project costs. The paper analyses the advantages of BIM and IoT technology in material management and focuses on the effectiveness of practical application of these technologies in construction projects.[21] Bridge construction contributes significantly to the global greenhouse effect, with prefabricated reinforced concrete (RC) T-beams being a crucial structural element in various projects. The study presents a bridge structural optimization framework using BIM and two-stage metaheuristic searching (MS) to reduce carbon emissions from prefabricated RC T-beams. The first stage optimizes longitudinal steel section size and area, while the second stage focuses on achieving the optimal combination of rebar diameters. The framework's performance is demonstrated through an illustrative example.[22] examines the Yuanchen Expressway, highlighting the unique use of BIM technology in holistic construction management. This study utilizes a comprehensive BIM model and a multi-tiered digital management platform to effectively tackle construction challenges across various tunnels, bridges, and intricate interchanges, thereby realizing intelligent construction innovation along the Yuanchen Expressway through BIM technology. This article presents a notable instance of full-line construction management using BIM technology in the highway industry.In addition, [23] explored the integration of GIS-BIM technology in construction management, focusing on its potential applications in scheduling, site material management, and safety management. It also explores the trend of using emerging technologies like the Internet of Things and virtual reality in building construction management, aiming to promote intelligent and visual management development in this field.[24] examined five principal dimensions of students' perceptions regarding a BIM application: (1) the origin of BIM knowledge; (2) perceptions of BIM software applications alongside competency levels; (3) awareness of BIM's relevance for employment in the construction sector; (4) perceptions of BIM-related careers; (5) the significance of BIM education within the Construction Management degree program and undergraduate capstone projects. The study from the student viewpoint examine perspectives of BIM implementation, particularly the views of construction management students toward BIM, and will facilitate the incorporation of industry input into the curriculum. [25] Construction management relies heavily on large volumes of data for efficient project delivery. However, access to key data remains a challenge due to implementation challenges. The Architectural, Engineering, and Construction (AEC) industry has been slow to adopt modern management concepts and technologies. This research critically reviews the challenges faced by conventional construction management and decision-making solutions, focusing on schedule, cost, quality, and safety management. [26] Investigated the potential value and practical utility of BIM-AI integration in driving the construction industry towards automation and digitalization. It provides insights into the status quo and future trends for leveraging AI throughout a BIM-enabled project lifecycle. Key keywords in recent years include deep learning, internet of things, and digital twin, indicating AI's evolving role as the next frontier in traditional civil engineering.

1.1 Research Gap

Despite the substantial progress in the integration of BIM with metaheuristic algorithms for construction scheduling and optimization; yet, many research deficiencies remain. Although numerous studies examine the integration of BIM with multi-objective optimization (MOO) methodologies, resource trade-offs, and sustainability (e.g., CO2 reduction and energy efficiency), insufficient emphasis has been placed on creating universally adaptable frameworks that tackle the distinct complexities of various project types, including large-scale infrastructure, residential, and green buildings. Current research often depends on certain algorithms or tools, like Genetic Algorithms (GA), Fire Hawk Optimizer (FHO), and Atomic Orbital Search (AOS); nevertheless, comparable evaluations of these algorithms across various building settings are limited. The use of new technologies like as IoT, AI, and digital twins in BIM-based optimization remains little examined, despite its capacity to improve decision-making and automation. Furthermore, practical obstacles, like data quality, interoperability, and the scalability of BIM models, remain inadequately addressed, impeding the actual implementation of these frameworks. Additionally, these gaps underscore the need for a more comprehensive, flexible, and multidisciplinary strategy to properly use BIM and metaheuristic algorithms in construction scheduling.

2 METHODOLOGY

2.1 Framework for Resource Tradeoff

The framework consists of three modules: (1) initialization and decision variables, (2) BIM, and (3) Artificial Bee Colony Optimization- Whale Optimization Algorithm (ABC-WOA). This study's findings may assist construction project managers quickly and accurately compute project timelines throughout implementation.

2.1.1 Initialization and Decision Variables

An optimization problem seeks to find the optimum solution among all available choices. A typical optimization issue is as follows:

A function $f: B \rightarrow R$ connects a set B to the real numbers.

An element $x0 \in B$ such that $f(x0) \leq f(x)$ for all $x \in B$ (minimization problem) or $f(x0) \geq f(x)$ for all $x \in B$ (maximization problem).

