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BIM-based resource trade-off in dam project scheduling using Atomic Orbital Search (AOS) algorithm

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ABSTRACT: Dam construction projects are considered complicated, large, and heavy projects throughout the world, requiring a high number of workers, stakeholders, equipment, cost, and time. Hence, their resource management and trade-off are one of the most important tasks for project managers and schedulers. Concerning the Building Information Modeling (BIM) method and metaheuristic algorithm, this study proposes a framework for resource trade-offs in dam construction project scheduling. Atomic Orbital Search (AOS) is employed as a newly developed metaheuristic algorithm based on quantum mechanics principles. First, a 3D model of the dam construction project is modeled using the BIM process and project management software. Regarding the minimization of time, cost, risk, and maximum quality, an optimization problem is formed, and the AOS's capacity to solve this issue is assessed, and its outcomes are compared with different four metaheuristic algorithms. Meanwhile, all optimization processes were carried out. To identify the statistical measures considering a predetermined stopping condition, 30 separate optimization runs are carried out. The outcomes show that the AOS algorithm can deliver competitive and exceptional results when handling trade-offs between various resource alternatives in dam construction. Consequently, project managers can use the AOS optimization algorithm in their large and intricate construction projects in dealing with resource trade-off problems.

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1- Introduction

Several large-scale projects are often undertaken by contractors who utilize various resources such as money, equipment, knowledge, and human resources. To ensure efficient scheduling and reduce project time, contractors engage in specialized activities [1]. Resources play a crucial role in all construction projects, and they can be classified into two main groups: non-renewable and renewable. Non-renewable resources encompass items like raw materials and budget, while renewable resources include human resources and equipment. Contractors frequently pool their resources to minimize costs and reduce waiting periods [2]. Consequently, schedulers need to perform a Time-Cost Trade-off (TCT) analysis to determine the most cost-effective project duration. Optimization algorithms have been employed to study TCT issues in the building and construction sector [3, 4]. Predictable durations and linear time-cost functions, assuming constant usage of discrete construction resources such as labor and machinery, are the fundamental and widely accepted assumptions in TCT analysis. Achieving the optimal global solution in large-scale TCT models often requires several iterations. To address TCT issues, evolutionary algorithms are considered more effective in avoiding local optimization, with approximately 23 optimal strategies believed to yield the best results [5, 6].

Time, cost, and quality are the three primary project criteria that all project managers continually strive to achieve in order to complete projects successfully with the least amount of time and money spent and the highest level of quality [7, 8]. Since TCT Problems have been explored in the literature of deterministic project scheduling, they serve as a useful model for most Time-Cost-Quality Trade-off Problems (TCQTP) [9]. For TCQRT issues, several optimization strategies have been put forward. With no restrictions on time or resources, the Critical Path Method (CPM) may be utilized as a fundamental quantitative project management approach. The CPM establishes the minimal time necessary to finish the project, assuming an optimal completion time. However, it is no longer used owing to drawbacks like its numerical complexity, particularly in significant building projects [10-12]. However, techniques for mathematical programming Create mathematical models from TCQRTP and utilize linear programming [13]. Volkerson and Perra introduced linear programming (LP) as a technique for optimal outcomes by assuming a continuous time-cost connection shown by linear relationships. Nevertheless, it could be employed when considering a linear relationship between time and cost for any network activity. The network grows excessively complicated as the number of activities rises, and the LP approach demands a significant amount of computing labor [14-16].

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Due to the many advantages and resource savings that come with adopting Building Information Models (BIM) throughout the design, planning, and construction of new structures, there has been an increase in interest in this technology over the last several decades. Based on early computer-aided design (CAD) initiatives in numerous sectors, 3D modeling emerged in the 1970s. The building industry was restricted for a considerable amount of time to the conventional 2D design, while several industries developed integrated analytic tools and object-based parametric modeling [17-22]. BIM is a digital representation of a facility's physical and functional properties, according to the National Building Information Modeling Standards (NBIMS) committee of the USA. When used as a solid foundation for choices throughout a facility's life cycle, which is defined as from initial conceptualization through destruction, a BIM is a shared knowledge resource [23-26].

Additionally, besides the uses mentioned above, BIM is also known as computational BIM, a novel method of problem-solving in which users create algorithms to automate the collection and manipulation of building-related data for increased productivity [27]. Due to its ability to identify possible issues early on before a project is executed, BIM methodology has the potential to alter the AECO business. It plays a crucial role in design contexts. BIM can plan, manage, and enhance the industry's work and production [28, 29]. Furthermore, regarding the parametric description of objects, BIM systems can distinguish between various building components by examining their use, structures, and functions as parametric features [30, 31].

Nonetheless, some research works on the role of BIM and optimization in tackling resource trade-off problems in the AEC industry have been published. For the discrete time/resource trade-off (DTRT) problem in project scheduling, Ranjbar, De Reyck, and Kianfar [32] created a heuristic approach. In another paper, Ranjbar and Kianfar [25] used a genetic algorithm to solve the DTRT problem. Furthermore, Demeulemeester, De Reyck, and Herroelen [33] proposed a branch-and-bound approach for project networks' DTRT problems. Hafezalkotob, Hosseinpour, Moradi, and Khalili-Damghani [2] proposed a game theory-based model on cooperatives for project time/multi-resource trade-off problems. Nguyen, Chou, and Tran [34] put up a system in project scheduling, including multi-objective optimization, BIM, and multi-criteria decision-making to make resource trade-offs. According to the authors, using visual analytics and a uniform solutions distribution, the proposed MOFBI algorithm could locate result curves. Nasiri and Lu [35] presented a streamlined TCT optimization approach to construct the first-order derivative function of direct project cost vs. project time and to discover the number and position of the total project cost's minimal solution(s). Baghalzadeh Shishehgarkhaneh, Moradinia, Keivani, and Azizi [36] used five metaheuristic algorithms to tackle the resource trade-off problems in dam construction projects. The authors concluded that GAs should be regarded as one of the feasible algorithms in time-cost-quality-risk (TCQR) trade-offs for dam construction projects. The publications in BIM-based optimization are listed in Table 1 by year of publication.

In the current study, the Atomic Orbital Search (AOS) algorithm proposed by Azizi [37] is employed for the TCQR trade-off in the Goocham dam project. Five miscellaneous resource options have been implemented for this problem. There is a research gap in the field of construction projects regarding the Time-Cost-Quality-Risk Trade-off (TCQRT) and the utilization of Building Information Modeling (BIM) procedures. While TCQRT analysis has been studied in construction projects, there is limited research that specifically addresses the trade-off concerning dam construction projects. Additionally, the integration of BIM processes in TCQRT analysis is relatively unexplored. Therefore, the research gap lies in the lack of focus on TCQRT and BIM in dam construction projects. The main contribution of this research is the application of the Atomic Orbital Search (AOS) algorithm for the TCQRT trade-off in the Goocham dam project. The study introduces five different resource options for addressing this problem. The novelty of the research lies in its approach to TCQRT analysis in dam construction projects, particularly considering the BIM procedure. By employing the recently proposed metaheuristic optimization algorithm (AOS) and integrating BIM processes, this study provides a new perspective on achieving optimal trade-offs in time, cost, quality, and risk within the context of dam construction projects. One of the primary justifications for selecting the AOS algorithm in this study is its status as one of the novel algorithms proposed in recent years. Its selection stems from the desire to assess its effectiveness in addressing trade-off problems. By evaluating the capabilities of the AOS algorithm, this research aims to shed light on its potential for handling trade-offs in construction projects. This research fills the gap by exploring the TCQRT and BIM in the specific domain of dam construction projects, contributing valuable insights and strategies for stakeholders and project teams involved in similar projects.

The research focuses specifically on dam construction projects, which are known to be complex and unique. Therefore, the findings and conclusions of this study may have limited generalizability to other types of construction projects with different characteristics and requirements. It is important to recognize that resource trade-off challenges may vary across various construction sectors, and further research is needed to assess the applicability of the proposed framework and algorithm in different contexts. Furthermore, while the study addresses the trade-off between time, cost, risk, and quality in dam construction projects, it is important to note that there are other factors and constraints that can impact project performance and success. The research does not consider other crucial aspects such as environmental sustainability, social impact, and regulatory compliance. Future studies should aim to incorporate a broader range of factors into the optimization model to provide a more comprehensive understanding of the trade-offs involved in construction project management.

Table 1. Summary of articles by year of publication based on integrating BIM and optimizations

Reference Number	Year	The primary purpose of the study	Algorithm
[38]	2022	Presenting time, cost, and quality trade-off model for project scheduling	AHP and NSGA-II
[39]	2022	Developing the trade-off among cost, time, and quality in the construction project toward reaching sustainability	SOS
[3]	2022	Resource trade-off in construction projects considering cost, time, risk, quality, and CO_2	FHO
[40]	2021	Integrating BIM with the Internet of Things (IoT) sensors to optimize the interior temperature.	IDW
[41]	2021	Camera placement in interior construction monitoring is optimized using BIM.	MPGA
[42]	2019	Optimization of materials layout by integrating 4D BIM.	SOS
[43]	2019	Using BIM, determine the optimum scan locations and the ideal path.	A^*
[44]	2019	Create automated route planning and a BIM-based approach.	A^*
[45]	2015	Optimization of activity level construction schedules by integrating BIM product models and metaheuristics.	PSO
[46]	2015	BIM-based 4D model for overlapping activities' minimizing.	GA
[47]	2014	a BIM-based active simulation method for reducing the simultaneous schedule-workspace interference level.	GA
[48]	2014	Create a BIM-based construction sequencing for the installation of the project's components.	GA
[49]	2014	Proposed a novel GA employing hardware with field-programmable gate arrays	GA
[50]	2011	presented a model-based planning system that uses BIM and Object Sequencing Matrix (OSM) to get the best staff assignment while working with limited resources and available space.	GA

IDW: Inverse Distance Weighting; MPGA: Modified parallel genetic algorithm; SOS: Symbiotic organisms search; ACO: Ant colony optimization; GA: Genetic Algorithm; PSO: Particle swarm optimization; NSGA-II: Non-dominated Sorting Genetic Algorithm II; FHO: Fire Hawk Optimizer; SOS: Symbiotic Organism Search;

The remainder of the paper is organized as follows: Section 2 describes the AOS algorithm, the case study project, and the statement of the optimization problem. Section 3 presents the results and discussion, and offers some optimal solutions. Finally, conclusions and future directions are provided in Section 4.

2- Methodology

2- 1- Atomic Orbital Search (AOS) Algorithm

An atomic orbital is a mathematical expression that depicts the wave-like behavior of one or two electrons in an atom based on atomic theory and quantum mechanics. The core concept behind the AOS algorithm is to use quantum-based atomic theory to deal with issues like electron density configuration and atoms' ability to absorb or emit energy. The quantum staircase analogy for electrons revolving around an atom's nucleus is shown in Fig. 1(A). The AOS algorithm explores multiple solution possibilities (X) in the quantum-based atomic model that represent the electrons encircling the nucleus. The thin, spherical, concentric layers of the electron cloud around the nucleus have been designated as the search space in this method. In the search space, each electron is shown by a solution candidate (X_i), with some decision variables (x_{ij}) also being used to define the solution candidates' location. The following are the mathematical equations for this purpose:

$$X=\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_m \end{bmatrix}=\begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^j & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^j & \dots & x_2^d \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_i^1 & x_i^2 & \dots & x_i^j & \dots & x_i^d \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_m^1 & x_m^2 & \dots & x_m^j & \dots & x_m^d \end{bmatrix}, \quad (1)$$

$$i=1,2,\dots,m.,\ j=1,2,\dots,d.$$

where m represents the number of electrons (solution candidates) inside the electron cloud (search space), and d shows the dimension of the problem determining the candidate position (electrons). The starting positions of the electrons within the electron cloud are randomly specified according to the mathematical equation below:

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

where $x_i^j(0)$ shows the solution candidates' initial position; $x_{i,max}^j$ and $x_{i,min}^j$ are the indication of the maximum and minimum bounds of the jth decision variables, respectively; and shows a randomly distributed number [0,1].

