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Article

Fire Hawk Optimizer for Resource Trade-off in Project Scheduling based on BIM

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Abstract: Project managers should balance a variety of resource elements in building projects while taking into account many major concerns, including time, cost, quality, risk, and the environment. This study presents a framework for resource trade-offs in project scheduling based on the Building Information Modeling (BIM) methodology and metaheuristic algorithms. First, a new metaheuristic algorithm called Fire Hawk Optimizer (FHO) is used. Using project management software and the BIM process, a 3D model of the construction is created. In order to maximize quality while minimizing time, cost, risk, and CO_2 in the project under consideration, an optimization problem is created, and the FHO's capability for solving it is assessed. A predefined stopping condition is taken into account while doing 30 independent optimization runs to obtain the statistical metrics, such as the mean, standard deviation, and the required number of objective function evaluations. The results show that the FHO algorithm is capable of producing competitive and exceptional outcomes when it comes to trade-off various resource options in projects.

Keywords: Fire Hawk Optimizer; optimization; metaheuristic algorithms; Building Information Modelling (BIM); resource management; project resource management

1. Introduction

Understanding the trade-off between the project's primary aims is one of the most critical components of planning and controlling construction projects. The time-cost trade-off (TCT) problem has triggered many studies so far. Regardless of overhead costs, reduced project activity time will increase project costs due to the increased resources given to speed activity implementation. In other words, shorter project durations are frequently linked with higher construction costs, necessitating TCT to minimize the cost of schedule compression [1]. Consequently, Schedulers should do a TCT study to find the most cost-effective duration for a project; some research has been done using optimization algorithms to tackle TCT problems in the building and construction industry. Furthermore, in recent years, most construction projects have considered some other factors in TCT problems like risk, quality, energy, and environmental factors. The construction sector is ultimately accountable for a wide variety of environmental problems caused by the construction and operation of structures. Construction processes contribute significantly to air pollution and greenhouse gas emissions, and building materials production emits more carbon dioxide (CO_2) than any other kind of industrial production. Delivering a project in the intended time, at the desired cost, with the appropriate quality, and with the least amount of risk or uncertainty is an essential success factor for project assessment. However, environmental issues have received a lot of attention lately [2].

The two kinds of optimization algorithms are exact and approximation optimization techniques; the best solution could be identified using exact algorithms. However, in the case of complicated optimization problems, they are insufficiently efficient, and their computing time grows exponentially concerning the problem's dimensions. As a result, given the limitations of exact methods and the need for precision and speed in identifying

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appropriate answers, approximate algorithms, such as metaheuristics, can find suitable solutions close to the optimal solution in a shorter amount of time could be utilized to solve complicated problems. In fact, the Greek prefix "meta," shown within the title, is utilized to demonstrate that these algorithms are "higher-level" heuristic algorithms differentiating with problem-specific heuristics [3]. Despite the fact that metaheuristic algorithms provide acceptable results, they do not deliver optimal solutions. In general, metaheuristics could be divided into four categories depending on the source of their inspiration, (i) Evolutionary Algorithms (EAs): They are effective heuristic search techniques based on Darwinian evolution that capture global solutions to complicated optimization problems while maintaining robustness and flexibility [4]; such as rat swarm optimizer (RSO) [5]; the wisdom of artificial crowds (WoAC) [6]; tuna swarm optimization (TSO) [7]; and artificial bee colony (ABC) [8]. (ii) Swarm Intelligence (SI): they are a computational intelligence approach for solving intricate problems. SI comprises a group study of how people in a population interact with one another on a local level. Nature is frequently a source of inspiration, especially for biological systems [9]. Furthermore, SI may be developed by the collective behaviour of artificial agents like robots in foraging robots [10]; (iii) Human and animal behaviour-based algorithms: they are inspired by some specific behaviour of individuals in society or animals in nature, such as Search Algorithm (CapSA) [11], Golden Tortoise Beetle Optimizer (GTBO) [12], Battle Royale Optimization (BRO) [13], passing vehicle search (PVS) [14], Dynamic Virtual Bats Algorithm (DVBA) [15], crow search algorithm (CSA) [16], and Tribe-Charged System Search (T-CSS) [17]. Finally, (iv) Physics-based algorithms: they are inspired by physics laws like Quantum mechanics, Universe theory, Newton's gravitational law, Electromagnetism, and Electrostatics, such as Material Generation Algorithm (MGA) [18,19], cyber-physical systems (CPS) [20], Archimedes optimization algorithm (AOA) [21], Lichtenberg Algorithm (LA) [22], Thermal Exchange Optimization algorithm (TEOA) [23], Charged System Search (CSS) [24,25], and Atomic Orbital Search (AOS) [26,27].

Building Information Modelling (BIM) is a management culture based on the digital construction of the project, and by involving all stakeholders and team members in the design phase, take a big step to reduce rework during the project and finally calculate the exact volume of work and project materials, provides accurate financial and time estimates for a construction project. In the 1970s, the introduction of 2D CAD revolutionized the drawing process by enabling information to be copied, electronically shared, and, in some situations, automated, which the drawing board was replaced by a computer in this evolutionary shift [28]. Eastman pioneered the use of virtual models in buildings in the 1970s, while van Nederveen and Tolman introduced the term Building Information Modelling (BIM) in 1992 for the first time [29]. Over the last two or three decades, the regular design practice in Architecture, Engineering, and Construction (AEC) sector has changed to BIM because of its ability to spend to project planning, execution, and maintenance throughout the entire value chain from planning to demolition phases. An exciting opportunity for project management could be provided via the integration of BIM through the early design phase in every project [30,31]. In comparison with a set of CAD drawings, BIM is a "richer repository"; some storing multi-disciplinary can build as construct information and the characteristics of buildings BIM model digitally and graphically. BIM allows the use of information in the architectural model by sharing and exporting the information demanded by the project team, saving time to re-create the model and speeding up the design while allowing more repetition [32]. So, a range of public policies aimed at improving the adequacy of the construction industry back up the BIM usage [33]. In other words, BIM is a faster and more profitable way to manage construction, increases design and construction quality, and reduces project execution time and cost [34]. The NBIMS defines BIM as "*creating an electronic model of a facility for visualization, engineering analysis, conflict analysis, code criteria checking, cost engineering, as-built product, budgeting, and many other purposes*" [35]. However, the main privileges of utilizing BIM in construction are ameliorated design quality and lifecycle management, effectively maintenance, accurate cost estimation, integrating workflow, efficient collaboration and interoperability between stakeholders and project team, streamlining information, and reducing energy consumption [36]. Moreover, the BIM-assisted estimate outperformed standard estimation approaches for the entry-level user. The more complicated the estimating processes, the more pronounced the benefits of BIM-based estimating tools over conventional estimating approaches became [37].

2. Literature Review

2.1. Studies of resource trade-offs

Various metaheuristic algorithms have been used to solve TCT problems recently. Feng, et al. [38] applied genetic algorithms (GAs) for TCT problems in construction. Van Eynde and Vanhoucke [39] offered a precise algorithm to provide the project's whole curve of non-dominated time-cost options. Sonmez and Bettemir [40] proposed a hybrid methodology developed utilizing simulated annealing (SA), genetic algorithms (GAs), and quantum simulated annealing techniques for the discrete TCT problems; the authors claimed that the hybrid method could ameliorate convergence of GA and provide some alternatives to TCT. Babu and Suresh [41] proposed that quality should add to the problems of TCT. The authors proposed a linear programming model for time-cost-quality trade-off (TCQT) problems; Khang and Myint [42] implemented the model at a cement factory in Bangkok, Thailand, to confirm the proposed model. Ndamlabin Mboula, et al. [43] introduced a novel scheduling technique called Cost-Time Trade-off efficient workflow scheduling, which consists of four basic steps: activity selection, assessment of the Implicit Requested Instance Types Range, evaluation of the spare budget, and selection of the VM. Hu and He [44] presented a time-cost-quality optimization model using a genetic algorithm. Afruzi, et al. [45] proposed a multi-objective imperialist competitive algorithm (MOICA) to solve the discrete TCQ tradeoff problem (DTCQTP). Sharma and Trivedi [46] developed a non-dominated sorting genetic algorithm II-based TCQT optimization model for project scheduling. Nonetheless, some researchers have considered other factors such as risk, CO_2 emission, and resource utilization. Ozcan-Deniz, et al. [47] evaluated environmental effect by considering total greenhouse gas emissions connected with a project and used NSGA-II to tradeoff time, cost, and environmental impact. Tran, et al. [48] created the opposition multiple objective symbiotic organisms search strategy, which could be useful way to address challenges including trade-offs between time, cost, quality, and task continuity. Luong, et al. [49] solved the TCQT problem using the opposition-based multiple objective differential evolution (OMODE) algorithm, which uses an opposition-based learning method for early population onset and generational jump. However, a few research has been carried out concerning time-cost-quality-risk trade-off problems. Mohammadipour and Sadjadi [50] considered risk in the TCQ trade-off. The authors provided proper linear programming to minimize the total additional cost of the project, the overall risk of the project, as well as the overall quality reduction in the project. Amoozad Mahdiraji, et al. [51] proposed a new technique for identifying the best implementation situation for each activity in a project by optimizing and balancing time, cost, quality, and risk. Tran and Long [52] proposed a multi-objective project scheduling optimization model using the DE method. By leveraging the existing data and resources, the authors stated that the suggested model could help project managers and decision-makers finish the project on schedule and with less risk. Sharma and Trivedi [53] presented a multimode resource-constrained time–cost–quality–safety trade-off optimization model using NSGA III algorithm. Keshavarz and Shoul [54] formulated a three-objective programming problem associated with the time-cost-quality trade-off problem using a fuzzy decision-making methodology.