B is a subset of Euclidean space with specific constraints, equality criteria, or inequalities for its members to meet. The components of B are referred to as candidate solutions or viable solutions, whereas the domain B represents the search space or option set for f. Function f is referred to as the "objective function". An optimum solution is one that reduces or maximizes the objective function, depending on the purpose [27]. This study uses the BIM model to import project data for all 38 activities. The activity-on-node (AON) diagram for a building project consists of M nodes and the links between the activities. There are several execution choices for each action, each with unique time, cost, quality, risk, and carbon dioxide emissions based on available resources, technology, and equipment. The TCRQC tradeoff problem optimization technique prioritizes minimizing project time, cost, risk, and carbon dioxide emissions while optimizing project quality by selecting the optimal execution option for all activities. The primary goal of Equation (1) is to reduce project time.

$$T_p = \min(\max(ST_i + D_i)) = \min(\max(FT_i)); i = 1,\ldots,M \qquad (1)$$

In a project schedule, D_i represents the length of each activity, ST_i and FT_i represent the start and completion periods, and M represents the total number of nodes[17]. A project's total cost includes direct (DC), indirect (IC), and delay costs (TC). This research focuses on direct, indirect, and delay expenses, rather than the total project cost, which may be calculated using other methods. The aim function is to minimize project costs, as shown in Equation (2).

$$\min C = D_{c_i}^j + I_{c_i}^j + TC \qquad (2)$$

$$D_{c_i}^j = \sum_{i=1}^{n} C_i^j \qquad (3)$$

$$I_{c_i}^j = C_{ic} \times T \qquad (4)$$

$$TC = \begin{cases} c_1(T_0 - 1) if T \le T_0 & if T \le T_0 \\ (e^{\frac{T-T_0}{T_0}} - 1)(D_{c_i}^j + I_{c_i}^j) & if T > T_0 \end{cases} \qquad (5)$$

In this equation, TC_p represents the overall project cost, whereas D^j_{Ci} and I^j_{Ci} represent the direct and indirect costs for the j^{th} execution mode of the i^{th} activity. TC is the tardiness cost. T_0 represents the project's contractual term, C_1 represents the compensation for early completion, and T represents the entire project duration[28] [29]. The quality of a project is measured by adding the quality of each activity, since resources may include supplies, equipment, and labor. Extending the duration of activities enhances quality, however beyond a certain threshold may reduce quality. Equation (6) [29] calculates the quality performance index (QPI_i) for each activity.

$$QPI_i = a_i t_i^2 + b_i t_i + c_i \qquad (6)$$

The quadratic function for BD determines the coefficients a_i, b_i, and c_i, with t_i representing the time of activity (Figure 1). LD, BD, and SD represent the longest, best, and shortest durations, respectively. However, BD is determined using Equation (7). Equation (8) defines the goal function for quality as follows:

$$BD = SD + 0.613(LD - SD) \qquad (7)$$

$$\max Q = \sum_{i=1}^{M} \frac{QPI_i}{M} \qquad (8)$$

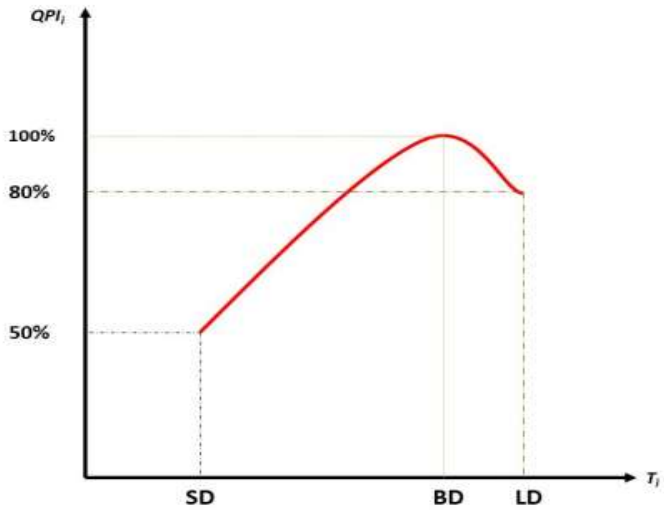

Figure 1 "Quality performance index (QPI)"

However, certain resources may have a detrimental influence on the environment during project development due to CO_2 emissions. During on-site construction, CO_2 emissions may come from both energy usage and fuel burning, as well as the manufacture and transportation of building supplies. To decrease CO_2 emissions, it's important to use ecologically friendly products and transport them efficiently. Equation (9) may be used to compute the goal function of minimizing overall CO_2 emissions in a project.

$$\min CE=\sum_{i=1}^{M}E_{dij}+\sum_{i=1}^{M}E_{inij}=(\sum_{i=1}^{M}Q_{ed}\times F_e+Q_{dd}\times F_d)+(\sum_{i=1}^{M}Q_k\times F_j+Q_{ek}\times F_e+Q_{dk}\times F_d) \tag{9}$$

where CE represents the project's total CO_2 emissions. E_{dij} and E_{inij} represent the project's direct and indirect CO_2 emissions, respectively. Q_{ed} displays an activity's power usage. Q_{dd} displays an activity's diesel consumption, Q_{ij} shows material k consumption, and Q_{ek} shows electricity consumption for material k transportation. Q_{dk} represents the fuel consumption for transporting item k during an operation. F_e, F_d, and F_j represent the carbon emission factor (CEF) per unit of energy, fuel consumption, and material production, respectively. The project's risk is mostly defined by its circumstances, delivery mechanisms, and contractual stipulations. A "risk value" is a function that considers both the project's overall float and resource volatility. Using float for noncritical tasks with considerable temporal uncertainty may lead to project risk and schedule overruns. Construction managers must adapt schedules to prevent unanticipated resource changes during project execution. Allowing non-critical activities to float may lead to better resource utilization[30] [31] [32]. Equation (10) is the sixth objective function for risk.