With lower energy levels, Electrons correspond to solution candidates with greater objective function values. In the mathematical model, those with lower objective function values show electrons with the highest levels of energy. The objective function values of several solution candidates are kept using the following vector equation.

$$E = \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_i \\ \vdots \\ E_m \end{bmatrix}, \qquad i = 1,2,\ldots,m. \tag{3}$$

where E represents a vector considering the objective function's values, E_i indicates the *ith* solution candidate's energy level, and m shows the solution candidates' number in the search space.

In the mathematical description of the quantum-based atomic orbital model, a random integer (n) is created to represent the number of imagined spherical layers (L) around the nucleus. This number represents the quantum number in the description of atoms based on quantum mechanics. Fig. 1 (A) elucidates a schematic representation of these elements. Furthermore, Fig. 1 (B) shows a schematic illustration using a Probability Density Function (PDF) based on a typical Gaussian distribution to locate solution candidates in imaginary layers.

Each imaginarily produced layer contains some solution candidates regarding specified specifics of determining the electrons' position using PDF. So, the following mathematical equations represent the vectors of the placements of the solution candidates (X^k) and the values of the objective function (E^k) in the imaginary layers:

$$E^k = \begin{bmatrix} E_1^k \\ E_2^k \\ \vdots \\ E_i^k \\ \vdots \\ E_p^n \end{bmatrix}, \qquad \begin{cases} i = 1,2,\ldots,p. \\ k = 1,2,\ldots,n. \end{cases} \tag{4}$$

Where the integer *n* indicates the maximum number of imagined levels, X_i^k shows the *kth* imaginary layer's *ith* solution candidate, p specifies the *kth* imaginary layer's solution candidates' overall number, *d* presents the dimension of the problem, and E_i^k is the *kth* imaginary layer's the *ith* solution candidate's objective function value. The nucleus layer positions the *LE* with the best objective function value among whole solution options, as shown in Fig. 1 (C).

The mathematical model determines the binding energy, which shows the energy required to remove an electron from its shell, in terms of the positions and objective function values of solution candidates in each layer. The mathematical formulas used in this situation are as follows:

$$BS^k = \frac{\sum_{i=1}^{p} X_i^k}{p}, \qquad \begin{cases} i = 1,2,\ldots,p. \\ k = 1,2,\ldots,n. \end{cases} \tag{5}$$

$$BE^k = \frac{\sum_{i=1}^{p} E_i^k}{p}, \qquad \begin{cases} i = 1,2,\ldots,p. \\ k = 1,2,\ldots,n. \end{cases} \tag{6}$$

Where E_i^k and X_i^k are the *kth* layer's objective function value and position of *ith* solution candidate, BE^k and BS^k are the the *kth* layer's binding energy and the binding state; *m* is solutions candidates' overall number, the binding state and binding energy of an atom are calculated based on the information given:

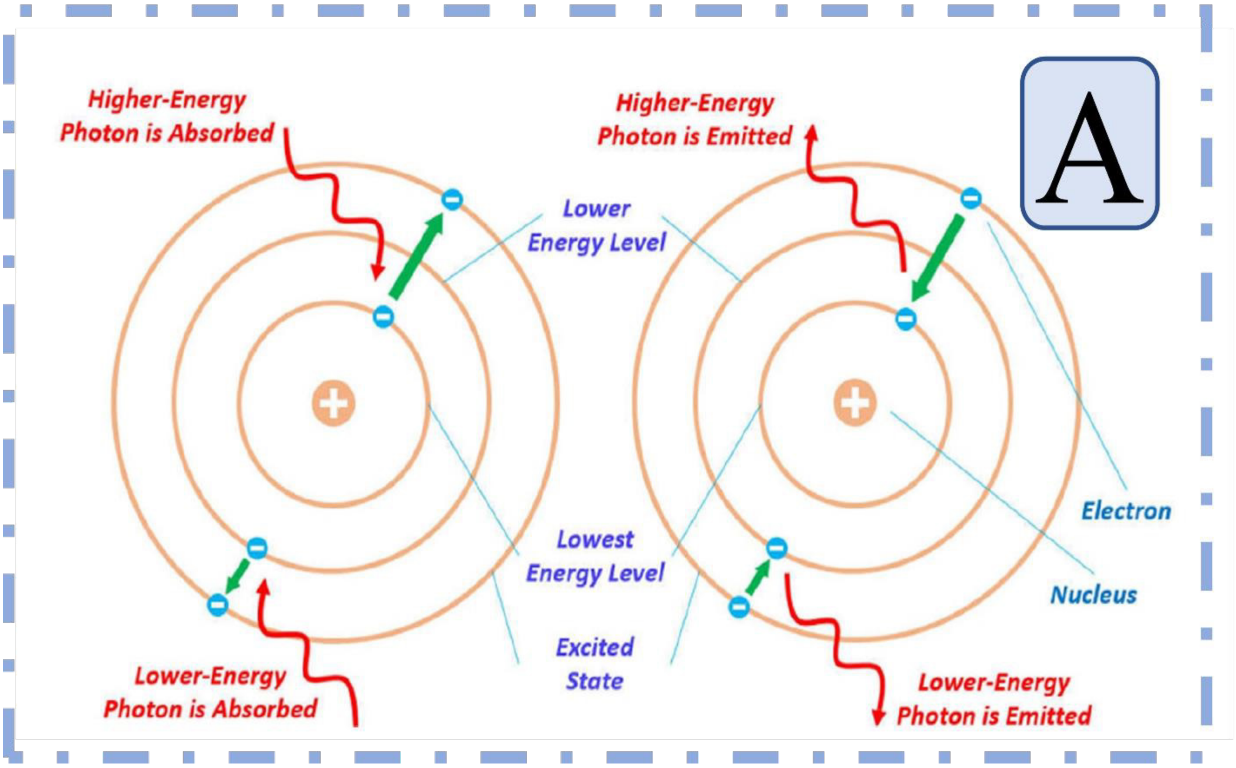
$$BS = \frac{\sum_{i=1}^{m} X_i}{m}, \qquad i = 1,2,\ldots,m. \tag{7}$$

$$BE = \frac{\sum_{i=1}^{m} E_i}{m}, \qquad i = 1,2,\ldots,m. \tag{8}$$

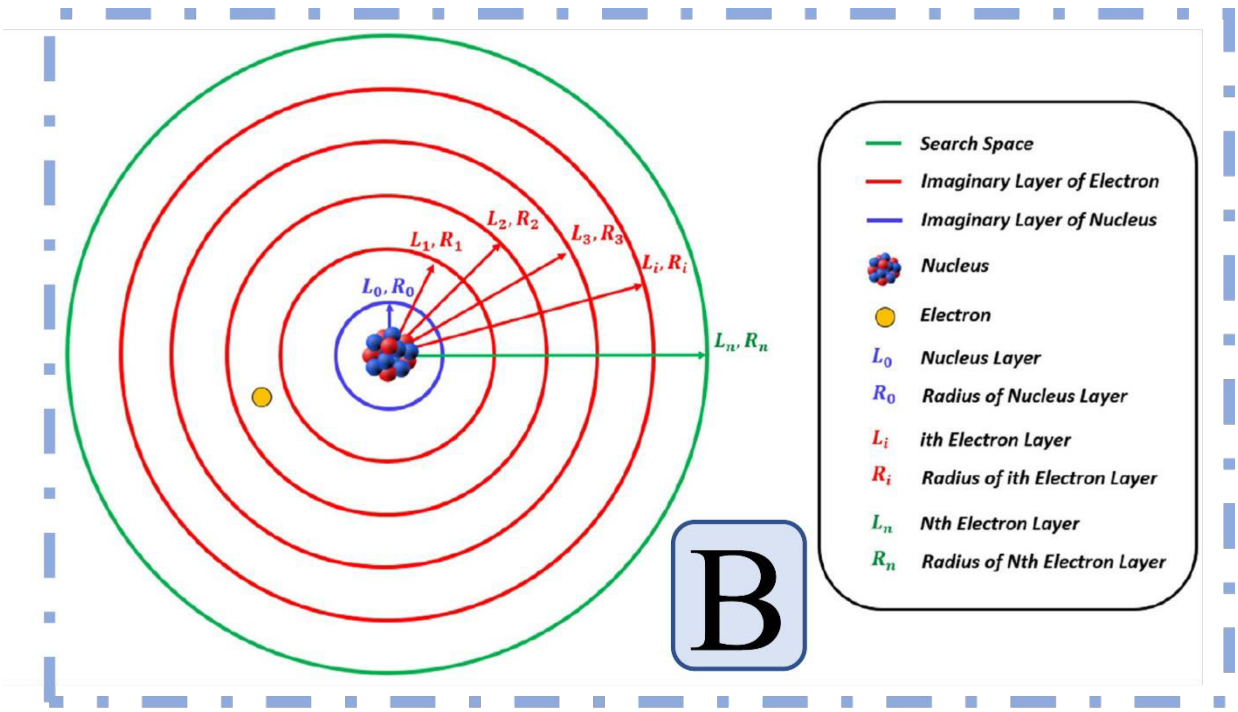
Where E_i and X_i are the ith solution candidate's objective function value and position in the atom; BE and BS are the atom's binding energy and states. A uniformly distributed random number (Ø) ranging from 0 to 1 is produced for every electron to mathematically describe photons' interaction with electrons surrounding the nucleus. The emission of photons is considered if a solution candidate's energy level in a specific layer is higher than the layer's binding energy ($E_i^k > BE^k$). During this procedure, the solution candidates tend to release an energy-carrying photon and simultaneously reach the atom's binding state (*BS*) and the electron state with the lowest energy level (*LE*) in the atom. The following mathematical equations are used in this approach to update the position of solution candidates:

$$X_{i+1}^k = X_i^k + \frac{\alpha_i \times \left(\beta_i \times LE - \gamma_i \times BS\right)}{k}, \qquad \begin{cases} i = 1,2,\ldots,p. \\ k = 1,2,\ldots,n. \end{cases} \tag{9}$$

where *BS* shows the atom's binding state; α_i, β_i, and γ_i are vectors, including randomly produced uniformly distributed in the range (0,1) that are used to calculate the quantity of released energy; The present and forthcoming positions for the *ith* solution candidate of the *kth* layer are X_i^k and X_{i+1}^k, respectively; *LE* represents the candidate solution with the lowest atomic energy level.



