buildings

MDPI

Article

BIM-Based Resource Tradeoff in Project Scheduling Using Fire Hawk Optimizer (FHO)

Milad Baghalzadeh Shishehgarkhaneh [1,†], Mahdi Azizi [2,†], Mahla Basiri [2] and Robert C. Moehler [3,*]

[1] Department of Construction Management, Islamic Azad University of Tabriz, Tabriz 5157944533, Iran
[2] Department of Civil Engineering, University of Tabriz, Tabriz 5166616471, Iran
[3] Department of Civil Engineering, Faculty of Engineering, Monash University, 23 College Walk, Clayton Campus, Melbourne 3800, Australia
* Correspondence: robert.moehler@monash.edu
† These authors contributed equally to this work.

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. The results show that the FHO algorithm is capable of producing competitive and exceptional outcomes when it comes to the trade-off of various resource options in projects.

Keywords: fire hawk optimizer; optimization; metaheuristic algorithms; building information modelling (BIM); resource management; project resource management

check for updates

Citation: Shishehgarkhaneh, M.B.; Azizi, M.; Basiri, M.; Moehler, R.C. BIM-Based Resource Tradeoff in Project Scheduling Using Fire Hawk Optimizer (FHO). *Buildings* **2022**, *12*, 1472. https://doi.org/10.3390/buildings12091472

Academic Editors: Saeed Reza Mohandes, Timothy Olawumi and Maxwell Fordjour Antwi-Afari

Received: 13 August 2022
Accepted: 13 September 2022
Published: 16 September 2022

1. Introduction

Understanding the trade-offs between a 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 to date [1]. Regardless of overhead costs, reduced project activity time will increase project costs due to the increased resources given to the_hastening of activity implementation. In other words, shorter project durations are frequently linked with higher construction costs, necessitating TCT to minimize the cost of schedule compression [2]. 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 of TCT problems, such as risk, quality, energy, and environmental factors [3–7]. 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 [8]. 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 [9].

A majority of real-world engineering problems are complicated; therefore, conventional methods are unable to solve these kinds of problems accurately. In other words, conventional optimization methods cannot find the optimum solution for time, cost, risk, and quality trade-off problems; hence, these problems have been solved by metaheuristic

optimization algorithms, such as rat swarm optimizer (RSO) [10]; the wisdom of artificial crowds (WoAC) [11]; tuna swarm optimization (TSO) [12]; artificial bee colony (ABC) [13]; Material Generation Algorithm (MGA) [14,15]; and Atomic Orbital Search (AOS) [16–18].

Building Information Modelling (BIM) is a management culture based on the digital construction of a project. By involving all stakeholders and team members in the design phase, BIM takes a big step towards reducing the need for reworks during the project and helps with calculating the exact volume of work and project materials needed, thereby providing 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. The introduction of 2D CAD led to an evolutionary shift, by which the drawing board was ultimately replaced by the computer [19]. 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 [20]. Over the last two or three decades, the regular design practice in the Architecture, Engineering, and Construction (AEC) sector has shifted towards BIM due to its ability to consider project planning, execution, and maintenance throughout the entire value chain from the planning to the demolition phases. An exciting opportunity for project management could be provided via the integration of BIM through the early design phase in every project [21,22]. In comparison with a set of CAD drawings, BIM is a "richer repository"; it is a multi-disciplinary tool, able to retain and evaluate various forms of construction information, and digitally and graphically model the characteristics of buildings. 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 [23]. Therefore, a range of public policies aimed at improving the adequacy of the construction industry are supported by the usage of BIM [24]. In other words, BIM is a faster and more profitable way to manage construction, increase design and construction quality, and reduce project execution time and cost [25]. 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*" [26]. However, the main privileges of utilizing BIM in construction are ameliorated design quality and lifecycle management, effective maintenance, accurate cost estimation, a better-integrated workflow, efficient collaboration and interoperability between the stakeholders and the project team, streamlined information sharing, and reduced energy consumption [27]. Moreover, the BIM-assisted estimate outperforms 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 [28].

2. Literature Review

2.1. Studies of Resource Trade-Offs

Various metaheuristic algorithms have recently been used to solve TCT problems. Feng, Liu and Burns [1] applied genetic algorithms (GAs) for TCT problems in construction. Van Eynde and Vanhoucke [29] offered a precise algorithm to provide the project's whole curve of non-dominated time–cost options. Sonmez and Bettemir [30] 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 [31] 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 [32] implemented the model at a cement factory in Bangkok, Thailand, to confirm the proposed model. Ndamlabin Mboula et al. [33] 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 [34] presented a time–cost–quality optimization model using a genetic algorithm. Afruzi et al. [35] proposed a multi-objective imperialist competitive algorithm (MOICA) to solve the discrete TCQ tradeoff problem (DTCQTP). Sharma and Trivedi [36] 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. [37] 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. [38] 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. [39] 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, scant research has been carried out concerning time-cost-quality-risk trade-off problems. Mohammadipour and Sadjadi [40] 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. [41] 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 [3] 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 [42] presented a multimode resource-constrained time–cost–quality–safety trade-off optimization model using the NSGA-III algorithm. Keshavarz and Shoul [43] 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. [44] integrated the BIM process with GA. Rahmani Asl et al. [45] proposed an integrated framework for BIM-based performance optimization to minimize the energy consumption while maximizing the efficient daylighting level for a residential dwelling. Sekhar and Maheswari [46] aimed to study the impact of BIM on managing and reducing change orders in off-site construction by optimizing the design via visualization throughout the planning phase. Kim et al. [47] 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 [48] proposed a framework for automated schedule generation using the BIM process and the 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 [49] introduced an integrated framework based on BIM, MIS, and simulation tools for TCT problems. Yongge and Ya [50] 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. [51] proposed an integrated framework taking into account BIM and a time–cost optimization model to optimize construction costs and duration. Gelisen and Griffis [52] modelled the 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. [53] 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 [54] 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 [55] 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. [56] proposed a framework for neutral BIM-based multi-disciplinary optimization of lifecycle energy and cost. Baghalzadeh Shishehgarkhaneh et al. [57] 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 CO_2 tradeoff in construction projects.

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. [58]. 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.

Table 1. Summary of previous related research works.