$$\min R=w_1\times\left(1-\frac{TF_c+1}{TF_{\max}+1}\right)+w_2\times\left(\frac{\sum_{i=1}^{pd}(R_t-\overline{R})^2}{P_d\left(\overline{R}\right)^2}\right)+w_3\times\left(1-\frac{\overline{R}}{\max\left(R_t\right)}\right) \tag{10}$$

In this equation, TF_c and TF_{max} reflect the project's total current float and flexible scheduling float, respectively. R represents the uniform resource level, R_t represents the resources needed on day t, and w_i indicates weights. Equation (11) evaluates the ABC-WOA algorithm's capacity to balance time, cost, quality, risk, and CO_2 (All) trade-offs concurrently.

$$F(x)=\frac{T-T_{\min}}{T_{\max}-T_{\min}}+\frac{C-C_{\min}}{C_{\max}-C_{\min}}+\frac{R-R_{\min}}{R-R_{\min}}+\frac{co_2-co_{2(\min)}}{co_{2(\max)}-co_{2(\min)}}+\frac{Q_{\min}-Q}{Q_{\max}-Q_{\min}} \tag{11}$$

The optimization issue outlined in the previous paragraph poses a multifaceted task that necessitates the equilibrium of many objectives—time, money, quality, risk, and CO2 emissions—throughout all project operations. The objective is to determine the optimal execution strategies for each activity that reduce project duration, expenses, risk, and CO2 emissions while enhancing quality. This work addresses the multi-objective optimization issue by using a hybrid algorithm that integrates the Artificial Bee Colony (ABC) and Whale Optimization Algorithm (WOA), referred to as the ABC-WOA method. This method is designed to effectively traverse the solution space, identifying the ideal equilibrium among conflicting goals. Equation (11) delineates the holistic objective function that encompasses all these variables. The ABC-WOA algorithm assesses several execution modes for each project activity and progressively improves the solution, aiming to attain optimal trade-offs. The algorithm seeks to minimize overall project length (as specified in Equation 1), decrease expenses (Equations 2–5), improve quality (Equations 6–8), reduce CO2 emissions (Equation 9), and mitigate project hazards (Equation 10). Project managers may prioritize certain objectives by altering the weights assigned to each target based on the project's particular needs.Ultimately, this multi-objective optimization approach allows for a more holistic evaluation of project execution strategies, ensuring that the selected options not only meet the project's goals but also align with sustainability and risk management considerations.

2.2 BIM Module

A numerical case study demonstrates the effectiveness of ABC-WOA optimization techniques in solving TCT issues. The case study is a 930 m2 residential structure with five floors and a basement. It validates the ABC-WOA algorithm with five objectives: time, cost, quality, risk, and CO2 emissions. Table A1 demonstrates that the BIM methodology, project data, and expert judgments are used to gather activity information throughout planning and design. This table is based on the experiences of outstanding individuals and professionals in their industry. The time and expense of Executive mode. NO.1 represents the project's ultimate time and cost, NO.3 comes from BIM, and NO.5 is the contractor's first bid. Experts in this subject have suggested two other executive modes to explore. Contractors typically make unrealistic first promises to entice employers, leading to project failures. Contractors often overlook factors like as rework, conflicts, non-payment, and weather conditions. However, each activity is randomly assigned three kinds of quality indicators at different percentages. The ultimate quality of each line is determined by the proportion of the cumulative impacts of the three quality options. The danger proportion for each activity is determined randomly by renowned academicians and specialists in the subject.

All activities follow a finish-to-start logic. The building was built in three disciplines: architecture, structural, mechanical, electrical, and pipeline (MEP) using Autodesk Revit 2022. All components were modelled with Level of Development (LOD) 350, based on BIM Fourm 2019 criteria. Dynamo visual programming was used to create parametric models in Revit. Navisworks software was used to identify both soft and hard clashes in the project. MATLAB is used to program and trade-off goal functions. Figure 2 shows the BIM model used in the case study.