2.2. Applications of building information modelling

In order to create a five-dimensional construction time-cost optimization model with the benefits of optimization and simulation, He, et al. [55] integrated the BIM process with GA. Rahmani Asl, et al. [56] proposed an integrated framework for BIM-based performance optimization to minimize the energy consumption while maximizing the efficient

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daylighting level for a residential dwellings. Sekhar and Maheswari [57] aimed to study the impact of BIM on managing and reducing change orders in off-site construction by optimizing design via visualization throughout the planning phase. Kim, et al. [58] investigated the 6–9 percentage quantity discrepancy in quantities obtained from diverse building interior components to increase the accuracy of cost estimates using BIM. ElMenshawy and Marzouk [59] proposed a framework for automated schedule generation using the BIM process and NSGA-II algorithm to solve the TCT problems; in which the authors claimed that the proposed model could choose a near-optimum scenario for the project. Mashayekhi and Heravi [60] introduced an integrated framework based on BIM, MIS and simulation tools for TCT problems. Yongge and Ya [61] proposed a model based on GA and BIM to solve time-cost-quality tradeoff problems in construction. For large-span spatial steel structure projects, Yu, et al. [62] proposed an integrated framework taking into account BIM and a time-cost optimization model to optimize construction costs and duration. Gelisen and Griffis [63] modelled a three-story Systems Engineering Facility III of Hanscom Air Force Base based on the BIM process to elucidate the effects of time and cost-based stochastic productivity. Khosakitchalert, et al. [64] suggested a technique for improving the accuracy of extracted quantities of compound components from incomplete or incorrect BIM models by eliminating excess quantities and adding missing quantities using information from BIM-based clash detection. Ma and Zhang [65] combined the 4D BIM with GA to solve the concurrency-based TCT problem; the authors asserted that the project manager could create a more exact construction schedule using the suggested optimization model without exceeding the contract's specified duration. Shadram and Mukkavaara [66] provided a methodology for determining acceptable design choices by integrating a multi-objective optimization technique with a BIM-driven design process to solve the trade-off problem between embodied and operational energy. Sandberg, et al. [67] proposed a framework for neutral BIM-based multi-disciplinary optimization of lifecycle energy and cost. Baghalzadeh Shishehgarkhaneh, et al. [68] employed the BIM process in time and cost management of dam construction projects in Iran.

Table 1 summarizes previous research works that are related to time, cost, quality, risk, and CO2 tradeoff in construction projects.

Table 1. Summary of previous related research works.

Authors	Time	Cost	Quality	Risk	CO2	Other parameters	BIM
Hajiagha, *et al.* [70]	×	×	×				
Tran and Long [52]	×	×		×			
Zheng [71]	×	×	×		×		
Al Haj and El-Sayegh [72]	×	×					
Khalili-Damghani, *et al.* [73]	×	×	×				
Moghadam, *et al.* [74]	×	×	×				
Zahraie and Tavakolan [75]	×	×				×	
Huynh, *et al.* [76]	×	×	×		×		
Banihashemi and Khalilzadeh [77]	×	×	×		×		
Ghoddousi, *et al.* [78]	×	×				×	
Mahmoudi and Feylizadeh [79]	×	×	×	×		×	
Ebrahimnezhad, *et al.* [80]	×	×	×				
Mungle, *et al.* [81]	×	×	×				
Koo, *et al.* [82]	×	×					
Heravi and Moridi [83]	×	×					
Mohammadipour and Sadjadi [50]		×	×	×			
Jeunet and Bou Orm [84]	×	×	×			×	
Hamta, *et al.* [85]	×	×	×				
Kosztyán and Szalkai [86]	×	×	×				
Current Study	×	×	×	×	×		×

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The current research work uses the Fire Hawk Optimizer (FHO), an unique metaheuristic algorithm inspired by the foraging behaviour of whistling kites, black kites, and brown falcons, which was developed by Azizi, *et al.* [69]. The key novelty in this study is the application and use of a novel metaheuristic optimization algorithm to the time-cost-quality-risk-CO_2 trade-off (TCQRCT) issue in a real building project based on the Building Information Modeling (BIM) procedure. The required number of objective function evaluations, the mean, the worst, and the standard deviation are all determined statistically via the use of 30 separate optimization runs. Based on a maximum of 5000 objective function evaluations, a predetermined stopping condition is also taken into consideration. However, being parameter-free, fast convergence behaviour, and the lowest possible objective function evaluation could be deemed the privileges of the FHO algorithm. On the other hand, the FHO method, like other metaheuristic algorithms, can only approximate problems; it cannot supply accurate answers.

3. Framework for resource tradeoff

The framework is made up of three primary parts: (1) the BIM module, (2) the metaheuristic optimization algorithm (Fire Hawk Optimizer (FHO)) module, and (3) the initialization and decision variables module.

3.1. BIM Module

A numerical case study is deemed to elucidate the efficiency of the FHO optimization algorithms in dealing with TCT problems. The case study is a five-floor residential building and a basement with a total floor area of 930 m2 that is used to validate the FHO algorithm with five objectives: time, cost, quality, risk, and CO_2 emissions. As shown in Table A1, all activity information is elicited by the BIM process, project data, and experts' judgments in planning and designing steps. The activity logic is finish to start for all activities. For modelling, the building was modelled in three different disciplines, including architecture, structure, mechanical, electrical, and pipeline (MEP) with Autodesk Revit 2022; meanwhile, all elements were modelled with Level of Development (LOD) 350 based on BIMFourm 2019 specification [87]. Subsequently, dynamo visual programming was used to generate parametric modelling in Revit. In the following stage, Navisworks software was employed for the project's soft and hard clash detection. Finally, MATLAB is used for programming and trade-off of objective functions. The framework of this paper is shown in Fig. 1.

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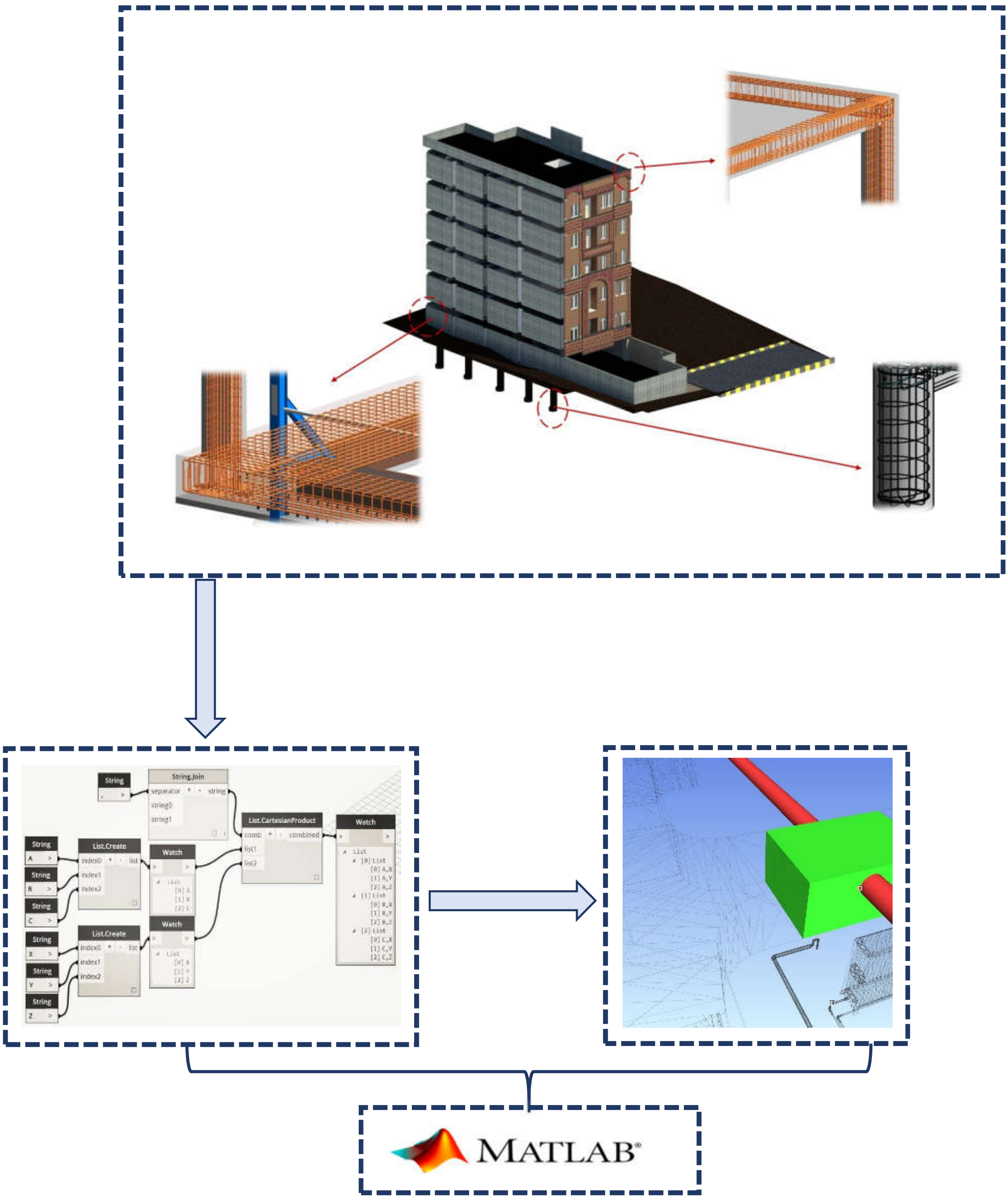

Figure 1. Framework of BIM-based modelling for resource trade-off.

3.2. Fire Hawk Optimizer (FHO)

3.2.1. Inspiration

Native Australians have long used fire to manage and preserve the balance of the surrounding ecology and terrain, and it has been a part of their cultural and ethnic traditions. People and other factors may spread intentionally started or naturally occurring fires caused by lightning, escalating the vulnerability of the native ecosystem and biodiversity. Furthermore, it was recently determined that black kites, whistling kites, and brown falcons are able to cause spreading fires throughout the region. The mentioned birds, known as Fire Hawks, strive to spread fire on purpose by carrying blazing sticks in

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their beaks and talons, a behaviour characterized as a natural catastrophe. The behaviour of these birds towards fires is seen in Fig. 2. The birds pick up burning sticks and deposit them in other unburned spots to make little fires to control and capture their prey. These little flames frighten the prey, such as snakes, rodents, and other animals, causing them to escape in a fast and panicked manner, making it much simpler for the hawks to capture them.

Figure 2. Photos of Fire Hawks' behaviour across the fires [69].

3.2.2. Mathematical Model

The FHO algorithm imitates the fire hawks' foraging behaviour, taking into consideration the procedure of starting and spreading flames as well as capturing prey. Initially, a set of possible solutions (X) are determined based on the fire hawks and prey's position vectors. A random initialization mechanism is used to establish the initial positions of these vectors in the search space.

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^j & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^j & \cdots & x_2^d \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^j & \cdots & x_i^d \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ x_N^1 & x_N^2 & \cdots & x_N^j & \cdots & x_N^d \end{bmatrix}, \quad \begin{cases} i = 1,2,\ldots,N. \\ j = 1,2,\ldots,d. \end{cases} \tag{1}$$

$$x_i^j(0) = x_{i,min}^j + rand.\left(x_{i,max}^j - x_{i,min}^j\right), \quad \begin{cases} i = 1,2,\ldots,N. \\ j = 1,2,\ldots,d. \end{cases} \tag{2}$$

where N elucidates the total number of solution candidates in the search space; X_i shows the *ith* solution candidate in the search space; d is the considered problem's dimension; $x_i^j(0)$ represents the initial position of the solution candidates; x_i^j is the *jth* decision variable of the *ith* solution candidate; $rand$ is a uniformly distributed random number in the range of [0,1]; and $x_{i,min}^{j}$ and $x_{i,max}^{j}$ are the minimum and maximum bounds of the *jth* decision variable for the *ith* solution candidate.

