

## RESEARCH ARTICLE

# AEHO: Apriori-Based Optimized Model for Building Construction to Time-Cost Tradeoff Modeling

**RAKESH GUPTA**  **AND MANOJ KUMAR TRIVEDI**

Department of Civil Engineering, MITS, Gwalior, Madhya Pradesh 474005, India

Corresponding author: Rakesh Gupta (rakeshgupta7sept@gmail.com)

**ABSTRACT** Time and cost are the two most crucial aspects to consider in planning any building project. The project's overall objective is to complete the projects on schedule, under cost, and to meet other project goals. In reality, construction managers have a demanding job that regularly monitors progress, evaluates goals, and takes necessary steps. Optimization is a deliberate attempt to increase profit margins and get the best outcomes under given conditions. Finding optimal planning and good administration is required for the project to be completed on time. There are several optimizing tools and strategies available. Maximizing the performance of the various approaches utilized at one point during the construction project might not be advantageous if the strategies applied do not increase efficiency. In this work, a model is developed using an Apriori-based swarm intelligence method, with the non-dominated solutions to the separation of Elephant Herding Optimization technique, named the AEHO model. This modeling approach follows the Apriori algorithm to generate the rules and then the EHO algorithm that contains population initialization, selection, and fitness evaluation for input parameters. This strategy optimizes construction time, cost, & environmental effects in an actual construction project. For this purpose, a case study of a building construction project has been employed to show the usability of the proposed method. The simulation was done in MATLAB to collect sixty construction projects in Iraq between 2008 and 2016. This study intends to minimize time and cost for construction projects that include repetitive project activities by using the learning curve phenomenon, which reduces time and cost savings when considering the project's start and finish dates. Also, a comparison has been made to the usefulness of the proposed AEHO model in optimal design over the existing PSO model. This comparison is demonstrated by measuring many performance measures and a comparison with an already existing PSO optimization model. In addition, a coefficient value plot is established for visualizing the provided objectives, and an Apriori method is presented for selecting one solution from the Pareto-optimal front that has been generated.

**INDEX TERMS** Apriori algorithm, building information modeling, construction projects, EHO, optimization, time-cost trade-off.

## I. INTRODUCTION

Building & construction industry has increasingly adopted the notion of sustainable architecture. The construction sector is the most powerful globally, contributing significantly to

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the country's GDP (Gross Domestic Product). Building construction is frequently a complicated process in which building operations and resources compete [1]. The construction sector constructs massive infrastructure for the general public to use and adore. However, it is the leading source of pollution and depletion of non-renewable energy supplies. But, the economy of every country, including India's, is built on the

construction industry. It is time-sensitive and necessitates a large amount of labor, materials, and machinery. It provides job opportunities to the local people. As a result, it contributes to the country's rapid economic growth. Technological revolutions have substantially influenced the construction business. The construction industry is undergoing significant cycle changes daily. Many related sectors, such as the manufacture of construction materials, cement, pipes, sanitary products, tiles, ready mix concrete, and so on, benefit from the rise of the construction industry. In addition, construction is considered a valuable asset that generates revenue for the country, promotes human resources development, and creates more jobs than other industrial sectors. Simulations have been used successfully to understand construction's complex interconnections and inconsistencies [2].

Thus, the design phase of a construction project is becoming essential in establishing how a project's sustainable objectives will be achieved. Given the importance of the construction sector, identifying the primary hurdles to its efficiency is crucial. In many nations, the construction industry has a low level of technology and a skewed relationship between building costs and time delays. Many clients nowadays expect construction performance management to adhere to the agreed-upon budget and produce a final product within the required time.

Time and cost are two major construction factors employed in project planning. The significance of time and cost efficiency in building projects has grown. It is essential to analyze the cost and time of each activity to accomplish strategic planning, from which the overall time & total cost of the project are calculated [3]. But, analyzing every feasible option and determining the ideal building designs based only on simulation is time-consuming and impracticable. Optimization is a deliberate attempt to expand profitability and get the best possible results in given conditions or circumstances [4]. Optimizing the performance of the various approaches utilized at one phase of a construction project may not be advantageous if the approaches employed do not increase efficiency. As a result, it is necessary to follow and execute the approaches at each stage of the construction process based on the information given. The methods and materials utilized in the building are also critical to the effective finishing of the project. It presented a simulation & multiobjective optimization (SO) integrated approach to minimize computational costs [5]. In this sense, the simulations serve as an assessment tool within optimization iterations. Thus, optimization techniques look through many viable strategies, whereas discrete-event simulation (DES) retains the intricate connections of the examined workflow. This optimization will forgo assessing all possibilities and instead pick near-best solutions.

In early operational research, heuristic principles and precise approaches to solving predominated to enhance decision-making in the building and engineering industries. On the other hand, they are not equipped to cope with issues of significant size. In recent years, there has been a spike

in interest in several metaheuristic algorithms derived from biological and animal behavior. Metaheuristics are high-level search frameworks designed for universal usage and may be implemented toward any optimization issue using the proper local dilemma-solving techniques. These metaheuristic algorithms can be thought of as general-purpose search strategies. Standard metaheuristic approaches are analyzed and ranked based on their affiliation with one of the following nine categories: biology-based methods, physics-based methods, social-based methods, music-based methods, chemical-based methods, sport-based methods, mathematics-based methods, swarm-based methods, and hybrid techniques, which are combinations of the categories mentioned above. Evolutionary algorithm, Simulated annealing, genetic algorithm, PSO algorithm, ant colony optimization algorithm, and shuffling frog-leaping are all metaheuristics algorithms. In theory, all optimization algorithms may be used to improve each project's life-related issues; however, the degree to which this is possible will depend on several factors. The ability of metaheuristics to more effectively handle inherently nonlinear, multi-modals, constrained optimization models, discontinuous models, and non-differentiable models is the primary driver behind the decision to emphasize these strategies in construction projects.

The author focused an emphasis on the incorporation of a variety of metaheuristic algorithms as a way to assist in the determination of the best method of operation to utilize while carrying out each stage of the life cycle of a project. Generally, a project's life cycle begins with (1) the initialization of a problem or a concept, which is then preceded by (2) the implementation stage, which may be further subdivided into the preliminary design and comprehensive design, (3) the project management plan, which incorporates aspects such as choosing methods of construction, outsource, resources requirement plan, deciding project assessment methods and able to perform a risk analysis, (4) the implementation stage, which incorporates budget plan, planning, a risk assessment, and a final assessment of the project's success or failure, and Project management (PM) should start as soon as the basic idea for the project is conceived and go on for the whole of the project life cycle in order to guarantee that the project goals will be accomplished in the most effective way possible.

#### A. NEED AND MOTIVATION FOR OPTIMIZATION

Time-cost optimization (TCO) is a procedure that identifies appropriate building operations for accelerating up and decides "by how much" to achieve the highest feasible reduction in time and cost. There are so many limitations that management doesn't know how much each solution will cost or how long it will take. As a result of all these uncertainties, the overall duration & cost of the project may vary significantly. Time (duration) & cost optimization are required since they can reduce the project's duration and overall cost. This time and cost optimization aid in achieving the highest advantage.

Despite different optimization methods and project management tools, several construction projects fail to meet

respective cost and schedule targets. Maximizing the efficiency of the numerous approaches utilized in the building process might not be advantageous if such approaches do not increase efficiency. As a result, following and executing the approaches at each step of the building process is necessary based on the provided information. The methods and materials utilized in the building are also critical to the practical and successful completion of a project. Thus, these two factors motivated the usage of optimization techniques to get optimized construction project delay and cost.

## B. RESEARCH CONTRIBUTIONS

The main contributions of this work are to fulfill desired objectives that comprise:

- Analyzing the time-cost estimate requirements for construction works.
- Identify the research gaps and criteria for construction projects depending on the application area, applicable method, methodologies employed, journals, and published year.
- The research aims to analyze strategies, procedures, and standards for determining the time-cost trade-off of construction projects.
- To evaluate how well the suggested optimization model performs compared to the already used model of optimization approach in estimating the time (duration) for construction projects, it will also calculate the cost.

The rest of this study is separated into sections: Section II examined several relevant works regarding construction projects utilizing various optimization approaches, then identified specific research gaps. Section III describes the research methodology for filling the gap by framing the issue, retrieving data, cost calculation methodologies, and analytical models. Section IV discusses the findings and associated discussion and dissemination techniques, and Section V summarizes the final results and methodologies, limits, and future work.

## II. RELATED WORK

This section deliberates the relevant study of many researchers in building information modeling for Time-Cost Trade-off models using swarm intelligence optimization techniques.

### A. EXISTING BUILDING INFORMATION MODELING METHODOLOGY

The A360 collaboration tool is a platform that delivers a centralized virtual area for storing BIM files, expressing them, & offering real-time comments from any device during the design process of BIM projects. The key point behind this research is to get a new solution to these problems identified by Arevalo *et al.* [6]. The results of a BIM project demonstrated a decrease in waste, which reduced design time.

In this research, Diaz *et al.* [7] focused on applying the BIM methodology to optimize the cost and time of road

projects, generating benefits for both the builder and the public entity that manages a country's budget. The results showed a significant reduction in time and a decrease in the total cost of the evaluated project.

To expedite the effective use of information integration for construction, Shi and Qiankun [8] developed a framework for data integration that was premised on CICS theory & peculiarities of constructing prefabricated buildings. This framework was proposed to speed up the development of comprehensive integration. The structure was then constructed based on a study of Geographic Information System (GIS), Building Information Modeling, Web Application, and components technology. Additionally, discussed the system's operating procedure and the functional modules' applicable principles. The implementation of the system into a real-world scenario brought to the completion of the creation of a BIM integration management system for the steel structure construction project.

In this work, [9] designed a dynamically multiobjective optimization model that depends upon building information modeling for construction site plans. This model provides the most up-to-date information on the construction project through BIM and construction plans. In this model, the influence of the building phase on the layout is presented. The overall cost of transportation and noise pollution levels were chosen as the primary objectives of optimization in this study. The use of multiobjective PSO, also known as MOPSO, is used to find trade-off solutions to strike a balance between the degree of noise pollution & total cost of transportation. The findings presented that dynamic CSLP (Construction Site Layout Plan) reduced transportation costs to 43.45 percent less than those associated layouts. It can significantly reduce the amount of money spent on transportation at the site. In addition, it adds noise pollution mitigation into CSLP to improve the site's sustainability.

