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Research Article

Solving the Problem of Time, Cost, and Quality Trade-Off in Project Scheduling under Fuzzy Conditions Using Meta-Heuristic Algorithms

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Balancing the project's time, cost, and quality involves deciding on different implementation methods for each project activity. Time and cost are minimized simultaneously, and the quality of the final product or service is maximized. Indeed, the use of search methods to determine the optimal execution methods of each activity requires the evaluation and review of various performance criteria such as time, cost, and especially the final quality of each activity. These performance measures, especially the quality of the different implementation methods, are reported and recorded in inaccurate, ambiguous, and vague numbers or concepts. In this research, new methods have been proposed to evaluate and investigate the trade-off of time, cost, and quality of the project in conditions of uncertainty. This means that by fuzzy number theory, the specifications and conditions of a project are included in the problem of balancing time, cost, and quality. In fact, time, cost, and quality are considered triangular and trapezoidal fuzzy numbers. Also, the fuzzy multiattribute utility function approach (in which the concept of fuzzy computational operators is included) has been used to evaluate different combinations of execution methods of project activities. Since different quality combinations can be obtained with different combinations of parameters involved in the implementation of an algorithm, the Taguchi experimental design method has been used to adjust the parameters of the proposed algorithm. To solve the proposed model, particle mass optimization algorithms and artificial bee colonies have also been studied.

1. Introduction

A project is a set of temporary efforts to achieve a specific goal (product creation or service delivery). The term "temporary" means that projects start and end at specific times, and the term "specific" also means that the service or product in question is well-defined and distinct from the results of other projects. One of the essential activities that must be done in the management and control of a project is deciding how and when to implement each activity. Project scheduling determines a time sequence in the form of a schedule to perform interrelated activities that form a network called a project. Dependence of activities is an order that must be observed in their precedence and latency due to technical limitations in project implementation. Indeed, following a logical sequence of actions or technical constraints in scheduling a project's activities alone cannot meet the expectations and demands of the various groups involved, such as project managers and stakeholders.

In general, in trying to schedule project activities, project managers always try to control the available resources along with time, cost, and quality constraints. Since the project is fundamentally unique, there is no logical standard for project planning. As a result, decisions are made in a triangle of time, cost, and quality (as in Figure 1).

It can be said that more effective and efficient implementation methods (using different resources and technologies) in project activities can lead to other times, costs, and qualities. In general, the use of cheap resources and technologies will generally lead to an increase in project

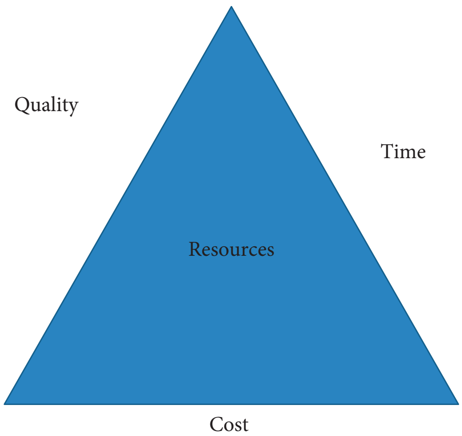

Figure 1: Project management triangle.

execution time. For example, hiring more skilled artisans or more workers in a construction project can reduce the time it takes to complete project activities, but project costs will undoubtedly increase. To determine the optimal combination of different methods of implementing the actions of a project, various approaches have been developed to solve the problem of time and cost trade-off. These approaches include innovative methods [1, 2], mathematical methods [3–6], and evolutionary methods [7–10]. However, it should be noted that reducing project time and costs may reduce the overall quality of the final product or service. For example, reducing the cost and time of projects such as the construction of subways, bridges, and roads can reduce the overall quality of the project, which, in the long run, will significantly increase the costs of the operation period, such as depreciation and maintenance costs.

All these reasons have caused the issue of trade-off of time, cost, and quality of the project in the last two decades to attract the attention of many researchers and extensive research in this field. Babu and Suresh [11] have proposed three linear programming models for this problem, considering a logical relationship between time, cost, and quality. Using the Babu and Suresh [11] approach in a cement plant construction project in Thailand, Khang and Myint [12] examine this approach's practical application, assumptions, and fundamental issues. Other researchers [13] have applied the concept of time, cost, and quality trade-off using the idea of multiobjective optimization. One of the most critical challenges in applying these approaches is using historical reports or the knowledge of elites, contractors, and engineers to determine resource utilization plans or procedures. Different programs for the exploitation of renewable or nonrenewable resources or other implementation methods will lead to various equipment, human resources, and materials allocation. This will undoubtedly affect project performance levels such as time, cost, and quality.

On the other hand, time, cost, and quality functions are generally not exact numbers and are sometimes difficult to express as actual numbers. In practice, project managers, engineers, or experts use uncertain, vague, or inaccurate terms to estimate and express these performance levels. For example, the quality of activity might be defined as "most likely equal to a, but certainly not less than b and not greater than C." However, most of the time, cost, and quality trade-off approaches use exact numbers to express different criteria and will be inefficient in analyzing vague, perceptual, and uncertain relationships between these performance criteria.

This paper examines the issue of cost-time trade-off by considering the project quality factor as one of the pillars of the project. New methods have been proposed in recent years regarding the issue of cost-time balance. In project scheduling calculations, the earliest time to complete the last activity is the project delivery date. Project completion time is generally reduced by revising network logic or shortening activities at a higher cost. As the duration of activities decreases, the quality of each movement, i.e., the proximity of the project deliverables to the expectations of the employer or the customer, decreases. In discussing the balance between the three functions of cost, time, and quality of the project, cost sensitivity analysis is performed to changes in the duration of the activity, which aims to obtain the best combination of time reduction of activities. In such a way, the total project costs are minimized, and the quality of the whole project is maximized.

As mentioned, uncertainty, ambiguity, and the perceptual and inferential performance of time, cost, and quality for all activities in a project are inevitable. In this research, considering the uncertainty for the mentioned functions and the trapezoidal or triangular fuzzy numbers to express these functions, the problem of time, cost, and the quality balance becomes a fuzzy problem of time, cost, and quality balance. Therefore, using fuzzy logic and multiattribute utility and fuzzy critical path. Using this algorithm, a better execution method with higher desirability is selected, and using the superinnovative particle swarm optimization algorithm and artificial bee colony can create space. The problem is searched, and according to the search and stop conditions, the best answer found is determined as the desired answer to the problem.