A
Higher-Energy Photon is Absorbed
Higher-Energy Photon is Emitted
Lower Energy Level
Lowest Energy Level
Excited State
Electron
Nucleus
Lower-Energy Photon is Absorbed
Lower-Energy Photon is Emitted



L_0, R_0
L_1, R_1
L_2, R_2
L_3, R_3
L_i, R_i
L_n, R_n
Search Space
Imaginary Layer of Electron
Imaginary Layer of Nucleus
Nucleus
Electron
L_0 Nucleus Layer
R_0 Radius of Nucleus Layer
L_i ith Electron Layer
R_i Radius of ith Electron Layer
L_n Nth Electron Layer
R_n Radius of Nth Electron Layer
B

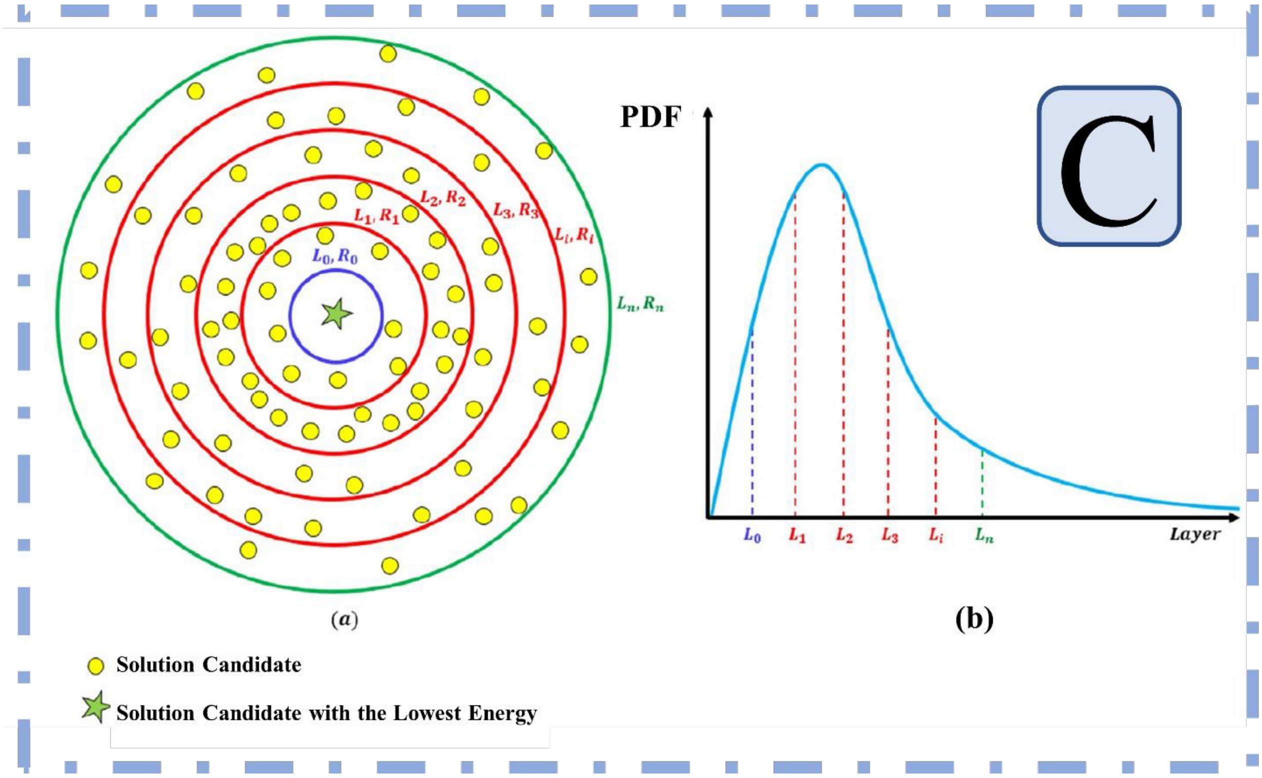


Fig. 1. Resemblance to a quantum staircase for the electrons around the atoms' nuclei (A). Presentation of imaginary layers surrounding the nucleus in a schematic (B). Diagrammatic depiction of calculating the position of potential solution candidates using PDF (C) [37].

If the energy level of a proposed solution in a given layer is lower than the layer's binding energy $(E_i^k < BE^k)$, photon absorption is evaluated. In this process, the following equation describes the updating of solution candidate positions:

$$X_{i+1}^{k} = X_{i}^{k} + \alpha_i \times \left(\beta_i \times LE^{k} - \gamma_i \times BS^{k}\right), \quad \begin{cases} i = 1,2,\ldots,p. \\ k = 1,2,\ldots,n. \end{cases} \tag{10}$$

where LE^k denotes the *kth* layer's solution candidate with the lowest energy level; The present and forthcoming positions for the *ith* solution candidate of the kth layer are X_i^k and X_{i+1}^k; BS^k shows the *kth* layer's binding state; α_i, β_i, and γ_i demonstrate vectors, or calculate the quantity of absorbed energy, including evenly distributed random integers in the range of (0,1).

Suppose the randomly produced number (*Ø*) for each electron is less than the *PR (Ø < PR)*. The transit of electrons across different layers around the nucleus relies on other processes, such as particle interactions or magnetic fields, resulting in energy absorption or emission since photons' impact on electrons is implausible. The method by which solution candidates' positions are updated in consideration of these impacts is as follows:

$$X_{i+1}^{k} = X_{i}^{k} + r_i, \qquad \begin{cases} i = 1,2,\ldots,p. \\ k = 1,2,\ldots,n. \end{cases} \tag{11}$$

where r_i indicates a vector, including produced numbers randomly in the range of (0,1); The present and forthcoming positions for the *ith* solution candidate of the *kth* layer are X_i^k and X_{i+1}^k; Meanwhile, the AOS algorithm's flowchart is represented in Fig. 2.

2- 2- Design Examples

This article applies time, cost, quality, and risk trade-offs to a project to build a dam using the Goocham storage dam in Iran's Kurdistan area as a case study. Each objective function has been examined alone and in combination. All methods were carried out in MATLAB at the same time using a Core i7-7700 HQ 2.80 CPU and 16 GB of RAM.

To store, control, and use the water required to irrigate agricultural regions in the Qorveh Plain Dehgolan, the Goocham Dam (Fig. 3), was built. Kurdistan's Goocham Dam is situated on the Cham Mirki River, near Goocham Village, and 18 kilometers northwest of Dehgalan City. The reservoir has a capacity of 64 million cubic meters and a height of 42

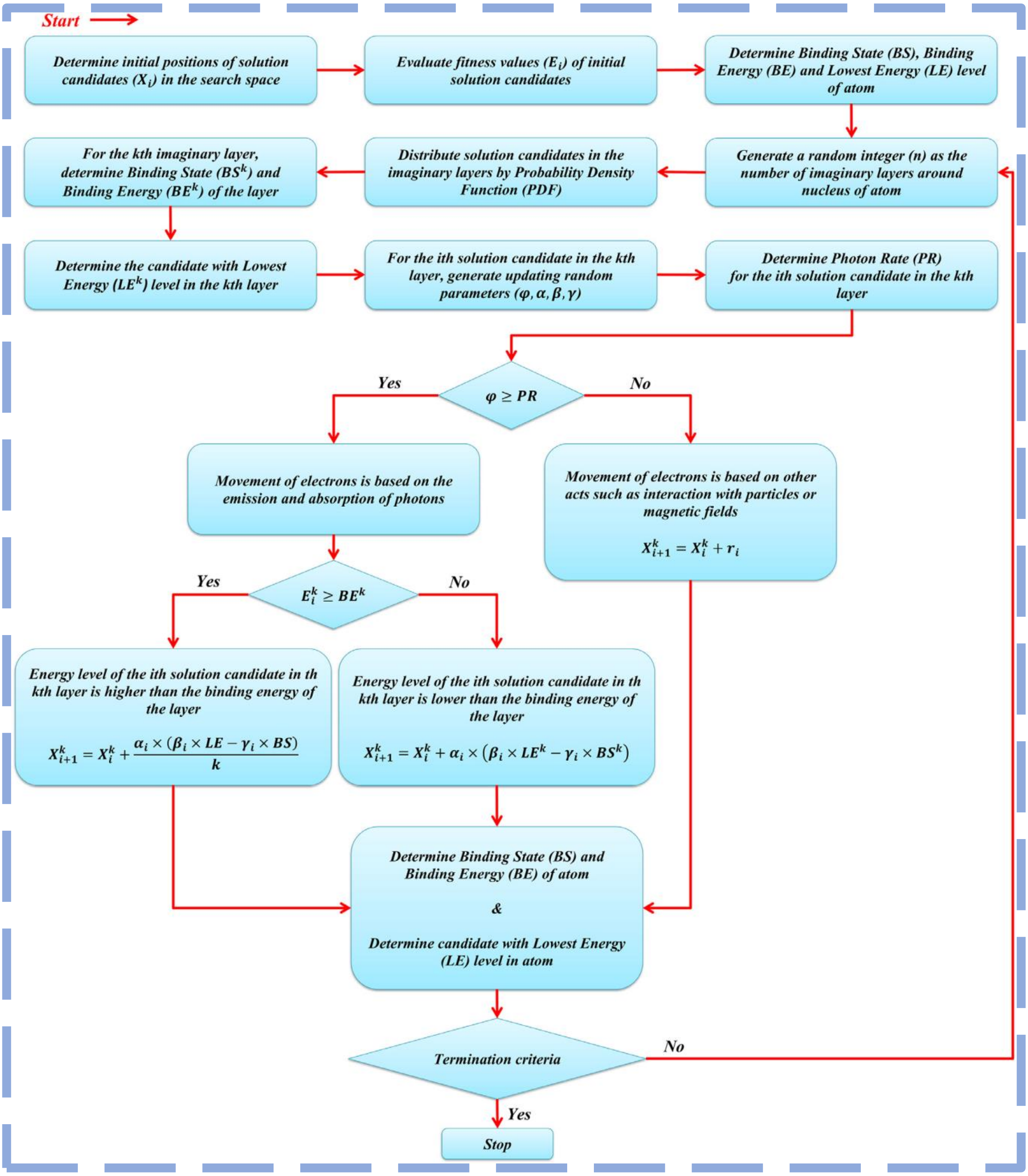


Fig. 2. The AOS's Flowchart

Fig. 3. Goocham Dam

(m). Additionally, the water diversion structure consists of 2 metal pipes with a diameter of 2 meters and a length of 328 meters. Its overflow is constructed of free-standing concrete with an altitude of 135 meters. The majority of the rock at the Goocham Dam site is made up of light tuffs, marls, and brown mud amongst conglomerate sandstone, black basalt, and silty clay soils. The duration (4D) and cost (5D) of the top 17 activities at Goocham Dam were calculated for the present research utilizing BIM using MS Project, Autodesk Revit, and Navisworks. As a consequence, various conflicts and modifications were discovered. The whole project's design was split into 14 equal-length portions to achieve this goal.

The Goocham Dam construction project in Iran involves a series of interdependent activities. The initial activity, "Materials Production and Deposition," sets the foundation for the entire project. It involves the production and deposition of necessary construction materials, such as concrete, steel, and aggregates. The subsequent activities, including "Excavation," "Water diversion system," and "Instrument Installation," rely on the availability of these materials. Excavation involves the removal of soil and rocks to prepare the site for further construction. The water diversion system, an essential component of the dam, must be established to redirect water flow during the construction process. Instrument installation, such as sensors and monitoring devices, is crucial for data collection and control throughout the project.

Once the initial groundwork is laid, several parallel activities can commence. Activities like "Watertight wall Execution," "Clay Core Execution," and "Upstream cofferdam Execution" are interconnected and can proceed simultaneously. The watertight wall execution ensures the impermeability of the dam structure, preventing water seepage. The clay core execution involves the placement of compacted clay within the dam, enhancing its stability and integrity. The upstream cofferdam execution creates a temporary barrier to divert water flow and allow construction in a dry environment. These activities are closely linked as they contribute to the fundamental structure and functionality of the dam. As the construction progresses, other activities, such as "Downstream slope Execution," "Shell Execution," and "Hydromechanical equipment Installation," become prerequisites for subsequent stages. The downstream slope execution involves the construction of a stable slope downstream of the dam, ensuring erosion control and overall safety. The shell execution focuses on the main dam structure, reinforcing its integrity and strength. Finally, the hydromechanical equipment installation includes the setup of equipment necessary for the operation and management of the dam, such as gates, valves, and turbines. These activities depend on the completion of earlier tasks, as they require a solid foundation and proper infrastructure to be effectively implemented. Fig. 4 represents the project network including the activities and the relations between them and prerequisite activities.