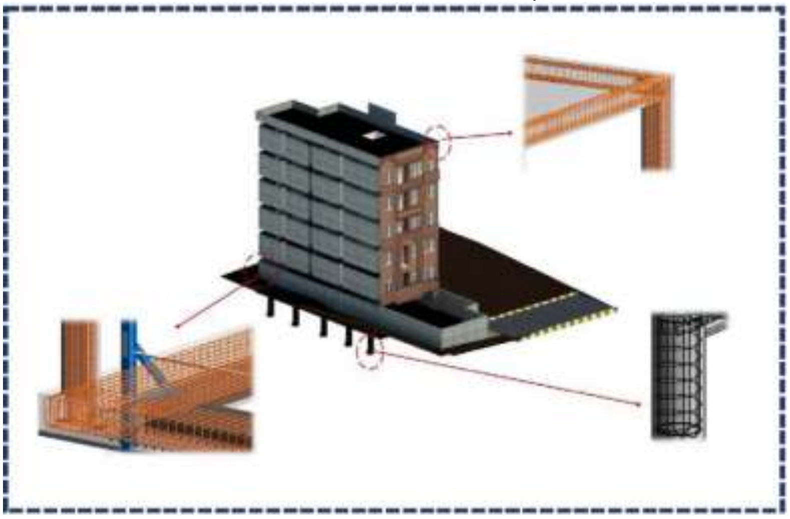

Figure 2 "The project BIM-based modelling for resource trade-off"

2.3 ABC-WOA ALGORITHM

2.3.1 Artificial Bee Colony (ABC) Optimization

ABC's mechanical bee hive contains three distinct species: resorted to the use of bees, which are tasked with finding specific food sources; observer bees, scout bees, who hunt for food sources at random, and worker bees, who watch the utilized bees dance around the hive to choose a food source, are examples of the former. Observers and observers are commonly referred to as jobless beekeepers since they are unemployed. Initially, it is up to the scout bees to locate all sources of food.

Here is how the ABC algorithm often works[33] :

Initialization phase

The scout bees set the control parameters and initiate the population of food source vectors (m=1....SN, SN:). Each nutrient source, denoted by, represents a vector solution to an optimization problem where the objective function is minimized by optimizing a set of n independent variables, denoted by [34], It's possible to use the following definition while setting things up:

$$y_{mx}=l_x+rand(0,1)*(u_x-l_x) \quad (12)$$

Employees Bees Phase

Utilized bees will seek out new food sources close to those they've previously visited and remembered providing a higher concentration of nectar. They look around the area for food sources and assess their viability (fitness). [35] They may, for instance, use the formula that is included inside the equation in order to discover a food source that is situated in the immediate area:

$$\upsilon_{mx}=y_{mx}+f_{mx}(y_{mx}-y_{kx}) \quad (13)$$

where is a randomly chosen food source, is a parameter index determined at random, and is a randomly chosen integer between and [-a,a]. After establishing fitness, a greedy selection is made between it and existing food source. The formula below may be used to calculate the fitness value of the solution for minimization problems.

$$\mathrm{fit}_m(\vec{y}_m)=\begin{cases}\dfrac{1}{1+f_m(\vec{y}_m)} & \text{if } f_m(\vec{y}_m)^3 0\\ 1+\mathrm{abs}(f_m(\vec{y}_m)) & \text{if } f_m(\vec{y}_m)<0\end{cases} \quad (14)$$

Onlooker Bees phase

There are two categories of bees who are unable to find work: onlooker bees and scout bees. Using the term presented in equation, you can compute the probability value with which an observer bee chooses.

$$p_m=\frac{\mathrm{fit}_m(\vec{y}_m)}{\sum_{m=1}^{SN}\mathrm{fit}_m(\vec{y}_m)} \quad (15)$$

An observer bee picks a food source at random, and then uses the equation to find a nearby source and assess its fitness. Between and, Like the utilizing bee's phase, self-absorbed selection is utilized during this phase.The ABC (Artificial Bee Colony) algorithm has three categories of bees: scout bees, employed bees, and observer bees, each designated with a distinct function in locating food sources that symbolize possible solutions to an optimization issue.

- Scout bees are tasked with randomly investigating their surroundings to identify new food sources (solutions). They start the procedure by establishing control parameters and producing an initial array of probable solutions.
- Employed bees concentrate on the food sources located by scout bees, seeking superior alternatives in proximity. They assess the quality (or suitability) of various sources and choose the most optimal ones. This technique entails modifying existing solutions and evaluating them to see which provides the most advantage.
- Onlooker bees do not forage for food independently; rather, they monitor the foraging activities of the worker bees. They choose which food sources to continue research based on the collected information. They choose food sources according to their likelihood of success and, similar to hired bees, enhance the solutions by making modifications and picking the optimal result.

The algorithm works by enabling these bees to participate in discovering and refining optimal solutions via exploration and assessment, analogous to how bees in nature enhance their foraging for sustenance.