In the following, in Section 2, the research background is examined. Section 3 describes the research method. In Section 4, the results are numbered and analyzed, and finally in Section 5, conclusions are made.

2. Literature Review

The early techniques used to schedule large projects date back to the late 1950s. The famous critical path method in 1961 and the modern project management (MPM) method in 1962 were designed for projects whose activities have a definite time. The biggest problem with these methods is that they take into account only the limitations of the prerequisite. Early models of problems with resource constraints were introduced in the early 1960s. The first systematic method developed to optimize the project schedule is the critical path method. This method, also called critical path analysis, results from a collaboration between DuPont and Remington Rand in the year 7 AD. In this method, the duration of the activities is estimated as a numerical value, and it is assumed that the changes in this period are minimal and negligible. This condition is evident in projects where similar examples have been implemented in the past or experiences from the duration of the activities are available.

Coinciding with the introduction of the critical path approach to project scheduling, the US Navy, in collaboration with Bose's management consultants Allen Hamilton and Lockheed Aircraft, introduced project evaluation and review techniques in the Polaris submarine project scheduling. The success of this method in scheduling the Polaris project led to the expansion of the use of this method in later years. The main application of the program evaluation and review method is in projects where there is uncertainty in the duration of activities, and a fixed numerical value cannot be used to estimate the time of activities.

2.1. Cost-Time Trade-Off Issue. The critical path method is a mathematical algorithm used to schedule a set of activities in various projects such as construction, engineering, facility maintenance, and software development. This method is related to the balance between completion time and project costs [14], and its application in definite conditions is more appropriate than possible conditions. The critical path method is used to determine the time-cost balance for activities that meet the completed time at the lowest cost and is also useful when there are similar experiences from previous projects [15].

Time-cost balance issues have focused on shortening the entire project time by reducing the time required to complete activities since the late 1950s. Researchers in linear scheduling models [1, 14, 16–19] and nonlinear scheduling models [20–22] are based on the assumption that time and cost balances for activities are linear. The relationship between the duration of activity and the cost of a straight line is expressed on a graph [23]. The cost of completing the activity varies linearly between normal time and reduced time. There is a continuous, linear relationship between cost and time for each activity in the classical case. One development considers this a situation where resources are limited, and the relationship between cost and time is discrete. These studies include the work of Demeulemeester et al. [24]. In this case, a certain amount of time is taken to perform the activity for a certain amount of resources. Erenguc et al. [25] considered developing this cost-time equilibrium model, in which activities can be reduced by allocating more resources to optimize the current net value of the project. Hazir et al. [26] presented the problem of discrete cost-time balance for the project scheduling problem in multimode concerning specific relationships. Ballestin and Blanco [27] also theoretically and practically optimized multiobjective functions in RCTSP. Lotfi et al. [28] have researched renewable energy. The most important innovations in their study included the use of robust two-level programming techniques and game theory (Stackelberg Competition) for locating renewable energy sites. The results show that the combination of uncertainties can increase energy production and supplier profits. In addition, the objective functions of the proposed model are compared with those under uncertain conditions. Sensitivity analysis of the main parameters is performed to validate the proposed model. As uncertainty increases, the energy produced decreases and the supplier's profit increases. Supplier profits gradually decrease as the discount rate increases. In addition, as the scale of the problems increases, the energy produced and the profit of the supplier increase. Babu and Suresh [29] conducted a study to balance the three factors at the same time. In their work, they made a Crashing Hypothesis and assumed that as the time of activity decreases, cost increases linearly and quality declines linearly. They considered three linear target functions in which the result analysis led to decision-making in balancing the mentioned factors. At the end of their paper, they proposed that neither the total quality of the project (whether weighted mean or arithmetic mean) nor the quality calculation as the product of the activities affects their work result procedure. Zheng et al. [30] made efforts to introduce optimal solutions based on genetic algorithm (GA). However, in all these studies, uncertainties were not considered due to complications, and the studies were conducted in a deterministic space. But in real-world projects, factors such as cost and time of the projects are always affected by many changes due to the uncertainties. Therefore, to solve this problem, Feng et al. [10], Azaron et al. [31], Abbasnia et al. [32], and Zhang and Li [33] studied the bi-objective balance of time and cost in a real-world uncertain space. Khang and Myint [34] implemented this model in a real-world project of construction of a cement factory in Thailand. The successful experience of meta-heuristic optimization algorithms in solving the two-factor problem of time-cost balance made the researchers focus on solving the three-factor problem of time-cost-quality optimization. Abolghasemian et al. [35] considered the sustainability pillars in scheduling projects and uncertainties in modeling them. To model the study problem, robust nonlinear programming (NLP) involving the objectives of cost, quality, energy, and pollution level is applied with resource constrained. Abolghasemian et al. [35] considered delay scheduling based on discrete-event simulation for construction projects. For this purpose, rework parameter and the variables of frequency, duration, and time of callback have been considered. Also, the effects of these parameters on tangible performance criteria have been investigated. The combined approach of discrete-event simulation and computational modeling is applied and then the results are compared. Measurements show that the systems fragmented by repeated and short repetitions while referring to early are in optimal performance.

2.2. Research Gap. The complexity of the proposed algorithms is significant for solving these problems. It can be very annoying for important issues, even with the advances in computer programming and the hardware used to run these programs today. Researchers are more likely to use innovative and meta-innovative methods to solve this problem to escape this complexity. The development of precision methods is also crucial because the only valid scale by which innovative and meta-innovative methods can be evaluated are these precise methods. In Table 1, previous studies are categorized with research methodologies.

3. General Definition of the Proposed Problem

As mentioned, a project involves a set of specific activities. Here, the activities of a project are numbered $j = 1, 2, \ldots, n$. The time or duration of an activity j is displayed with D_j.

As soon as another activity starts, it is impossible to stop the action, and there is no interruption in implementing project works. Due to technological and executive needs, there are prioritized relationships between project activities. These relationships are represented by a set of prerequisites for a P_j activity. These sets mean that the activity cannot start before the prerequisite activity $i \in P_j$. The basic premise is that these networks are nonrotational. In the display of each project, two additional activities $j = 0$ and $j = n + 1$ are defined, which indicate the beginning and completion of the whole project. These two activities are virtual, have zero execution time, and do not use any resources.

The project's time, cost, and quality are determined by the time, cost, and quality of the constituent activities. On the other hand, these criteria for each of the activities in the project network depend on its implementation method. In fact, the implementation method includes the program of utilizing various resources (equipment, human resources, materials, etc.) and specific implementation techniques. For example, consider the concreting activity in a construction project. This activity can be done in three ways.