Each part was modeled using a sweeping blend form in the family environment of Revit 2020 before being transferred to the project environment. Therefore, the materials and other necessary data were taken from Revit's material take-off. The project's schedule was made in MS Project using the information provided, giving the duration and cost of the project regarding the BIM. Finally, Navisworks created an animation of the building process; consequently, certain conflicts with the integrated model were found. The 11th segment of the Goocham dam is shown in Fig. 5 as a Revit model.

In the context of the BIM process, Navisworks played a crucial role as a coordination and visualization tool. Its primary purpose was to integrate diverse multidisciplinary models generated by different teams or disciplines involved in the construction project. By combining these models, Navisworks provided a comprehensive and unified view of the entire project.

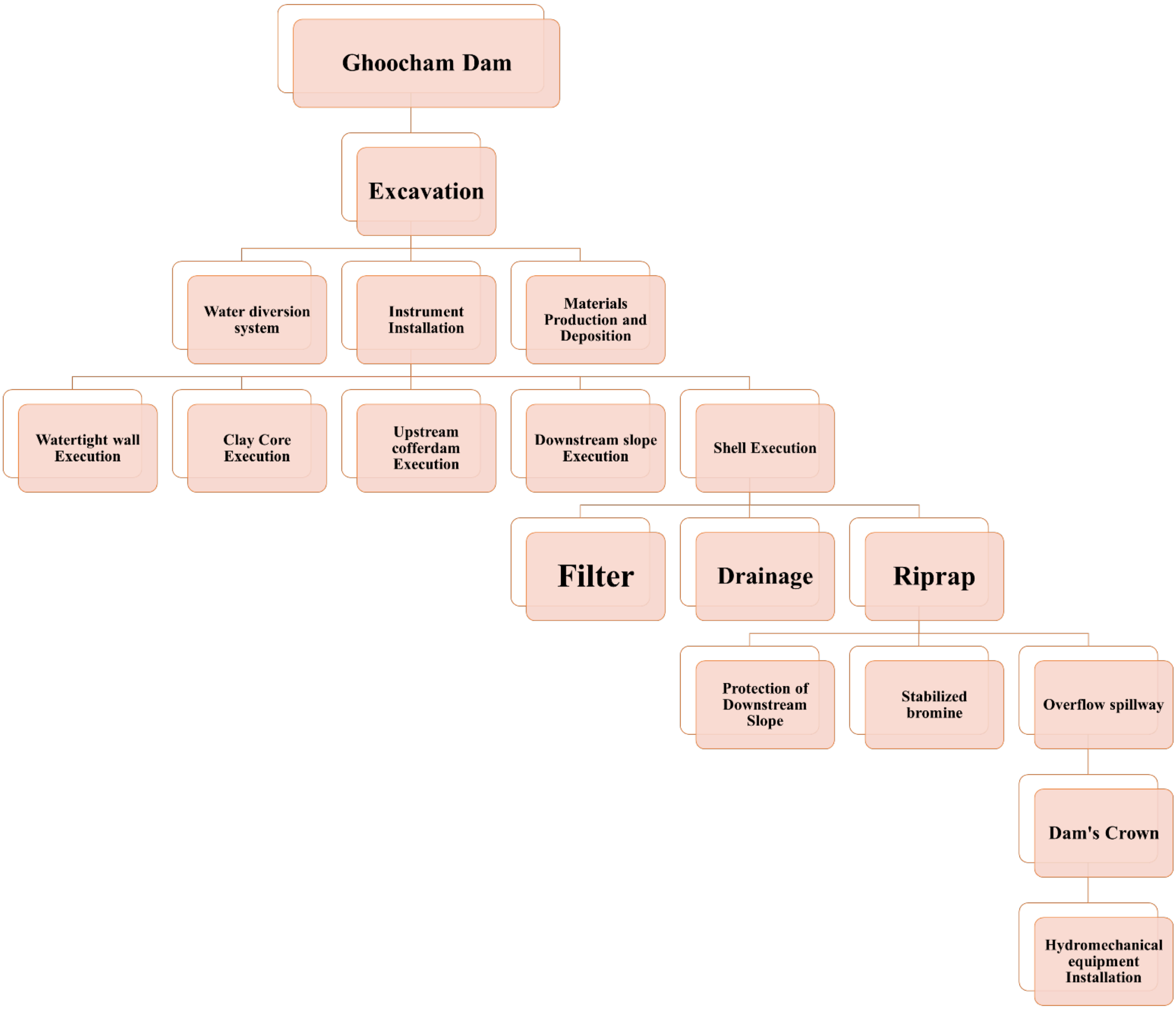


Fig. 4. The project network including the activities and the relations between them and prerequisite activities.

One of the key functions of Navisworks was clash detection. It meticulously examined the overlapping elements from various models and identified clashes or conflicts that could arise during construction. This clash detection feature helped in pinpointing potential clashes early on, allowing for timely resolution and mitigation of conflicts. By identifying clashes beforehand, Navisworks contributed to smoother construction processes, reduced rework, and improved coordination among different building elements. Dynamo, on the other hand, served as a valuable parametric modeling and scripting tool within the BIM workflow. It offered the capability to automate repetitive tasks, thereby boosting the efficiency of the BIM process. With Dynamo, custom scripts and workflows could be created to streamline various aspects of the project. Parametric modeling was a significant advantage of Dynamo. It enabled the generation of complex geometric forms and structures, providing greater design flexibility and innovation. By defining parameters and relationships, designers and engineers could explore different design iterations, test alternative scenarios, and quickly adapt the models to changing requirements. Moreover, Dynamo facilitated the manipulation of BIM data, allowing for data extraction, transformation, and analysis. This capability proved valuable in extracting specific information from the BIM models, generating reports, and conducting data-driven analyses for decision-making purposes.

The integration of Navisworks and Dynamo within the BIM process empowered project teams to achieve enhanced coordination, collaboration, and efficiency. Navisworks ensured the seamless integration of multidisciplinary models and the detection of clashes, while Dynamo automated repetitive tasks, empowered parametric modeling, and facilitated advanced data manipulation. Together, these tools played a pivotal role in optimizing the BIM workflow, resulting in improved project outcomes.

Since the real construction time is reported as 1154 days and BIM reached 690.13, the BIM is capable of reducing the time of the projects by up to 40%. For cost item, the BIM can reach 46046055812 which is 7% lower than the reported cost for the real construction scenario as 49730044381.

2- 3- Statement of the optimization problem

The present research uses the BIM model to import all of the project's data for the 17 activities listed in Table 1A. There are several ways to carry out each operation, and each has its own time, cost, quality, and risk parameters depending on the number of resources, equipment, and technology used. By selecting the appropriate course of action for each activity, the TCRQC trade-off issue optimization technique seeks to maximize project quality while minimizing project time, cost, and risk. As a result, the first objective function in Eq. 12 is to shorten the project's duration:

$$T_p = \mathrm{IF}\left[\min\left(\max\left(ST_i + D_i\right)\right)\right] = \mathrm{IF}[\min\left(\max\left(FT_i\right)\right)];\quad i = 1,\ldots,M \tag{12}$$

Where D_i displays the time spent on every activity; ST_i and FT_i represents the activity's start and end timings; M shows the overall number of nodes for the project schedule [33]. Moreover, indirect costs (*IC*), direct costs (*DC),* and delay charges (*DCs*) are included in a project's overall cost. There are numerous methods for identifying a project's overall cost; however, this research takes into account direct expenses, indirect costs, and delay costs for theoretical reasons. As shown in Eq. 13, the next objective function is to reduce the project's cost:

$$\min C = D_{C_i}^j + I_{C_i}^j + DCs \tag{13}$$

$$D_{C_i}^j = \sum_{i=1}^{n} C_i^j \tag{14}$$

$$I_{C_i}^j = C_{ic} \times T \tag{15}$$

$$DCs = \begin{cases} C_1\left(T_0 - T\right) & \text{if } T \le T_0 \\ \left(e^{\frac{T-T_0}{T_0}} - 1\right)\left(D_{C_i}^j + I_{C_i}^j\right) & \text{if } T > T_0 \end{cases} \tag{16}$$

Where is the total cost of the construction project; and represent the direct and indirect costs, respectively, associated with the *jth* execution mode of the *ith* activity; C_i^j elucidates the cost in conjunction with *jth* mode of *ith* activity; $D_{C_i}^j$ and $I_{C_i}^j$ are the direct and indirect costs in conjunction with *jth* execution mode of *ith* activity, respectively; DCs is the delay charges; T_0 elucidates the project's planned execution time; C_1 shows a reward for early work completion, and T is the overall project execution time [51, 52]. The quality of the whole project is the average quality of the project activities since project resources may comprise a variety of materials, tools, and labor. The quality will increase as the activities are extended, but going beyond a certain point will result in a decline in quality. Therefore, the quality performance index (QPIi) given in Eq. 17 denotes the level of each activity's quality [52].

$$QPI_i = IF(a_i t_i^2 + b_i t_i + c_i) \tag{17}$$

Where t_i shows the activity *ith's* duration; a_i, b_i, and c_i is the clarification of coefficients determined by the quadratic function in relation to BD (Fig. 6). The longest, best, and shortest durations are LD, BD, and SD, respectively. BD is nonetheless determined using Equation 18. Finally, the objective function for quality is expressed as follows in Equation 20:

$$BD = SD + 0.613\left(LD - SD\right) \tag{18}$$

$$\max Q = \sum_{i=1}^{M} \frac{QPI_i}{M} \tag{19}$$

The real project risk is defined mainly through the project's conditions, contract terms, and delivery systems. A "risk value" is a function that includes the following 2 sections: (i) the project's total float; and (ii) the volatility of resources. When non-critical procedures have a significant level of temporal uncertainty, the use of float may raise project risk and schedule overruns. Consequently, construction and project managers must implement schedule modifications to prevent unanticipated resource use changes during the project's execution. Floating non-critical activities may improve resource utilization [53-55]. Therefore, the fourth objective function for risk can be expressed as Equation 20:

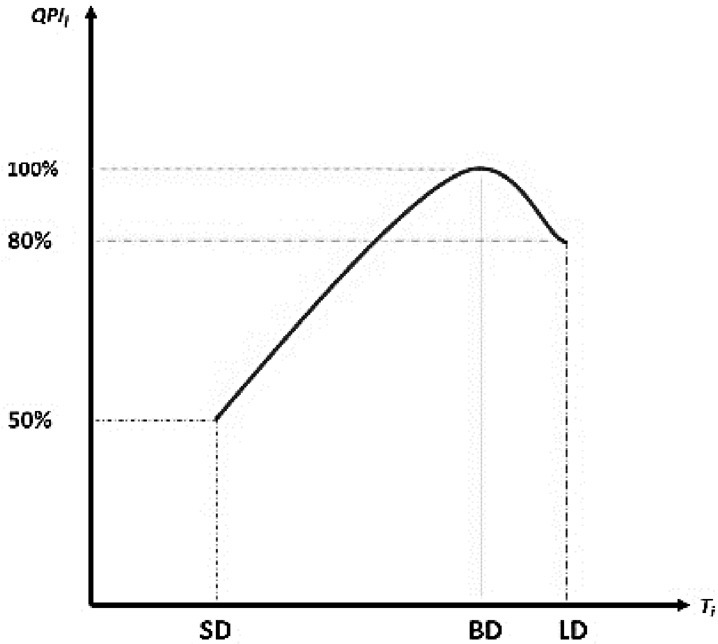


Fig. 6. The quality performance index (QPIi) used in this study

Table 2 . Optimization algorithms' specific setting parameters

Algorithms	Number of Population (n_{pop})	Maximum Iterations	Crossover Probability (p_c)	Mutation Probability (p_m)	Initial Temperature	Temp. reduction Rate	Rate of Cannibalism	Maximum Fault
SA	50	1000	-	-	0.025	0.99	-	-
BWO	50	1000	0.8	0.4	-	-	0.5	-
BRO	50	1000	-	-	-	-	-	4
BHM	50	1000	-	-	-	-	-	-

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

Where TF_{max} and TF_c are the project's total flexible scheduling float and total current float; $\bar{R}$ is uniform resource level; R_t is the resource needed on day t, and wi demonstrates the weight.