The specified optimization problem is taken into account during the objective function evaluation of solution candidates so as to identify the Fire Hawks in the search space. Predators and prey may be distinguished from one other by the greater objective function values of certain solution candidates. The selected Fire Hawks are employed to spread flames around the prey in the search zone, making hunting easier for the hunter. The main fire, which is originally employed by the Fire Hawks to spread flames over the search region, is also assumed to be the best global solution. These features are shown schematically in Figures 3a and 3b, and are mathematically represented as follows:

$$PR = \begin{bmatrix} PR_1 \\ PR_2 \\ \vdots \\ PR_k \\ \vdots \\ PR_m \end{bmatrix}, \qquad k = 1,2, \dots, m. \tag{3}$$

$$FH = \begin{bmatrix} FH_1 \\ FH_2 \\ \vdots \\ FH_l \\ \vdots \\ FH_n \end{bmatrix}, \qquad l = 1,2, \dots, n. \tag{4}$$

where FH_l explains the *lth* fire hawk in a complete search space of *n* fire hawks; and PR_k reveals the *kth* prey in the search space depending the whole number of *m* preys.

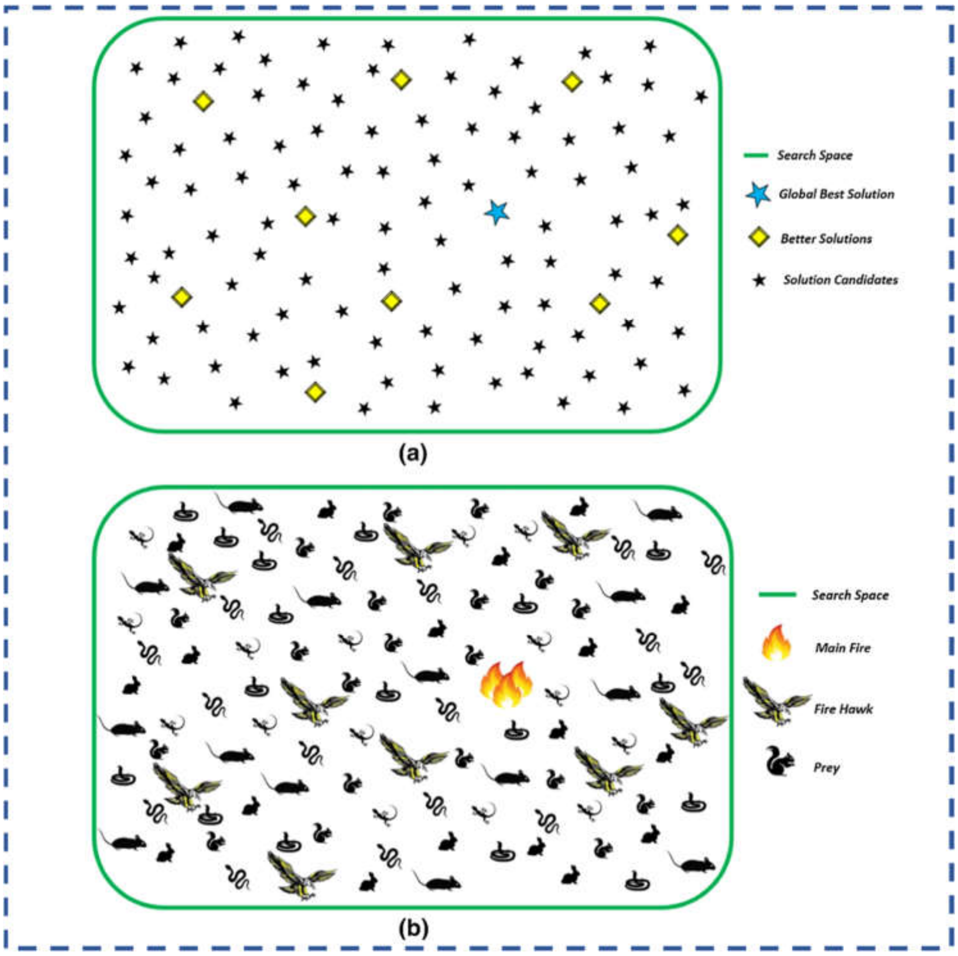

Figure 3. Schematic representation of identifying fire hawks and prey in the search space [69].

The distance among the Fire Hawks and their prey is determined in the following step of the algorithm. These principles are shown graphically in Figure 4(a), where D_k^l is shown using the following equation:

$$D_k^l = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \qquad \begin{cases} l = 1,2, \dots, n. \\ k = 1,2, \dots, m. \end{cases} \tag{5}$$

Where m and n demonstrate the overall number of preys and fire hawks in the search space, respectively; D_k^l shows the total distance between the *lth* fire hawk and the *kth* prey; and (x_1, y_1) and (x_2, y_2) represent the coordinates of the Fire Hawks and prey in the search space.

The territory of these birds is recognized using the nearest prey in the vicinity, using the method described above to determine the overall distance among Fire Hawks and prey. Fig. 4(b) depicts graphically the process of establishing the Fire Hawks' territorial boundaries in the search area.

After that, the Fire Hawks collect hot coals from the primary fire to start a fire at the designated spot. These two behaviours may be employed as location updating processes in FHO's main search loop since some birds are willing to utilize burning sticks from other Fire Hawks' territories, as illustrated in the equation below:

$$FH_l^{new} = FH_l + (r_1 \times GB - r_2 \times FH_{Near}), \qquad l = 1,2, \dots, n. \tag{6}$$

where GB demonstrates the global best solution in the search space considered as the primary fire; FH_l^{new} shows the novel position vector of the *lth* Fire Hawk (FH_l); and r_1 and r_2 are uniformly distributed random numbers in the range of (0, 1) for illustrating Fire Hawks' movements towards the vital fire and the other Fire Hawks' territories; and FH_{Near} shows one of the Fire Hawks in the search space.

Prey movement throughout each Fire For the algorithm's following stage, which involves updating positions, the hawk's territory is seen as a crucial aspect of animal behaviour. The following equation could be employed to take these activities into account while updating a position:

$$PR_q^{new} = PR_q + (r_3 \times FH_l - r_4 \times SP_l), \qquad \begin{cases} l = 1,2, \dots, n. \\ q = 1,2, \dots, r. \end{cases} \tag{7}$$

where GB is the global best solution in the search space considered as the main fire; PR_q^{new} is the novel position vector of the *qth* prey (PR_q) surrounded by the *lth* Fire Hawk (FH_l); SP_l is a safe place under the *lth* Fire Hawk territory; and to ascertain the motions of prey in the direction of the Fire Hawks and the safe location, r_3 and r_4 are uniformly distributed random integers in the range of (0, 1).

Furthermore, the prey may move into the territory of other Fire Hawks. At the same time, there is a chance that the prey may approach the Fire Hawks that are trapped by neighbouring Fire Hawks may even try to hide in a more secure region beyond the Fire Hawk's territory. The following equation could be employed to account for these activities throughout the position updating process (Fig. 4(e)):

$$PR_q^{new} = PR_q + (r_5 \times FH_{Alter} - r_6 \times SP), \qquad \begin{cases} l = 1,2, \dots, n. \\ q = 1,2, \dots, r. \end{cases} \tag{8}$$

where PR_q^{new} shows the new position vector of the *qth* prey (PR_q) flanked by the *lth* fire hawk (FH_l); SP elucidates a safe place outside the *lth* Fire Hawk's territory; FH_{Alter} is one of the fire hawks in the search space; r_5 and r_6 indicate uniformly distributed random numbers in the range of (0, 1) to determine the movements of preys towards the other Fire Hawks and the safe region outside the territory.

The mathematical presentation of SP_l and SP is stated as follows, taking into account the fact that the safe place in nature is a location where the majority of animals assemble to collect so as to be safe and sound during a hazard:

$$SP_l = \frac{\sum_{q=1}^{r} PR_q}{r}, \qquad \begin{cases} q = 1,2, \dots, r. \\ l = 1,2, \dots, n. \end{cases} \tag{9}$$

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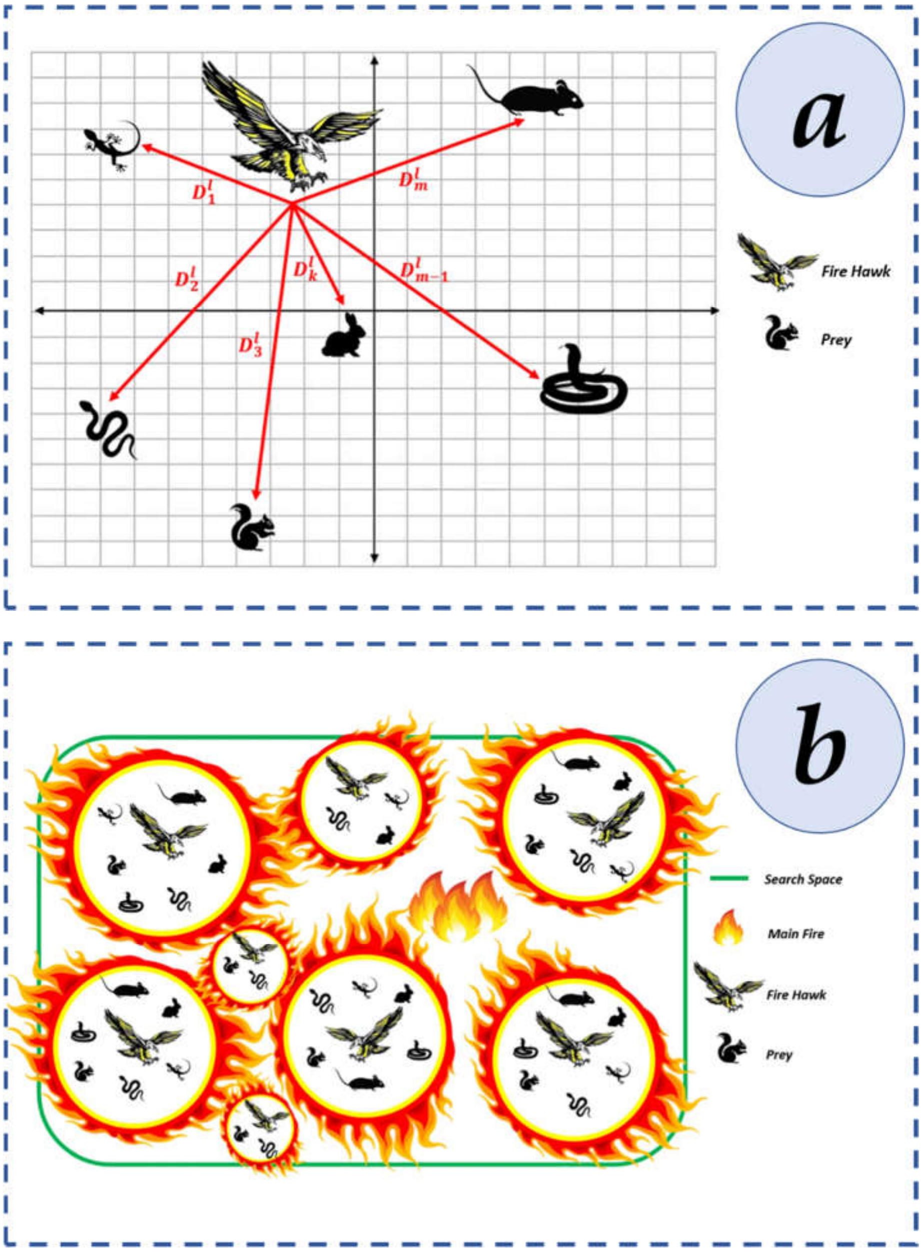
$$SP = \frac{\sum_{k=1}^{m} PR_k}{m}, \qquad k = 1,2, \dots, m. \tag{10}$$