(1) Making concrete on-site by a mixer and a skilled worker

(2) Use ready-mixed concrete and transport it to the site using appropriate equipment

(3) Using prefabricated concrete blocks and transporting them to the site.

The project completion time can be calculated by summing the critical route activity times. The project's cost will be obtained from the sum of the costs of each project activity. A weighting approach will also be used to determine the overall quality of the project. The weight of each activity indicates its importance and impact on the overall quality of the project. Usually, using more effective execution methods reduces the time to perform an action, but you have to pay more for using more efficient resources and technologies. This means paying more for the quality of an action. Finding a solution to the problem of balancing time, cost, and quality involves determining the optimal combination of execution methods for all the activities that make up the project so that an optimal variety of time, cost, and quality is created for the project.

Performance criteria of time, cost, and quality related to different implementation methods of each activity are collected and calculated by project managers or engineers based on past or current experiences or based on the opinion of experts. Of course, it is not possible to express these parameters, especially the quality of an activity, in precise and specific values. In addition, due to environmental and temporal conditions, and especially the mentality of managers and engineers in estimating various parameters, project activities' evaluation or performance criteria are expressed in an uncertain, vague, and inaccurate manner. On the other hand, fitting and estimating the relationship between the implementation method of activity and the performance criteria related to that activity can be very weak due to the uniqueness of the project or its activities and other factors such as environmental conditions, equipment specifications, staff efficiency, material supply conditions, and coordination problems between stakeholders and retailers. Therefore, the existence of uncertainty and ambiguity in evaluating and expressing the performance of each project activity as well as the project as a whole is obvious and unavoidable.

In time balance, cost, and project quality, very strong and efficient models over time have been presented. However, as a development on the current models, as well as to investigate the issue of time balance cost and quality due to the ambiguity and uncertainty in determining and expressing the performance criteria of each project activity (the issue of time balance, cost, and fuzzy quality), the multiattribute utility technique will be studied. In this technique, time, cost, and quality of each project activity and time, cost, and overall quality of the project are considered as fuzzy numbers.

3.1. Research Assumptions. In the previous section, along with a description of the proposed problem, the various assumptions and topics in the problem are examined. Still, in general, the assumptions considered in this dissertation can be presented as follows:

(i) There is no interruption in the implementation of various project activities.

(ii) Due to technological and executive needs, project activities have prioritized relationships.

(iii) The activities that make up the project or its network are nonrotating.

(iv) Each project activity can be implemented in a small number of different implementation methods.

(v) Activities are definite, but each activity's duration, cost, and quality are uncertain, vague, and inaccurate.

(vi) Using effective and efficient execution methods reduces the execution time of each activity.

(vii) The use of effective and efficient execution methods increases the quality of execution of each activity.

(viii) Applying effective and efficient implementation methods increases the costs of each activity.

(ix) Data on each activity's time, cost, and quality are trapezoidal or triangular fuzzy numbers.

(x) To calculate the desirability of each execution method in the problem of balance of time, cost,

TABLE 1: Categorized previous study.

Author(s)	Reference number	Method					
		GT[1]	Robust	LP[2]	NLP[3]	GA[4]	Simulation
Lotfi et al.	43	*	*				
Babu and Suresh	44			*			
Zhang et al.	45					*	
Lotfi et al.	51				*		
Abolghasemian et al.	52						*

Note. [1]Game theory (GT). [2]Linear programming (LP). [3]Nonlinear programming (NLP). [4]Genetic algorithm (GA).

and fuzzy quality, the multiattribute utility technique is used. Then, the best answer (best execution method) is found using a meta-innovative algorithm.

(xi) The total project time is calculated based on the time of activities located in the critical path, and the fuzzy critical path method is used to find the end time of the project. The project's total cost is obtained from the sum of the cost of each independent activity in the project, and the total quality of the project is obtained through a weighting approach to each activity and the sum of the weighted quality of each activity for all projects activities.

3.2. An Overview of the Issues of Trade-Off of Cost, Time, and Quality of the Project. When a project is completed, the time-cost trade-off issue is an issue for the project manager, and quality or performance becomes a key issue [36]. In balancing the cost and time of the project, in a situation where the quality decreases after reducing the time of activities, the reduction of project activities is not desirable. As a result, it is better to increase the project completion time [20, 37]. In such cases, which may occur during the implementation of the project, preventive measures are taken to prevent rework or changes. Contractor time, cost, and project management requirements are important elements in determining the success of information systems and technology projects [38]. The quality of the method obtained helps project managers determine changes in project activities' quality. It helps them achieve the correct initial activities with the actual quality compared to the planned quality [39].

Project quality results from the accumulated contributions of all activities implemented throughout the project life cycle. If the project's output meets the expectations of the project contractor, the project is considered successful [40]. The project contractor prioritizes the availability of results in the long run because the project must be profitable. Completing the project on time and within budget is not enough because the work must also be of acceptable quality.

Previous research has shown that project quality is more important than other factors such as time and cost and is also satisfactory for defining a successful project. The contractor's consent is essential for success because the project output is passed on to the contractor [41].

Scheduled projects are usually supplemented by rework or modification in time-cost balance issues. The project is a set of one-time activities limited by time, cost, and quality factors, and its success depends on establishing a good balance between the three factors mentioned [42]. If any of the factors are overemphasized, the weight of the project falls on the other two factors. Therefore, the failure of project activities should be considered an essential factor in balancing issues.

3.3. Proposed Model. The proposed model in this dissertation is in the multiobjective project scheduling problem in multimode mode. Over the past decade, the issue of multimode project scheduling has become a standard issue in the subject literature, which can be summarized as follows. The multimode project scheduling problem considers an active project, each numbered $j = 1, 2, \ldots, n$. As soon as another activity starts, it is impossible to stop the activity, and there is no interruption in implementing project works. Due to technological and executive needs, there are prioritized relationships between project activities. These relationships are represented by the set of prerequisites for an activity P_j. These sets mean that the activity cannot start before the prerequisite activity $i \in P_j$. Introductory relationships with an activity on node network can be displayed. The basic premise is that these networks are nonrotational. Each of the activities in this network can be completed with different implementation methods (using other resources and technologies). These execution methods or different modes of activity execution are finite, and using each of them will lead to extra time, cost, and quality for each activity. In fact, in the execution of activity j, there are k_j types of execution methods, each of which is numbered with the numbers $k = 1, 2, \ldots, K$. The time, cost, and quality of performing the activity in executable mode are displayed with D_{jk}, C_{jk}, and Q_{jk}, respectively. In the display of each project, two additional activities $j = 0$ and $j = n + 1$ are defined, which indicate the beginning and completion of the whole project. These two activities are virtual, have zero execution time, and do not use any resources.