In this work, Lin *et al.* [10] investigated how integrating modeling and virtual reality technologies with building information modeling (BIM) may make 3D visualization more successful. According to the statistics, the essential parts of combining a BIM model with a Virtual reality environment are modeling transformation, materials attachments, and light and shadow configurations. When loading the BIM model into a VR context, the faces of the modeling were too excessive for a system to function correctly. Consequently, the BIM model requires modification, either in the form of model reduction or adjustments to the textural components. During the transfer process, the substance of the model can undergo a transformation, which would require a new design in the virtual reality setting. Real-time depiction of light and shadows can potentially harm system performance.

### B. TIME-COST TRADE-OFF (TCT) MODELS

Regarding the construction project management process, the project time can frequently be shortened by speeding up parts of the project's operations in exchange for an increased cost. It is known as the TCT dilemma, which has received

significant attention in this research concerning project management. TCT considerations, on the other hand, are notoriously tricky and need planners to pick the most appropriate resources for each project assignment. These resources might include the number of workers, the equipment, the procedures, and the technology. Obtaining optimum decisions is challenging and time-consuming due to the many potential combinations involved. Combinatorial optimization issues fall under this category. In this work, Hegazy [11] and Jalali [12] came up with a workable model for TCT optimization depending on the general idea of Genetic Algorithms (GAs). GAs model, with its comprehensive optimizing search, seeks to decrease the entire project cost like a fitness function.

Additionally, the model considers any project-specific limits on time or cost. The concept has been developed into a VBA macro application so it can use its benefits to its full potential. It integrates the manual processes of TCT analysis with the automated processes of conventional managing resources. Numerous experiments are carried out to illustrate the advantages of the new TCT model, and the specifics of the model itself are discussed. The advancements made throughout this study give instructions for creating and putting into practice real-world applications of GA in the field of civil engineering.

In this paper, [13] applied the fuzzy logic theory to consider the factors that may impact the overall amount of time and a building project's direct and indirect costs. An application of a multiobjective optimization technique built on GA is made to give a trade-off between the amount of time needed for implementation & overall cost. By using  $\alpha$ -cuts techniques based on fuzzy logic theory, the project leader can also have a variety of non-dominated solutions or Pareto solutions, each of which is determined by their assessment of tolerated risk. The suggested model guides the decider to pick the optimal Pareto front solution utilizing an acceptable value of  $\alpha$ -cut.

In the context of a building construction project, time, quality, and money are three critical objectives that compete with one another. In this work, Hu and He [14] proposed a model for optimizing time, cost, & quality that allows supervisors to optimize several objectives. The model is based on the project decomposition structure technique, which categorizes the available resources for a construction project into tasks, and then further categorizes those resources into construction personnel, materials, equipment, and administrative. The resources employed in particular construction activity would eventually affect construction time, cost, & quality. Finally, a sophisticated TCQT model will be constructed, relying on correlation coefficients between various building activities. Within the framework of the model is an implementation of a genetic algorithm tool to resolve extensive nonlinear time-cost-quality issues. The construction of the three-level home is used as an example and assists in making a successful decision regarding construction practices. The standard cost-time assumption is shown to be fair by the computationally expensive curves in the visual graphics included in the case

study. These curves also illustrate that this TCQ trade-off model is elegant.

The multiobjective TCTP model developed in this research is driven by ACOA approaches. Kuang and Xiong [15] set out to study the usefulness of an alternate smart search strategy in time-cost optimization. The suggested model determines the best solutions and identifies the Pareto front by combining the modified adaptive weight approach (MAWA). A software program implements the notion of the ACOA-based based multiobjective TCTP model, and a testing phase is run. The findings demonstrate that the ACOA is an effective method for finding optimal results in time-cost trade-off issues. The model might help decision-makers simultaneously arrive at an ideal project length and cost.

In this research, Li *et al.* [16] presented a novel predicting approach based on SVM in light of the scarcity of building safety data and the difficulties in collecting it. They used the SVM to examine specific casualty data and build a forecasting model. In comparison to artificial neural networks, the results showed that the method had reduced simulation error and higher predicting precision (Backpropagation, BP). As a consequence, it has several uses in the field.

In this study, Huang *et al.* [17] considered the project quality and the standard method of calculating the time-cost trade-off when making project expedition decisions. It built the optimal solution on the concept of multiple attribute utility function theory and merged time quality and cost schedule. It is also easy to understand. The selection technique & global pheromone were tuned to demonstrate the benefits of avoiding local optimums, fast convergence, & high dependability. The Cost-Quality-Time-Security model, the fundamental notion of the PSO Algorithm, integer programming and the construction of multiple-attribute utility functions were presented in this work by Liu *et al.* [18].

The problem of time-cost trade-off analysis is a tough assignment since both the activity length and the cost have an element of uncertainty. This uncertainty element should be considered while carrying out schedule optimization. In a paper [19], Suliman *et al.* suggested a hybrid method that coupled SA (Simulated Annealing) algorithms with fuzzy logic to handle the time-cost trade-off dilemma that arises with building projects when there is an element of uncertainty. The use of fuzzy set theory was used to describe the behavior of administrators in forecasting the amount of time and expense associated with a particular alternative inside an activity. To find the time-cost profiles that were best for the various risks that were being taken, SA was utilized as a search technique.

In this paper, El-Kholy [20] provided a linear programming model as a potential method of resolving the time-cost trade-off issue. It considered variations in the number of funds and ambiguity over the period simultaneously. It used two challenges to illustrate how well the model works and its improvements. To solve the two problems, they used four hypothetical situations to assess the impact of taking into account fund fluctuation and temporal uncertainty in various



ways. The findings, with a confidence level of 95 percent, indicate that a 10 percent variability in funding will increase the actual cost by about 20 percent for the pre-specified project time frame. Also, ignoring a ten percent variation in time, as opposed to accounting for it, would result in an increase in length of around 16.5 percent to thirty percent at an actual cost established in advance. In addition, a 10% variance in both the sum of funds and the amount of time can increase actual costs by much more than 25% for a specific project deadline.

No matter how well you plan or estimate, you won't be able to avoid risks and uncertainties. For this reason, a model capable of representing uncertainty in real life is required to address time-cost trade-off problems. In this part, Al-Zarrad and Fonseca [21] applied fuzzy logic to consider the factors that may impact the length and expense of the project by employing the TDABC (time-driven activity-based costing) optimization approach. The provided model has the potential to solve the time-cost trade-off dilemma while also considering the unpredictability of the project's length and cost. It could make it easier to establish a more dependable timetable and reduce the likelihood of projects cost overruns in construction or falling behind the timeline.

There has been an increase in the number of studies conducted on optimizing construction management projects for both time and money. Eirgash *et al.* [22] applied an optimization engine built on a genetic algorithm to carry out such an optimization procedure for the sake of this study. The impacts of some variables in GA have also been researched to establish the variability of the optimum solution. This variability offers strategic decision-makers flexibility to make effective time-cost decision-making from the various possible configurations of time-cost alternative solutions. According to the findings, the optimization engine used functions admirably for the optimization challenges examined.

In this study, the goal of Wasana *et al.* [23] wanted to evaluate and contrast the results of building projects that used PFC and TOC. It was the purpose of this particular investigation. This study used four case studies and collected data using semi-structured interviewing and document analysis to accomplish the research objective. The research outcomes indicated that the performance of selected PFC projects was inferior to that of TOC regarding duration, quality, and cost performance. Many obstacles caused this discrepancy.

An integer linear programming problem was used by San Cristobal Mateo [24] to make a decision-CPM network in this study to reach the overall optimum in a road-building project that covers time, cost, and safety. When employing this model, one may consider the impacts of utilizing several methodologies to accomplish tasks.

### C. SWARM INTELLIGENCE OBJECTIVES TRADE-OFF MODEL

SI allows simple agents with minimal capacities to develop clever solutions for high-dimensional and challenging

problems; hence, Swarm intelligence has lately originated in various areas [25].

The classical approach to multiobjective problem-solving focuses on "trial and error," which entails extensive manual design parameters modification and performance assessment depending on on-site observations and analytical & experimental models. Li *et al.* [26] designed a multiobjective optimized platform for discovering the trade-off optimum ventilation system design utilizing the non-dominated Pareto sorting-based PSO (NSPSO) method to simplify the design optimization procedure.

Aside from the time & cost of operations, each resource utilization selection will provide a specific performance quality based on the resources used. The multiobjective Ant Colony Optimisation approach is utilized to optimize the trade-off between such time, cost, and risk dimensions. The optimization algorithm was performed using various parameters, each with a different weightage. Vijayan [27] analyses the trade-off between the factors to determine the overall duration, cost, and risk associated with the project when completed in different combinations of solutions. The strategy can optimize any project's time, cost, & risk by quantifiable metrics. The risk levels may change depending on various circumstances, and the risk values are chosen mainly depending on the project.

A multi-robot system is required for a collaborative construction task to search for randomly dispersed building bricks and impulse such blocks to predetermined places. To solve this issue, Meng and Gan [28] offer a bio-inspired Swarm intelligence-based method for a distributed multi-robot system that combines exploratory search and dynamic task allocation to a collective building.

The purpose of this research was to aid decision-makers in determining the best trade-off solution between construction costs and CO2 emissions. In this paper, [29] investigated the construction project's planning while considering a precise trade-off between TCQ, carbon dioxide emission, & resilience of the design. Sociologist the name of Robert K. Merton is the one who initially proposed the idea of a "reference group." He believed that some members of each community, such as notable heroes or entertainers, affected the members of that society. Liu *et al.* [30] presented a model for optimization using PSO as their solution. This process was accomplished by searching for solutions using particle swarms. Finally, decision-makers could pick the ultimate trade-off solution from such a group of optimum solutions depending on their personal preferences from among the available options.