where PR_q shows the *qth* prey surrounded by the *lth* fire hawk (FH_l); PR_k is the *kth* prey in the search space.



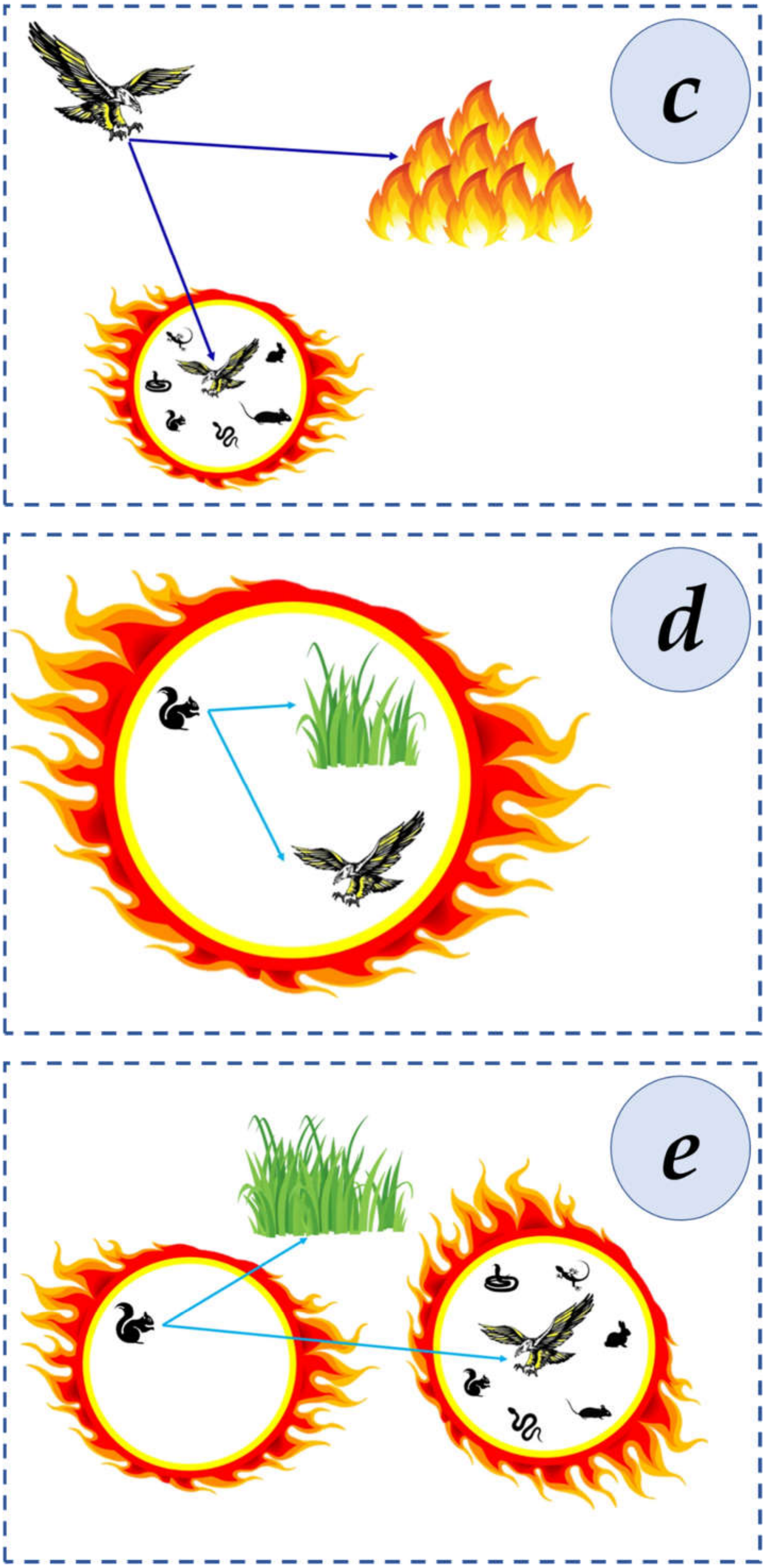

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Figure 4. Schematic representation for measuring the total distance between the Fire Hawks and the prey (a). Schematic representation of illustrating territory of Fire Hawks in the search space (b). Schematic representation of the Fire Hawks' position updating procedure in the search space (c). Schematic representation of the preys' position updating process inside the fire hawks' territory (d). Schematic representation of the preys' position updating process outside the fire hawks' territory (e) [69].

The FHO algorithm's pseudo-code is shown in Fig. 5, and the algorithm's flowchart is shown in Fig. 6. A Gaussian distribution is the most common distributions used in randomization techniques, and it is used to calculate the number of preys in each search loop, which is equal to the overall number of solution candidates minus the number of fire hawks.

```
procedure Fire Hawk Optimizer (FHO)
        Determine initial positions of solution candidates (Xi) in the search space with N candidates
        Evaluate fitness values for initial solution candidates
        Determine the Global Best (GB) solution as the main fire
        while Iteration < Maximum number of iterations
            Generate n as a random integer number for determining the number of Fire Hawks
            Determine Fire Hawks (FH) and Preys (PR) in the search space
            Calculate the total distance between the Fire Hawks and the preys
            Determine the territory of the Fire Hawks by dispersing the preys
            for l=1: n
                Determine the new position of the Fire Hawks by Eq. 6.
                for q=1:r
                    Calculate the safe place under lth Fire Hawk territory by Eq. 9.
                    Determine the new position of the preys by Eq. 7.
                    Calculate the safe place outside the lth Fire Hawk territory by Eq. 10.
                    Determine the new position of the preys by Eq. 8.
                end
            end
            Evaluate fitness values for the newly created Fire Hawks and preys
            Determine the Global Best (GB) solution as the main fire
        end while
        return GB
end procedure
```

Figure 5. Pseudo-code of FHO.

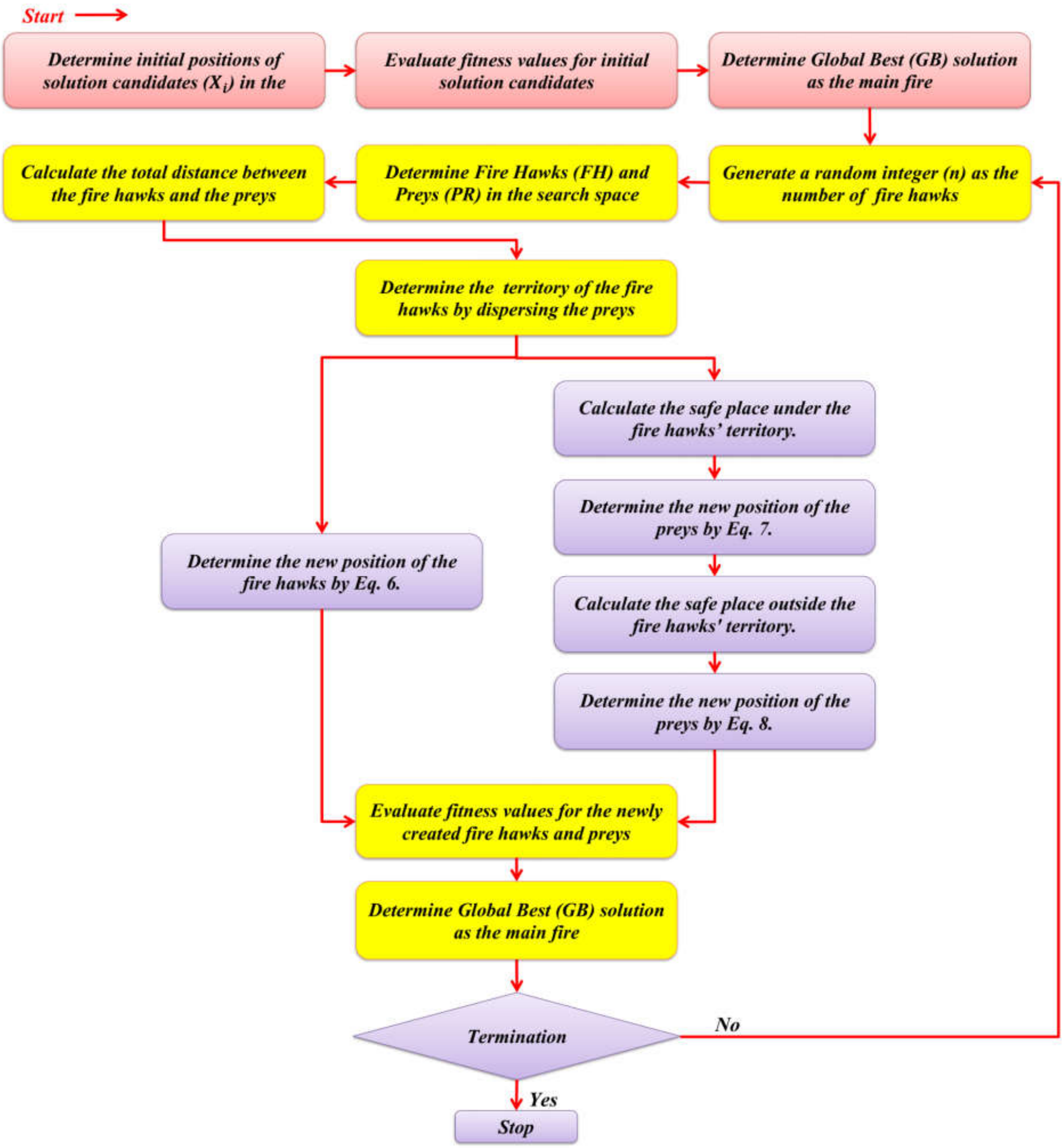

Figure 6. Flowchart of FHO.