A timetable for assigning end times F_j to different activities is defined. The purpose of the proposed model is to perform all project activities only in one of the possible modes so that the prerequisite relationships are satisfied and create a balance between the three objective functions of cost, time, and quality of the project.

3.3.1. Proposed Model. This model lists all the constraints required for a multimode project scheduling problem. This model is the basis of most of the research that has been done in this field, which is described in detail in the second chapter, so it is fully described in this section. The parameters used in the model are as follows:

(i) Model Assumptions

The network of nodes AON as a graph $G = (V, E)$
Virtual activity 1 Initial activity and virtual activity n End activity of the network
Divide the project into smaller phases
Time is a continuous element

(ii) Indices

i, j: index of the number of activities $i, j = \{1, 2, \ldots, n\}$
m: the number of times to perform each activity $m = \{1,2, \ldots, n\}$

(iii) Symbolization

d_{jm}: time to perform j^{th} activity in m mode
D_j: the time to perform the w activity by considering the execution modes m^{th}
c_{jm}: the cost of doing j activity in m mode
C_j: the cost of performing the j^{th} activity by considering the executive modes m
q_{jm}: the quality of j activity in m mode
Q_j: the quality of performing the j activity by considering the execution modes m
w_j: the weighting factor of the effect of the quality of j activity on the quality of the whole project
P_j: a set of prerequisite activities for j
TH: schedule horizon

(iv) Variable

x_{jm}: if hm activity is performed in j^{th} mode, it is equal to one; otherwise, it is zero.
F_j: the time of completion of j activity

The first model:

$$\min Z_1 = F_n, \tag{1}$$

$$\min Z_2 = \sum_{j=1}^{n} C_j, \tag{2}$$

$$\max Z_3 = \sum_{j=1}^{n} w_j \cdot Q_j, \tag{3}$$

$$\sum_{m=1}^{m_j} x_{jm} = 1, \quad \forall j = 1, 2 \ldots, n, \tag{4}$$

$$D_j = \sum_{m=1}^{m_j} x_{jm} \cdot d_{jm}, \quad \forall j = 1, 2 \ldots, n, \tag{5}$$

$$F_j \geq F_k + D_j, \quad \forall j = 1, 2 \ldots, n, \forall k \in P_j, \tag{6}$$

$$C_j = \sum_{m=1}^{m_j} x_{jm} \cdot c_{jm}, \quad \forall j = 1, 2 \ldots, n, \tag{7}$$

$$Q_j = \sum_{m=1}^{m_j} x_{jm} \cdot q_{jm}, \quad \forall j = 1, 2 \ldots, n, \tag{8}$$

$$\begin{gathered} x_{jm} \in \{0, 1\}, \quad \forall j = 1, 2 \ldots, n, m = 1, 2, \ldots, m_j, \\ F_j \in R, \quad \forall j = 1, 2 \ldots, n. \end{gathered} \tag{9}$$

Constraint (4) ensures that j activity must be performed in only one of its modes. The next constraint (5) determines the time required for each project activity by considering the execution mode of each activity. One of the essential limitations of the specified project scheduling problem is the operational sequence of activities based on the prerequisite relationships of the activities. This limitation is given in equation (6). In this equation, the completion time of an activity is always greater than the completion time of its prerequisite activities plus the duration of that activity.

Limits (7) and (8), as well as Limit (5), indicate the cost and quality of each activity, taking into account the relevant execution mode. Limitations (1)–(3) indicate the time, cost, and overall quality of the project, respectively. The first chapter states that the project completion time (constraint (1)) can be calculated by summing the critical path activity times. Project cost will also simply be obtained from the sum of the costs of each project activity (constraint (2)). In constraint (3), a weight combination approach was used to determine the overall quality of the project. The weight of each activity indicates its importance and impact on the overall quality of the project. Usually, using more effective execution methods will reduce the time required to perform the activity. Still, more costs will have to be paid in connection with the use of more efficient resources and technologies. This means paying more for the quality of an activity.

Finding a solution to the problem of balancing time, cost, and quality involves determining the optimal combination of execution methods for all the activities that make up the project so that an optimal combination of time, cost, and quality is created for the project. Given the conflict in the intended objective functions, the multiobjective solution approach should solve the proposed model. Therefore, the next section examines the methods of achieving the goal and presents the desired method.

3.3.2. Multiple Attribute Utility Method. Researchers have developed a variety of methods for solving multiobjective problems. Some of these methods are:

(1) Hierarchical Method: in this method, the goals are arranged and optimized for their priority.
(2) Utility Method: in this method, a utility function is defined as a linear combination of objectives in which each of the objectives is given a separate weight. This function will be considered the target of the problem and will be optimized.

(3) Ideal Planning: in this method, an ideal level is defined for each goal. Here, the goal is to find a sequence that is as close as possible to the ideal value of the target. In this method, sometimes one of the goals is considered the main goal of the problem and the other goals are considered the constraints of the problem.

(4) Simultaneous or Pareto Method: in this method, innovative or superinnovative methods will be used to produce or estimate efficient and effective solutions.

(5) Interactive or Conversational Method: in this method, decision-makers state their priorities regarding several answers obtained from the solution method and then agree on some answers.

Each of the methods described has its advantages and disadvantages. Methods 1, 2, and 3 require more information and parameters. Methods 1 and 2 are practical but cannot produce good and efficient answers. Methods 3, 4, and 5 are more complete than the first two methods and have been further studied. In general, the method chosen to solve the problem depends on the characteristics of the problem and the space under discussion. This dissertation uses another method called multiple attribute utility. The multiple attribute utility technique was introduced in the eighteenth century by [43]. Multiple attribute utility is an analytical method for deciding problems based on several criteria. The application of the multiple attribute utility method in construction includes studies in procurement route selection [44] and evaluation of construction engineering performance [45].