Eq. 21 is used to assess the capacity of the AOS algorithm to concurrently optimize the time-cost-quality-risk (All) trade-off:

$$F(x) = \text{IF}\left(\frac{T - T_{min}}{T_{max} - T_{min}} + \frac{R - R_{min}}{R_{max} - R_{min}} + \frac{Q_{min} - Q}{Q_{max} - Q_{min}}\right) + \frac{C - C_{min}}{C_{max} - C_{min}} \tag{21}$$

In this research, all algorithms have been established and executed with precise parameters, as indicated in Table 2. The simulated annealing algorithm emulates the gradual cooling of metals to optimize a process. It imitates the reduction of atomic movements and the decrease in lattice defects' density, mirroring the behavior of metals as they cool. This iterative approach aims to reach the state with the lowest energy [56]. The Black Widow Optimization Algorithm (BWO) draws inspiration from the distinctive mating behavior of black widow spiders. It incorporates a distinct phase known as cannibalism, where individuals with inadequate fitness are eliminated from the population, promoting early convergence [57]. Furthermore, the Battle Royale Optimization (BRO) algorithm is a population-based approach where each individual is symbolized as a soldier or player seeking to navigate towards the safest and most advantageous position to maximize their chances of survival. The algorithm incorporates an interesting mechanism where the death of players results in their departure from local optima, and their subsequent

Table 3.Statistical outcomes for algorithms regarding 30 independent runs in time optimization

Algorithms	*Best*	*Mean*	*Worst*	*Std.*	N_{fe}	*CT (s)*	*percentage error*
SA	546.73	566.60	610.31	19.16	50000	2.41	4.87
BHM	526.14	529.67	533.67	1.68	50000	1.80	0.92
BRO	526.90	529.35	532.67	1.53	50000	4.86	1.07
BWO	530.75	532.01	535.42	1.082	50000	13.85	1.81
AOS	521.30	521.30	521.30	5.24E-08	50000	1.75	0

respawn in random areas facilitates exploration within the search space [58]. Finally, the Black Hole Mechanics (BHM) algorithm consists of two main components: a mathematical kernel and a physical simulation. The mathematical kernel calculates the optimal direction for each variable based on the given cost function. It then transfers the generated data to the identified path. Meanwhile, the physical simulation manages both the exploration and exploitation stages. This simulation is built upon the principles derived from the mechanics of black holes [59].

3- Results and Discussion

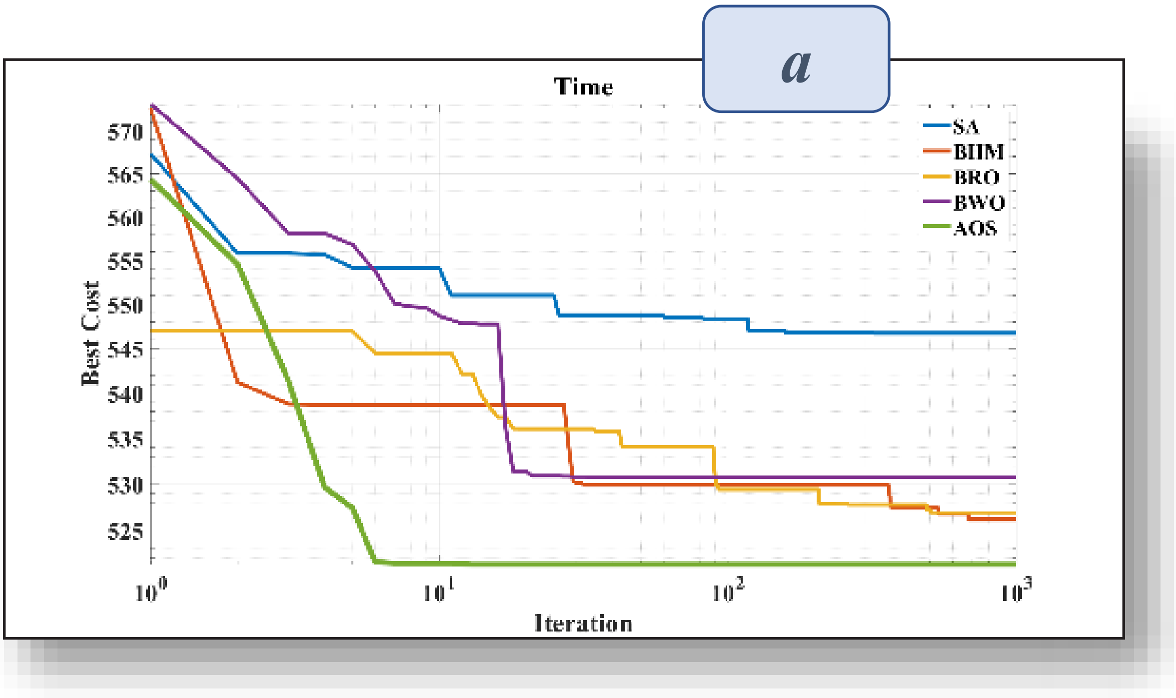
According to Table 1A (Appendix), the basis of this research, there are five resource options for each of the main activities of the Goocham Storage Dam. To complete this table, the insights of several exceptional individuals and specialists in this industry were used. The cost and duration of executive mode NO.1 show the contractor's first proposals, NO.3 is derived from BIM, and NO.5 is the actual cost and time of the project derived from the final construction status. Moreover, two alternative executive modes were explored based on the views of experts in this sector. Undoubtedly, contractors' early proposals are often nonsensical and fantastical to catch employers' attention; hence, most projects fail. Since the majority of contractors do not account for rework, conflicts, non-payment by employers, extreme weather conditions, etc., each activity is randomly assigned three quality indicators with different percentages. The quality of each line is determined by calculating the proportion of the cumulative influence of these three quality modes. Finally, for each action, the risk percentage is determined randomly concerning the opinions of eminent academics and specialists in the area.

According to Table 1(A), the overall project duration based on contractor bids, BIM, and actual duration is 790, 906, and 1489 days, respectively. According to the 2010 project contracts, the overall cost of the project regarding suggestions, BIM, and actual costs is 35,825,939.56, 44,670,213.59, and 48,244,124.9 dollars, respectively. BIM might drastically decrease the cost and time required to construct the Goocham dam by detecting conflicts and facilitating communication and collaboration between stakeholders and the project team. However, based on the BIM and optimization process using metaheuristic algorithms, contractors and organizations might make rational resource-based proposals to employers. As balancing the project's time, cost, quality, and risk within the project's scope has become a crucial criterion for determining a project's success, stakeholders and project teams are more concerned with finding a TCQRT.

The convergence curves for the first phase (time) employing various techniques are shown in Fig. 7(a). It is noted that the AOS method converges to the optimum value of 521.30 days in the first iterations, whereas other algorithms converge more slowly. During this phase of optimization, Fig. 7(b) represents the status of the optimization variables or the genotype space. As shown in the aforementioned figures, the stage's chosen algorithms gravitated toward mode number 1, which stands for the contractor's offerings. The statistics make it clear that, in light of the algorithm's findings, the contractors recommended a perfect and almost ideal period throughout the project's first phase. They did not, however, consider risks and uncertainties. Time overrun, which is seen as a project failure, might be caused by the project's need for reworks and by contractors and owners failing to cooperate and communicate. However, using BIM techniques across the whole life cycle could reduce the overall project execution time, which was reduced by an exponential amount in the Goocham Dam, from 1489 to 906 days.

Table 3 presents the optimization results using different algorithms for the first phase (time). The AOS algorithm is ranked first among meta-heuristic algorithms, while BHM is ranked second; hence, the AOS algorithm balances exploration and exploitation processes. Also, the SA algorithm has the largest error rate, at roughly 4.81 percent, while the BHM algorithm has the lowest error rate, at 0.92 percent. Therefore, the AOS method should be judged suitable for the Goocham dam project's time optimization.

Furthermore, Table 3 presents the statistical findings of the optimal time for the AOS and various optimization strategies based on 30 separate runs. To compare and study algorithms, the value of Nfe (number of function evaluations) is assumed to remain constant throughout all algorithms. Overall, it is noteworthy that the AOS optimization method outperforms



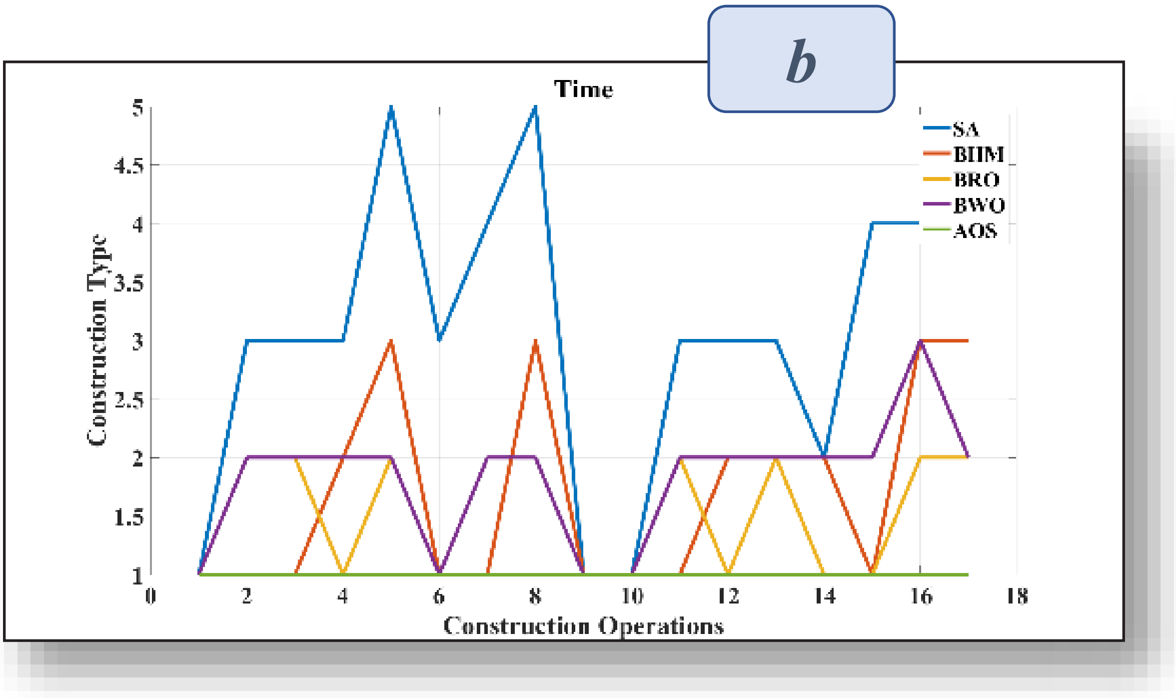


Fig. 7. Best optimization runs of the AOS and different methods' convergence histories for time (a). The genotype of the best AOS and other methods for time optimization runs (b).