Authors	Time	Cost	Quality	Risk	CO_2	Other Parameters	BIM
Hajiagha et al. [59]	×	×	×				
Tran and Long [3]	×	×		×			
Zheng [60]	×	×	×		×		
Al Haj and El-Sayegh [61]	×	×					
Khalili-Damghani et al. [62]	×	×	×				
Moghadam et al. [63]	×	×	×				
Zahraie and Tavakolan [64]	×	×				×	
Huynh et al. [65]	×	×	×		×		
Banihashemi and Khalilzadeh [66]	×	×	×		×		
Ghoddousi et al. [67]	×	×				×	
Mahmoudi and Feylizadeh [68]	×	×	×	×		×	
Ebrahimnezhad et al. [69]	×	×	×				
Mungle et al. [70]	×	×	×				
Koo et al. [71]	×	×					
Heravi and Moridi [72]	×	×					
Mohammadipour and Sadjadi [40]		×	×	×			
Jeunet and Bou Orm [73]	×	×	×			×	
Hamta et al. [74]	×	×	×				
Kosztyán and Szalkai [75]	×	×	×				
Current Study	×	×	×	×	×		×

3. Framework for Resource Tradeoff

The framework is made up of three primary parts: (1) the initialization and decision variables module, (2) the BIM Module, and (3) the metaheuristic optimization algorithm (Fire Hawk Optimizer (FHO)) module. The results of this study provide helpful references that construction project managers can utilize to rapidly and precisely calculate schedules when implementing a project.

3.1. 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 $f : B \to R$ 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 [76]. The BIM model is utilized in this research to import all of the project's data for all 38 activities listed in Table A1. A construction project's activity-on-node (AON) diagram is made up of M nodes and the relationships between the 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 depend 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 Equation (1):

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

where $\mathrm{D_i}$ shows the duration of each activity in the project; $\mathrm{ST_i}$ and $\mathrm{FT_i}$ are the start and finish times of an activity, respectively; M demonstrates the total number of nodes in the project scheduling [9]. 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 Equation (2):

$$\min \mathrm{C} = \mathrm{D}^{\mathrm{j}}_{\mathrm{C_i}} + \mathrm{I}^{\mathrm{j}}_{\mathrm{C_i}} + \mathrm{TC} \tag{2}$$

$$\mathrm{D}^{\mathrm{j}}_{\mathrm{C_i}} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{C}^{\mathrm{j}}_{\mathrm{i}} \tag{3}$$

$$\mathrm{I}^{\mathrm{j}}_{\mathrm{C_i}} = \mathrm{C_{ic}} \times \mathrm{T} \tag{4}$$

$$\mathrm{TC} = \begin{cases} \mathrm{C_1}(\mathrm{T_0} - \mathrm{T}) & \text{if } \mathrm{T} \leq \mathrm{T_0} \\ \left(\mathrm{e}^{\frac{\mathrm{T}-\mathrm{T_0}}{\mathrm{T_0}}} - 1\right)\left(\mathrm{D}^{\mathrm{j}}_{\mathrm{C_i}} + \mathrm{I}^{\mathrm{j}}_{\mathrm{C_i}}\right) & \text{if } \mathrm{T} > \mathrm{T_0} \end{cases} \tag{5}$$

where $\mathrm{TC_p}$ is total project's cost; $\mathrm{D}^{\mathrm{j}}_{\mathrm{C_i}}$ and $\mathrm{I}^{\mathrm{j}}_{\mathrm{C_i}}$ are the direct and indirect cost associated with the *jth* execution mode of *ith* activity, respectively; TC is the tardiness cost; $\mathrm{T_0}$ elucidates contractual planned duration of the project; $\mathrm{C_1}$ shows reward for completing the task early; and T is total project duration [77,78]. 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 (QPI_i), which is given by Equation (6) [78].

$$\mathrm{QPI_i} = \mathrm{a_i t_i^2} + \mathrm{b_i t_i} + \mathrm{c_i} \tag{6}$$

where $\mathrm{t_i}$ is duration of activity *i*; $\mathrm{a_i}$, $\mathrm{b_i}$, and $\mathrm{c_i}$ are coefficients decided by the quadratic function regarding BD (Figure 1). LD, BD, and SD are the longest, best, and shortest durations, respectively. However, BD is calculated by Equation (7). Finally, the objective function for quality is formulated in Equation (8), as follows:

$$\mathrm{BD} = \mathrm{SD} + 0.613(\mathrm{LD} - \mathrm{SD}) \tag{7}$$

$$\max Q = \sum_{i=1}^{M} \frac{QPI_i}{M} \tag{8}$$

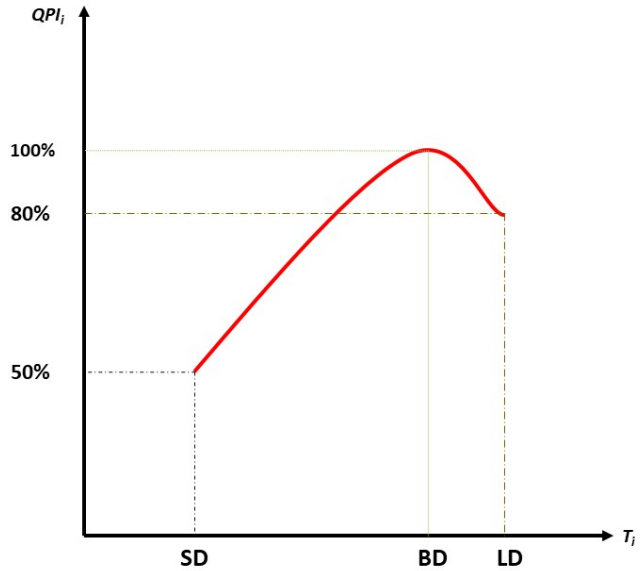

Figure 1. Quality performance index (QPI).

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. Thus, the objective function to minimize the total amount of CO_2 in the project can be calculated by Equation (9).

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

where CE is the total CO_2 emission in the project; E_{dij} and E_{inij} are the direct and indirect CO_2 emissions in the project, respectively; Q_{ed} shows an activity's electricity consumption; Q_{dd} elucidates an activity's diesel consumption; Q_{ij} shows the consumption of material *k* in an activity; Q_{ek} indicates the electricity consumption for the transportation of material *k* for an activity; Q_{dk} shows the diesel consumption for the transportation of material *k* for an activity; F_e, F_d, and F_j are the 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, and (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 [79–81]. Consequently, the fifth objective function for risk can be formulated as Equation (10):

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

where TF_c and TF_{max} show the total current float and total flexible scheduling float of the project; $\overline{R}$ elucidates the uniform resource level; R_t represents the resources required on day t; and w_i represents the weights.