Multiple attribute utility means the degree of utility associated with the output of each design. A plan may be chosen according to the priority of the decision-makers or the importance of each independent criterion or function. Each option or design that is evaluated is measured through multiutility functions that express each independent criterion in sequence and are formed using a set of weights. Each weight indicates the decision-maker's priority or the importance of each action. If there are $J \geq 1$ criteria for each option or scheme, the vector $Y = (y_1, \ldots, y_J)$ represents a vector of functions for that scheme. Therefore, the multiple utility combination for calculation in this scheme is calculated according to the following method.

$$U = \sum_{j=1}^{J} w_j u_j, \quad \left\{U \in [0,1]; u_j \in [0,1]\right\}, \tag{10}$$

where u_j, $(j = 1, 2, \ldots, J)$ is a function of the single-characteristic utility for the function j. w_j is the weight for z, and the sum of all weights is 1, i.e., $\sum_{j=1}^{J} w_j = 1$. Individual utility functions are classified into three types: exposure to risk, risk aversion, and neutral risk [46]. The neutral risk utility function is most commonly used and is calculated as follows:

$$u_j = a_j y_j + b_j, \tag{11}$$

where a_j and b_j are fixed values and can be calculated based on the best and worst performances whose level sizes reach the lowest level of zero and the highest level of 1, respectively. Considering the project criteria such as time, cost, and quality in relation to the combination of construction methods, equations for calculating single-characteristic values for time, cost, and quality of a project are expressed as follows:

$$\begin{aligned} u_D &= \frac{D^+ - D}{D^+ - D^-}, \\ u_C &= \frac{C^+ - C}{C^+ - C^-}, \\ u_Q &= \frac{Q - Q^-}{Q^+ - Q^-}. \end{aligned} \tag{12}$$

In the above relationships, D, C, and Q represent time, cost, and quality of the project, respectively. D^+ and D^- represent the largest and smallest project times, respectively. C^+ and C^- also represent the highest and smallest costs of the whole project, respectively. Q^+ and Q^- represent the maximum and minimum overall quality of the project, respectively. If the weights of the three criteria are equal to w_D, w_c, and w_Q, then the desirability of the composite characteristic is obtained through the following equation. The optimal design is the design that has the most desirable composite feature:

$$U = w_D u_D + w_C u_C + w_Q u_Q. \tag{13}$$

Considering the concepts presented in the previous section, the appropriate modeling of the multiple attribute utility method for the problem of time, cost, and quality balance will be as follows.

$$\begin{aligned} &\max U = w_D u_D + w_C u_C + w_Q u_Q, \\ &\quad u_D = \frac{D^+ - F_n}{D^+ - D^-}, \\ &\quad u_C = \frac{C^+ - \sum_{j=1}^{n} C_j}{C^+ - C^-}, \\ &\quad u_Q = \frac{\sum_{j=1}^{n} w_j \cdot Q_j - Q^-}{Q^+ - Q^-}, \\ &\sum_{m=1}^{m_j} x_{jm} = 1, \quad \forall j = 1, 2 \ldots, n, \\ &\quad D_j = \sum_{m=1}^{m_j} x_{jm} . d_{jm}, \quad \forall j = 1, 2 \ldots, n, \\ &\quad F_j \geq F_k + D_j, \quad \forall j = 1, 2 \ldots, n, \forall k \in P_j, \\ &\quad C_j = \sum_{m=1}^{m_j} x_{jm} . c_{jm}, \quad \forall j = 1, 2 \ldots, n, \\ &\quad Q_j = \sum_{m=1}^{m_j} x_{jm} . q_{jm}, \quad \forall j = 1, 2 \ldots, n, \\ &\quad x_{jm} \in \{0, 1\}, \quad \forall j = 1, 2 \ldots, n, m = 1, 2, \ldots, m_j, \\ &\quad F_j \in R, \quad \forall j = 1, 2 \ldots, n. \end{aligned} \tag{14}$$

As stated in the previous sections, the performance criteria of time, cost, and quality related to the different implementation methods of each activity are collected and calculated by project managers or engineers based on past or current experiences or based on expert opinion. Of course, it is not possible to express these parameters, especially the quality of an activity, in precise and specific values. In addition, due to environmental conditions, especially the mentality of managers and engineers in estimating various parameters, project activities' evaluation, or performance criteria is expressed in an uncertain, vague, and inaccurate manner. On the other hand, fitting and estimating the relationship between the implementation method of activity and the performance criteria related to that activity can be due to the uniqueness of the project or its activities and other factors such as environmental conditions, equipment specifications, staff efficiency, supply conditions, and coordination problems. Therefore, the existence of uncertainty and ambiguity in evaluating and expressing the performance of each project activity and the project as a whole is evident and unavoidable.

Therefore, as a development of the present models and also to investigate the problem of time, cost, and quality balance due to the ambiguity and uncertainty in determining and expressing the performance criteria of each project activity (time, cost, and fuzzy quality balance problem), the multiattribute utility technique will be studied in the next section.

4. Adjust the Parameters Using the Taguchi Method

Under the topics discussed in the previous section, the design method of Taguchi experiments with a smaller number of tests leads to a reasonable cost and time savings. It provides the data needed to analyze and achieve the optimal conditions. This advantage has caused the attention of many researchers in recent years to adjust the parameters required by their proposed algorithms [47–49]. In this dissertation, by the above research, the best parameters and operators for implementing algorithms are obtained using this method. For more details on applying the Taguchi experimental design method to parameterization, see [49].

4.1. Select the Appropriate Orthogonal Array. First, how to use the Taguchi method and select the appropriate orthogonal array in this study with one of the methods developed in this dissertation (PSO) is described. This example also demonstrates the effectiveness of the Taguchi method in saving cost and time compared to the complete factorial experiment design method.

In this algorithm, using preliminary experiments for the parameters and operators mentioned above, there are four 3-level factors and one 5-level factor. Factors and their levels are shown in Table 2. In total, to implement the algorithm to solve the problem, $81 \times 10 \times 10 \times 5 \times 10$ experiments with the complete factorial method are required, which is equal to 12150 experiments.

Table 2: Candidate factors and levels in the group particle optimization algorithm (PSO).