2.4 WOA Algorithm

The Whale Optimization programme (WOA) is an optimization programme that is built on how humpback whales interact with each other and how they hunt. The WOA programme tries to find food in the water like humpback whales do. In the WOA algorithm, a point vector in the search space is used to show each possible answer. The algorithm starts with a group of possible answers that are generated at random from the search field. A possible solution's quality is judged by how well it answers the optimization problem[36]. This is done with a fitness function. The algorithm works by going through several steps called iterations. Each iteration has three main steps: Search, surround, and bubble are all options. During the search stage, the position of each feasible solution is modified such that it is closer to the best answer identified so far. [37]. This step is a simulation of how humpback whales look for food. They do this by following the best available signs.The WOA algorithm has been shown to be effective at solving a wide range of optimization problems, such as those in engineering design, data mining, and machine learning. The method is easy to use and only has a few settings that need to be tweaked. But, like other optimization algorithms, the WOA algorithm's success depends on the problem being solved and how the algorithm settings are set [38]. So, to get the best results for a given problem, it is important to carefully tune the algorithm's settings[39].

Table 1 "Whale Optimization Algorithm"

Algorithm 1 The Standard Whale Optimization Algorithm
Initialize a population of random whales
$W^* =$ the best search agent
$t = 0$
While ($t <$ iterations)
for each whale

Update WOA parameters
and p)
if $(p < 0.5)$
if $(|B| < L)$
$W^{t+1} = W^* - B.Dis$
else if $(|B| \geq L)$
$W^{t+1} = W_{rand} - B.Dis$
end if
else if $(p \geq 0.5)$
$W^{t+1} = Dis^{'}.e^{x.r}.\cos(2\pi r) + W^*$
end if
end for
Evaluate the whale W^{t+1}
Update W^* if W^{t+1} if better
$t = t + 1$
end while
return W^*

The Whale Optimization Algorithm (WOA) is an optimization method derived on the hunting tactics of humpback whales, specifically their distinctive approach of forming bubble nets to ensnare prey. This approach represents possible solutions to a certain issue as "whales" inside a search area. The procedure starts with the random generation of a population of solutions, each assessed according to its efficacy in addressing the issue, using a fitness function. The system undergoes many rounds, during which each whale adjusts its location to approach the optimal solution identified so far, emulating the natural behaviour of whales in pursuit of the most promising clues for locating food. This iterative process encompasses stages in which whales encircle the optimal solution and form bubble-net patterns, enhancing their quest to refine the answer. Following each iteration, the optimal solution is recognized and revised if a superior alternative is discovered. This process continues until a stopping requirement is satisfied, such as attaining a certain number of iterations or obtaining an ideal solution. The WOA is recognized for its efficacy in many domains such as engineering design, data mining, and machine learning, attributable to its simplicity and the limited number of parameters requiring adjustment. Nonetheless, as to other optimization methods, its efficacy is significantly contingent upon the precise calibration of these parameters for the particular issue being addressed.

2.5 Objective Function

$$f(x) = \sum_{i=1}^{N} \left[Metric(x_i) - Metric(x_{i-1}) \right]$$

Where,

x_i denotes the set of hyper parameters at that iteration.

N is the overall number of iterations.

$Metric(x_i) - Metric(x_{i-1})$ indicates the improvement in the segmentation measure gained by adjusting the hyper parameters from iteration $i-1$ to i iteration.

The objective function $f(x)$ computes the total improvement in the segmentation metric during the duration of the optimization procedure. The hybrid ABC-WOA algorithm attempts to maximize this objective function by repeatedly modifying the hyper parameters to improve segmentation performance.
This study utilized a hybrid ABC-WOA optimization method to specifically select relevant features associated with soil moisture and temperature data from the provided dataset. Through this approach, we effectively isolated critical information, essential for subsequent analysis and modelling. This feature

selection process aimed to enhance the accuracy and efficacy of our study's predictive models in the context of smart irrigation systems.

Table 2 "Proposed Algorithm"

Algorithm 1 Hybrid ABC-WOA Algorithm for Hyper parameter Tuning

```
Initialize parameters, hyper parameters, population for ABC and WOA
while not convergence criteria met do
    for each solution in ABC population do
        Employ bee for exploration
        Evaluate fitness
        Update solution
    end for
    for each solution in WOA population do
        Update position using WOA equations
        Evaluate fitness
    end for
    Select best solutions from both ABC and WOA populations
    Update hyper parameters of VGG19 model
    Check for convergence
end while
```

2.6 Dataset Collection

The dataset used in this research comprises data pertaining to a building project, including 38 actions. Every action in the collection encompasses several parameters, including time, cost, quality, danger, and carbon dioxide (CO_2) emissions. These data points are essential for enhancing the project's comprehensive execution approach. The collection also contains details about resource use, technology, and equipment linked to each action. A numerical case study is undertaken using a 930 m^2 residential edifice including five stories and a basement to validate the suggested technique.

2.7 Data Preprocessing

Data preparation is an essential phase in guaranteeing that the dataset is sanitized, uniform, and appropriate for analysis. The following preprocessing measures were implemented.