Finally, to assess the capability of the FHO algorithm for the time–cost–quality–risk–CO_2 (All) trade-off, simultaneously, Equation (11) is used:

$$F(x) = \frac{T - T_{min}}{T_{max} - T_{min}} + \frac{C - C_{min}}{C_{max} - C_{min}} + \frac{R - R_{min}}{R_{max} - R_{min}} + \frac{CO_2 - CO_{2(min)}}{CO_{2(max)} - CO_{2(min)}} + \frac{Q_{min} - Q}{Q_{max} - Q_{min}} \quad (11)$$

3.2. 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 m^2 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 the planning and designing steps. In other words, in completing this table, the experiences of various elite people and experts in this field have been used. The time and cost of executive mode NO.1 are the actual time and cost of the project extracted from the final status of the construction, NO.3 are obtained from BIM, and NO.5 are the contractor's initial offers. In addition, two other executive modes were considered based on expert opinions in this field. Admittedly, contractors' initial offers are often illogical and dreamy to attract the attention of employers, which is why most projects fail. Because most contractors do not consider rework, clashes, non-payment by employers, severe weather conditions, etc.; however, each activity is randomly written with three types of quality indicators at distinct percentages. The final quality in each line is obtained from the percentage of the total effects of those three quality modes. Finally, for each activity, the risk percentage is randomly deemed based on the viewpoints of elite professors and experts in this field.

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 specifications. 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 BIM model in the case study is shown in Figure 2.

3.3. Fire Hawk Optimizer (FHO)

3.3.1. 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 their beaks and talons, a behaviour characterized as a natural catastrophe. The birds pick up burning sticks and deposit them in other unburned spots to make small fires to control and capture their prey. These small flames frighten their 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.

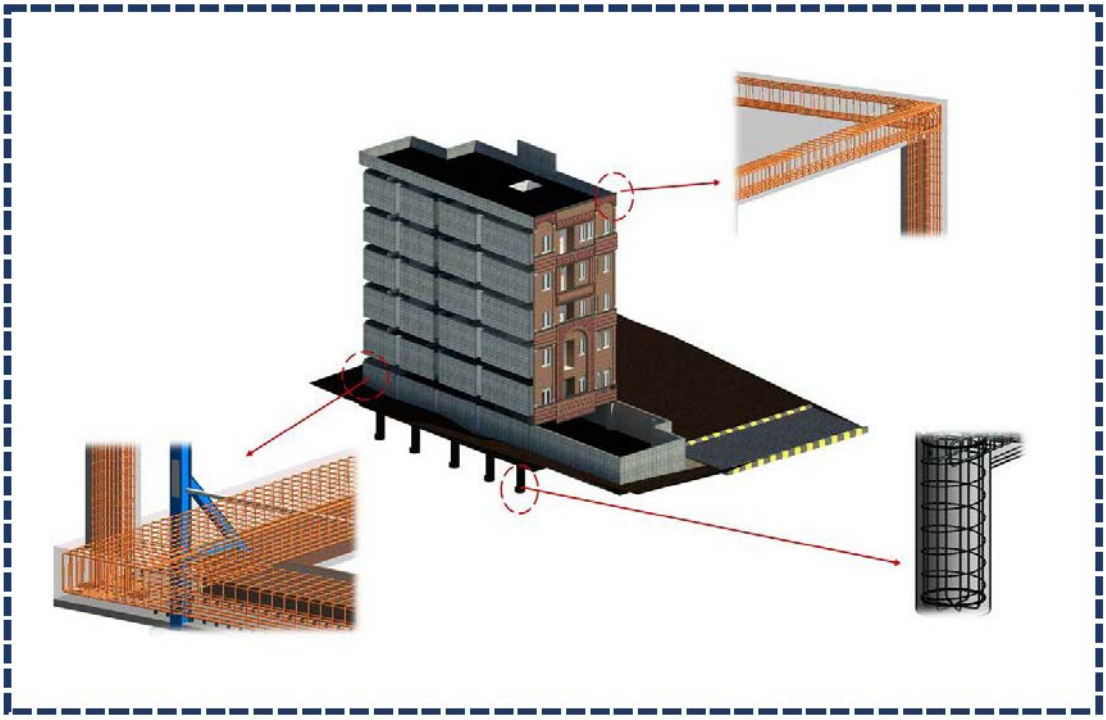

Figure 2. The project BIM-based modelling for resource trade-off.

3.3.2. 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.

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^j & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^j & \cdots & x_2^d \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^j & \cdots & x_i^d \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ x_N^1 & x_N^2 & \cdots & x_N^j & \cdots & x_N^d \end{bmatrix}, \qquad \begin{cases} i = 1, 2, \ldots, N. \\ j = 1, 2, \ldots, d. \end{cases} \tag{12}$$

$$x_i^j(0) = x_{i,min}^j + \text{rand.}\left(x_{i,max}^j - x_{i,min}^j\right), \qquad \begin{cases} i = 1, 2, \ldots, N. \\ j = 1, 2, \ldots, d. \end{cases} \tag{13}$$

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 mathematically represented as follows:

$$PR = \begin{bmatrix} PR_1 \\ PR_2 \\ \vdots \\ PR_k \\ \vdots \\ PR_m \end{bmatrix}, \qquad k = 1, 2, \ldots, m. \tag{14}$$

$$FH = \begin{bmatrix} FH_1 \\ FH_2 \\ \vdots \\ FH_l \\ \vdots \\ FH_n \end{bmatrix}, \qquad l = 1, 2, \ldots, n. \tag{15}$$

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.

The distance among the Fire Hawks and their prey is determined in the following step of the algorithm, where D_k^l is shown using the following equation:

$$D_k^l = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \qquad \begin{cases} l = 1, 2, \ldots, n. \\ k = 1, 2, \ldots, m. \end{cases} \tag{16}$$

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.

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:

$$FH_l^{new} = FH_l + (r_1 \times GB - r_2 \times FH_{Near}), \qquad l = 1, 2, \ldots, n. \tag{17}$$

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 informs 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:

$$PR_q^{new} = PR_q + (r_3 \times FH_l - r_4 \times SP_l), \qquad \begin{cases} l = 1, 2, \ldots, n. \\ q = 1, 2, \ldots, r. \end{cases} \tag{18}$$

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 flames. 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:

$$PR_q^{new} = PR_q + (r_5 \times FH_{Alter} - r_6 \times SP), \begin{cases} l = 1, 2, \ldots, n. \\ q = 1, 2, \ldots, r. \end{cases} \tag{19}$$

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 so as to be safe and sound during a hazard:

$$SP_l = \frac{\sum_{q=1}^{r} PR_q}{r}, \qquad \begin{cases} q = 1, 2, \ldots, r. \\ l = 1, 2, \ldots, n. \end{cases} \tag{20}$$

$$SP = \frac{\sum_{k=1}^{m} PR_k}{m}, \qquad k = 1, 2, \ldots, m. \tag{21}$$

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.