The efficient control and management of construction costs may be assisted by an accurate construction cost estimation, which has the potential to be successfully realized. Ye [31] introduced a unique construction project of a cost prediction system based on a PS-guided Back propagation neural network and improved BPNN using the PSO technique. PSO approach is utilized to enhance BPNN. It is

possible for such results, particularly the quality, to be obtained and documented using inaccurate or ambiguous data instead of numerically accurate. In this paper, Zhang and Xing [32] found a solution to the fuzzy TCQT (Time, Cost, and Quality, and a fuzzy multiple-attribute utility) issue; a fuzzy multiobjective PSO was presented to assess various methods. The fuzzy multiple-attribute utility technique is included in the PSO process to facilitate the search for TCQT outcomes. The suggested approach is applied, and then analytical studies are used to justify the implementation. An alternate solution-providing approach is anticipated to emerge from the study to solve time-cost-quality trade-off dilemma.

#### D. RESEARCH GAPS

In this section II, various optimization strategies have been discussed, and potential research voids have been uncovered due to such conversations. It is essential to minimize the spending on construction and the time it takes at each step. Project delays and materials are the most significant impact on construction costs. The efficient control and management of construction costs may be assisted by an accurate construction cost estimation, which has the potential to be successfully realized. The time-cost concerns have been analyzed using several different approaches; however, each of these approaches could only optimize a single parameter. In addition, offering a variety of low-cost materials maximizes the project's cost while simultaneously preserving the project's strength. In addition, the findings indicated that the panelized PFC technique, as opposed to the sub-assemblies and element PFC approach, is more likely to result in efficient time and cost performances.

Nevertheless, the advantages that have been highlighted might not be realized in a setting that more closely resembles real life. Additionally, it investigated several mathematical techniques and software-based models for optimization purposes. It may be necessary to aid construction managers in picking just one solution from among the generated Pareto-optimal solutions under the relevance of the solutions. But still, there is an urgent need to optimize the factor. The combination of rule mining in swarm intelligence has not been done yet so that it can improve the project's time-cost trade-off.

A basic technique for dealing with a multiobjective situation is to weigh numerous targets to achieve one target. Unfortunately, appropriately allocating the weights often becomes difficult. A prominent alternate strategy is to produce a complete set of non-dominated alternatives. The great majority of the combinatorial optimization discussed in this study is limited. Alternatives that break restrictions are infeasible and several methods for dealing with unworkable alternatives have been employed. An easy technique is to reject and arbitrarily regenerate a substitute. This strategy, however, may not work for a severely limited situation with a limited number of impracticable alternative solutions. It may be simpler to obtain optimal near to unworkable alternatives

by changing an impracticable one from a practicable one by applying a particular repair approach. In these kinds of instances, the rejecting approach suffers as well. Another technique is the penalty mechanism, which keeps constraints after punishing these. Nevertheless, selecting the appropriate penalty parameters is a challenging and problem-specific task. The parameterless penalty approach was devised to circumvent the requirement to define penalty parameters. Remarkably, this suitable method was not used in any of the works analyzed in this study. The research community on the topics covered in this study seems to be trailing behind in this respect.

However, many meta-heuristic optimization techniques were used for time-cost trade-off analysis in construction projects. But no one approach has been implemented with association rule mining to find correlation among input parameters to know which parameters are affected the time ad cost. The model must be formulated based on reasonable assumptions to bridge the gap between a real-world problem and a formulated model. So, our study presents an Apriori-based EHO for time-cost trade-off optimization to take advantage of both algorithms. Where an apriori algorithm generates the rules on the input parameters, then the EHO approach uses population initialization, clan update, and weaker clan separation. The contribution of this project is to bridge the gaps left by earlier studies. Besides, these number of rules have been generated by Apriori and measure the R-squared coefficient as a quality indicator to fulfill the project's objectives.

### III. RESEARCH METHODOLOGY

This section formulates the problems based on research gaps that are identified in the works of literature with different trade-offs of optimal design. A new proposed model has been introduced to overcome these problems and implemented in this work.

#### A. PROBLEM FORMULATION

The most crucial objective is to complete all of the scheduled tasks of a project on time in the building and construction industry. The customer and the contractor must work together to reduce the time & cost spent on the project. Every construction project must give careful consideration to both the passing of time and the available budget. If the project is not finished on time, even within the allotted time frame, the business might suffer damages. As a result, ensuring that the project is finished within the allotted period is of the utmost significance. The amount of time spent, the amount of cost spent, and the risks involved in delivering the project are among the most critical factors of every project. The proposed model is regarded as one of the most important tools, even more important than the scheduling programs. It can increase the quality of tasks completed in a timely and cost-effective manner in projects. Now, these performance metrics are taken as an objectives-based optimization problem which is formulated in the following way:

The project timing and cost indicators are listed below.

1) CALCULATING THE TOTAL COST

A construction project’s overall cost is intended by adding the costs of each construction activity plus the administrative costs AC (i). As a result, the total cost C is computed following the eq. (1):

$$C = \sum_{i=1}^k (LCost_{(i)} + MCost_{(i)} + ECost_{(i)} + ACost_{(i)}) \tag{1}$$

where,

- $LCost_{(i)}$  = labor costs in constructions activity i
- $MCost_{(i)}$  = materials costs
- $ECost_{(i)}$  = equipment costs
- $ACost_{(i)}$  = administrator costs
- k = total activities of construction.

2) CALCULATION OF THE OVERALL DURATION OF THE CONSTRUCTION PROJECT

The total time length T of construction projects may be computed by employing nodes as activities in acyclic digraph networks.

$$T = \max_{i=1,n} (EST_{(i)} + Dur_{(i)}) \tag{2}$$

$EST(i) = \max_{h=1,i-1} (EST(h) + Dur(h))$ , as well as the earliest start time of an activity i derivative by antecedents, and 1st  $EST(1) = 0$ .

The previous study used a meta-heuristic technique to optimize time & cost via particle swarm optimization. However, the approach has some drawbacks, including difficulty defining internal design parameters, especially for complex problems, the potential for premature convergence and being stuck in local minima, and the inability to solve scattering problems.

Numerous optimization strategies for project plan cost optimization have been developed to reduce the abovementioned drawbacks. The primary purpose of the project TCT analysis is to find the best project length and the corresponding minimum overall project cost time plan. The purpose of this research is to:

- Determines the time duration of the project with cost.
- Half the duration and cost of a project.
- Determine an optimal number of teams & training rates.
- Impact of each skill or activity on others.

The PTCTP model aims to optimize a large-scale construction time-cost problem while providing construction managers with a strategic tool for balancing essential construction materials in a highly competitive environment.

**B. PROPOSED APRIORI-BASED ELEPHANT HERDING OPTIMIZATION (AEHO) SWARM INTELLIGENCE MODEL**

The current study attempts to create an Apriori-based EHO model that can accurately estimate the cost and length of construction work. This research’s prime objective is to integrate and implement a novel method for predicting the time

**TABLE 1. Description of the input factors.**

Factors	Description
C	The substantial volume: The works of concrete include lean concrete, beams, screed concrete, columns, foundation & slabs.
B	The brick volume.
EN	The elevator numbers within constructions.
FT	Footing Type: 1 for the Raft footing & 2 for the Separate form of the footing.
AGF	The ground floor area
TFA	Total floors area
FN	Floors no.
SS	The security of the status: 1 for Safe, 2 for Moderate & 3 for Not safe

and cost of construction works using the EHO algorithm. This proposed model was created using the number of input parameters listed below. Table 1 shows the definitions of the input parameters, and these parameters for building projects are displayed in fig.3.

1) APRIORI ALGORITHM NOTION

The basic idea behind the Apriori technique is to create the candidate sets iteratively, that is, hunt for (k+1) – itemset, by leveraging the frequent K-itemset [33]. It first produces a 1-frequent itemset, then produces a 2-frequent itemset that uses this achieved 1-frequent itemset, and then produces a 3-frequent itemset based on the 2-frequent itemset, etc. until all the frequent patterns have been produced, and after that, finds the association rules based on the frequent itemsets.

**Algorithm 1** Pseudocode of Apriori Algorithm

```

Input: Input parameters dataset
Output: Number of rules for large itemsets
Large1 = {large itemsets of 1-item};
For (i = 2; Largei-1 ≠ ∅; i++) do begin
    Candidatei = Apriori_generate (Largei-1); //Generate new candidate set
    For all transactions, Tr ∈ Dataset do begin
        CandidateTr = subset (Candidates, Tr); // candidate set in Tr
        For all Candidate cand ∈ CandidateTr do
            cand.count++;
        End of for
    Largek = {cand ∈ Candidatei | cand.count ≥ minsupp};
    End of for
End of for
Solution = ∪i Largei;
    
```

The Apriori candidate produces, and the test approach decreases the size of candidate sets in several circumstances. Unfortunately, while mining a massive set of databases, the Apriori algorithm would yield too many candidates for frequent items, requiring the program to check the database repeatedly while looking for frequent patterns. So, it will

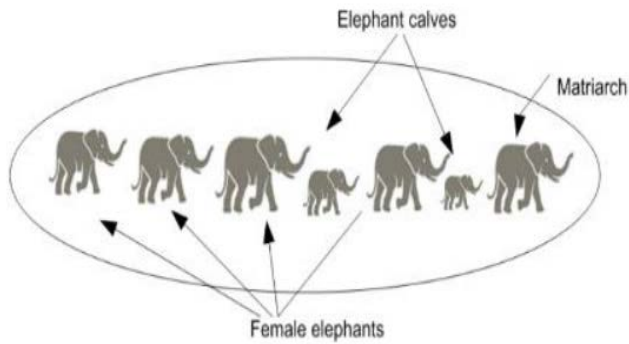


FIGURE 1. Elephants Clan [34].