3.3. Initialization and decision variables

Finding the best answer from among all feasible alternatives is the goal of an optimization problem. A common optimization problem is as follows:

A function $f : B \rightarrow R$ from some set B to the real numbers.

An element $x_0 \in B$ such that $f(x_0) \leq f(x)$ for all $x \in B$ (minimization problem) or $f(x_0) \geq f(x)$ for all $x \in B$ (maximization problem).

where B represents a portion of Euclidean space and is often defined by a set of constraints, equality requirements, or inequalities that B members must satisfy. Candidate solutions or feasible solutions signify the components of B, while the domain B denotes the search space or option set of *f*. Function f is referred to as the "objective function". A potential solution that minimizes (or maximizes, if that is the goal) the objective function is known as an optimal solution [87]. The BIM model is utilized in this research to import all of the project's data for all 38 activities listed in Table 1. A construction project's activity-on-node (AON) diagram is made up of M nodes and the relationships between the

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activities. Each activity has a number of execution options, each with its own time, cost, quality, risk, and carbon dioxide emissions associated with it, all of which are depending on the amount of resources, technology, and equipment used. The TCRQC tradeoff problem optimization approach tries to minimize project time, cost, risk, and carbon dioxide emissions while simultaneously maximizing project quality by picking the best execution option for all activities. Consequently, the first objective function is to minimize the time of the project in Eq.11:

$$T_p = \min(\max(ST_i + D_i)) = \min(\max(FT_i))\,; \quad i = 1, \dots, M \tag{11}$$

Where D_i shows the duration of each activity in the project; ST_i and FT_i are the start and finish times of activity, respectively; M demonstrates the total number of nodes in the project scheduling [2]. Furthermore, a project's total cost comprises direct costs (*DC*), indirect costs (*IC*), and tardiness costs (*TC*). There are other techniques for calculating the entire cost of a project; for theoretical reasons, this study simply considers direct costs, indirect costs, and tardiness costs. The following objective function is to minimize cost of the project as indicated in Eq.12:

$$\min C = D^j_{C_i} + I^j_{C_i} + TC \tag{12}$$

$$D^j_{C_i} = \sum_{i=1}^{n} C^j_i \tag{13}$$

$$I^j_{C_i} = C_{ic} \times T \tag{14}$$

$$TC = \begin{cases} C_1(T_0 - T) & \text{if } T \le T_0 \\ \left(e^{\frac{T-T_0}{T_0}} - 1\right)\left(D^j_{C_i} + I^j_{C_i}\right) & \text{if } T > T_0 \end{cases} \tag{15}$$

Where TC_p is total project's cost; $D^j_{C_i}$ and $I^j_{C_i}$ are the direct and indirect cost associated with the *jth* execution mode of *ith* activity, respectively; *TC* is the tardiness cost; T_0 elucidates contractual planned duration of the project; C_1 shows reward for completing the task early; and T is total project duration [88,89]. Due to the fact that a project's resources may include a range of materials, equipment, and labour, the overall project's quality is calculated as the sum of the quality of each activity. Increasing the length of activities improves the quality level; nevertheless, extending the time beyond a certain point decreases the quality somewhat. Hence, The quality of each activity is indicated by the quality performance index (*QPIi*) which is given by Eq.16 [89].

$$QPI_i = a_i t_i^2 + b_i t_i + c_i \tag{16}$$

Where t_i is duration of activity *i*; a_i, b_i, and c_i are coefficients decided by the quadratic function regarding BD (Fig. 7). LD, BD, and SD are the longest, best, and shortest duration, respectively. However, BD is calculated by Eq.17. Finally, the objective function for quality is formulated in Eq. 18 as follows:

$$BD = SD + 0.613(LD - SD) \tag{17}$$

$$\max Q = \sum_{i=1}^{M} \frac{QPI_i}{M} \tag{18}$$

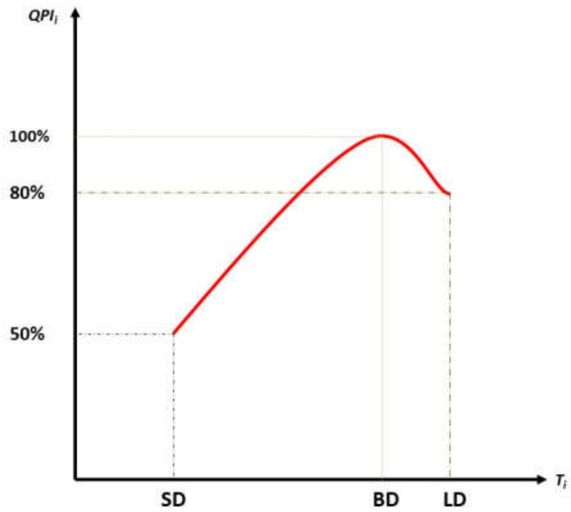


Figure 7. Quality performance index (QPI).

However, some resources might have a negative impact on the environment during the development phase of a project by generating CO_2. CO_2 emissions can occur in two ways during the on-site construction process: directly from electricity consumption and fuel combustion, and indirectly from the manufacturing of building materials and their transportation. CO_2 emissions can be reduced by not only selecting environmentally friendly materials, but also by ensuring that materials are transported in the shortest possible manner. So, the objective function to minimize the total amount of CO_2 in the project can be calculated by Eq.19.

$$\min \mathrm{CE} = \sum_{i=1}^{M} E_{dij} + \sum_{i=1}^{M} E_{inij} = (\sum_{i=1}^{M} Q_{ed} \times F_e + Q_{dd} \times F_d) + (\sum_{i=1}^{M} Q_k \times F_j + Q_{ek} \times F_e + Q_{dk} \times F_d) \quad (19)$$

Where CE is the total CO_2 emission in the project; E_{dij} and E_{inij} are the direct and indirect CO_2 emission in the project, respectively; Q_{ed} shows activity's electricity consumption; Q_{dd} elucidates activity's diesel consumption; Q_{ij} shows consumption of material *k* in activity; Q_{ek} indicates electricity consumption for transportation of material *k* for activity; Q_{dk} shows diesel consumption for transportation of material *k* for activity; F_e, F_d, and F_j are carbon emission factor (CEF) per electricity unit, diesel unit consumption, and per unit production of material k, respectively. Concerning the project's risk, the actual project risk is mostly determined by the project's circumstances, delivery systems, and contract terms. A “risk value" is described as a function that combines the two components: (i) the project's overall float; (ii) resource volatility. When noncritical operations have a high degree of temporal uncertainty, the usage of float may result in increased project risk and schedule overruns. Thus, construction managers are required to execute schedule adjustments to minimize unplanned changes in resource use throughout the duration of the project's execution. Allowing noncritical operations to float may result in more effective resource use [90-92]. Consequently, the fifth objective function for risk can be formulated as Eq.20:

$$\min R = w_1 \times \left(1 - \frac{TF_c + 1}{TF_{max} + 1}\right) + w_2 \times \left(\frac{\sum_{i=1}^{Pd}(R_t - \bar{R})^2}{P_d(\bar{R})^2}\right) + w_3 \times \left(1 - \frac{\bar{R}}{\max(R_t)}\right) \quad (20)$$

Where TF_c and TF_{max} show total current float and total flexible scheduling float of the project; $\bar{R}$ elucidates uniform resource level; R_t is resource required on day *t*; and w_i demonstrates the weights.

Finally, to assess the capability of the FHO algorithm to the time-cost-quality-risk-CO_2 (All) trade-off simultaneously, Eq. 21 is used for this purpose:

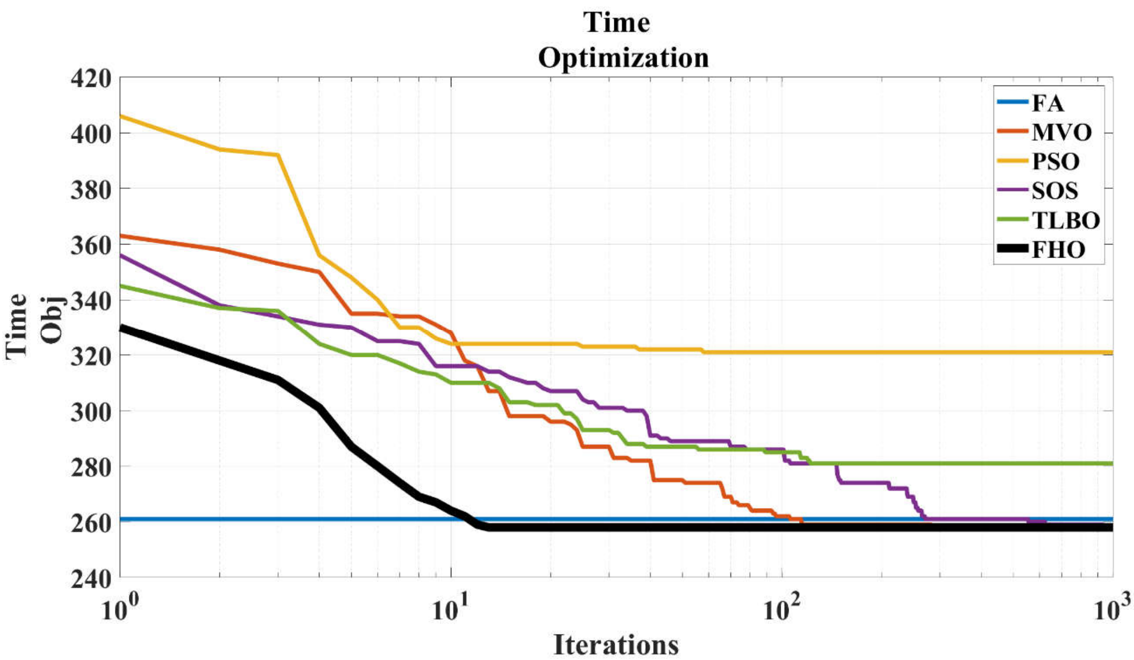
$$F(x) = \frac{T - T_{min}}{T_{max} - T_{min}} + \frac{C - C_{min}}{C_{max} - C_{min}} + \frac{R - R_{min}}{R_{max} - R_{min}} + \frac{CO_2 - CO_{2(min)}}{CO_{2(max)} - CO_{2(min)}} + \frac{Q_{min} - Q}{Q_{max} - Q_{min}} \quad (21)$$

4. Optimization Results

Five different metaheuristic algorithms were chosen to compare the efficacy of the FHO algorithm in solving resource trade-off problems in construction projects, including Firefly Algorithm (FA) [93], Multi-Verse Optimizer (MVO) [94], Particle Swarm Optimization (PSO) [95], Symbiotic Organisms Search (SOS) algorithm [96], and Teaching-learning-based Optimization (TLBO) [97]. All optimization processes have been conducted via MATLAB programming software using a PC with 8 GM RAM, CORE i7, and 2.8 GHz frequency. Table 2 shows the best findings of the FHO alongside other alternative algorithms for each scenario. However, for statistical purposes, 30 independent optimization runs are carried out for determining the statistical measurements as the mean, worst, standard deviation, and computational time. A predefined stopping criterion is also considered based on a maximum number of 5000 objective function evaluations while the number of populations for each algorithm is determined by the maximum number of objective function evaluations and the maximum number of iterations. Fig. 8 illustrates the convergence history of FHO and alternative algorithms in dealing with the mentioned trade-off problems.