Table 4. Statistical findings of algorithms regarding 30 independent runs in cost optimization

Algorithms	*Best*	*Mean*	*Worst*	*Std.*	N_{fe}	*CT (s)*	*Percentage error*
SA	36266567.61	1.49×10^{10}	4.05×10^{11}	1.13×10^{11}	50000	2.45	*1.79*
BHM	36119823.65	2.31×10^{11}	3.75×10^{11}	9.47×10^{11}	50000	1.81	*1.38*
BRO	35999010.06	1.95×10^{11}	3.76×10^{11}	9.01×10^{10}	50000	4.57	*1.04*
BWO	35670839.86	1.47×10^{11}	3.74×10^{11}	1.03×10^{10}	50000	14.05	*0.12*
AOS	35625940.19	2.79×10^{11}	3.69×10^{11}	1.54×10^{11}	50000	1.77	*0*

other algorithms in terms of the Goocham dam's time optimization. It has been shown that the BWO optimization methods' computing time (CT) is much higher than that of other optimization techniques. In contrast, the AOS algorithm provided the lowest CT, and the second-lowest CT among optimization algorithms was given by the BHM algorithms, 1.80 (s).

Regarding the Standard Deviation (Std.), the AOS algorithms had the lowest value of Std., which is almost negligible. Still, the SA algorithm had the maximum weight of Std., indicating that the data are more dispersed. It is clear that the Std values are influenced by the substantial discrepancy between the "best" and "worst" values. The most significant Std value demonstrates that the algorithm was unable to produce a consistent result because it was always trapped in the local results, especially for high-dimensional problems. The Std value measures how close the results obtained from the 30 different trials were to its average value (mean value). The SA optimization algorithms computed the maximum worst value for the worst cost determined by algorithms, showing the SA algorithm's uncertainty in a single run.

Since the non-optimized BIM-based time of the Ghocham dam's construction project is 690.13 days which is the summation of the times for different activities in Table 1A, the optimized BIM scheme by AOS is capable of providing a total time of 521.30 days which is 24% lower than the non-optimized procedure.

The convergence curves for the second phase (cost) employing various techniques are shown in Fig. 8(a). It has been noted that the AOS method converges to the optimum value of 35625940.19 $ rapidly in the first iterations, while other algorithms converge more slowly. The genotype space throughout this phase's optimization procedure is described in Fig. 8(b). Similar to the first phase, the contractors had almost enough surveying and estimating done at the beginning of the project. However, when conflicts and reworks grew, a lack of efficient cost and budget management and the waste of materials might cause a cost overrun. In terms of BIM, it tremendously dropped the project's cost from 48,244,124 $ to 44,670,213 $, a 7.40 % reduction.

The optimization outcomes for the second phase (cost) utilizing various techniques are shown in Table 4. The percentage of changes or rate of error relative to the best response provided by the best algorithms—in this case, the AOS—is shown in the current table. One of the most important characteristics of meta-heuristic algorithms, a correct balance between the phases of exploration and exploitation, is provided by the AOS algorithm. When compared to other experimental algorithms, particularly SA, the aforementioned method may provide exceptional results. In terms of results, the SA optimization method fails to decrease the cost of the Goocham dam. Additionally, the SA algorithm is associated with the largest error rate (1.79%), while the AOS algorithm is associated with the lowest error percentage.

The statistical findings of the optimal cost of the Goocham dam for various optimization techniques based on 30 separate runs are shown in Table 4. Overall, the second phase objective function value provided by the BWO algorithm was the best. The BWO optimization method required more time to compute than the other algorithms (14.05 sec), similar to the first phase, and was followed by the BWO optimization algorithm with roughly 4.57 seconds (s). In contrast, the AOS algorithm showed the superior and lowest value of CT in all optimization techniques, recorded at only 1.77. (s). The SA optimization methods computed the worst value with the greatest worst value, indicating that they are not suitable algorithms for a single run of cost optimization. The BRO optimization algorithm's Std, on the other hand, shows how near the outcomes from the 30 separate runs are to its mean value at its lowest value.

Regarding the fact that the non-optimized BIM-based cost of the Ghocham dam's construction project is 44,670,213 $ which is the summation of the times for different activities in Table 1A, the optimized BIM scheme by AOS is capable of providing a total cost of 35625940.19 $ which is 20% lower than the non-optimized procedure.

The convergence curves for the third phase (quality) employing various techniques are shown in Fig. 9(a). In the first iterations, it is shown that the BWO algorithm converges swiftly to the optimum value of 79.24, followed by the

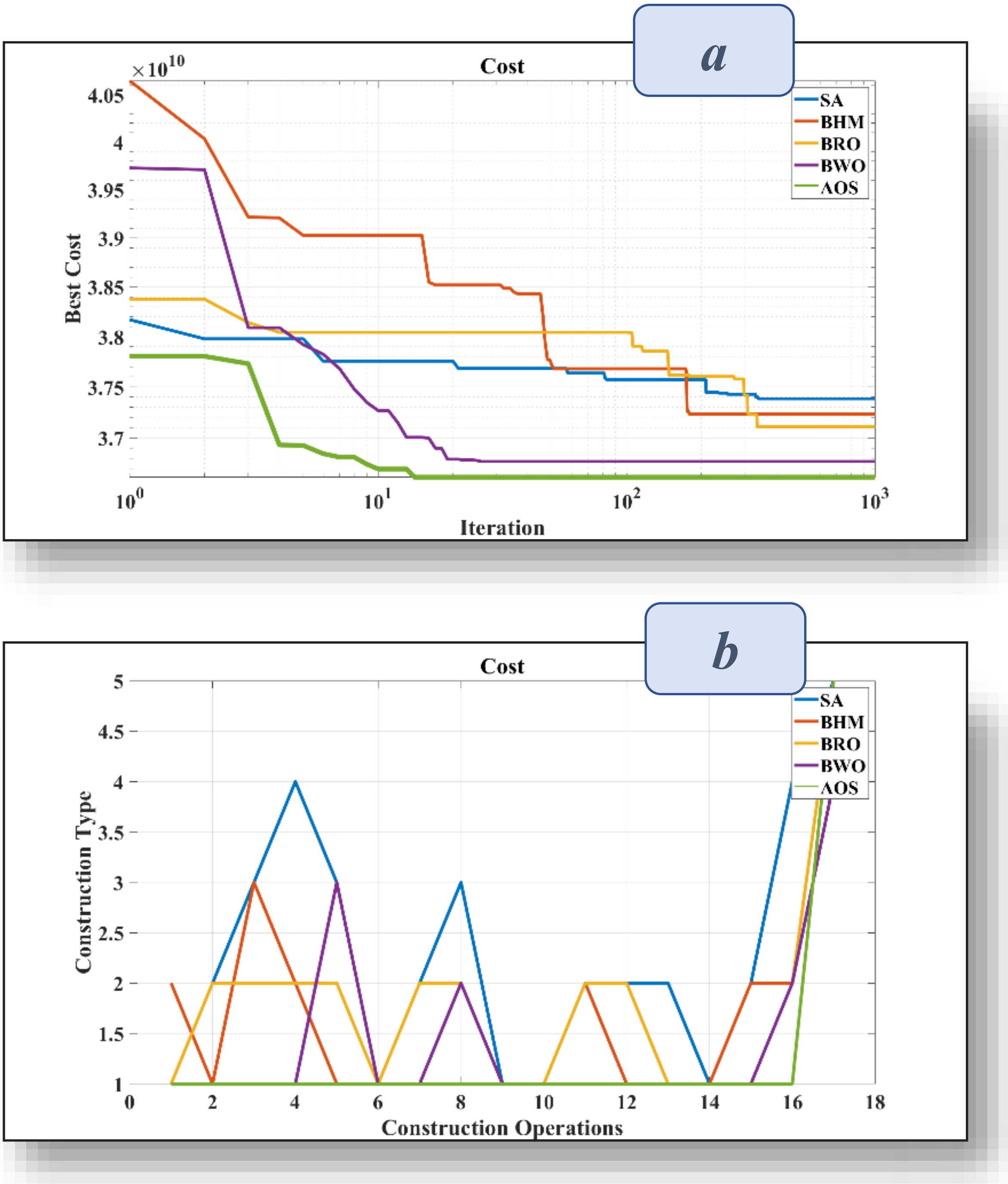


Fig. 8. Best optimization runs of the AOS and different methods' convergence histories for cost (a). The genotype of the best AOS and other methods for cost optimization runs (b).

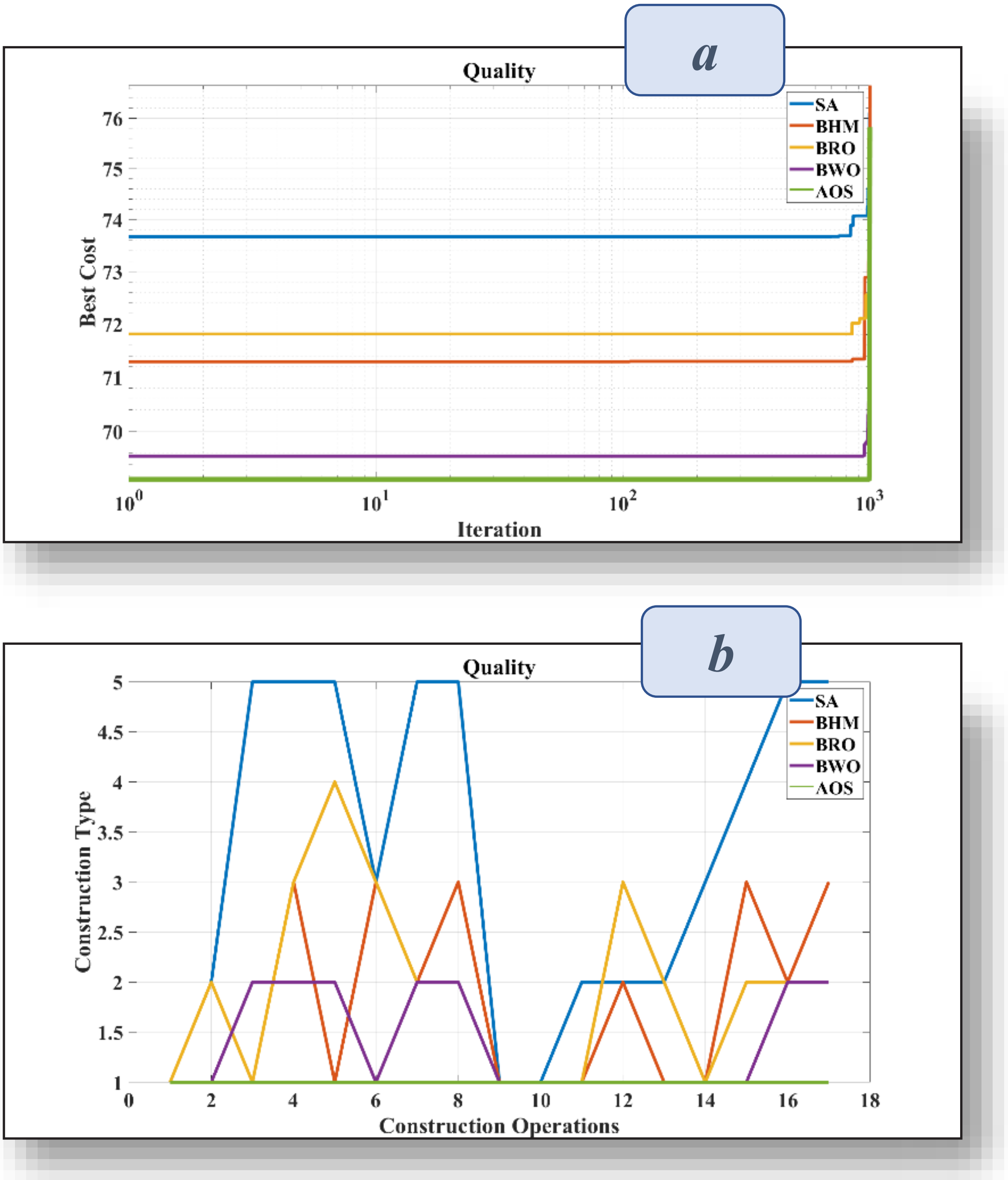


Fig. 9. Best optimization runs of the AOS and different methods' convergence histories for quality (a). The genotype of the best AOS and other methods for quality optimization runs (b).