The FHO algorithm's pseudo-code is shown in Figure 3.

```
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 3. Pseudo-code of FHO.

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) [82], Multi-Verse Optimizer (MVO) [83], Particle Swarm Optimization (PSO) [84], Symbiotic Organisms Search (SOS) algorithm [85], and Teaching-learning-based

Optimization (TLBO) [86]. 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. Figure 4 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	118,230	117,056	119,564.8	117,104.6	117,512	116,783
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

Table 3 demonstrates the statistical results of 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, similar to the 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 the FHO and PSO algorithms, needing significantly more time to conduct the optimization process in this case. 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; conversely, 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, followed by the FA. Meanwhile, the PSO achieved the greatest standard deviation of all algorithms studied in this case. Therefore, the FHO algorithm could be an acceptable metaheuristic for project and construction management cost optimization.

Table 3. The statistical outcomes of the algorithms.

	FA	MVO	PSO	SOS	TLBO	FHO (Current Study)
Time						
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 3. *Cont.*

	FA	MVO	PSO	SOS	TLBO	FHO (Current Study)
Cost						
Best	118,230	117,056	119,564.8	117,104.6	117,512	**116,783**
Mean	118,558.6	117,511.9	135,480.6	117,498.3	118,322.9	116,839.7
Worst	118,780	118,284.6	155,151.7	117,920	119,070	117,011
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
Quality						
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
Risk						
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	9.03×10^{-16}	8.45×10^{-02}	2.47×10^{-1}	0.01	6.99×10^{-2}	9.03×10^{-16}
Computational time (s)	2.27	1.56	2.05	1.39	1.43	8.67
CO_2						
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	1.45×10^{-14}	0.92	6.20	0.24	4.19	0.06
Computational time (s)	1.93	1.59	2.29	1.38	1.42	12.52
All						
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	2.26×10^{-16}	0.04	0.21	0.01	0.04	2.26×10^{-16}
Computational time (s)	1.98	1.70	2.42	1.38	1.43	10.96

The statistical outcomes of the case study's quality optimization indicate that the FHO method can deliver acceptable quality. Additionally, 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 set the highest standard. However, in terms of computing time for quality optimization, in this case, the SOS algorithm required the least time, contrasted to the FHO approach, which required around 0.78 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. Nonetheless, similar to the 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 computational time as possible 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.

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 realizing environmentally friendly construction. In contrast, the PSO algorithm provided the highest value for CO_2 in this scenario, indicating its unfavorable 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.

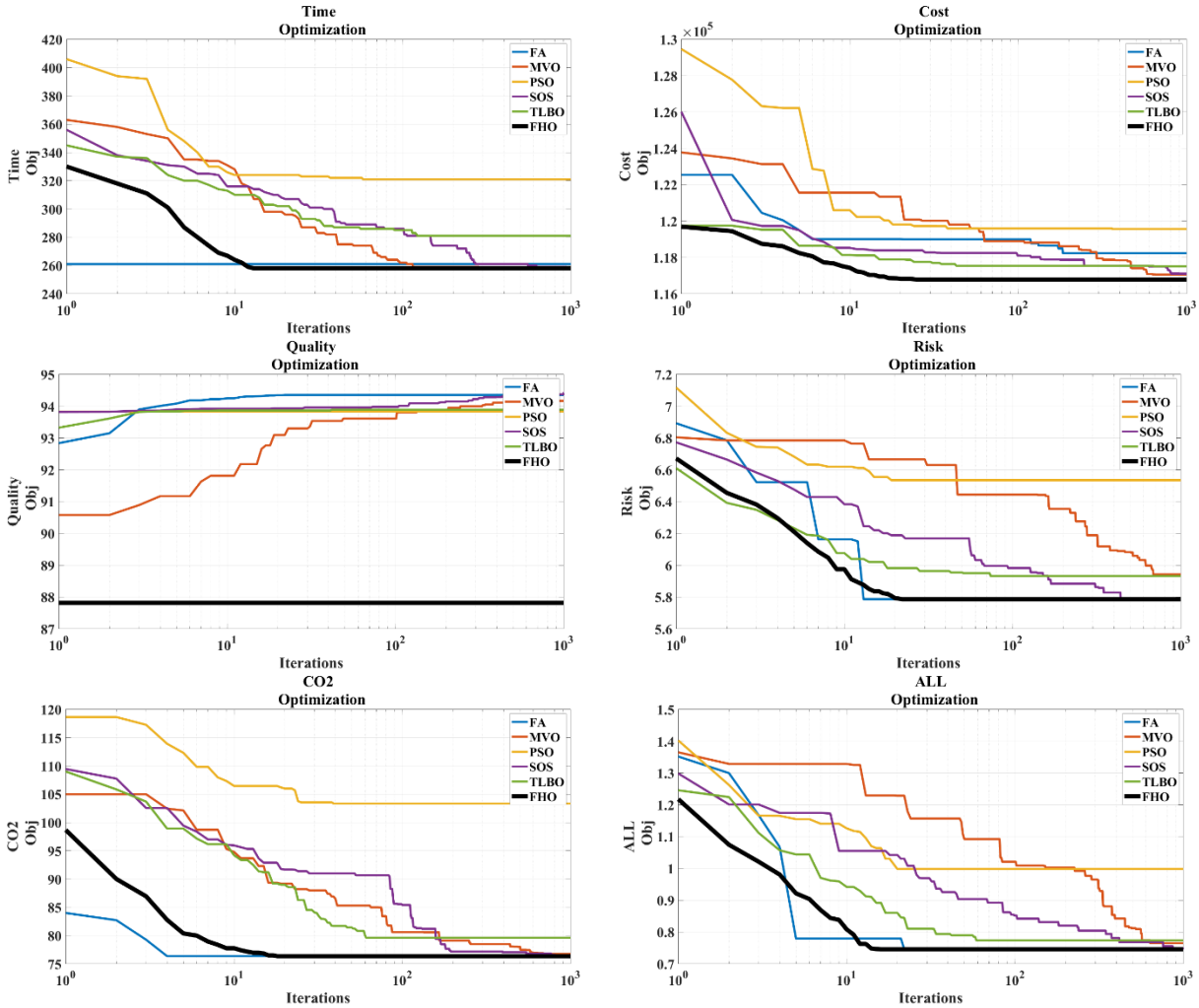

Figure 4. Convergence history of 30 independent optimization runs of FHO and alternative algorithms.

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.

5. Discussion

The results and comparisons revealed that the FHO algorithm could outperform for some optimization problems in the studied case study; hence, the project managers should use this optimization process in their organizations or projects to obtain the most optimum solutions regarding time, cost, quality, risk, and CO_2.

The modes of all activities are shown in Table 4. It is clear that for the time optimization in the case study, all the mentioned algorithms opted for the third mode (BIM) as the BIM process was able to provide the optimum and best time for this residential building. Furthermore, regarding the cost, the first and second modes are preferable, followed by the third mode (BIM). Regarding the quality, almost all algorithms preferred the second mode, which is between the actual and the BIM. Undoubtedly, the first mode is the most

preferable mode for all mentioned algorithms, indicating the proper mode for providing the optimum risk in the case study. Regarding the CO_2 and the All optimizations, the third mode is superior to the others. Meanwhile, it should be noted that the 4th and 5th modes were not preferred by any algorithms for any of the problems in the current case.

Table 4. Modes of different activities in optimization process.

Number	Objective	Mode of Activities
1	Time	FA:5555555555555555555555555555555555555 MVO:5555555555555555555555555535555555555 PSO:5443532555525552555444551345311324544 5 SOS:5555555555555555555555555555535555555555 TLBO:5555555545145544455545245555355545335 55 FHO:5555555555555555555555555555535555555555
2	Cost	FA:4333434334324233343334333232343434342 MVO:4442324442333324344344243243243244433 2 PSO:2332322525343454334454243443342434223 4 SOS:4342343233444234344243253343243243433 2 TLBO:4344444242424324434243244323444424433 2 FHO:4342444244442423434424324424324424343 2
3	Quality	FA:3333113333311113113133333331331133311 MVO:1333113131131333133113111133313311 3 11 PSO:1111111111111111111111111111111111111 SOS:1311333313133331331311333331331331 33 TLBO:1131111111111111111111111113311111111111 FHO:1534421441154535422255453525444225442 2
4	Risk	FA:2222222222222222222222222222222222222 MVO:2222222222222552523222222222222222252222 PSO:2233432222222525322542543132323241242 4 SOS:2222222222222222222222222222222222222 TLBO:2322232232222222223223122222232222222 2 FHO:2222222222222222222222222222222222222