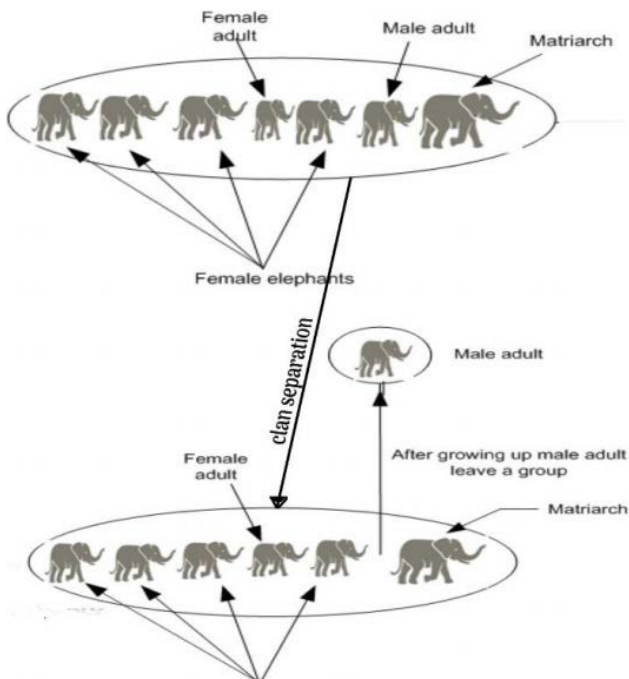


FIGURE 2. Adult (mature) Male Elephant separation [36].

require more resources and time to complete one scan. As a result, it will be expensive.

## 2) ELEPHANT HERDING OPTIMIZATION TECHNIQUE

Elephants are highly sociable animals congregating in groups predominately made up of females and their young. A few elephants form an elephant clan, which the Matriarch commands. A tribe comprises a female and their children or a group of associated females. Male elephants choose to live in isolation and leave their family gathering when they reach adulthood, but female elephants prefer to dwell in family gatherings. The elephants' grouping behavior is considered to develop an optimization strategy in the EHO technique. The technique stimulates the herding behavior of a group of elephants [34], [35]. The following summarises herding behavior:

- Elephant swarms are composed of various sub-swarms known as clans, including calves and females, as seen in Fig. 1.

## Algorithm 2 Pseudocode of EHO Algorithm

### Required variables:

$P_{cl,m}$  = m-th elephant position in clan cl  
 $P_{new,cl,m}$  = m-th new elephant position in clan cl  
 $P_{best,cl}$  = best fittest elephant in clan cl  
 $\alpha \in \{0, 1\}$  = scaling factor  
 $r \in \{0, 1\}$  = influencing factor of matriarch in clan cl  
 $\beta \in \{0, 1\}$  = influencing factor of clan centre on new elephant position  
 $P_{centre,cl}$  = clan centre  
 $P_{worst,cl}$  = worst elephant in cl  
 $P_{UB}$  = upper bound elephant position  
 $P_{LB}$  = lower bound elephant position  
 $random \in \{0, 1\}$  = stochastic distribution  
**Output:** optimal results

### Strategy:

**Step 1. Initialization:** Set counter for generation  $i = 1$ , population initialization, the maximum number of generations Max\_Generation

**Step 2. While  $i < \text{Max\_Generation}$  do**

All elephants are sorted based on their fitness value

**For all**  $cl = 1$  to  $ncl$  (in elephant population for all of clans cl), **do begin** //clan update operator

**For all**  $m = 1$  to  $ncl$  (in clans for all elephants), **do**

Modify  $P_{cl,m}$  and generate  $P_{new,cl,m}$  using

$$P_{new,cl,m} = P_{cl,m} + \alpha (P_{best,cl} - P_{cl,m}) * r$$

if  $P_{cl,m} = P_{best,cl}$  then

modify  $P_{cl,m}$

generate the  $P_{new,cl,m}$  using

$$P_{new,cl,m} = \beta * P_{centre,cl}$$

**end of if**

**end of for m**

**end for cl** // end of clan update operator

**For all**  $cl = 1$  to  $ncl$  (in elephant population for all of clans cl) **do begin** //separation operator

Change the worst elephant in cl using

$$P_{worst,cl} = P_{LB} + (P_{UB} - P_{LB} + 1) * random$$

**the end for cl** // end of separation operator

Assess the population with new modified positions

$i = i + 1$

**Step 3. End of while loop**

- In Fig. 1, each clan is overseen by a matriarch (adult female).
  - When a male calf achieves adulthood in a group, he departs the group, as seen in Fig. 2.
- a) Clan update Operator: The future location of the elephants in the clan  $cl$  may be updated with the help of



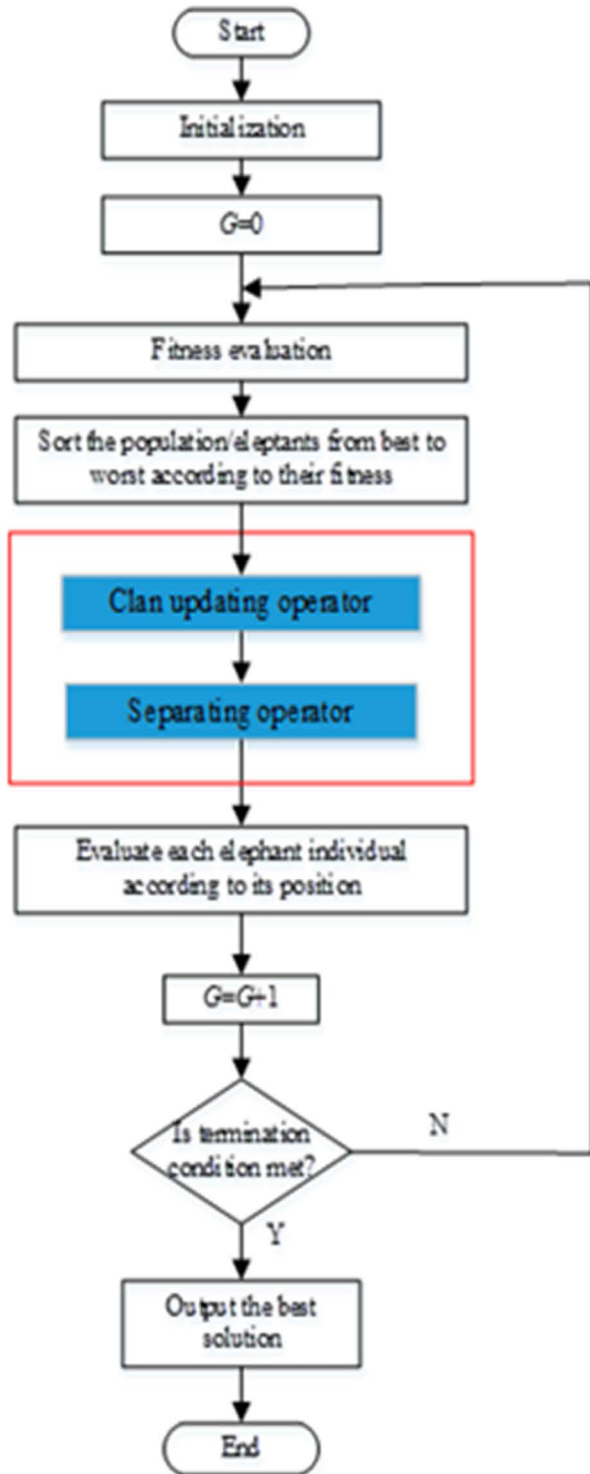


FIGURE 3. Flowchart for basic EHO algorithm.

this updating operator in EHO, which uses an eq. (3).

$$P_{new,cl,m} = P_{cl,m} + \alpha (P_{best,cl} - P_{cl,m}) * r \quad (3)$$

The used parameters in the above equation (3) are defined in algorithm 2.

$$P_{new,cl,m} = \beta * P_{centre,cl} \quad (4)$$

Algorithm 3 Proposed AEHO

Required: Input and Output factors of construction projects, min\_sup, min\_conf

Strategy:

- Step 1. Start
- Step 2. Calculate the statistical parameters of input factors
- Step 3. Divide these project data into two parts, one for building the model and another for validation
- Step 4. Apply Apriori association rule mining to generate the rule of different input factors
- Step 5. Use these rules in EHO to build the model
- Step 6. Initializing the parameters  
Determine the initial generations Gen = 1;  
Initialization of population P at rand;  
Determine a maximum number of generations, i.e., MaxGen.
- Step 7. While the termination condition has not been reached, do
- Step 8. Arrange the population into groups based on the individuals' levels of fitness.
- Step 9. For all the clans cl, do
- Step 10. For elephant m in the clan, cl do
- Step 11. Generate  $P_{(new,cl,m)}$  and update  $P_{cl,m}$  by Equation (3)
- Step 12. If  $P_{cl,m} = P_{best,cl}$  then
- Step 13. Generate  $P_{(new,cl,m)}$  and update  $P_{cl,m}$  by Equation (4)
- Step 14. End if
- Step 15. End for
- Step 16. End for
- Step 17. For all clans cl, do
- Step 18. Replace the worst individual  $c_i$  by equation (5)
- Step 19. End for
- Step 20. Analyze each elephant about the position it occupies.
- Step 21. Gen = Gen + 1
- Step 22. End while
- Step 23. Calculated cost, time, matrices
- Step 24. Validate the model
- Step 25. Stop

The center individuals of clan cl are intended via Eq. (5) for the dth-dimension where  $1 \leq d \leq D$ .

$$P_{centre,cl} = \frac{1}{n_{cl}} \sum_{m=1}^{n_{cl}} P_{cl,m,d} \quad (5)$$

where,

$n_{cl}$  = no. of elephants in clan cl.

$P_{cl,m,d}$  = d-th dimension of elephant individual  $P_{cl,m}$ .