Table 5. Statistical findings for algorithms concerning 30 independent runs in quality optimization.

Algorithms	*Best*	*Mean*	*Worst*	*Std.*	N_{fe}	*CT (s)*	*Percentage error*
SA	79.03	77.10	76.10	0.78	50000	2.46	0.26
BHM	78.29	77.60	76.65	0.35	50000	1.97	1.19
BRO	79.23	76.01	73.49	1.40	50000	4.69	0.01
BWO	79.24	75.39	73.78	1.24	50000	14.35	0
AOS	75.81	74.83	73.84	0.00275	50000	1.68	4.32

BRO method (79.23). In comparison, some algorithms' convergence rates are slower. The quality values that the BHM and BRO optimization algorithms provide, nevertheless, are quite competitive. The genotype space throughout the third phase's optimization procedure is shown in Fig. 9(b). It is clear that using BIM for dam construction management may provide enterprises with possible value.

Table 5 displays the outcomes of optimization for the third phase (quality) utilizing various techniques. The proportion of alterations or errors to the best answer supplied by the best algorithms is shown in this table. However, the BWO algorithm outperforms other metaheuristic algorithms, with a score of 79.24, followed by the BRO optimization method. Furthermore, the SA algorithm is responsible for the lowest Std of about 0.002, while the AOS algorithm is responsible for the lowest error of 1.09%.

Based on 30 independent runs, Table 5 presents the statistical findings of the optimal quality of the Goocham dam for various optimization strategies. Overall, the BWO and BRO optimization algorithms provided the highest objective function value for the third phase of the Goocham dam construction. Additionally, compared to the other methods, the BWO optimization approach required greater computing time, lasting around 14.35 seconds (s). The AOS optimization algorithm's Std, on the other hand, shows how near the outcomes from the 30 separate runs are to their mean value at their lowest value. In the study, the BRO optimization method was unable to provide a reliable result. Overall, based on the outcomes, the BWO optimization methods showed a satisfactory performance in the Goocham dam's quality optimization.

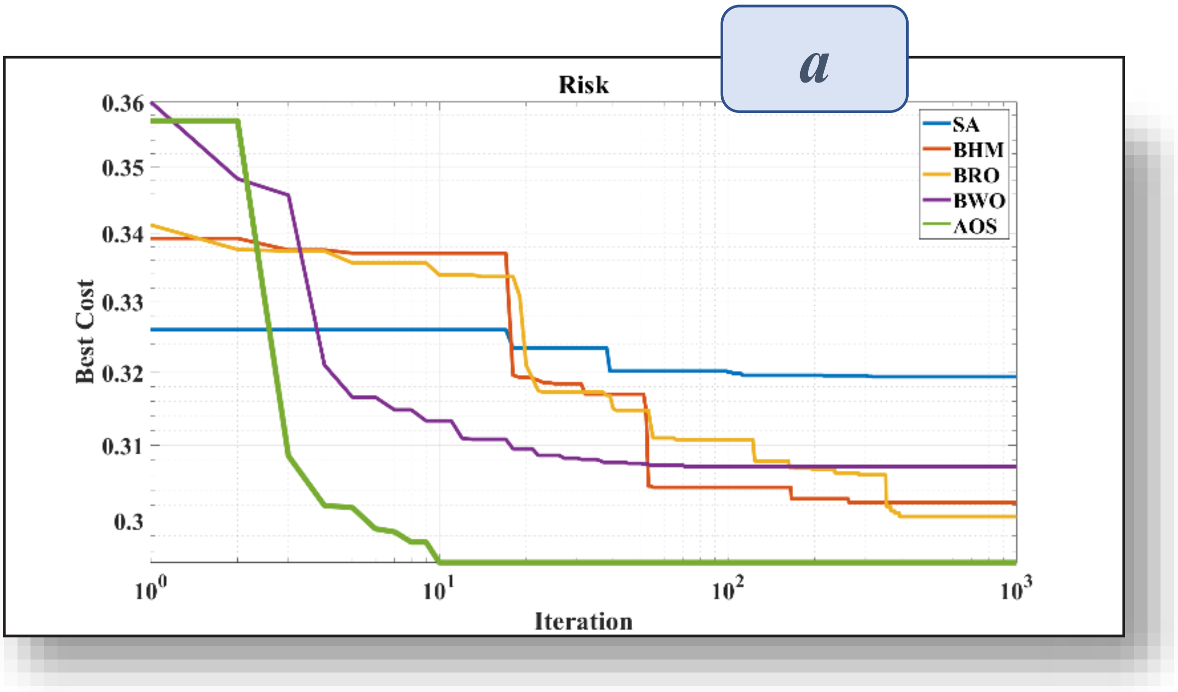
The convergence curves for the fourth phase (risk) employing various techniques are shown in Fig. 10(a). In the first iterations, the AOS algorithm is shown to swiftly converge to the optimum value of 0.29. In comparison, some algorithms' convergence rates are slower. The genotype space throughout the risk phase optimization procedure is shown in Fig. 10(b).

The optimization outcomes for the fourth phase (risk) using various techniques are shown in Table 6. The AOS algorithm, the best algorithm, reports its proportion of alterations or errors to the best solution in this table. Additionally, the SA algorithm is associated with the most error, which is around 8.43 percentage points, and the BRO algorithm is associated with the lowest error, which is 2.02 percent.

Based on 30 independent runs, Table 6 presents the statistical findings for the Goocham dam's optimal risk for several optimization techniques. For the fourth phase of the Goocham dam, the AOS optimization method provided the best objective function value overall. The SA optimization methods delivered the poorest value, indicating their low dependability for a single trial run of risk optimization. Despite taking roughly 13.04 (s) longer to compute than the other algorithms, the BWO optimization method had the lowest risk value when compared to the SA optimization strategy. However, the AOS algorithm's CT is 1.47, higher than SA's.

The Std, which measures how closely the outcomes from the 30 separate runs match their mean value, was also produced using the AOS optimization method with the lowest value. In striking contrast, the SA optimization algorithm was unable to provide a reliable analytical result owing to the larger value of Std than other methods. However, based on the outcomes, the AOS optimization method- played a crucial part in the Goocham Dam's risk optimization.

The convergence curves for the fifth phase (all) employing various techniques are shown in Fig. 11(a). In the first iterations, it is shown that the AOS algorithm could fast converge to the optimum value of 1.92. On the other hand, some algorithms' convergence rates are slower. The current state of the genotype space or optimization variables during this phase is shown in Fig. 11(b). As can be observed, the algorithms used for this phase tended to favor the first mode, which reflects the contractor's bids, over other executive modes, such as modes number 3 and 5, which have lower values in the majority of situations. The algorithms also tended to favor modes 2 and 4 in certain circumstances, which necessitates paying more attention to the interpolation procedure.



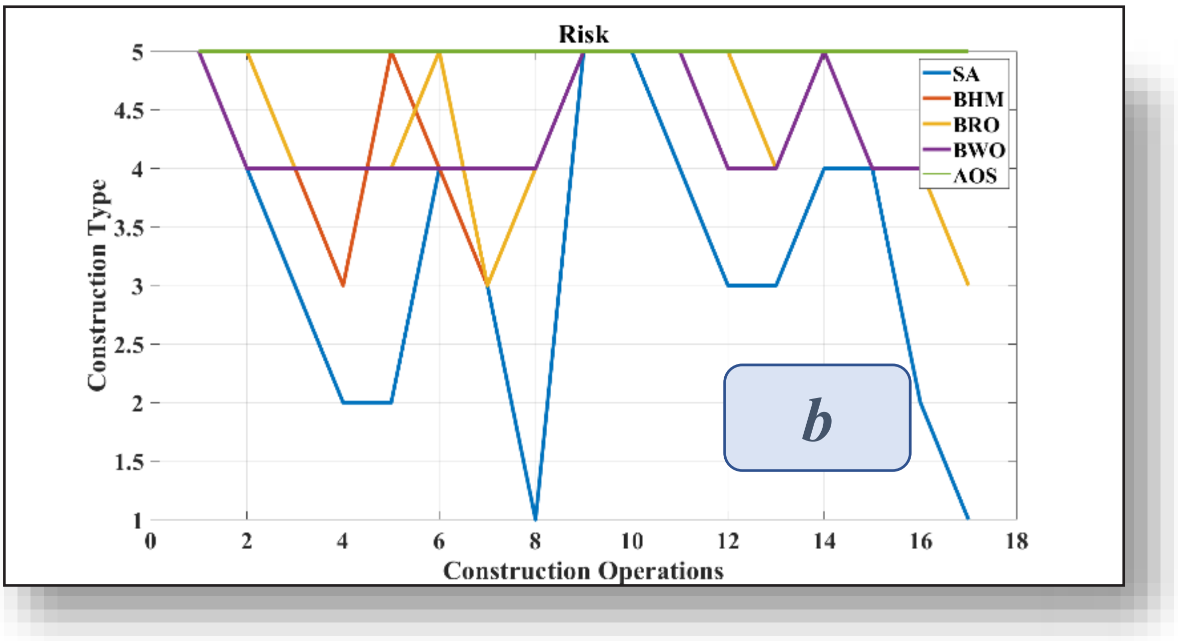


Fig. 10. Best optimization runs of the AOS and different methods' convergence histories for risk (a). The genotype of the best AOS and other methods for risk optimization runs (b).