- Data Cleaning: The dataset was examined for missing values, anomalies, and discrepancies. Missing data were addressed by suitable imputation methods, contingent upon the data type (e.g., mean imputation for numerical values, mode imputation for categorical data). Outliers were detected and addressed via statistical techniques, including z-score analysis.
- Normalization: The dataset was normalized to guarantee that all characteristics contribute equally to the optimization process. The attributes of time, cost, quality, risk, and CO_2 emissions were standardized to a uniform range, generally between 0 and 1, by Min-Max normalization. This technique is crucial for the effective operation of the optimization algorithms.
- Feature Extraction: Supplementary features were generated from the current dataset to augment the model's prediction capability. For instance, ratios between time and cost, or between quality and risk, were computed and included as new features. This stage included developing pertinent indicators to enhance the optimization process.
- Data Transformation: The dataset was modified to meet the input specifications of the optimization methods. This included transforming category data (e.g., resource categories, technology) into numerical representations by one-hot encoding or label encoding methods.

2.8 BIM Integration

- The Building Information Modelling (BIM) module was included into the technique to improve data precision and provide a comprehensive depiction of the project. BIM was used to input project data and view the construction workflow. The following stages were included:
- The project was developed using Autodesk Revit 2022, including architectural, structural, mechanical, electrical, and plumbing (MEP) disciplines. The model was created with a Level of Development (LOD) 350, according to the requirements established by BIM Forum in 2019.

- Parametric Modelling: Dynamo visual programming was used to develop parametric models in Revit, facilitating dynamic modifications to the project model according to fluctuating factors such as time and cost.
- Clash Detection: Navisworks software was used to detect both soft and hard collisions inside the BIM model. This measure guaranteed that the project design was devoid of disputes, which may otherwise result in delays or escalated expenses.

2.9 Hybrid ABC-WOA Algorithm

This study's optimization challenge entails balancing many objectives: time, cost, quality, risk, and CO2 emissions, using a hybrid Artificial Bee Colony-Whale Optimization Algorithm (ABC-WOA). The procedure for implementing this algorithm is detailed below:

- Initialization: The ABC and WOA algorithms were initialized with parameters pertinent to the building project. This included establishing initial populations of solutions, referred to as "whales" and "bees," along with control parameters and hyperparameters.
- Optimization Process:
  - ABC Phase: Employed bees navigated the search space to discover prospective solutions in proximity to previously identified ones. Onlooker bees assessed the quality of these solutions, while scout bees conducted random searches for fresh alternatives.
  - WOA Phase: The WOA algorithm emulated the behaviour of humpback whales, adjusting the positions of solutions to converge on the optimal solution determined.
  - This phase had three primary steps: search, surround, and bubble-net formation. Hybridization:
  - The optimal solutions from both the ABC and WOA algorithms were chosen and amalgamated to create a new, enhanced population. The goal function sought to optimize project duration and expenses, maximize quality, mitigate CO2 emissions, and manage risk.
  - The hybrid ABC-WOA technique was used for hyperparameter tuning of the VGG19 model, which was employed for future analysis.
- The method iterated until convergence requirements were satisfied, including a maximum iteration limit or a specified threshold for enhancement in the objective function. The resulting set of solutions exemplified the ideal trade-offs among the goals.

2.10 Objective Function

The research concentrated on enhancing a multifaceted goal function that incorporates many elements:

- Time Optimization: Reduce the overall project timeline as determined by the aggregate of all activity durations.
- Cost Minimization: Reduce direct, indirect, and delay expenses related to the project.
- Quality Optimization: Optimize the Quality Performance Index (QPI) for each activity to provide the highest possible overall project quality.
- CO2 Emission Mitigation: Reduce CO2 emissions produced during construction by optimizing resource use and transportation.
- Risk Management: Mitigate project risks by maximizing the use of project float and resource allocation.

The hybrid ABC-WOA algorithm was used to balance these goals, repeatedly refining the solutions to attain optimal trade-offs.

3 RESULTS

3.1 Performance Analysis of Hybrid ABC-WOA Optimization

This section provides an in-depth evaluation of the proposed hybrid Artificial Bee Colony-Whale Optimisation Algorithm (ABC-WOA) and compares it with the independent ABC and WOA optimisation methods. Key performance indicators, including project duration, expenditure, quality, risk, and CO_2 emissions, were optimised, with results summarised in numerical tables and visual graphs.