- b) Separation Operator: This operator is in charge of separating the weak elephant in the clan. The weak elephant is an adult elephant on the verge of leaving the tribe. In equation (6), the separating operator is explained.

$$P_{worst,cl} = P_{LB} + (P_{UB} - P_{LB} + 1) * random \quad (6)$$

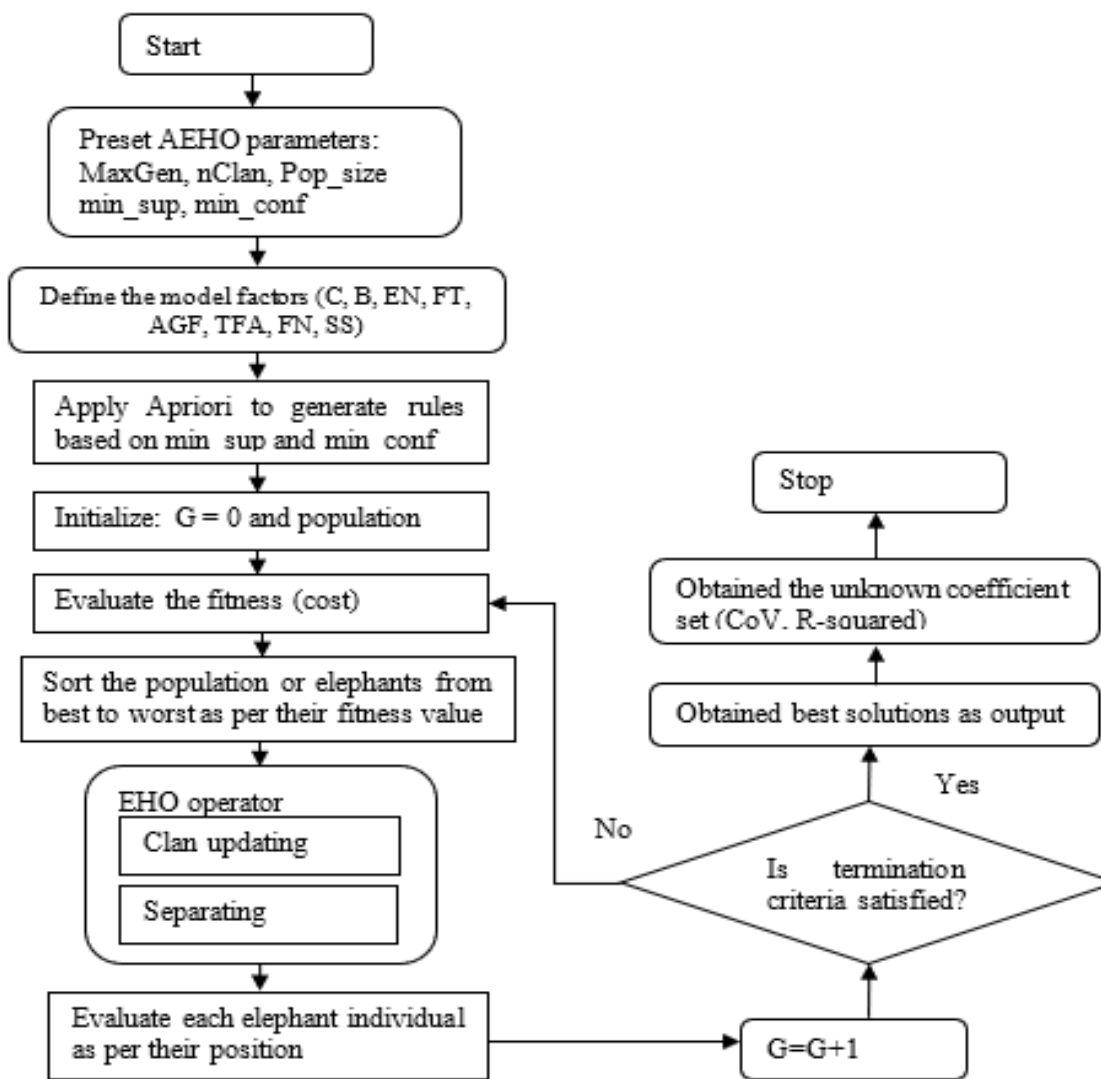


FIGURE 4. Flowchart for the Proposed AEHO Model.

TABLE 2. Simulation environment configuration.

Resources	Description
Simulation tool	MATLAB R2021a
RAM	16
Processor	Intel core i5 9 <sup>th</sup> Gen
Hard disk drive	512 GB
Operating system	Window 10

The used parameters in the above equation (6) are defined in algorithm 2.

Figure 3 displays the flowchart of basic EHO, which is summarised based on the descriptions of the clan update and the separation operator. The EHO’s basic steps are outlined here in the proposed algorithm: AEHO (see algorithm 3). Figure 4 also shows the associated flowchart.

Figure 4 depicts the overall proposed flowchart for the AEHO model used in this current case study. The work

started by defining the model parameters and presetting all initial parameters. When carefully considering how the AEHO parameters should configure, it could be possible to obtain a noticeable improvement in the algorithm’s overall performance. The model parameters have been taken as input parameters for the model. The Apriori rule mining technique is put into play to accomplish this so that it may generate the rules. These rules are generated based on minimum support and minimum confidence, then apply the EHO optimization technique to calculate the time-cost trade-off based on fitness or objective function. In this process, population and iteration have initialized and calculated the fitness and sorted the population by the best fitness. EHO has worked into two operators: the clan update operator and the separation operator. Each elephant has evaluated by their position. Then, perform the successive iterations until it does not reach the termination criteria. If it reaches the termination criteria, it obtains the best solutions and finally obtains the coefficient sets as a quality

TABLE 3. Sample of input and output factors.

Item	Project ID	SS	FN	C	B	EN	FT	AGF	GFA	Cost	Duration
1	Building of Hajj and Umrah/ Anah/Anbar	3	2	440	465	0	1	498	815	565.167	203
2	Event hall of the Ebad al-Rahman mosque/ Yusufiya / Baghdad	1	1	155	108	0	1	402	320	177.765	95
3	Secondary Safiq Amin/ Muqtadfiya/ Diyala	1	2	632	550	0	1	936	1610	844.313	204
4	Secondary Anjad Al Zahawi/ Baquba/ Diyala	1	2	563	412	0	1	716	1210	665.824	186
5	Secondary Prince Ali/ Tarmiyah/ suburb of Baghdad	3	2	612	638	0	1	833	1424	842.628	235
6	Secondary of the last prophets/ Yusufiya/Baghdad	1	2	481	508	0	1	661	1110	581.117	182
7	School of Habib Ben Khedi/ Nineveh	3	2	705	735	0	1	958	1650	1058.018	247
8	Abi Darda School/Kirkuk	1	2	815	850	0	1	1095	1900	1032.063	217
9	Falhoja Islamic High School/Falhoja/Anbar	3	2	285	297	0	1	415	664	439.354	195
10	Abu Ghraib secondary school/Abu Ghraib/suburb of Baghdad	2	2	571	590	0	1	782	1330	811.354	211
11	Apartments for health staff/Ramadi/Anbar	3	1	312	220	0	1	765	650	495.48	134
12	Secondary Al-Moutasem/ Samarra/Salah al-Din	3	2	653	615	0	1	1095	1900	662.535	261
13	Residential Units for Employees/ Nukhayb / Anbar	3	2	98	140	0	1	239	344	237.018	177
14	Local Council Building/Wasit	1	2	429	444	1	1	556	920	636	174
15	Information Building for Local Council / Wasit	1	1	205	28	0	1	116	60	35.451	81
16	Halls for the pilgrims/Nukhayb/Anbar	3	1	256	235	0	1	545	450	324.805	122
17	Directorate of AL-Awqaf/Kut /Wasit	1	2	831	490	0	1	743	1260	768.365	189
18	Directorate of AL-Awqaf/Ishaq/Salah Eddin	2	2	330	345	0	1	578	960	577.922	193
19	Directorate of AL-Awqaf/ Haditha/Anbar	3	2	345	340	0	1	578	960	660.144	210
20	College of Languages / University of Baghdad / Baghdad	2	2	6900	1550	0	1	4450	8000	5352.919	538
21	Expanding the building of the Faculty of Engineering /University of Baghdad /Baghdad	1	2	723	996	0	1	930	1600	907.072	204
22	Internal departments for students of Baghdad University/Baghdad	2	1	295	220	0	1	765	650	395.99	123
23	Administrative Building / Ministry of Electricity/Baghdad	1	2	460	385	1	1	765	1300	756.976	190
24	Administrative Building /Council of Governors Baghdad/Baghdad	1	7	8283	2528	4	2	1590	9800	7205.39715	787
25	Medina High School/ Taji Beach/Baghdad	1	2	863	533	0	1	985	1700	864.573	208
26	Administrative building /Council of Governors AL-Anbar/AL-Anbar	3	4	1620	1036	2	2	985	3400	2454.04215	456
27	Administrative building/Council of Governors Nineveh /Nineveh	3	3	1359	766	2	1	985	2550	1698.39	353
28	Administrative building/Council of Governors Salah Eddin/ Salah Eddin	3	5	6321	1805	4	2	1777	7850	5759.73615	731
29	Administrative Building /Ministry of Oil /Baghdad	1	6	7109	2185	4	2	1489	7850	5613.8334	659
30	Directorate of AL-Awqaf Nineveh/Nineveh	3	5	1149	1077	4	2	1777	7850	1774.3005	731
31	Administrative Building/Ministry of Municipalities/Baghdad	1	7	1575	1487	3	2	1284	7850	1981.57365	711
32	Administrative building for the University of Basra/Basra	1	4	987	872	2	2	2209	7850	1217.26185	560
33	An educational building in the Faculty of Medicine of Al-Kindi Baghdad/Baghdad	1	3	1513	610	1	2	892	2295	1470.26355	283
34	Internal departments for students of Diyala University/ Diyala	2	6	2885	1217	2	2	892	4590	3082.2435	584
35	Administrative building of Babylon University / Babylon	1	5	1865	1016	2	2	837	3575	2254.33425	439
36	Services building for the Ministry of Oil/Baghdad	1	2	413	385	1	1	578	960	557.589	175

TABLE 3. (Continued.) Sample of input and output factors.