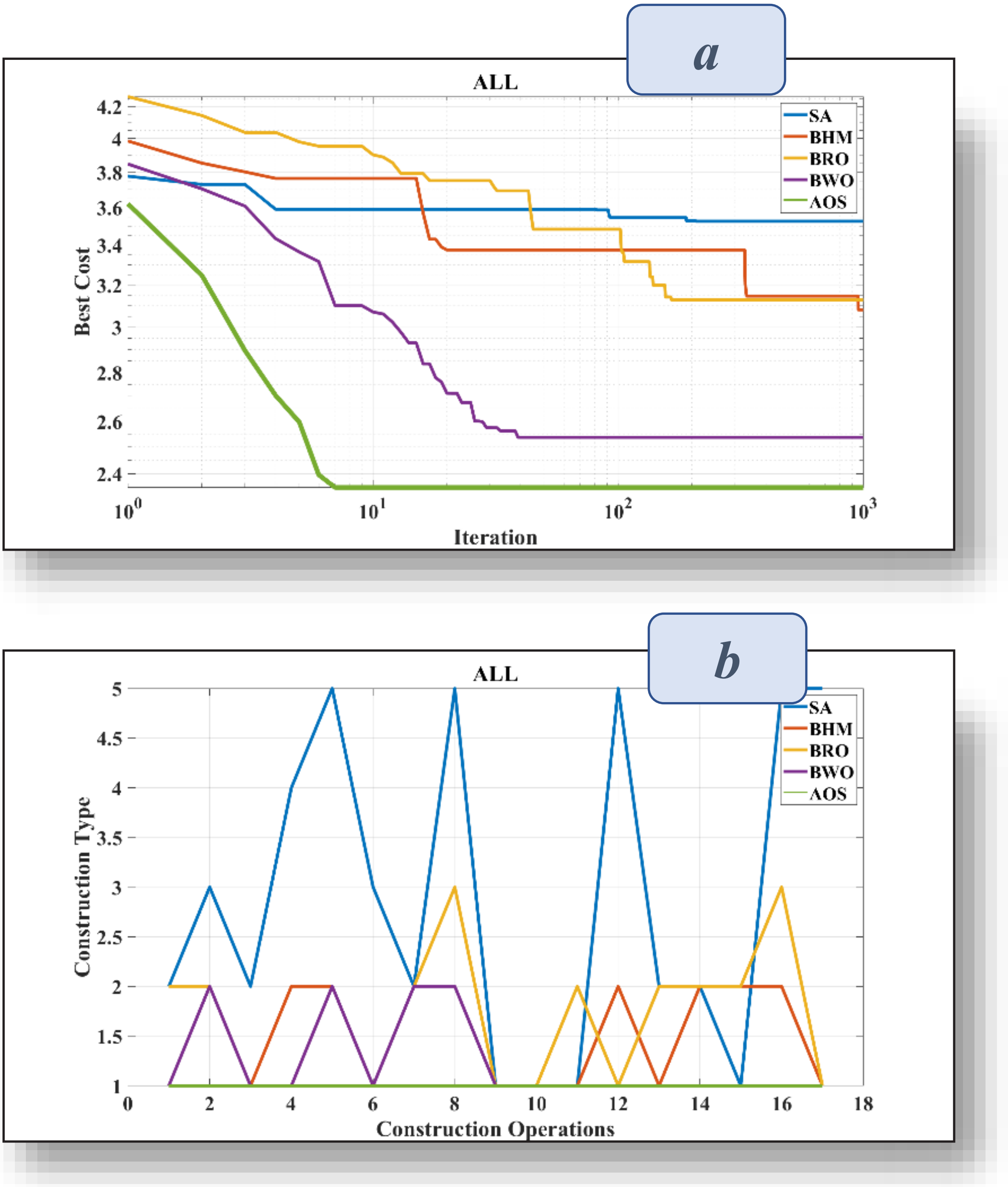


Fig. 11. Best optimization runs of the AOS and different methods' convergence histories for all (a). The genotype of the best AOS and other methods for all optimization runs (b).

Table 6. Statistical outcomes for algorithms based on 30 independent runs in risk optimization

Algorithms	*Best*	*Mean*	*Worst*	*Std.*	N_{fe}	*CT (s)*	*Percentage error*
SA	0.3194	0.3436	0.3996	0.0221	50000	2.46	8.43
BHM	0.3023	0.3051	0.3100	0.0019	50000	1.92	2.65
BRO	0.3005	0.3060	0.3112	0.0027	50000	4.33	2.02
BWO	0.3071	0.3082	0.3103	0.0008	50000	13.04	4.27
AOS	0.2945	0.2945	0.2945	3.22E-10	50000	1.67	0

Table 7. Statistical findings for algorithms concerning 30 independent runs in all optimization

Algorithms	*Best*	*Mean*	*Worst*	*Std.*	N_{fe}	*CT (s)*	*Percentage error*
SA	3.52	4.03	4.48	0.2517	50000	2.43	50.01
BHM	3.08	3.20	3.27	0.0406	50000	2.08	31.09
BRO	3.12	3.25	3.38	0.0581	50000	4.56	33.09
BWO	2.53	2.64	3.03	0.0910	50000	12.56	7.93
AOS	2.35	2.35	2.35	4.44089E-16	50000	1.57	0

The optimization outcomes for each method for the fifth phase are shown in Table 7. The best algorithms—in this phase, the GA algorithm—report the percentage of changes or rate of the error to the optimal solution. As a result, the GA algorithm may be regarded as the best method for addressing TCQRT issues in the more complicated hydropower project. Additionally, the SA algorithm has the largest error rate, at 83.14 percent. The TSO algorithm has the lowest error, with a percentage error of 22.08214.

The Time-Cost-Quality-Risk Trade-off of the Goocham dam using the AOS algorithm and other optimization methods is shown statistically in Table 7 below, based on 30 separate runs. All things considered, the objective function for the fifth phase of the Goocham dam was best served by the AOS optimization algorithm, meaning that the AOS algorithm yielded adequate results for the TCQRT of the Goocham dam. The SA optimization methods returned the poorest result, demonstrating their low dependability after only one try at all optimization. The BWO optimization algorithm has the longest CT of all the steps, at about 12.57 (s). However, the AOS algorithm's CT is 1.54 times higher than SA's.

The Std, which measures how closely the outcomes from the 30 separate runs match their mean value, was also produced using the AOS optimization method with the lowest value. However, the SA optimization method was unable to provide a consistent outcome in the study due to the larger value of Std than other algorithms. But according to the findings, only the AOS optimization method effectively supported the TCQRT in the Goocham dam.

3- 1- Optimum Solutions

In the pursuit of constructing the Goocham Storage Dam, a critical infrastructure project, the need for optimizing the project's time, cost, quality, and risk has emerged as a crucial criterion for success. Based on the insights derived from contractors' proposals, Building Information Modeling (BIM) techniques, and the actual project execution, it is evident that there is a considerable disparity in terms of duration and cost. While contractors' initial proposals often lack practicality and fail to account for various factors, such as rework, conflicts, and extreme weather conditions, BIM has shown promising potential in reducing costs and streamlining communication and collaboration among stakeholders. To bridge the gap between contractors' offerings and the actual execution, it becomes imperative to explore rational resource-based proposals and incorporate effective risk management strategies. By leveraging these optimization solutions, along with enhanced collaboration and continuous monitoring, the construction process for the Goocham Storage Dam can be significantly improved, leading to a successful and efficient project outcome. The following are the optimum solutions regarding infrastructure construction projects:

1.Utilize BIM (Building Information Modeling): BIM is a powerful tool for streamlining the construction process. It allows stakeholders to create a digital representation of the project, including its physical and functional characteristics. By implementing BIM techniques across the entire project lifecycle, you can benefit from improved coordination, clash detection, and visualization, which can significantly reduce conflicts and enhance communication among the project team. Additionally, BIM can facilitate the collaboration of multiple disciplines, such as architects, engineers, and contractors, leading to better decision-making and more efficient workflows. By leveraging BIM, you have already achieved a reduction in the project's execution time from 1489 to 906 days, highlighting its effectiveness in expediting construction.

2.Consider rational resource-based proposals: In the optimization process, metaheuristic algorithms can be employed to generate rational resource-based proposals. These algorithms use computational techniques inspired by natural phenomena, such as genetic algorithms or simulated annealing, to search for optimal solutions. By incorporating the insights derived from BIM and employing metaheuristic algorithms, contractors and organizations can propose resource plans that are more realistic, efficient, and aligned with the project's goals. This approach helps balance the project's time, cost, quality, and risk factors, leading to improved project outcomes.

3.Incorporate risk management: While risk percentages have been determined randomly based on expert opinions, it is essential to conduct a comprehensive risk assessment to identify specific risks associated with each activity. This assessment should consider factors such as rework, conflicts, non-payment by employers, extreme weather conditions, and other potential sources of uncertainty. Once the risks are identified, develop a robust risk management strategy that includes risk mitigation plans and contingency measures. This proactive approach will enable you to minimize the impact of risks, optimize resource allocation, and ensure the project stays on track.

4.Enhance collaboration and communication: Time overrun and project failures can often be traced back to a lack of cooperation and communication among contractors, owners, and other stakeholders. To address this, emphasize effective collaboration and communication channels throughout the project lifecycle. Encourage regular project meetings, utilize collaborative software platforms, and establish clear lines of communication to foster a collaborative environment. Additionally, promotes transparency and information sharing to ensure that all stakeholders have access to the necessary project data and can make informed decisions. By fostering strong collaboration and communication, you can prevent delays, resolve issues promptly, and keep all parties aligned toward project success.

5.Continuously monitor and evaluate: Regular monitoring and evaluation of the project's progress, cost, and quality indicators are crucial for identifying any deviations from the plan. Implement a robust monitoring system that tracks key performance metrics, such as project milestones, resource utilization, and quality benchmarks. Compare the actual project performance against the established baselines and identify areas that require attention or improvement. This proactive approach allows you to take timely corrective actions, address issues promptly, and maintain project success.

The efficiency and effectiveness of the construction process for the Goocham Storage Dam project can be enhanced by implementing these solutions. However, it should be noted that these recommendations are based on the information provided.

Since the optimization procedure in each algorithm provided a globe best solution candidate as the best agent thah satisfies the considered objective function adequately, this solution should be verified using the table of activities which have been done in this project at the end of each optimization process. This validation was conducted by using the design variables related to the global best solution in each algorithm so the results of the optimization process have been verified by finding the related activities in the table and finding the objective function utilizing the mentioned formulas.

4- CONCLUSION

The gathered results show that project management is practicable when used to plan, direct, and manage resources to achieve specific goals in other development projects while taking time, cost, quality, and risk indicators into account. This research uses the Goocham dam in Iran as a case study to examine the usage of BIM, the Atomic Orbital Search (AOS) algorithm, and other alternative metaheuristic algorithms in managing the construction of dams. A TCQR trade-off was then examined. The findings clearly show that, although not offering the best time and cost, the BIM implementation method may reduce the time and cost of dam construction projects. The BIM technique may also be used by the project team and contractors to ensure that their dam projects are of the highest possible quality. These findings demonstrate that the AOS optimization algorithms have produced more suitable optimum solutions, with the following broad conclusions:

I.There was a cost and time decrease of 7% and 40%, respectively, as a result of the application of BIM in the construction management of the Goocham dam.

II. When compared to the BIM process and the actual execution time of the Goocham dam project, the application of the AOS optimization algorithms shortens the project's execution time and cost by around 24% and 20%, respectively. In addition, when compared to other algorithms, the AOS optimization method had the lowest computing time for time optimization.

III. The AOS algorithm performs the best in terms of lowering project expenses, while other algorithms charge higher prices and are thus less cost-effective. The best and shortest computing time (CT), accounting for 1.79 seconds was provided by the AOS optimization technique.

IV. The only algorithms that perform optimally in the third phase (quality) are BWO and BRO. The AOS algorithm computed the lowest quality, unlike other algorithms that perform well.

V. Only the AOS optimization method offered the lowest risk index, showing that it performed well in Goocham dam risk optimization.

VI. Of all the phases, the BWO optimization technique had the longest computing time (CT).

Only the AOS algorithm in the TCQRT quickly converges to the ideal value in the first iterations. The other algorithms' rates of convergence, in comparison, are slower.

VII. Future research should concentrate on evaluating and contrasting the performance of various innovative metaheuristic optimization algorithms with conventional algorithms like GAs. Additionally, they may evaluate how well the metaheuristic algorithms utilized in this work perform in other infrastructure projects when it comes to maximizing the survival pyramid's component efficiency. Finally, future research works can consider the following fields:

- Machine Learning for Predictive Analytics: ML algorithms can be utilized to analyze historical project data and patterns, enabling the development of predictive models for various aspects of construction projects. This can include predicting project durations, identifying potential risks, optimizing resource allocation, and estimating costs. By leveraging ML techniques, construction managers can make more accurate forecasts and proactive decisions.
- Virtual Reality for Design Visualization and Stakeholder Collaboration: VR technology can be leveraged to create immersive virtual environments that allow stakeholders to visualize and experience construction designs before they are built. This can facilitate better communication, collaboration, and decision-making among project teams, clients, and other stakeholders. VR simulations can also be used for safety training and identifying potential hazards in construction sites.
- Augmented Reality for On-site Construction Assistance: AR applications can provide real-time, context-aware information and guidance to construction workers on-site. By overlaying digital information onto the physical environment, AR can assist with tasks such as accurate positioning of building components, providing step-by-step instructions, and displaying relevant project data. This technology can enhance worker productivity, reduce errors, and improve overall construction quality.

Conflict of Interests

The authors have declared no conflict of interest.

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