5	CO_2	FA:4444444444444444444444444444444444444 MVO:1554423214222544434233144443445444444 PSO:1554423214222544434233144443445444444 SOS:4444444444444444444444444444444444444 TLBO:5444345444454344454444445445444544444 FHO:4444444444444444444444444444444444444
6	All	FA:3333333333333333333333333333333333333 MVO:3333333333333332333333333333333333353 PSO:3332334322324413333353523433322233333 SOS:3333333333333333333333333333333333333 TLBO:3333333333333333333333333233333333332333 FHO:3333333333333333333333333333333333333

Notably, there have been several instances in the construction industry when bad project management caused things to spiral out of control. The newest Veterans Affairs medical facility was supposed to have been built in Colorado by 2013, with a projected project cost of $328 million, according to a news report. However, the actual cost, which was $1.73 billion, went above budget by more than $1 billion. Additionally, the project took 5 years longer to finish than expected. This illustration demonstrates the seriousness with which optimization procedures and practical project management techniques, such as BIM, in construction should be approached [87]. Considering the current case study, the BIM process and the FHO algorithm could decrease the total cost from approximately $125,630 to nearly $116,839.70, a 7% reduction in cost. Therefore, implementing the BIM process in large-scale projects such as the Veterans Affairs medical facility could save $121 million. Furthermore, since BIM and the FHO algorithm could diminish the total time from 313

to 258 days (17.5%), they could decrease the total time of the project's execution, thereby decreasing the indirect and direct costs, as well as the CO_2 emission caused by the logistics and equipment at the project's site. Furthermore, project managers and schedulers of all projects are able to analyze and propose the most feasible resource options, considering the organization's goals and scopes, to the employers or owners by using the BIM process and an optimization process with metaheuristic algorithms, such as the FHO algorithm.

6. Conclusions

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 perform 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 the case study, accounting for 258 days.
- The FHO can provide 116,783 ($) for the cost of the case study, which is the best among all 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, compared to other alternative algorithms.
- Based on the best results of the TCQRCT problem, the FHO algorithm can provide a score of 0.74, which is much better than the other algorithms.

Based on the results and conducted analysis, the main reasons for the superiority of the FHO algorithm compared to the other mentioned metaheuristics algorithms are threefold; namely, fast convergence behavior, being parameter-free, and the lowest possible objective function evaluation. The limitation of this research work is that only a residential building was used as the case study, and thus, future works should evaluate the capability of the FHO algorithm for other case studies, such as residential projects or infrastructure construction projects, and compare the results with those of other metaheuristic algorithms. Furthermore, the FHO algorithm should be tested for future studies utilizing intricate optimization problems in miscellaneous fields, such as real-size engineering design problems such as truss structures. Additionally, future works should focus on proposing and developing the multi-objective version of the FHO algorithm (MOFHO) in order to optimize the time, cost, quality, risk, and CO_2 in a two-by-two manner.

Author Contributions: Conceptualization, M.B.S. and M.A.; methodology, M.B.S. and M.A.; software, M.B.S., 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.C.M.; visualization, M.B.S. and M.B.; supervision, M.A.; project administration, R.C.M.; funding acquisition, R.C.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

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

Appendix A

Table A1. Project data of case study.

NO	Activity	Logical	Mode 1					Mode 2					Mode 3					Mode 4					Mode 5				
			Time	Cost $	Quality %	Risk	CO_2	Time	Cost $	Quality %	Risk	CO_2	Time	Cost $	Quality %	Risk	CO_2	Time	Cost $	Quality %	Risk	CO_2	Time	Cost $	Quality %	Risk	CO_2
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
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	Brickworks 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	Brickworks 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
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

References

1. Feng, C.-W.; Liu, L.; Burns, S.A. Using Genetic Algorithms to Solve Construction Time-Cost Trade-Off Problems. *J. Comput. Civ. Eng.* **1997**, *11*, 184–189. [CrossRef]
2. Chen, P.-H.; Weng, H. A two-phase GA model for resource-constrained project scheduling. *Autom. Constr.* **2009**, *18*, 485–498. [CrossRef]
3. Tran, D.H.; Long, L.D. Project scheduling with time, cost and risk trade-off using adaptive multiple objective differential evolution. *Eng. Constr. Archit. Manag.* **2018**, *25*, 623–638. [CrossRef]
4. Orm, M.B.; Jeunet, J. Time cost quality trade-off problems: A survey exploring the assessment of quality. *Comput. Ind. Eng.* **2018**, *118*, 319–328. [CrossRef]
5. Shankar, N.R.; Raju, M.; Srikanth, G.; Bindu, P.H. Time, cost and quality trade-off analysis in construction of projects. *Contemp. Eng. Sci.* **2011**, *4*, 289–299.