37	Administrative building of the Ministry of oil/Waest	2	6	1200	1088	2	2	578	2880	1026.0201	511
38	Administrative building for the Ministry of Labor and Social Affairs/Wasit	2	5	1068	915	1	2	534	2200	1495.8027	422
39	Administrative building of the Ministry of oil/ Salah Eddin	3	4	928	717	1	2	567	1880	1392.3546	382
40	Residential units for doctors/Baghdad	1	3	1235	1117	2	2	1051	2730	1697.97495	302
41	Immigration and Displaced Building/ Wasit	2	4	1068	1140	2	2	710	2400	1709.4084	373
42	Internal departments for students of Baghdad University/Baghdad	1	5	1268	1415	2	2	710	3000	1873.13285	416
43	Administrative building of the Ministry of oil /Nineveh	3	2	1038	1196	1	1	1370	2400	1715.766	287
44	Directorate of AL-Awqaf /AL-Anbar	3	5	1828	2116	3	2	1040	4500	3445.0983	571
45	Internal departments for students of University of Karbala/Karbala	2	4	1605	1709	1	2	1040	3600	2441.6721	427
46	Fatima Al - Zahra Secondary School/Wasit	2	2	241	243	0	1	322	494	307.585	170
47	Directorate of AL-Awqaf / Baghdad	1	5	1279	1140	1	2	593	2470	1554.1911	395
48	Administrative building of the Ministry of Finance/Baghdad	1	4	1479	1360	2	2	865	2964	1923.39945	362
49	Administrative building of the Ministry of Interior	3	4	2440	2244	3	2	1394	4888	3695.29965	528
50	Internal sections for officers and security associates/Ministry of Interior / Baghdad	1	2	1687	1701	0	1	1952	3458	1956.013	287
51	Abdullah bin Rawahah School/Baghdad	1	2	326	230	0	1	387	612	335.235	160
52	Administrative building of the Ministry of Interior/Baghdad	1	4	1087	689	1	2	589	1960	1214.8521	321
53	Administrative building of the Ministry of Interior/Kirkuk	2	5	1321	850	1	2	589	2450	1582.87395	433
54	Administrative building of the Ministry of Municipalities/Salah Eddin	3	4	1848	1396	2	2	966	3332	2601.17445	452
55	Administrative building of the Ministry of Municipalities/AL-Anbar	3	6	2255	1433	2	2	829	4248	3177.9678	621
56	Administrative building of the Ministry of Municipalities/Najaf	1	6	2217	1305	2	2	754	3840	2322.09285	502
57	Administrative building of the Ministry of Municipalities/Babylon	2	5	2947	1950	2	2	1106	4800	3250.77585	536
58	Administrative building of the Ministry of Municipalities / Ninawa	3	5	5652	3315	4	2	1849	8175	6263.49045	746
59	Administrative building of the Ministry of Municipalities/ Wasit	2	4	720	480	1	2	402	1280	899.02575	323
60	Administrative building of the Ministry of Interior/Baghdad	1	5	1350	910	1	2	578	2400	1421.4354	392

index and stops the process. Otherwise, it starts again from fitness evaluation until termination criteria are met.

#### IV. EXPERIMENTAL RESULTS AND EVALUATION

The results of the investigation are presented and discussed in this section. In the beginning, a general description of the data analysis is given. After that, it gives case studies and analysis of the study's findings by research method in various subsections of this section. In addition, it presents the findings

of a comparison made between two distinct models of the scenario.

##### A. SYSTEM CONFIGURATION

This section provides details on how simulations were conducted for the proposed model. It also provides the system and resource characteristics in table 2, including the software and hardware. These simulation configurations are used to



**TABLE 4. Statistical summary of input factors.**

Description	Mean	Standard Deviation	Range	Min.	Max.
SS	1.88	0.88	2.00	1.00	3.00
FN	3.35	1.69	6.00	1.00	7.00
C	1515.83	1773.45	8262.50	20.50	8283.00
B	955.62	669.25	3287.00	28.00	3315.00
EN	1.17	1.26	4.00	0.00	4.00
FT	1.50	0.50	1.00	1.00	2.00
AGF	941.27	631.60	4334.00	116.00	4450.00
GFA	2869.47	2419.05	9740.00	60.00	9800.00

conduct experiments to achieve the desired results. An experimental setting for the proposed algorithm is also given in table 6.

### B. DATA DESCRIPTIVE ANALYSIS

We collected data on sixty distinct construction projects across Iraq built by private contractors working for the government between 2008 and 2016. The focus areas (samples were collected) reflect about 80 percent of the projects carried out in Iraq regarding the project's technique, the materials utilized, and the contemporary design. Table 3 used ten factors, eight input factors and two output factors (cost amount and time (or duration)).

According to the findings of Frank and Ildiko [37], to get a high level of accuracy, the authors suggested it must be greater than 5. The ratio for the current case study was 60/8, which equals 7.5; this number is higher than the specified requirement. There were 60 samples (projects), of which used only 12 examples to verify the suggested model. Of these 48 samples, representing 80 percent of the total, they were included in creating the proposed models. Table 4 presents the descriptive statistics about the dataset used for this investigation.

### C. CASE STUDY AND DISCUSSION

The preliminary work in 2020, Khalaf *et al.* [38] have done is utilized as a preliminary step for forming assumptions that will be proved or disproved by the next debate. The vast majority of previous case studies in the body of literature don't provide details about the pairwise comparison matrix to determine weight indexes and tasks related to the project, nor do they provide specifics regarding the day-to-day allocation of resources. Consequently, it has been utilized in numerous case study projects to evaluate the operating effectiveness of the new AEHO (Apriori-based EHO). It has been done to research the effectiveness of the suggested AEHO. Table 4 contains the specifics of one of the case study projects discussed in this article to demonstrate something. This project is a building construction project, and it is positioned in several cities and towns around Iraq.

Optimization strategies and methodologies make it possible to determine the optimal (min or max) value, also known as an objective function, whose value depends on one variable or a set of variables. It can do this by finding maximum or minimum function values. The type of functionalities, the computations characterizing the problem, the number

of objectives, and the search space research technique are some criteria that may be used to categorize algorithms. The improvement of sustainable construction typically involves the solution of multiple-attributes problems. It means that the objective function depends on many factors, such as the thermal transmittances of the exterior materials or the quality of existing technologies, such as heating, air circulation, air conditioning, and renewable energy sources. The objective functions often implemented are connected to the four primary categories: energy usage, cost, environmental effect, and housing comfort (thermal, visual, or acoustic). Depending on the research project's goals, the objective functions can be optimized alone (through a technique known as single-objective optimization) or collectively (through multiobjective optimization) when many facets of the investigation have to be enhanced. In multiobjective optimization, the outcome is typically described by many compromise solutions recognized as the Optimal solutions Front. It is because this kind of research generally requires at least 2 contradictory functions. Unless some selection metrics among objectives are stated, the outcome will be a set of compromise solutions (a priori methods). Because all these studies usually contain many factors, developed appropriate software to assist researchers and innovators in determining the best possible combination of solutions to put into practice. The application of MATLAB is by far the most popular of such programs.

The project had eight input factors for each of its sixty Project\_Ids, and each Projects\_Id includes various executing modes that various values for each objective have followed. The duration and cost for each method are estimated using many resources that are involved with that method. Table 5 shows an example snapshot of the dataset, including all of the building project's features. It employed the AEHO approach to decrease a construction project's cost or/and time (duration). Models have been presented to investigate the effects of swarm size on outcomes. In an AEHO technique, the goal of the objective function is to decrease the gap between expected and actual time (duration) or/and expected and actual cost. AEHO model proposals for estimating cost and/or duration and obtaining findings that are as close to the observed results as possible.

It may find statistics of samples used in constructing the suggested AEHO model in Figure 5. Models that are evaluated utilizing optimization methods can create estimations into data ranges that are accessible, and these estimations are then used in the other simulation process. Therefore, the amount of the dataset used for the modeling process is crucial because of its effect on the models' accuracy. The sample size and the factor distributions of the data affect the behavior of any model that is adjusted using these data. Histograms serve as a graphical representation of the data in figure 5, which can find above.

An EHO method is presented in this work as a solution to the particular challenge of reducing the association rules. The Apriori algorithm starts with the generation of a data collection, then incorporates the support and confidence level



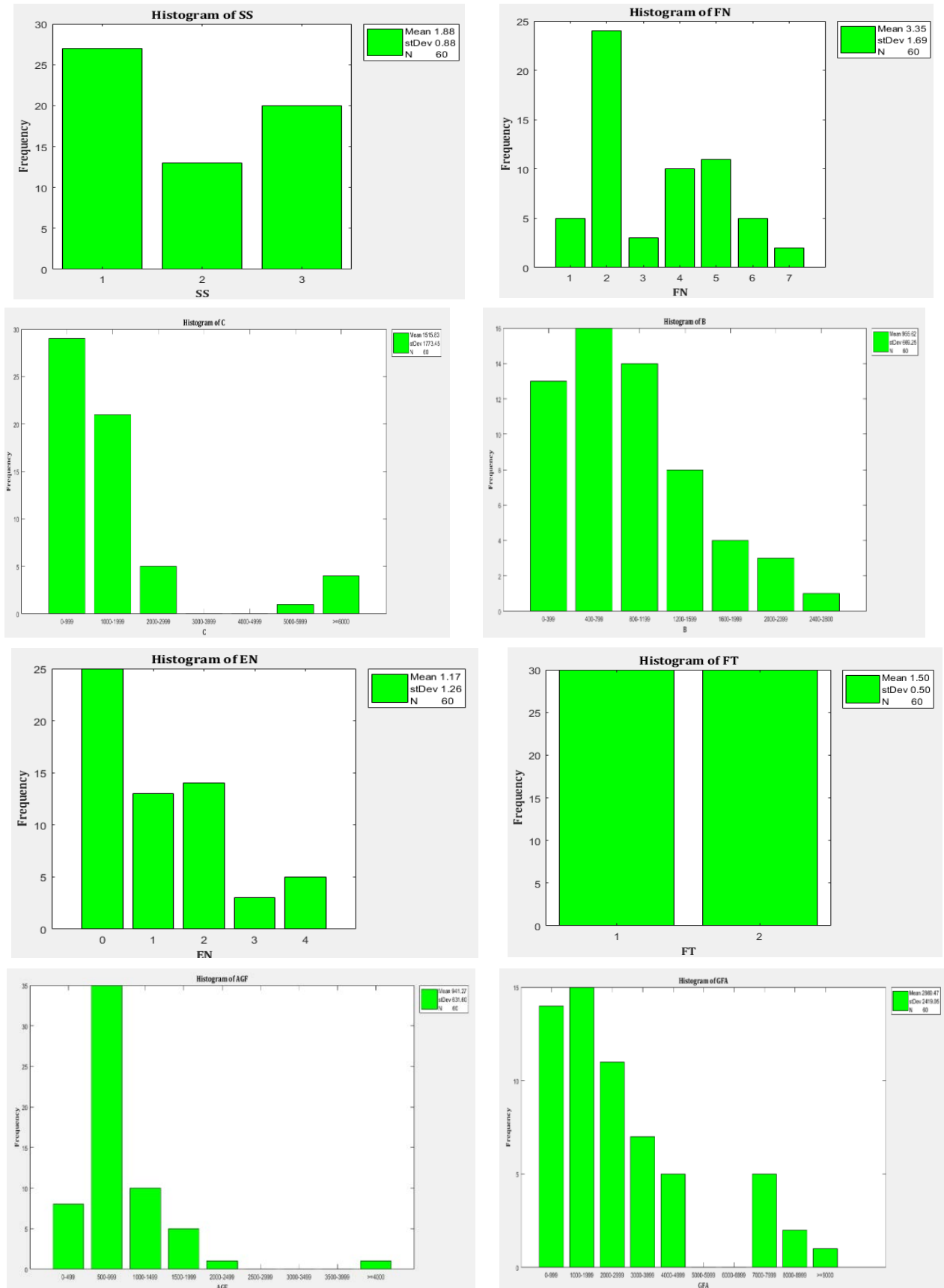


FIGURE 5. Histograms of all eight independent input factors.