Factors	PSO symbol	PSO levels
C2	A	A(1): 0.6 A(2): 0.75 A(3): 0.9
Iteration	B	B(1): n B(2): $2 * n$ B(3): $3 * n$
W	C	C(1): 0.85 C(2): 1.2 C(3): 1.4
Population size	D	D(1): $0.5 * n$ D(2): n D(3): $2 * n$
C1	E	E(1): 0,9 E(2): 1 E(3): 1.1 E(4): 1.2 E(5): 1.4

Due to the importance of reducing cost and time in the implementation of algorithms, especially in scheduling the implementation of this approach, designing experiments is not cost-effective, so Taguchi fractional factorial designs will effectively save time and money. Taguchi standard and simple designs have been used in fewer experiments at the optimum point and in estimating the effect of important factors. In the first step, the required number of degrees of freedom must be calculated to implement the Taguchi method to fit the appropriate orthogonal array. In this case, one degree of freedom is required for the total average, four degrees of freedom for the five-level factor, and two degrees of freedom for each three-level factor (in general, for four two-level factors, $8 = 4 = 2$ degrees of freedom). Therefore, the sum of the required degrees of freedom is equal to

$$(2 \times 4) + 4 + 1 = 13. \quad (15)$$

Therefore, an array with at least 13 rows must be selected. According to the Taguchi standard orthogonal arrays, it is clear that in orthogonal arrays L16 and L18, this condition is established that the L18 array is selected according to the levels of factors. Using the L18 array is that the number of parameters and array levels do not match the PSO algorithm. Therefore, this array is modified with matching techniques. Because in the proposed particle optimization method, there are four 3-level parameters, and in the L18 array, there are six three-level parameters, the two columns of the L18 array must be removed. Also, using the virtual level technique, the six-level column is converted to a five-level parameter, one of which must be executed twice in L18 in this column, and the fifth level is selected.

In the virtual surface technique, the accuracy of repeated surfaces is twice the parameter accuracy of other levels. When modifying arrays, the point to note is that the modified array remains orthogonal. Tables 3 and 4 show the structure of the L18 array and the modified array structure for the proposed particle mass optimization algorithm. The total number of implementations of the previous example problem using the Taguchi method will be $540 = 10 \times 18 \times 10$ times, and if 12150 has been performed using the full-factorial test design method, 11610 = 540–11250 tests have been saved in time and cost.

Before implementing the algorithms, appropriate parameters and candidate levels were first selected for all algorithms using preliminary experiments to solve the problem under study. Then, using the method mentioned above, the appropriate orthogonal arrays are selected for execution according to these factors (parameters and operators). Finally, with the implementation of each algorithm, the best factors were obtained, which will be explained in the following sections on how to select the best parameter.

It should also be noted that, in most articles and previous researches, the parameters and operators of meta-innovative methods with which the algorithm presented in the research are compared, either user-defined or adapted from previous research, and only the parameters and operators of the proposed algorithm are adjusted. The quality of the answer of an algorithm and its optimal parameters depends largely on the type of objective function and the problems used in it [50]. For this reason, in this study, for the conditions to be equal for all the proposed algorithms and other algorithms, the Taguchi method and parameter adjustment are applied to all algorithms.

4.2. Factor Adjustment and Levels of Each Factor Model-Solving Algorithms. To solve the problem, two meta-heuristic algorithms, including group particle optimization (PSO) and artificial bee colony (ABC) optimization, are compared. For each of these algorithms, appropriate parameters have been selected using preliminary experiments shown in Tables 2 and 5 that the best and best combination of parameters and operators should be selected using the Taguchi method. The meaning of n in Table 6 is the number of project activities in each problem instance.

4.3. Creating Sample Problems. According to the article mentioned in the first section, sample problems are created completely randomly, which is used to evaluate the performance of the proposed algorithms. These issues include 10 combinations of the number of activities () and the maximum number of executable modes (). To be more confident and eliminate random factors, each issue was run independently 3 times. The independence of each repetition means that the results after each performance are completely independent and not interdependent. To perform the experiments, all the algorithms used in this dissertation were programmed with MATLAB software on a personal computer with a 2.27 GHz 5i core microprocessor and 4.00 GB memory and then executed.

4.4. Selecting the Best Factors. In each test run, the value of the objective function obtained must be converted according to the Taguchi method to the signal-to-noise ratio, a response variable, and analyzed according to its changes.

Table 3: L18 orthogonal array suitable for particle mass optimization algorithm.

Trial	A	B	C	D	E	F	G
1	0	0	0	0	0	0	0
2	0	0	1	1	2	2	1
3	0	1	0	2	2	1	2
4	0	1	2	0	1	2	3
5	0	2	1	2	1	0	4
6	0	2	2	1	0	1	5
7	1	0	0	2	1	2	5
8	1	0	2	0	2	1	4
9	1	1	1	1	1	1	0
10	1	1	2	2	0	0	1
11	1	2	0	1	2	0	3
12	1	2	1	0	0	2	2
13	2	0	1	2	0	1	3
14	2	0	2	1	1	0	2
15	2	1	0	1	0	2	4
16	2	1	1	0	2	0	5
17	2	2	0	0	1	1	1
18	2	2	2	2	2	2	0

Table 4: Modified array L18 for particle mass optimization algorithm.

Trial	A	B	C	D	E
1	0	0	0	0	0
2	0	0	1	1	1
3	0	1	0	2	2
4	0	1	2	0	3
5	0	2	1	2	4
6	0	2	2	1	4
7	1	0	0	2	4
8	1	0	2	0	4
9	1	1	1	1	0
10	1	1	2	2	1
11	1	2	0	1	3
12	1	2	1	0	2
13	2	0	1	2	3
14	2	0	2	1	2
15	2	1	0	1	4
16	2	1	1	0	4
17	2	2	0	0	1
18	2	2	2	2	0

Table 5: Factors and candidate levels in artificial bee colony (ABC) optimization algorithm.

Factors	HS Symbols	HS levels
Number of bee	NP	NP(1): n NP(2): $2 * n$ NP(3): $3 * n$
Abandoned limit	LIM	LIM(1): 50 LIM(2): 70 LIM(3): 100
Iteration	INT	INT(1): n INT(2):$2 * n$ INT(3): $3 * n$

Table 6: Modified Taguchi L9 orthogonal array for artificial bee colony optimization algorithm.

Trial	NP	LIM	INT
1	0	0	0
2	0	1	1
3	0	2	2
4	1	0	1
5	1	1	2
6	1	2	0
7	2	0	2
8	2	1	0
9	2	2	1

$$\frac{S}{N_s} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right). \quad (16)$$

In Taguchi's method, the S/N ratio is a ratio variable to which the objective function is converted in each execution to make a decision. In this research, according to the selected S/N_s ratio appropriate to the nature of the problems of this research, the maximum S/N_s ratio for each factor in each algorithm is selected as the optimal factor.