Table 2. The best outcomes of the FHO and alternative algorithms for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Time	261	258	321	258	281	258
Cost	118230	117056	119564.8	117104.6	117512	116783
Quality	94.35	94.16	93.82	94.41	93.89	87.81
Risk	5.78	5.94	6.53	5.78	5.93	5.78
CO_2	76.35	76.74	103.35	76.35	79.60	76.35
All	0.74	0.76	0.99	0.74	0.77	0.74



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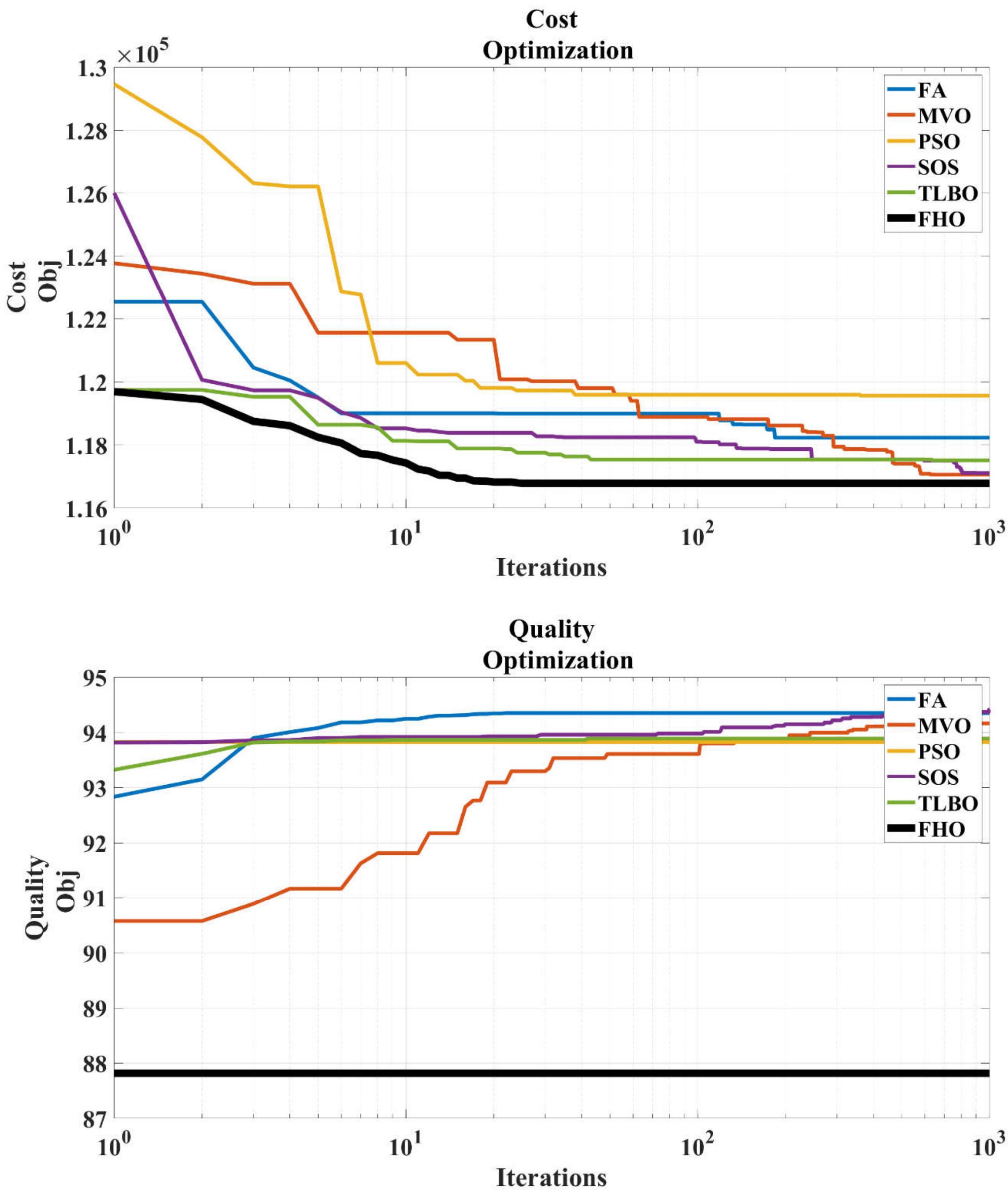

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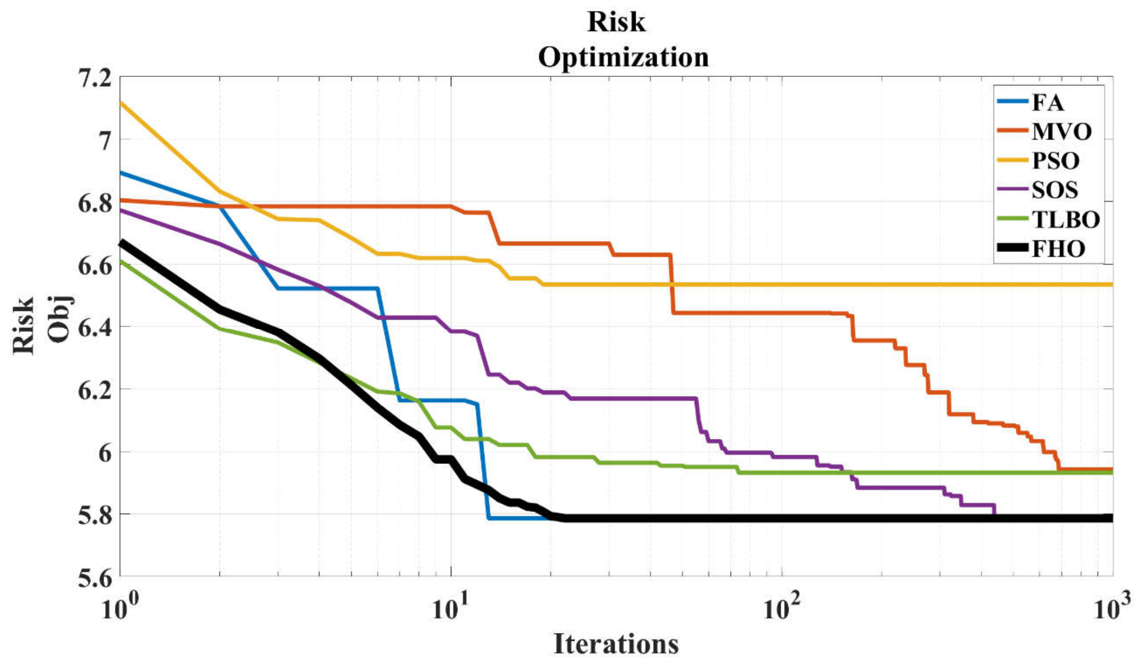