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Final Rules Above Minimum Support:0.2

Final Rules:

Rule # 1 : Floor Number-II -->Footing-Raft
Support = 4.000000      Confidence = 100.000000      Lift = 2.000000

Rule # 2 : Brick Very Low -->Concrete Very Low
Support = 4.166667      Confidence = 100.000000      Lift = 1.304348

Rule # 3 : Elevators-1 -->Concrete Very Low
Support = 2.166667      Confidence = 100.000000      Lift = 1.304348

Rule # 4 : Total Area Very Low -->Concrete Very Low
Support = 4.833333      Confidence = 100.000000      Lift = 1.304348

Rule # 5 : Elevators-0 -->Footing-Raft
Support = 4.166667      Confidence = 100.000000      Lift = 2.000000

Rule # 6 : Security Status Safe, Floor Number-II -->Footing-Raft
Support = 2.000000      Confidence = 100.000000      Lift = 2.000000

Rule # 7 : Security Status Safe, Brick Very Low -->Concrete Very Low
Support = 2.000000      Confidence = 100.000000      Lift = 1.304348

Rule # 8 : Security Status Safe, Total Area Very Low -->Concrete Very Low
Support = 2.333333      Confidence = 100.000000      Lift = 1.304348
    
```

FIGURE 6. Generated rules by Apriori.

TABLE 6. Adopted parameters values of the AEHO.

Parameters	Values
Scale factors	$\alpha=0.7, \beta=0.1$
number of clans	6
MaxGen	60
Population size	60
No. of elephant in each clan	10
Maximum FE	$0.3 \times 10^4$
min_supp	0.2
min_confid	0.8

of the customers, and finally generates an association rule set. Because such association rule sets can be both discrete and continuous, it is necessary to prune them using weak rule sets. There is a requirement for optimization of the results. EHO is an algorithm presented for association rule optimization to optimize them. After computing the clan update value and using the confidence value as the clan value, an optimum association rule set is constructed. Figure 6 represents some final rules generated by Apriori that are above minimum support 0.2. Here the minimum criteria for Apriori are  $\text{min\_supp} = 0.2$  and  $\text{min\_confid} = 0.8$ . It has obtained 812 rules with support, confidence, and lift values of all activities.

Table 6 represents the adopted parameters' values for the final analysis. According to the range of activities and how they are carried out. When done by hand, determining the best practical approach (or approaches) to taking care of a project is next to the complex. Consequently, the computational work is carried out using MATLAB R2017a, within which the suggested model is written using MATLAB programming language. The first thing that must do is to determine the values for the algorithm's parameters. As a result, several

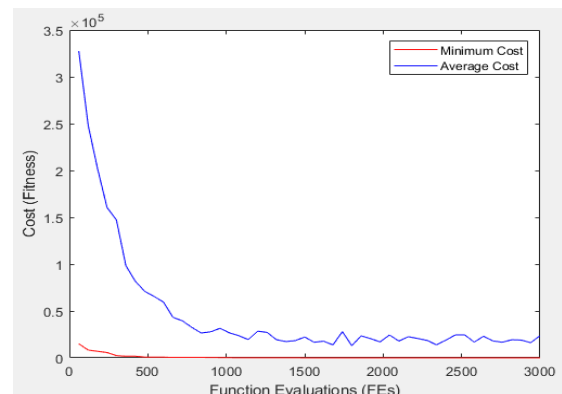


FIGURE 7. Plot of the Time-cost trade-off.

separate tests with a wide range of values for all these parameters were carried out. The starting population numbers and the maximum number of generations changed between 10 and 60, with a constant interval of 10.

This research used statistical approaches such as correlation coefficient (R), coefficient of variation (CoV), and standard variation analysis to assess and analyze the capability of the suggested models. These statistical methods were performed to analyze and evaluate the models' capacity.

When selecting undetermined coefficients, the RMSE (root means square error) was employed as an objective function to guide the process. In addition to that, six other clans were employed and analyzed. In this investigation, variation in objective functions held constant at sixty was shown to be constant after sixty iterations (as seen in Figures 8 and 9 for both duration and cost models, respectively). Several swarm sizes tried to see which could minimize the error.

Table 4 contains descriptions of all sixty projects found with Pareto-optimal solutions. Figure 7 also displays the cost



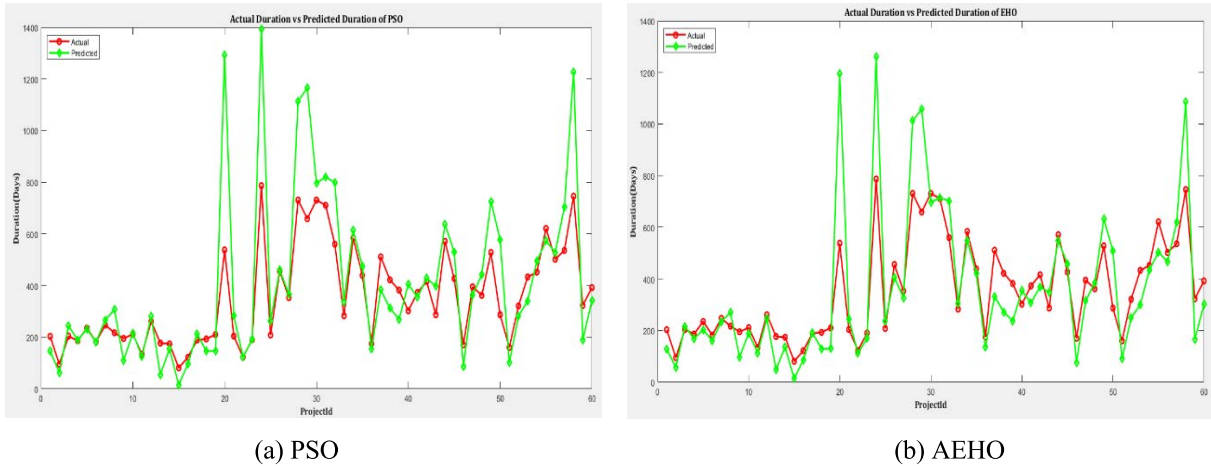


FIGURE 8. Actual duration vs. predicted duration trade-off.

trade-off graphs between function evaluation and minimum and average costs, respectively.

**D. MODEL VALIDATION**

A recently published standard PSO model has shown its effectiveness in addressing multiobjective issues. Consequently, the case study project results acquired from the model generated by Khalaf *et al.* and generated model are contrasted with the same algorithm settings (60 Maximum generation, 60 population numbers, and 0.07 and 0.1 scaling factor) to verify the proposed AEHO model. This case study project included eight input factors or activities with various executing modes such as mean, median, standard deviation, covariance, R-square, and a conventional PSO model-based TCT optimization model. As indicated in Table 2, the new model’s Pareto-optimal solutions are either equivalent to or better than the current model’s; hence, Table 6 validates the proposed model’s adaptability. In addition, the effectiveness of the suggested model over the existing model is proved in the following sub-section by assessing several performance indicators.

**E. COMPARISON BASED ON PERFORMANCE METRICS**

Statistical approaches such as the coefficient of variation (CoV) and coefficient of determination (R2) were employed to analyze and examine the ability of the presented models. Data is compared to the fitted regression line using the R-squared value. The simulation results are obtained from similar conditions of experimental configuration, same as existing work to perform the comparison. Table 7 shows the cost and time comparisons between PSO and AEHO values. The table depicts the improvement in AEHO values due to lower R2 values.

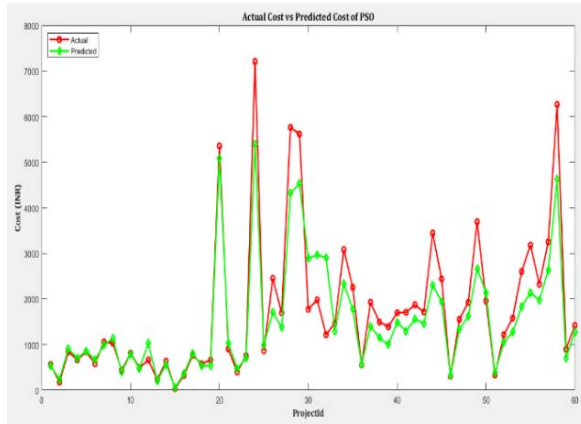
Figure 10 illustrated the plot of statistical coefficients, namely, CoV and R2, for time-cost trade-offs using standard PSO and proposed AEHO. The percentage of the standard deviation of a data set to the predicted mean is what statisticians refer to as the coefficient of variation (CoV).

The coefficient of variation reflects data degree in a sample that differs from the mean value of the population. It can establish if the predicted value of the investment is justified by the level of variability, or the downside risk, that it has experienced over time and determined by looking at the historical performance of the investment. Using the CoV makes comparing the overall precision of two analytical systems easier. As a rule of thumb, a  $CoV \geq 1$  indicates a relatively high variation, while a  $CoV < 1$  can be considered low. The lower R2 indicates that the construction of the building projects will be less expensive and take less time.

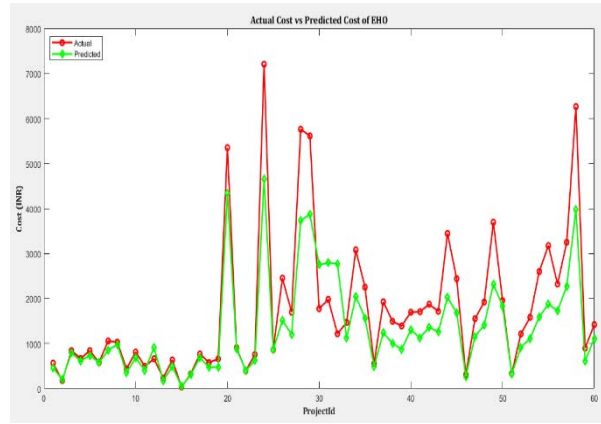
Figure 11 visualizes the bar graph plot of statistical parameters like standard deviation, median, and mean for time-cost trade-offs using standard PSO and proposed AEHO. Standard deviations aren’t “good” or “bad”. These are measures of the level to which the data is distributed. A low standard deviation suggests that the data points are near the mean, while a high standard deviation shows that the data are scattered across a vast range of values and are less likely closer to the mean. The factors are used to determine the overall trend of the data. It finds a specific value inside the data space that may be interpreted as a data summary and possesses specific attributes. The mean and the median are the two essential descriptive measurements used to calculate the central tendency. The average value of the data is another name for the mean. An excellent central tendency should reduce, as much as possible, the total squared deviation of data points from the measured value. Such parameters are often instrumental in analysis.