4.4.1. Selecting the Optimal Factors of Model-Solving Algorithms. The results of the whole implementation of the model-solving algorithms by designing Taguchi experiments to adjust the parameters are shown as S/N_s ratio in Figures 2 to 9.

According to the above figures, the best factors for the final implementation of the algorithms for solving the model are given in Tables 7 and 8.

4.5. Computational Results. Therefore, the use of methods is meta-innovative, so first, with the parameters and optimal operators of each algorithm obtained by the Taguchi method in the previous section, the results of the implementation of the algorithms are presented on the sample problems created in this chapter. In the sample of problems created to perform experiments by changing dimensions such as the number of project activities and execution modes of each activity, due to differences and nonuniformity of the scale of the value of the objective functions, the percentage of relative deviation in (17) has been used to compare algorithms.

$$\text{RPD} = \frac{\text{Max}_{\text{sol}} - \text{ALG}_{\text{sol}}}{\text{Max}_{\text{sol}}} \times 100. \quad (17)$$

In the results section, we compare the performance of algorithms for the size of the problem, which changes with an increasing number of activities. That ALGsol is the result of the algorithm, and Maxsol is the maximum amount of answers. In this ratio, the lower the RPD, the better the response quality and performance of the algorithm. After summarizing the RPD results, the performance of the algorithms is plotted in the form of graphs and tables.

4.5.1. Results of Implementation of Algorithms. The proposed algorithms for solving the model were described in the previous sections. The RPD results obtained from implementing the studied algorithms are shown in Table 9. Table 9 shows the high-quality performance of the particle mass optimization algorithm with an average of 0.015 in solving the problem of time, cost, and fuzzy quality balance developed in the previous chapter. Comparing the two proposed particle mass and artificial bee colony algorithms, it can be seen that the PSO algorithm performed better. Figure 10 also shows a comparison diagram of the two proposed algorithms.

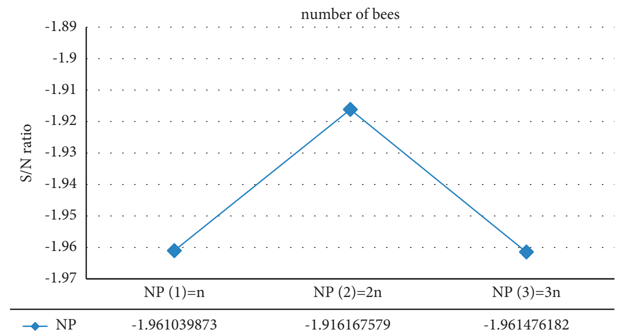

Figure 2: Graph of average S/N ratio for each level of NP factor of ABC algorithm in model solving.

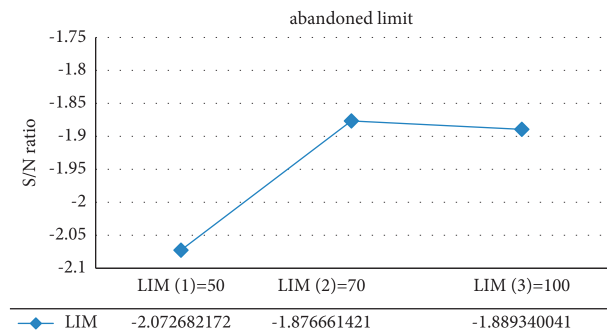

Figure 3: Graph of the average S/N ratio for each level of the ABC algorithm lim factor in model solution.

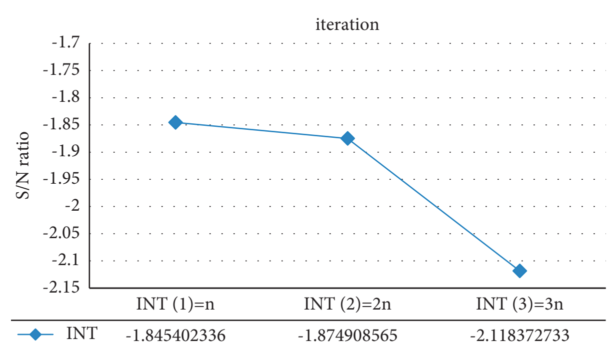

Figure 4: Graph of the average S/N ratio for each level of the int factor of the ABC algorithm in solving the model.

Since different combinations of parameters are involved in the implementation of an algorithm, different quality answers can be achieved. In this section, the topics related to

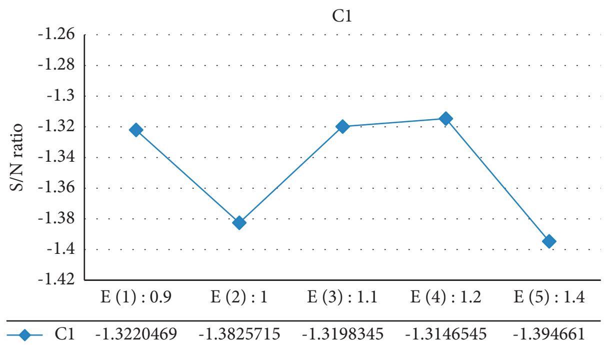

Figure 5: Graph of average S/N ratio for each level of factor C1 of PSO algorithm in model solution.

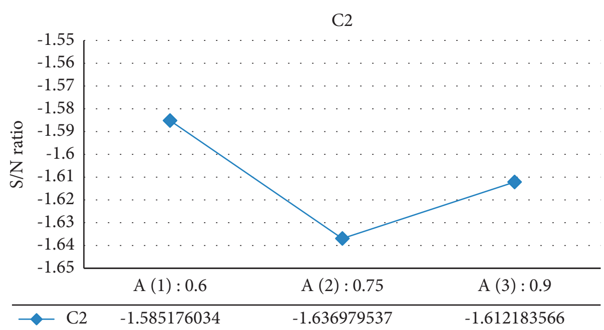

Figure 6: Graph of average S/N ratio for each level of factor C2 of PSO algorithm in model solving.

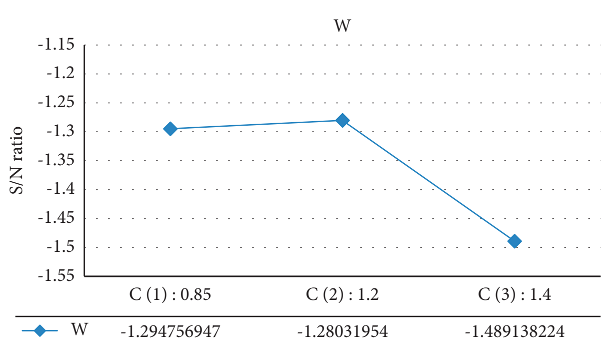

Figure 7: Graph of average S/N ratio for each level of factor W of PSO algorithm in model solution.

setting the parameters of the algorithm were presented. After using the previous research and preliminary experiments in this issue, the appropriate values of the parameters and operators of the algorithms and levels of each were determined, and the appropriate arrays of the design method of Taguchi experiments for execution were determined.