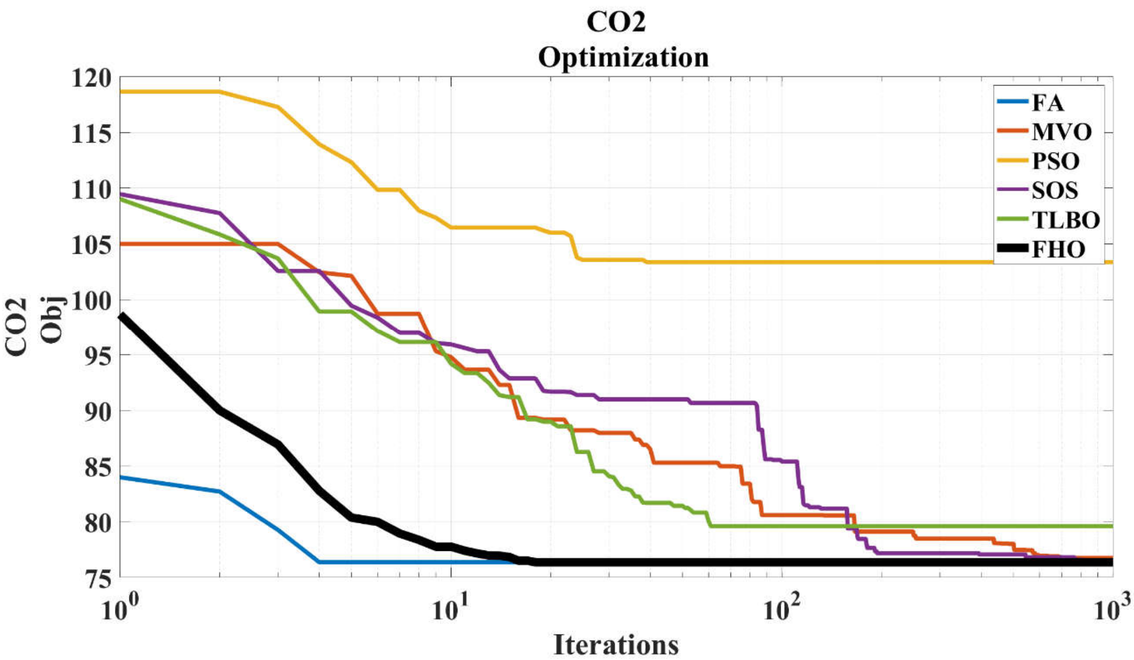

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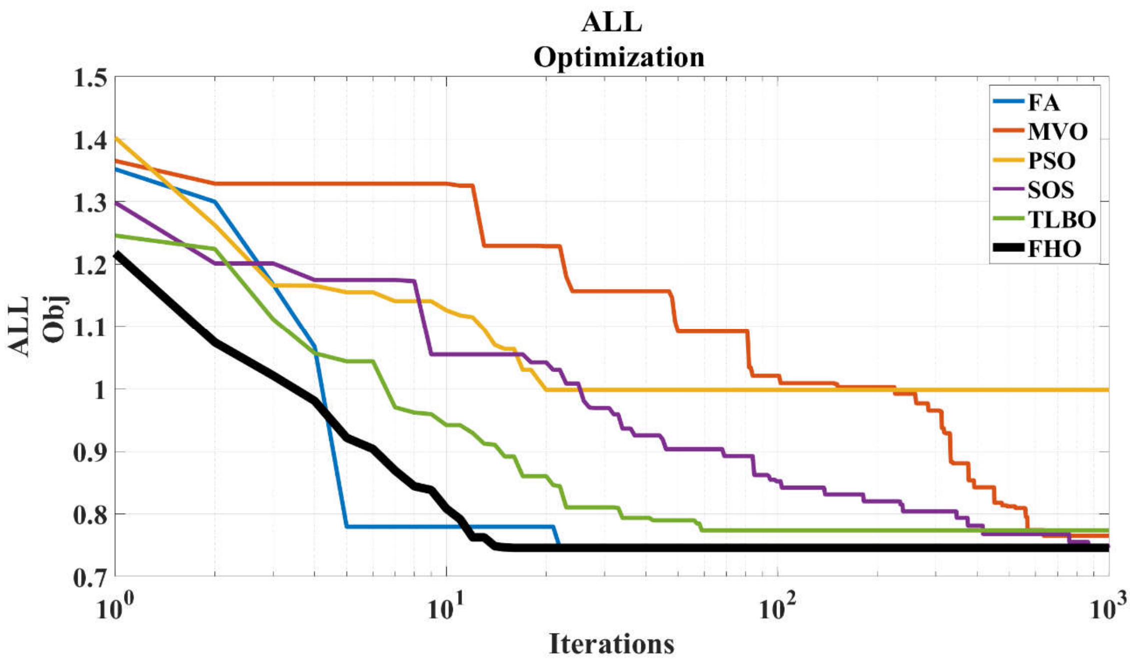

Figure 8. Convergence history of 30 independent optimization runs of FHO and alternative algorithms.

Table 3 demonstrates the statistical results of time optimization in the case study. As can be seen, the FHO algorithm could dominate most of the alternative metaheuristic algorithms in the first scenario of time optimization in the case study, which calculates 258 days as the best and optimum time, like MVO and SOS algorithms. Regarding standard deviation (Std), the FA algorithm delivers the most minimal result, followed by the FHO algorithm, accounting for 0.18. In comparison, the PSO algorithm provides the most significant value of Std, registered at about 35.07. Moreover, the SOS algorithm could conduct the time optimization process in the smallest feasible time (1.40 s); on the other hand, the longest computing time is acquired by FHO and PSO algorithms, needing significantly more time to conduct the optimization process in this case.

Table 3. Statistical outcomes for the time optimization for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Best	261	258	321	258	281	258
Mean	261	258.9	392.7	260.76	300.6	258.03
Worst	261	261	453	266	316	259
Std	0	1.21	35.07	1.71	9.04	0.18
Computational time (s)	2.19	1.61	2.35	1.40	1.44	8.66

Table 4 summarizes the vital information concerning the statistical analysis used in the cost optimization in the case study. Evident is the fact that the FHO algorithm outperforms other alternative metaheuristic algorithms in the case study's second scenario (cost optimization); in other words, the FHO algorithm can compute the project's lowest cost, in contrast to the PSO algorithm's maximum optimal value of cost. However, the FHO algorithm took the most computational time in this case, followed by the FA; on the contrary, the SOS algorithm took the least computing time for cost optimization in the project mentioned above. Additionally, the FHO algorithm supplied the smallest feasible Std value, which the FA follows. Meanwhile, the PSO achieved the greatest standard

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deviation of all algorithms studied in this case. As a result, the FHO algorithm could be an acceptable metaheuristic for project and construction management cost optimisation.

Table 4. Statistical results for the cost optimization for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Best	118230	117056	119564.8	117104.6	117512	116783
Mean	118558.6	117511.9	135480.6	117498.3	118322.9	116839.7
Worst	118780	118284.6	155151.7	117920	119070	117011
Std	148.09	271.58	9952.33	222.75	397.19	59.57
Computational time (s)	2.16	1.57	2.13	1.39	1.44	9.66

Table 5 shows the statistical outcomes of the case study's quality optimization, indicating that the FHO method can deliver acceptable quality. Simultaneously, the SOS algorithm achieved the most outstanding quality value, about 94.41, followed by the FA algorithm. Additionally, the SOS algorithm could provide the smallest standard deviation, in this case, roughly 0.04. In sharp contrast, the FHO has set the highest standard. However, in terms of computing time for quality optimization, the SOS algorithm required the least time, in this case, contrasted to the FHO approach, which required around 0.78 seconds (s). As a consequence, although the FHO algorithm can provide an acceptable level of quality, the SOS method could be a preferred choice for project managers in this circumstance.

Table 5. Statistical results for the quality optimization for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Best	94.35	94.16	93.82	94.41	93.89	87.81
Mean	94.46	94.24	93.89	94.54	94.01	89.63
Worst	94.56	94.40	94.12	94.62	94.27	91.46
Std	0.04	0.05	0.06	0.04	0.08	0.78
Computational time (s)	9.05	1.44	2.11	1.40	1.44	2.03

The statistical analysis findings for risk optimization are indicated in Table 6. Nonetheless, similar to FA and SOS algorithms, the FHO could calculate the lowest value for risk in the case study, accounting for nearly 5.78. Furthermore, the SOS algorithm required as little as possible computational time in this scenario, followed by the TLBO algorithm. Hence, the FHO algorithm could be a well-suited algorithm for risk optimization in project scheduling. Meanwhile, the FHO algorithm could calculate the lowest value for Std in this scenario.

Table 6. Statistical results for the risk optimization for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Best	5.78	5.94	6.53	5.78	5.93	5.78
Mean	5.78	6.07	7.13	5.79	6.03	5.78
Worst	5.78	6.28	7.46	5.82	6.20	5.78
Std	9.03E-16	8.45E-02	2.47E-01	0.01	6.99E-02	9.03E-16
Computational time (s)	2.27	1.56	2.05	1.39	1.43	8.67

Table 7 illustrates the case study's statistical analysis for CO_2 emission optimization. Considering sustainability in construction, the FHO could be an ideal algorithm for project engineers to reduce the carbon footprint since it could calculate the lowest CO_2 in the case study, thereby reaching environmentally-friendly construction. Contrastingly, the PSO algorithm provided the highest value for CO_2 in this scenario, indicating its unfavourable performance in achieving the project with the lowest carbon footprint. However, the SOS algorithm gave the lowest computational time, registered at 1.38 (s), followed by TLBO. As a result, considering the average computational time, the FHO algorithm could be considered an appropriate alternative to optimize the amount of carbon dioxide in construction projects.

Table 7. Statistical results for the CO_2 optimization for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Best	76.35	76.44	103.35	76.35	79.60	76.35
Mean	76.35	77.87	116.23	76.68	88.24	76.40
Worst	76.35	80.41	129.54	77.20	94.47	76.59
Std	1.45E-14	0.92	6.20	0.24	4.19E+00	0.06
Computational time (s)	1.93	1.59	2.29	1.38	1.42	12.52

Finally, Table 8 illustrates the statistical analysis for all trade-off in the considered project. As can be seen, the FHO algorithm could outperform other metaheuristic algorithms in dealing with the TCQRCT problem by considering a residential dwelling as a case study, followed by the FA and SOS algorithms. Regarding Std. value, the FHO and FA algorithms gave the lowest value, indicating its superior performance. However, the SOS algorithm required the lowest computational time to conduct TCQRCT in the case study, followed by the TLBO with nearly 1.43 (s). The FHO algorithm could be unique for TCQRCT problems in construction projects without considering computational time.

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Table 8. Statistical results for all optimization for the case study.

	FA	MVO	PSO	SOS	TLBO	FHO (current study)
Best	0.74	0.76	0.99	0.74	0.77	0.74
Mean	0.74	0.84	1.42	0.75	0.86	0.74
Worst	0.74	0.95	1.67	0.78	0.94	0.74
Std	2.26E-16	0.04	0.21	0.01	0.04	2.26E-16
Computational time (s)	1.98	1.70	2.42	1.38	1.43	10.96

5. Conclusion

This paper established a unique framework that involves building information modelling (BIM) and a novel metaheuristic algorithm to solve the resources trade-off problem in construction projects. For this purpose, Fire Hawk Optimizer (FHO) is used as a novel metaheuristic algorithm. A 3D BIM-based modelling of the case study was created using different software, including Revit, Navisworks, Lumion, and also dynamo was utilized to make parametric modelling. The key results and main outcomes of this research work are summarized as follows:

Based on the outcomes of best optimization runs conducted by different methods in dealing with time optimization, the FHO algorithm could reach the lowest time for case study, accounting for 258 days.

The FHO can provide 116783($) for the cost of the case study, which is the best among other approaches.

Regarding quality optimization, the FHO is capable of providing reasonable quality value, but the SOS algorithm gave the best results.

The FHO algorithm is able to provide the best results for both risk and CO_2 optimization in the case study than other alternative algorithms.

Based on the best results of the TCQRCT problem, the FHO algorithm can provide 0.74, which is much better than other algorithms.

Based on the results and conducted analysis, the main reason for the superiority of the FHO algorithm comparing other mentioned metaheuristics algorithms is threefold, namely fast convergence behavior, being parameter-free, and the lowest possible objective function evaluation. The FHO algorithm should be tested for future studies utilizing intricate optimization problems in miscellaneous fields, such as real-size engineering design problems like truss structures.