**F. COMPLEXITY ANALYSIS OF PROPOSED AEHO ALGORITHM**

The stages in the AEHO algorithm are used as a basis for analyzing the computational complexity of the AEHO algorithm. Let’s say the population size, numP, and the dimensions, Dim, stand for themselves. Step eight, which has a temporal complexity of O, involves sorting the population according to the fitness of the individuals (numP). Execute



(a) PSO



(b) AEHO

FIGURE 9. Actual cost vs. predicted cost trade-off.

TABLE 7. Comparison of performance parameters between PSO and AEHO.

Algorithms/Parameters	PSO		AEHO	
	Time	Cost	Time	Cost
Mean	1.09	1.13	1.26	1.27
Median	1.13	0.97	1.30	1.27
Std Deviation	0.23	0.72	0.27	0.80
CoV	0.06	0.51	0.07	0.63
R2	0.89	0.80	0.87	0.78

the clan-update operator for each clan  $cl$  from step 9 through step 16 with a temporal complexity of  $O(\text{numP} \times \text{Dim})$ . Execute the separation operator for all clans  $cl$ , with computational time complexity of  $O$ , in steps (17) through (19). ( $\text{numP}$ ). Evaluate each elephant based on its location in step (20), taking into account the temporal difficulty of the task ( $\text{numP}$ ). To accomplish this goal, the entire amount of time complexity of optimizing elephant herding is  $O(T \times \text{numP} \times \text{Dim})$ . Based on the findings presented above, the overall time complexity of the EHO method is  $O(T \times \text{numP} \times \text{Dim})$ , which is solely linked to  $T$ ,  $\text{numP}$ , &  $\text{Dim}$ . It is because the low-order components were omitted from the calculation.

G. ANALYSIS

Just after the design of the proposed model, a few different stages were considered. These stages include: I) trying to extrapolate the conclusive model based on the collected dataset using apriori and EHO algorithm; (ii) determining several independent validation standards to prove the model, and (iii) being able to conduct a comparison analysis utilizing designing concepts and the physics of the issue. Moreover, the 3 stage relies on design methods and should be completed by an engineer familiar with the modeled issue. The first two processes are entirely statistical. The first and second stages were completed successfully above for this issue. The Apriori algorithm could generate significant rules to tell the association between each input parameter and which parameter

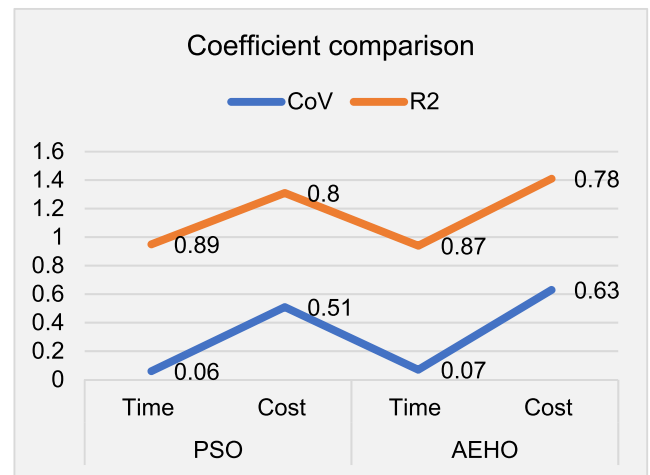


FIGURE 10. Plot of statistical coefficients.

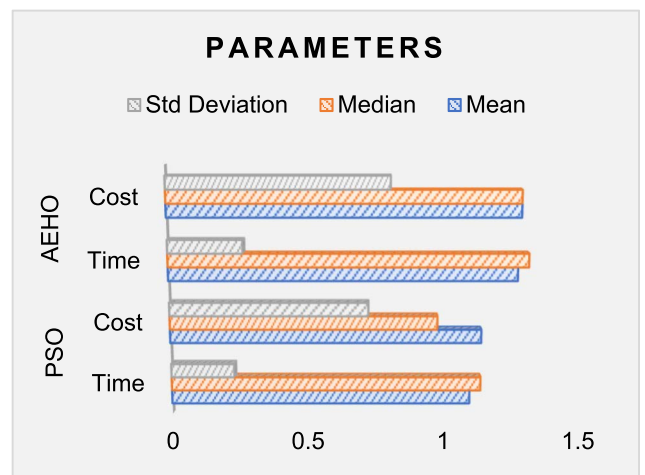


FIGURE 11. Plot of statistical parameters.

can affect the cost and time. Following that, an EHO algorithm was used to optimize the time and cost of building construction. A comparison study was carried out to provide

an additional evaluation for the model of cost and time value that had been constructed. This research's main objective is to evaluate the influence that specific factors have on the values of both cost and time. Figure 10 represents the prediction values for both the cost and the time the proposed model was completed as a function of the coefficient's variable and the R2 score value used as parameters. Figure 11 displayed the statistical parameters in respect of both time and cost factors between the PSO and AEHO model on the input parameters ( $C$ ,  $B$ ,  $EN$ ,  $FT$ ,  $AGF$ ,  $TFA$ ,  $FN$ ,  $SS$ ). Figures 10 and 11 show that a rise in the volumes of  $C$ ,  $B$ ,  $EN$ ,  $FT$ ,  $AGF$ ,  $TFA$ ,  $FN$ , and  $SS$  up to a particular level contributes to rises in cost and time. It signifies that the proposed structure is utilized as guidance to select the best parameter to achieve the best results appropriately. In addition, Figure 10 illustrates that the CoV and R2-score are the variables that have the most significant influence on the values of cost and duration. In addition to these comparisons, a complexity analysis is also done, and the calculated time complexity is  $O(T \times \text{numP} \times \text{Dim})$  for the proposed AEHO model.

## V. CONCLUSION, LIMITATIONS, AND FUTURE SUGGESTIONS

The construction of structures and exceptionally high elevated buildings has evolved into one of the most profitable businesses. As a result, wealthy individuals spend a significant portion of their assets in this sector. The primary purpose of this research was to establish a meta-heuristic model for evaluating the cost & time (duration) associated with construction projects. This research study employed sixty different construction projects to develop the suggested model while it was still in the preliminary design stages. The proposed method guides the selection of critical criteria that affect cost and length, like total area, ground floor area, safety status, no. of levels, brick and concrete volume, and elevators. This proposed model is Apriori-based EHO to build construction projects by evaluating the time-cost trade-off on eight input factors.

The findings of the case study project provide evidence of the capabilities of the established model. The parameter metrics like R Squared are 0.87 and 0.78 for time and costs in AEHO, while the covariance value for time and cost is 0.07 and 0.63, respectively. Covariance is a measure of how two factors/variables. The results show that the AEHO methodology is an effective method for evaluating project management issues and that it can find the best solutions for various criteria. Its calculated performance measures show the advantages of proposed AEHO over PSO and justify that Pareto-optimal solutions obtained by proposed AEHO outperform existing models in terms of fitness objective.

To tackle multiobjective optimization issues, AEHO can be adapted to discrete spaces. Furthermore, additional changes will be hybridized with AEHO, such as employing Chaos theory. In addition, the suggested method can use with existing SI algorithms to improve efficiency. Glowworm swarm

optimization or Ant colony optimization with other association rule mining techniques like FP-growth, Eclat etc., can be considered as the other possible methodologies to reduce the time and cost tradeoff by improving the AEHO algorithm to enhance this work further.

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**RAKESH GUPTA** received the M.Tech. degree in construction technology and management from the IPS College, Gwalior.

He worked as a site engineer at various construction sites, from 2008 to 2011. He also worked as an Assistant Professor in civil engineering, from 2012 to 2017. He is currently a Research Scholar with the Madhav Institute of Technology and Science, Gwalior. He has published research papers on construction cost time optimization for civil engineering projects. His research interest includes construction time cost optimization for civil engineering projects.



**MANOJ KUMAR TRIVEDI** received the B.Tech. degree in civil engineering from the University of RIT, Jamshedpur, the M.Tech. degree in water resources from the University of IIT, Kharagpur, and the Ph.D. degree in hydraulics from UOR, Roorkee.

He is currently a Professor with the Civil Engineering Department, Madhav Institute of Technology and Science, Gwalior. He has a membership in three professional bodies. He has published several research papers in different national and international journals and conferences, such as ASCE, in 2012; *International Journal of Civil Engineering Research, Science, Engineering and Technology, Civil Engineering and Mechanics*, in 2015; *IRJMST*, in 2014; and *Journal of Agriculture and Biotechnology (ASAE)*, in 2013. His area of specialization is in water resources, highway engineering, and construction coast management.

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