6. Lotfi, R.; Yadegari, Z.; Hosseini, S.; Khameneh, A.; Tirkolaee, E.; Weber, G. A robust time-cost-quality-energy-environment trade-off with resource-constrained in project management: A case study for a bridge construction project. *J. Ind. Manag. Optim.* **2022**, *18*, 375–396. [CrossRef]
7. Monghasemi, S.; Nikoo, M.R.; Fasaee, M.A.K.; Adamowski, J. A novel multi criteria decision making model for optimizing time–cost–quality trade-off problems in construction projects. *Expert Syst. Appl.* **2015**, *42*, 3089–3104. [CrossRef]
8. Abbasi, S.; Noorzai, E. The BIM-Based multi-optimization approach in order to determine the trade-off between embodied and operation energy focused on renewable energy use. *J. Clean. Prod.* **2021**, *281*, 125359. [CrossRef]
9. Nguyen, D.-T.; Chou, J.-S.; Tran, D.-H. Integrating a novel multiple-objective FBI with BIM to determine tradeoff among resources in project scheduling. *Knowl.-Based Syst.* **2022**, *235*, 107640. [CrossRef]
10. Dhiman, G.; Garg, M.; Nagar, A.; Kumar, V.; Dehghani, M. A novel algorithm for global optimization: Rat Swarm Optimizer. *J. Ambient Intell. Humaniz. Comput.* **2021**, *12*, 8457–8482. [CrossRef]
11. Yampolskiy, R.V.; Ashby, L.; Hassan, L. Wisdom of Artificial Crowds—A Metaheuristic Algorithm for Optimization. *J. Intell. Learn. Syst. Appl.* **2012**, *4*, 98–107. [CrossRef]
12. Xie, L.; Han, T.; Zhou, H.; Zhang, Z.-R.; Han, B.; Tang, A. Tuna Swarm Optimization: A Novel Swarm-Based Metaheuristic Algorithm for Global Optimization. *Comput. Intell. Neurosci.* **2021**, *2021*, 9210050. [CrossRef] [PubMed]
13. Karaboga, D.; Basturk, B. Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In Proceedings of the Foundations of Fuzzy Logic and Soft Computing, Berlin/Heidelberg, Germany, 18–21 June 2007; pp. 789–798.
14. Talatahari, S.; Azizi, M.; Gandomi, A.H. Material Generation Algorithm: A Novel Metaheuristic Algorithm for Optimization of Engineering Problems. *Processes* **2021**, *9*, 859. [CrossRef]
15. Azizi, M.; Shishehgarkhaneh, M.B.; Basiri, M. Optimum design of truss structures by Material Generation Algorithm with discrete variables. *Decis. Anal. J.* **2022**, *3*, 100043. [CrossRef]
16. Azizi, M. Atomic orbital search: A novel metaheuristic algorithm. *Appl. Math. Model.* **2021**, *93*, 657–683. [CrossRef]
17. Azizi, M.; Talatahari, S.; Giaralis, A. Optimization of Engineering Design Problems Using Atomic Orbital Search Algorithm. *IEEE Access* **2021**, *9*, 102497–102519. [CrossRef]
18. Azizi, M.; Mohamed, A.W.; Shishehgarkhaneh, M.B. Optimum design of truss structures with atomic orbital search considering discrete design variables. In *Handbook of Nature-Inspired Optimization Algorithms: The State of the Art*; Springer: Cham, Switzerland, 2022; pp. 189–214.
19. Cunz, D.; Larson, D. Building information modeling. *Under Constr. Am. Bar Assoc.* **2006**, 1–3. Available online: http://www.imageserve.com/naples2013/eunder_construction_12_06.pdf (accessed on 12 September 2022).
20. Borrmann, A.; König, M.; Koch, C.; Beetz, J. *Building Information Modeling: Technologische Grundlagen und Industrielle Praxis*; Springer: Wiesbaden, Germany, 2015.
21. Khondoker, M.T.H. Automated reinforcement trim waste optimization in RC frame structures using building information modeling and mixed-integer linear programming. *Autom. Constr.* **2021**, *124*, 103599. [CrossRef]
22. Baghalzadeh Shishehgarkhaneh, M.; Fard Moradinia, S. The role of Building Information Modeling (BIM) in reducing the number of project dispute resolution sessions. In Proceedings of the 8th National Conference on Civil Engineering, Architecture and Sustainable Urban Development of Iran, Mashhad, Iran, 5 November 2020.
23. Farzaneh, A.; Monfet, D.; Forgues, D. Review of using Building Information Modeling for building energy modeling during the design process. *J. Build. Eng.* **2019**, *23*, 127–135. [CrossRef]
24. Charef, R.; Alaka, H.; Emmitt, S. Beyond the third dimension of BIM: A systematic review of literature and assessment of professional views. *J. Build. Eng.* **2018**, *19*, 242–257. [CrossRef]
25. Charef, R.; Emmitt, S.; Alaka, H.; Fouchal, F. Building Information Modelling adoption in the European Union: An overview. *J. Build. Eng.* **2019**, *25*, 100777. [CrossRef]
26. Seyis, S. Mixed method review for integrating building information modeling and life-cycle assessments. *Build. Environ.* **2020**, *173*, 106703. [CrossRef]
27. Daqiqnia, A.H.; Fard Moradinia, S.; Baghalzadeh Shishehgarkhaneh, M. Toward Nearly Zero Energy Building Designs: A Comparative Study of Various Techniques. *AUT J. Civ. Eng.* **2021**, *5*, 12.
28. Nadeem, A.; Wong, A.K.D.; Wong, F.K.W. Bill of Quantities with 3D Views Using Building Information Modeling. *Arab. J. Sci. Eng.* **2015**, *40*, 2465–2477. [CrossRef]

29. Van Eynde, R.; Vanhoucke, M. A reduction tree approach for the Discrete Time/Cost Trade-Off Problem. *Comput. Oper. Res.* **2022**, *143*, 105750. [CrossRef]
30. Sonmez, R.; Bettemir, Ö.H. A hybrid genetic algorithm for the discrete time–cost trade-off problem. *Expert Syst. Appl.* **2012**, *39*, 11428–11434. [CrossRef]
31. Babu, A.J.G.; Suresh, N. Project management with time, cost, and quality considerations. *Eur. J. Oper. Res.* **1996**, *88*, 320–327. [CrossRef]
32. Khang, D.B.; Myint, Y.M. Time, cost and quality trade-off in project management: A case study. *Int. J. Proj. Manag.* **1999**, *17*, 249–256. [CrossRef]
33. Ndamlabin Mboula, J.E.; Kamla, V.C.; Tayou Djamegni, C. Cost-time trade-off efficient workflow scheduling in cloud. *Simul. Model. Pract. Theory* **2020**, *103*, 102107. [CrossRef]
34. Hu, W.; He, X. An Innovative Time-Cost-Quality Tradeoff Modeling of Building Construction Project Based on Resource Allocation. *Sci. World J.* **2014**, *2014*, 673248. [CrossRef]