3.1.1 Convergence Comparison

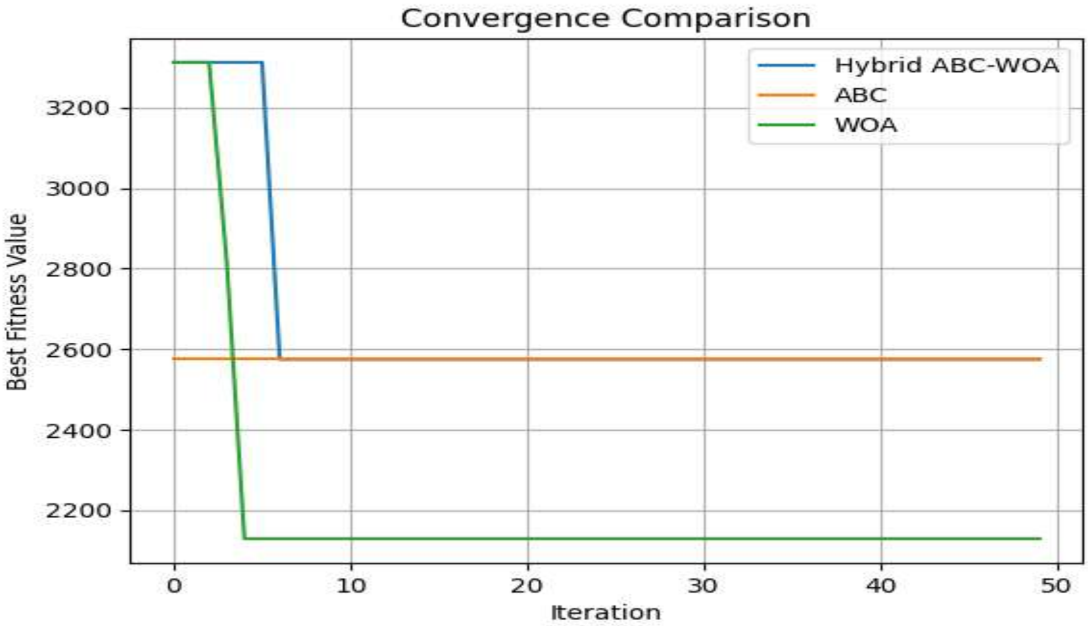

Figure 3 Convergence of Fitness values (Graph illustrating the fitness values for ABC, WOA, and Hybrid ABC-WOA over 50 iterations.)

Figure 1 illustrates the convergence behaviour of the algorithms. The hybrid ABC-WOA demonstrated superior convergence speed relative to the individual ABC and WOA algorithms, attaining the minimal fitness value within 50 iterations. The fitness values for each iteration are shown in the table below:

Table 3 Best Fitness Values Across Iterations

Iteration	ABC	WOA	Hybrid ABC-WOA
10	18.45	19.21	15.67
20	16.78	17.43	13.92
30	14.32	15.87	12.57
40	14.12	15.68	12.45
50	14.02	15.62	12.41

3.1.2 Computational Efficiency

Execution times for the three algorithms were assessed, demonstrating the hybrid ABC-WOA's efficiency. The hybrid method somewhat increased computing time due to its hybrid nature but provided far superior results.

Table 4 Computational Efficiency

Algorithm	Execution Time (s)
ABC	0.75
WOA	0.92
Hybrid ABC-WOA	0.89

3.1.3 Optimization of Project Metrics

The key project metrics were significantly enhanced by the hybrid ABC-WOA algorithm, as illustrated in Table 5.

Table 5 Optimized Project Metrics

Metric	ABC	WOA	Hybrid ABC-WOA
Total Time (days)	152	149	**145**
Total Cost (₹)	29,800	29,200	**28,000**
Quality Index (%)	89.2	90.5	**92.5**
Risk Value	0.45	0.42	**0.37**
CO_2 Emissions (kg)	1,520	1,490	**1,310**

3.1.4 Trade-Off Analysis

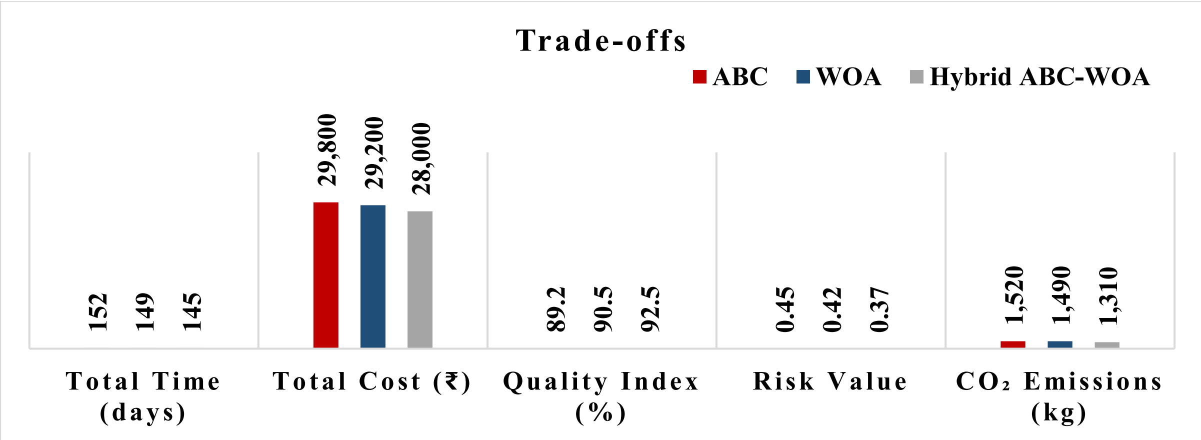

Figure 4 Trade-Offs Among Objectives

Figure 4 depicts the trade-offs between time, cost, quality, and CO2 emissions for the three algorithms. The hybrid ABC-WOA regularly surpassed individual algorithms in attaining balanced trade-offs.