In this regard, first, how to create sample problems was described. With this example, the optimal-level problems of the parameters of 2 meta-heuristic algorithms were obtained by the Taguchi experimental design method. The results of comparing the algorithms in most of the samples show better performance of the particle mass optimization method. In the innovative oven methods, both Taguchi and

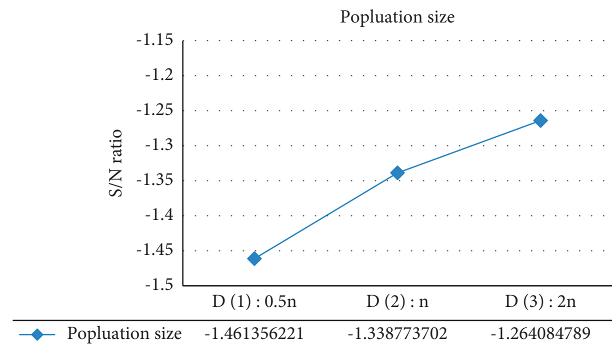

Figure 8: Graph of the average S/N ratio for each level of the POPSIZE factor of the PSO algorithm in solving the model.

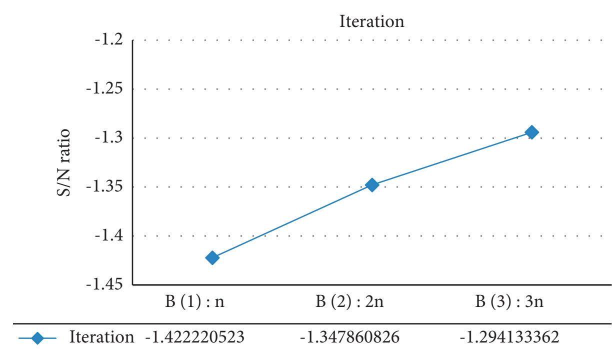

Figure 9: Graph of average S/N ratio for each level of INT factor of PSO algorithm in model solving.

Table 7: Optimal parameters and operators of ABC algorithm.

Factors	Optimum level
NP	2n
LIM	70
INT	N

Table 8: Optimal parameters and operators of PSO algorithm.

Factors	Optimum level
C_2	0.6
ITERATION	3n
W	1.2
POPSIZE	$2n$
C_1	1.2

restart phase methods were used to improve the performance of these methods.

5. Managerial Insight and Practical Implication

Researchers in previous studies have used innovative and ultra-innovative methods to solve these problems to avoid further complexity. The development of accurate methods is also very important because they are the only valid scale by

Table 9: Mean relative deviation percentage (RPD) of algorithms for each combination of sample problems in problem solving.

Average	10	9	8	7	6	5	4	3	2	1	Problem number
0.165	0.198	0.203	0.168	0.170	0.139	0.143	0.175	0.152	0.166	0.143	ABC
0.015	0.027	0.030	0.021	0.009	0.018	0.016	0.005	0.003	0.012	0.009	PSO

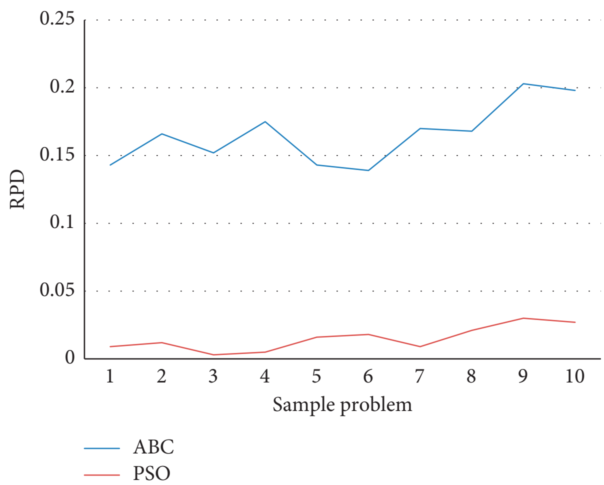

Figure 10: RPD diagram of the performance of the algorithms for each sample problem.

which innovative and meta-innovative methods can be evaluated. In this article, considering the quality coefficient of the project as one of the pillars of the project, it examines the cost-time exchange. In recent years, new methods of cost-time balance have been proposed. In project scheduling calculations, the first time to complete the last activity is the project delivery date. Project completion time is generally reduced by revising network logic or shortening activities at a higher cost. As the duration of activities decreases, the quality of each move, i.e., the proximity of the project delivery products to the expectations of the employer or the customer, decreases. In the discussion of the balance between the three functions of cost, time, and project quality, cost sensitivity analysis is performed against changes during the duration of the activity, which aims to obtain the best combination of reducing the time of activities. In this way, the total cost of the project is minimized and the quality of the whole project is maximized.

6. Conclusion

The general approach of this dissertation in dealing with the issue of uncertainty in the management and planning environment of project activities has been different from previous research. This means that instead of considering the expected value of various parameters of project activities during modeling, fuzzy number theory has been used as a tool to analyze and optimize the planning and management of project activities.

Accordingly, in the third part, the project's balance of time, cost, and quality are modeled as a fuzzy model. In the designed model, the performance measures of each activity, such as time, cost, and quality, are considered exemplary or trapezoidal fuzzy numbers. It is assumed that there is no interruption in the implementation of various project activities, and each project activity can be implemented in a small number of different implementation methods. Due to the multiobjective nature of the problem ahead, the multiattribute utility technique has been used to calculate the desirability of each implementation method in terms of fuzzy time, cost, and quality.

Although the issue of balancing time, cost, and quality of project activities is one of the most important issues in the field of project planning and management, very little research has examined this type of issue. In many studies, the goal is to minimize the overall execution time of the project. However, for many project managers, balancing the performance metrics of a project is very important. Another key hypothesis that has been considered in less research is the focus of the present study on solving the problem of fuzzy time, cost, and quality balance through two meta-heuristic algorithms of particle mass optimization and fuzzy multiobjective artificial bee colony.

Data Availability

All data used to support the findings of the study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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