35. Afruzi, E.N.; Najafi, A.A.; Roghanian, E.; Mazinani, M. A multi-objective imperialist competitive algorithm for solving discrete time, cost and quality trade-off problems with mode-identity and resource-constrained situations. *Comput. Oper. Res.* **2014**, *50*, 80–96. [CrossRef]
36. Sharma, K.; Trivedi, M.K. AHP and NSGA-II-Based time–cost–quality trade-off optimization model for construction projects. In *Artificial Intelligence and Sustainable Computing, Proceedings of the 4th International Conference on Sustainable and Innovative Solutions for Current Challenges in Engineering & Technology, ICSISCET 2022, Gwalior, India, 18–19 December 2022*; Springer: Singapore, 2022; pp. 45–63.
37. Ozcan-Deniz, G.; Zhu, Y.; Ceron, V. Time, cost, and environmental impact analysis on construction operation optimization using genetic algorithms. *J. Manag. Eng.* **2012**, *28*, 265–272. [CrossRef]
38. Tran, D.-H.; Luong-Duc, L.; Duong, M.-T.; Le, T.-N.; Pham, A.-D. Opposition multiple objective symbiotic organisms search (OMOSOS) for time, cost, quality and work continuity tradeoff in repetitive projects. *J. Comput. Des. Eng.* **2018**, *5*, 160–172. [CrossRef]
39. Luong, D.-L.; Tran, D.-H.; Nguyen, P.T. Optimizing multi-mode time-cost-quality trade-off of construction project using opposition multiple objective difference evolution. *Int. J. Constr. Manag.* **2021**, *21*, 271–283. [CrossRef]
40. Mohammadipour, F.; Sadjadi, S.J. Project cost–quality–risk tradeoff analysis in a time-constrained problem. *Comput. Ind. Eng.* **2016**, *95*, 111–121. [CrossRef]
41. Amoozad Mahdiraji, H.; Sedigh, M.; Razavi Hajiagha, S.H.; Garza-Reyes, J.A.; Jafari-Sadeghi, V.; Dana, L.-P. A novel time, cost, quality and risk tradeoff model with a knowledge-based hesitant fuzzy information: An R&D project application. *Technol. Forecast. Soc. Chang.* **2021**, *172*, 121068. [CrossRef]
42. Sharma, K.; Trivedi, M.K. Latin hypercube sampling-based NSGA-III optimization model for multimode resource constrained time–cost–quality–safety trade-off in construction projects. *Int. J. Constr. Manag.* **2020**, 1–11. [CrossRef]
43. Keshavarz, E.; Shoul, A. Project Time-Cost-Quality Trade-off Problem: A Novel Approach Based on Fuzzy Decision Making. *Int. J. Uncertain. Fuzziness Knowl.-Based Syst.* **2020**, *28*, 545–567. [CrossRef]
44. He, W.; Shi, Y.; Kong, D. Construction of a 5D duration and cost optimisation model based on genetic algorithm and BIM. *J. Eng. Des. Technol.* **2019**, *17*, 929–942. [CrossRef]
45. Rahmani Asl, M.; Zarrinmehr, S.; Bergin, M.; Yan, W. BPOpt: A framework for BIM-based performance optimization. *Energy Build.* **2015**, *108*, 401–412. [CrossRef]
46. Sekhar, A.; Maheswari, J.U. BIM integration and value engineering: Design for assembly, optimization, and real time cost visualization in off-site construction. In Proceedings of the Construction Research Congress 2022, Arlington, VA, USA, 9–12 March 2022; pp. 791–801.
47. Kim, S.; Chin, S.; Kwon, S. A Discrepancy Analysis of BIM-Based Quantity Take-Off for Building Interior Components. *J. Manag. Eng.* **2019**, *35*, 05019001. [CrossRef]
48. ElMenshawy, M.; Marzouk, M. Automated BIM schedule generation approach for solving time–cost trade-off problems. *Eng. Constr. Archit. Manag.* **2021**, *28*, 3346–3367. [CrossRef]
49. Mashayekhi, A.; Heravi, G. A decision-making framework opted for smart building's equipment based on energy consumption and cost trade-off using BIM and MIS. *J. Build. Eng.* **2020**, *32*, 101653. [CrossRef]
50. Yongge, X.; Ya, W. Study on trade-off of time-cost-quality in construction project based on BIM. In Proceedings of the 2015 International Conference on Economics, Social Science, Arts, Education and Management Engineering, Xi'an, China, 12–13 December 2015; pp. 864–870.
51. Yu, J.; Wang, J.; Hua, Z.; Wang, X. BIM-based time-cost optimization of a large-span spatial steel structure in an airport terminal building. *J. Facil. Manag.* **2021**, *20*, 469–484. [CrossRef]
52. Gelisen, G.; Griffis, F.H. Automated Productivity-Based Schedule Animation: Simulation-Based Approach to Time-Cost Trade-Off Analysis. *J. Constr. Eng. Manag.* **2014**, *140*, B4013007. [CrossRef]
53. Khosakitchalert, C.; Yabuki, N.; Fukuda, T. Improving the accuracy of BIM-based quantity takeoff for compound elements. *Autom. Constr.* **2019**, *106*, 102891. [CrossRef]

54. Ma, G.; Zhang, L. Exact Overlap Rate Analysis and the Combination with 4D BIM of Time-Cost Tradeoff Problem in Project Scheduling. *Adv. Civ. Eng.* **2019**, *2019*, 9120795. [CrossRef]
55. Shadram, F.; Mukkavaara, J. An integrated BIM-based framework for the optimization of the trade-off between embodied and operational energy. *Energy Build.* **2018**, *158*, 1189–1205. [CrossRef]
56. Sandberg, M.; Mukkavaara, J.; Shadram, F.; Olofsson, T. Multidisciplinary Optimization of Life-Cycle Energy and Cost Using a BIM-Based Master Model. *Sustainability* **2019**, *11*, 286. [CrossRef]
57. Baghalzadeh Shishehgarkhaneh, M.; Fard Moradinia, S.; Keivani, A. Time and cost management of dam construction projects based on Building Information Modeling (BIM) (A Case Study in Kurdistan Province). In Proceedings of the 7th International Congress on Civil Engineering, Architecture and Urban Development, Tehran, Iran, 7–9 December 2021.
58. Azizi, M.; Talatahari, S.; Gandomi, A.H. Fire Hawk Optimizer: A novel metaheuristic algorithm. *Artif. Intell. Rev.* **2022**. [CrossRef]
59. Hajiagha, S.H.R.; Akrami, H.; Hashemi, S.S.; Mahdiraji, H.A. An integer grey goal programming for project time, cost and quality trade-off. *Eng. Econ.* **2015**, *26*, 93–100.