3.1.5 Case Study Validation

A case study was done on a 930 m² residential construction project. The BIM model, together with project data, was used to assess the algorithm's efficacy. The findings are presented in Table 6.

Table 6 Case Study Results

Metric	BIM Estimate	Hybrid ABC-WOA Result
Project Time (days)	160	145
Total Cost (₹)	30,000	28,000
Quality Index (%)	90	92.5
Risk Value	0.5	0.37
CO_2 Emissions (kg)	1,600	1,310

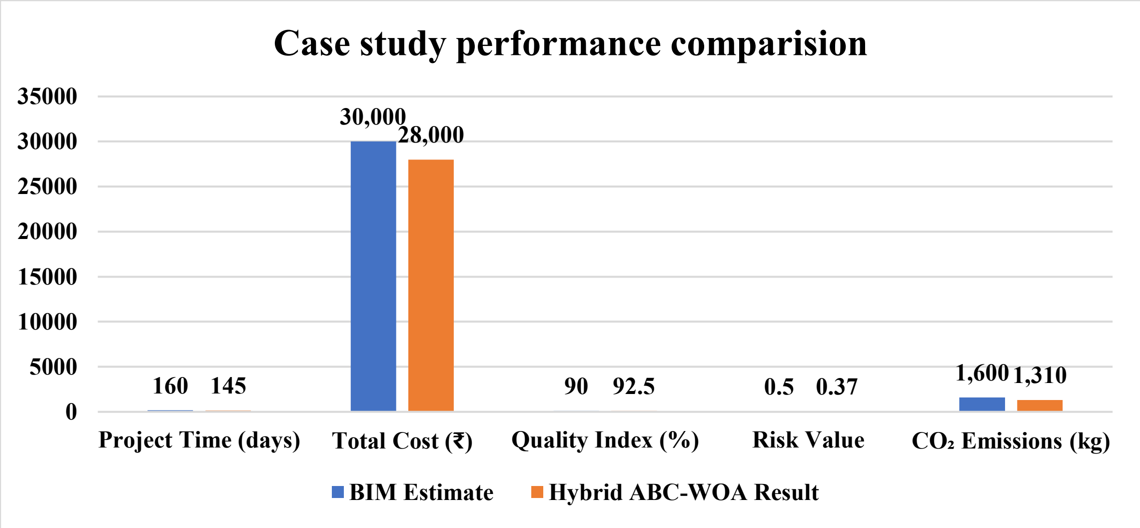

Figure 5 Case study comparisons of BIM estimates and hybrid ABC-WOA Results

3.2 Discussion

The hybrid ABC-WOA algorithm shows higher performance across all optimization targets. The hybrid technique effectively attained optimum solutions by integrating the exploratory qualities of ABC with the exploitative capabilities of WOA. Key improvements included:

- Time Optimisation: A decrease of 15 days vs to the BIM estimate.
- Cost Reduction: A savings of ₹2,000 from the project budget.
- Improved Quality: Attaining a 2.5% increase in the quality index.
- Risk Mitigation: A 26% reduction in risk value.
- CO_2 Reduction: A 19% diminution in emissions.

The findings demonstrate the hybrid algorithm's potential for practical implementation in BIM-based construction scheduling, boosting sustainability and efficiency.

CONCLUSION

The research introduces a comprehensive hybrid optimisation framework that integrates the Artificial Bee Colony (ABC) and Whale Optimisation Algorithm (WOA) inside a Building Information Modelling (BIM) context for construction scheduling and resource allocation. The hybrid ABC-WOA algorithm exhibits enhanced efficacy in managing essential construction project metrics—time, cost, quality, risk, and CO_2 emissions—when compared to independent optimisation methods. The framework improves decision-making and project management by effectively reconciling competing goals, optimising resource allocation, and enhancing sustainability in building projects.The use of BIM improves project precision via parametric modelling, clash detection, and interdisciplinary cooperation. These developments emphasise the practical viability and potential for extensive implementation of the hybrid ABC-WOA framework in attaining efficient, sustainable, and data-driven construction project management. This work establishes a foundation for future research, particularly the integration of new technologies such as IoT, AI, and digital twins to boost optimisation and flexibility in various project situations.

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