Author Contributions: Conceptualization, M.B.S. and M.A.; methodology, M.B.S. and M.A.; software, M.B.S. and M.A. and M.B.; validation, M.A. and M.B.; formal analysis, M.B.S. and M.A.; investigation, M.B.S.; resources, M.B.S.; data curation, M.A.; writing—original draft preparation, M.B.S.; writing—review and editing, M.A. and R.M.; visualization, M.B.S. and M.B.; supervision, M.A.; project administration, R.M.; funding acquisition, R.M. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

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Appendix

Table 1A - Project data of case study

NO	Activity	Logical	Mode 1					Mode 2					Mode 3					Mode 4					Mode 5				
			Time	Cost $	Quality %	Risk	CO2	Time	Cost $	Quality %	Risk	CO2	Time	Cost $	Quality %	Risk	CO2	Time	Cost $	Quality %	Risk	CO2	Time	Cost $	Quality %	Risk	CO2
1	Foundation	-	26	8100	90.65	14.96667	225.3313	24	7850	89.2	12	198.45	20	8120	92.1	12.5	187.52	15	8400	78.9	12.9	98.32	13	9408	74.955	16.31367	108.152
2	Retaining wall	1FS+1	15	2252	94.905	13.21667	137.9707	13	2150	94.51	10.5	125.08	11	2220	95.3	11.3	111.04	9	2410	87.1	11.54	54.25	8	2699.2	82.745	14.40617	59.675
3	Columns of ground	2FS	13	2015	91.155	10.33333	116.3133	10	1980	90.21	8	101.3	7	2042	92.1	9.4	98	6	2100	85.45	9.5	36.32	5	2352	81.1775	11.26333	39.952
4	Beam and roof of ground	3FS+1	10	4325	91.98	11.95167	188.2833	8	3652	91.4	9.65	169.91	6	3920	92.56	9.8	152.36	4	4150	86.41	10.3	111.25	3	4648	82.0895	13.02732	122.375
5	Columns of 1st floor	4FS+2	13	1550	93.605	5.58	190.8767	10	1200	92.65	4.2	178.35	7	1356	94.56	5.4	148	6	1420	89.36	6	128.6	5	1590.4	84.892	6.0822	141.46
6	Beam and roof of 1st floor	5FS+1	10	3600	95.625	12.82	177.7653	8	3200	94.8	10.3	177.88	6	3410	96.45	10.65	125.36	4	3540	85.45	11.02	45.25	3	3964.8	81.1775	13.9738	49.775
7	Columns of 2nd floor	6FS+2	13	1550	92.04	8.038	158.5137	10	1200	91.3	6.32	143.65	7	1356	92.78	7.05	127.63	6	1420	84.12	7.8	35.98	5	1590.4	79.914	8.76142	39.578
8	Beam and roof of 2nd floor	7FS+1	10	3600	97.575	9.275	183.8583	8	3200	96.5	7.25	169.25	6	3410	98.65	8.25	145.25	4	3540	88.89	8.5	89.54	3	3964.8	84.4455	10.10975	98.494
9	Columns of 3rd floor	8FS+2	13	1550	93.99	6.903333	150.1917	10	1200	93.4	5.3	145.25	7	1356	94.58	6.4	111.25	6	1420	78.45	6.45	74.63	5	1590.4	74.5275	7.524633	82.093
10	Beam and roof of 3rd floor	9FS+1	10	3600	91.475	3.541667	167.4697	8	3200	90.5	2.65	151.72	6	3410	92.45	3.47	134.89	4	3540	82.1	3.9	125.25	3	3964.8	77.995	3.860417	137.775

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11	Columns of 4th floor	10FS+2	13	1550	92.825	6.316667	114.523	10	1200	91.4	4.5	106.58	7	1356	94.25	6.8	89.25	6	1420	86.45	7	65.32	5	1590.4	82.1275	6.885167	71.852
12	Beam and roof of 4th floor	11FS+1	10	3600	96.375	15.29833	156.7313	8	3200	95.3	11.85	143.56	6	3410	97.45	13.9	124.58	4	3540	91.2	14.2	43.56	3	3964.8	86.64	16.67518	47.916
13	Columns of 5th floor	12FS+2	13	1550	95.315	11.845	163.6473	10	1200	94.62	9.45	144.32	7	1356	96.01	10.02	135.98	6	1420	86.41	11.3	97.2	5	1590.4	82.0895	12.91105	106.92
14	Beam and roof of 5th floor	13FS+1	10	3600	98.57	4.689	139.1107	8	3200	97.4	3.21	126.98	6	3410	99.74	5.4	111.04	4	3540	91.02	5.52	56.98	3	3964.8	86.469	5.11101	62.678
15	Columns of ridge roof	14FS+1	5	420	91.815	5.851667	124.31	3	356	91.6	4.25	114.25	2	411	92.03	6.08	98.4	1	580	83.25	6.85	75.98	1	649.6	79.0875	6.378317	83.578
16	Beam and roof of ridge floor	15FS+1	6	1110	92.96	3.342333	168.6317	4	980	92.45	2.51	156.32	3	995	93.47	3.25	132.07	2	1020	87.98	3.65	100.36	2	1142.4	83.581	3.643143	110.396
17	Brick-works of ground	4FS+1	14	1620	94.035	1.658333	166.89	11	1480	93	1.05	157.45	9	1620	95.07	2.14	127.8	8	1740	79.99	2.45	98.65	7	1948.8	75.9905	1.807583	108.515
18	Mechanical installations of ground	17FS+2	10	1300	95.355	8.316667	109.0827	8	1220	94.5	6.5	101.98	6	1352	96.21	7.4	84.52	4	1480	82.14	7.65	24.65	3	1657.6	78.033	9.065167	27.115
19	Electrical installations of ground	17FS+2	15	1250	95.54	6.08	128.7647	13	1100	95.3	4.9	121.07	9	1260	95.78	5.01	99.04	6	1350	89.65	5.63	68.42	5	1512	85.1675	6.6272	75.262
20	Brick-works of 1st floor	6FS+1	14	1800	92.21	5.149333	125.9527	11	1620	90.7	3.54	114.06	9	1870	93.72	5.89	101.5	8	1942	80.45	6	45.65	7	2175.04	76.4275	5.612773	50.215
21	Mechanical installations of 1st floor	20FS+2	10	1600	97.525	5.934667	130.917	8	1520	97	4.22	125.97	6	1710	98.05	6.41	97.65	4	1780	91.45	6.54	82.63	3	1993.6	86.8775	6.468787	90.893

22	Electrical installations of 1st floor	20FS+2	9	1420	97.65	3.786333	167.2277	7	1350	96.4	2.87	151.26	5	1420	98.9	3.61	134.95	4	1500	87.26	3.75	111.52	3	1680	82.897	4.127103	122.672
23	Brickworks of 2nd floor	8FS+1	14	1800	93.495	5.546667	193.3917	11	1620	92.3	4.2	178.32	9	1870	94.69	5.3	152.47	8	1942	83.45	5.5	97.52	7	2175.04	79.2775	6.045867	107.272
24	Mechanical installations of 2nd floor	23FS+2	10	1680	94.93	12.066	138.6687	8	1532	94.15	9.34	126.47	6	1750	95.71	10.98	110.8	4	1780	88.98	11.36	64.52	3	1993.6	84.531	13.15194	70.972
25	Electrical installations of 2nd floor	23FS+2	9	1420	92.55	10.74167	181.7427	7	1350	90.47	8.45	175.65	5	1420	94.63	9.41	134.74	4	1500	78.32	9.5	86.52	3	1680	74.404	11.70842	95.172
26	Brickworks of 3rd floor	10FS+1	14	1800	94.16	2.455	165.5457	11	1620	93.32	1.65	149.08	9	1870	95	2.91	134.29	8	1942	85.65	3.2	98.42	7	2175.04	81.3675	2.67595	108.262
27	Mechanical installations of 3rd floor	26FS+2	10	1680	91.82	2.866	178.6877	8	1530	91.24	2.04	170.36	6	1740	92.4	3.09	134.95	4	1780	86.97	5.2	74.77	3	1993.6	82.6215	3.12394	82.247
28	Electrical installations of 3rd floor	26FS+2	9	1420	90.435	8.185	159.032	7	1350	90	6.45	156.65		1420	90.87	7.14	114.78	4	1500	82.42	7.65	64.52	3	1680	78.299	8.92165	70.972
29	Brickworks of 4th floor	12FS+1	14	1800	96.155	12.95467	159.094	11	1620	94.98	10.32	142.36	9	1870	97.33	11	130.02	8	1942	86.41	11.4	111.78	7	2175.04	82.0895	14.12059	122.958
30	Mechanical installations of 4th floor	29FS+2	10	1695	93.375	8.26	163.8757	8	1570	92.63	6.4	153.21	6	1760	94.12	7.5	126.97	4	1780	86.35	7.7	42.63	3	1993.6	82.0325	9.0034	46.893
31	Electrical installations of 4th floor	29FS+2	9	1420	94.63	6.648667	158.8867	7	1350	94.17	4.98	147.36	5	1420	95.09	6.5	124.36	4	1500	87.42	6.52	35.59	3	1680	83.049	7.247047	39.149
32	Brickworks of 5th floor	14FS+1	14	1800	93.02	4.885	128.853	11	1620	92.83	3.45	120.32	9	1870	93.21	5.34	99.99	8	1942	88.2	5.98	65.42	7	2175.04	83.79	5.32465	71.962

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33	Mechanical installations of 5th floor	32FS+2	10	1680	94.025	3.137667	124.2857	8	1530	93.4	2.09	111.14	6	1740	94.65	3.77	101.65	4	1780	85.72	3.89	85.41	3	1993.6	81.434	3.420057	93.951
34	Electrical installations of 5th floor	32FS+2	9	1420	95.065	2.351333	213.33	7	1350	94.42	1.52	199.32	5	1420	95.71	2.95	165.42	4	1500	90.45	3.02	123.65	3	1680	85.9275	2.562953	136.015
35	Rooftop	34FS	15	935	93.62	8.639667	188.6087	10	870	92.41	6.47	178.65	7	890	94.83	8.45	143.68	5	920	80.65	9.2	99.98	4	1030.4	76.6175	9.417237	109.978
36	Elevator	34FS+2	17	2400	90.805	7.126	105.351	15	2150	90.56	5.24	100.36	11	2350	91.05	7.23	79.65	8	2680	82.42	7.77	24.63	7	3001.6	78.299	7.76734	27.093
37	Facade	34FS+5	55	5320	91.575	4.351333	194.41	52	4580	91.15	3.12	189.32	37	5120	92	4.63	142.62	29	5980	79	4.97	75.63	25	6697.6	75.05	4.742953	83.193
38	Outdoors	35FS+1	37	2420	92.63	11.958	143.945	32	2100	91.78	9.12	134.65	25	2850	93.48	11.25	111.45	19	3412	84.53	11.32	80.25	16	3821.44	80.3035	13.03422	88.275