60. Zheng, H. The bi-level optimization research for time-cost-quality-environment trade-off scheduling problem and its application to a construction project. In Proceedings of the Tenth International Conference on Management Science and Engineering Management, Baku, Azerbaijan, 30 August–2 September 2016; pp. 745–753.
61. Al Haj, R.A.; El-Sayegh, S.M. Time–cost optimization model considering float-consumption impact. *J. Constr. Eng. Manag.* **2015**, *141*, 04015001. [CrossRef]
62. Khalili-Damghani, K.; Tavana, M.; Abtahi, A.-R.; Santos Arteaga, F.J. Solving multi-mode time–cost–quality trade-off problems under generalized precedence relations. *Optim. Methods Softw.* **2015**, *30*, 965–1001. [CrossRef]
63. Moghadam, E.K.; Sharifi, M.; Rafiee, S.; Chang, Y.K. Time–Cost–Quality Trade-Off in a Broiler Production Project Using Meta-Heuristic Algorithms: A Case Study. *Agriculture* **2019**, *10*, 3. [CrossRef]
64. Zahraie, B.; Tavakolan, M. Stochastic time-cost-resource utilization optimization using nondominated sorting genetic algorithm and discrete fuzzy sets. *J. Constr. Eng. Manag.* **2009**, *135*, 1162–1171. [CrossRef]
65. Huynh, V.-H.; Nguyen, T.-H.; Pham, H.C.; Huynh, T.-M.-D.; Nguyen, T.-C.; Tran, D.-H. Multiple Objective Social Group Optimization for Time–Cost–Quality–Carbon Dioxide in Generalized Construction Projects. *Int. J. Civ. Eng.* **2021**, *19*, 805–822. [CrossRef]
66. Banihashemi, S.A.; Khalilzadeh, M. Time-cost-quality-environmental impact trade-off resource-constrained project scheduling problem with DEA approach. *Eng. Constr. Archit. Manag.* **2020**, *28*, 1979–2004. [CrossRef]
67. Ghoddousi, P.; Eshtehardian, E.; Jooybanpour, S.; Javanmardi, A. Multi-mode resource-constrained discrete time–cost-resource optimization in project scheduling using non-dominated sorting genetic algorithm. *Autom. Constr.* **2013**, *30*, 216–227. [CrossRef]
68. Mahmoudi, A.; Feylizadeh, M.R. A grey mathematical model for crashing of projects by considering time, cost, quality, risk and law of diminishing returns. *Grey Syst. Theory Appl.* **2018**, *8*, 272–294. [CrossRef]
69. Ebrahimnezhad, S.; Ahmadi, V.; Javanshir, H. Time-cost-quality trade-off in a CPM1 network using fuzzy logic and genetic algorithm. *Int. J. Ind. Eng. Prod. Manag.* **2013**, *24*, 361–376.
70. Mungle, S.; Benyoucef, L.; Son, Y.-J.; Tiwari, M. A fuzzy clustering-based genetic algorithm approach for time–cost–quality trade-off problems: A case study of highway construction project. *Eng. Appl. Artif. Intell.* **2013**, *26*, 1953–1966. [CrossRef]
71. Koo, C.; Hong, T.; Kim, S. An integrated multi-objective optimization model for solving the construction time-cost trade-off problem. *J. Civ. Eng. Manag.* **2015**, *21*, 323–333. [CrossRef]
72. Heravi, G.; Moridi, S. Resource-constrained time-cost tradeoff for repetitive construction projects. *KSCE J. Civ. Eng.* **2019**, *23*, 3265–3274. [CrossRef]
73. Jeunet, J.; Bou Orm, M. Optimizing temporary work and overtime in the Time Cost Quality Trade-off Problem. *Eur. J. Oper. Res.* **2020**, *284*, 743–761. [CrossRef]
74. Hamta, N.; Ehsanifar, M.; Sarikhani, J. Presenting a goal programming model in the time-cost-quality trade-off. *Int. J. Constr. Manag.* **2021**, *21*, 1–11. [CrossRef]
75. Kosztyán, Z.T.; Szalkai, I. Hybrid time-quality-cost trade-off problems. *Oper. Res. Perspect.* **2018**, *5*, 306–318. [CrossRef]
76. Azizi, M.; Mousavi, A.; Ejlali, R.; Talatahari, S. Optimum design of fuzzy controller using hybrid ant lion optimizer and Jaya algorithm. *Artif. Intell. Rev.* **2020**, *53*, 1553–1584. [CrossRef]
77. Panwar, A.; Jha, K.N. Integrating Quality and Safety in Construction Scheduling Time-Cost Trade-Off Model. *J. Constr. Eng. Manag.* **2021**, *147*, 04020160. [CrossRef]
78. Zhang, L.; Du, J.; Zhang, S. Solution to the time-cost-quality trade-off problem in construction projects based on immune genetic particle swarm optimization. *J. Manag. Eng.* **2014**, *30*, 163–172. [CrossRef]
79. Al-Gahtani, K.S. Float Allocation Using the Total Risk Approach. *J. Constr. Eng. Manag.* **2009**, *135*, 88–95. [CrossRef]
80. Garza, J.M.d.l.; Prateapusanond, A.; Ambani, N. Preallocation of Total Float in the Application of a Critical Path Method Based Construction Contract. *J. Constr. Eng. Manag.* **2007**, *133*, 836–845. [CrossRef]
81. Long, L.D.; Tran, D.-H.; Nguyen, P.T. Hybrid multiple objective evolutionary algorithms for optimising multi-mode time, cost and risk trade-off problem. *Int. J. Comput. Appl. Technol.* **2019**, *60*, 203–214. [CrossRef]
82. Yang, X.-S. Firefly algorithm, stochastic test functions and design optimisation. *arXiv* **2010**, arXiv:1003.1409. [CrossRef]

83. Mirjalili, S.; Mirjalili, S.; Hatamlou, A. Multi-Verse Optimizer: A nature-inspired algorithm for global optimization. *Neural Comput. Appl.* **2015**, *27*, 495–513. [CrossRef]
84. Eberhart, R.; Kennedy, J. Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; pp. 1942–1948.
85. Tejani, G.G.; Savsani, V.J.; Patel, V.K. Adaptive symbiotic organisms search (SOS) algorithm for structural design optimization. *J. Comput. Des. Eng.* **2016**, *3*, 226–249. [CrossRef]
86. Rao, R.V. Teaching-learning-based optimization algorithm. In *Teaching Learning Based Optimization Algorithm*; Springer: Cham, Switzerland, 2016; pp. 9–39.
87. Gutierrez, G.; Gardella, R.; Ryan, B. New Colorado VA Hospital Is State of the Art, and More than $1 Billion Over Budget. Available online: https://www.nbcnews.com/storyline/va-hospital-scandal/new-colorado-va-hospital-state-art-more-1-billion-over-n898091 (accessed on 18 August 2020).