Many-objective optimization for construction project scheduling using non-dominated sorting differential evolution algorithm based on reference points

Ali Kaveh*, Farivar Rajabi, Sajjad Mirvalad

School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran

Abstract

Scheduling is considered to be one of the most significant factors in the success of construction projects. In recent years, global construction markets have become increasingly competitive, and the number of project stakeholders has grown significantly. As a result, concurrently pursuing multiple project objectives, such as optimizing the time, cost, resources, environmental impact, safety risks, and quality of a project, is imperative. Several types of research efforts have focused on multiple-objective construction scheduling models to deal with the above mentioned objectives. However, there is still a need to integrate all these objectives in the scheduling process to take into account most aspects of a project. To fill this gap, a many-objective optimization model regarding time, cost, resource, environmental impact, safety, and quality based on a newly developed many-objective optimization algorithm, Non-dominated Sorting Differential Evolution algorithm based on Reference points (NSDE-R) is presented in this study. To determine the most proper schedule based on decision-makers' priorities, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is merged with the optimization algorithm. The proposed model's applicability is demonstrated employing a case study of a building construction project.

Keywords: Many objective optimization; Tradeoff; Construction project scheduling; NSDE-R; Multi-criteria decision making; Evolutionary computation; TOPSIS; Construction management.

* Corresponding author E-mail address: alikaveh@iust.ac.ir (A.Kaveh)
Mobile Number:

1 Introduction

Because of today's competitive construction environment, companies should focus on maintaining the objectives of a project to be able to survive. Construction projects involve many parties; this matter will inevitably lead to conflicts of interest because of differences in expectations of a project. A construction project is comprised of a variety of activities with specific priorities among them. Activities can be accomplished in either one or many different modes. Various modes of activity are possible, depending on some variables, like the construction method, resource utilization, and the consumption material. Choosing an activity mode in the project scheduling process depends on the project's goals and limitations. Several objectives, such as time, cost, resource usage, environmental impact, safety, and quality, can be affected by choosing different combinations of available execution modes. Therefore, a reasonable balance needs to be achieved between these contradictory objectives when choosing a suitable option for each activity. However, it is time-consuming to examine all combinations of options, especially when numerous activities are involved in a project. Consequently, there is an urgent need for optimization tools that can accommodate multiple, conflicting objectives of construction projects. The multi-objective scheduling problem (MOSP) describes these kinds of problems. Prior studies have examined how construction scheduling and selecting different combinations of project activities impact several factors, including time, cost, resource use, environmental impact, safety, and quality. Applying a tradeoff between different objectives in MOSPs has received increasing attention from project management researchers in recent years.

The two main approaches to solve complex optimization models are mathematical programming and meta-heuristics. Although the first group usually provides accurate solutions, they are sometimes time-consuming and rely on an appropriate initial point and gradient information of the objective function. With these methods, problems must be defined in continuous space, whereas many problems are defined in discrete space. Meta-heuristics, on the other hand, find approximately optimal solutions within a reasonable time. In addition, stochastic methods can be applied to all disciplines. Many efficient single-objective optimization algorithms have been developed in the last two decades [1]. These algorithms identify the best result after searching through possible feasible solutions. Multi-objective optimization techniques are used in various fields, including construction scheduling, engineering design, and many others. Using these methodologies, decision-makers can identify the best solutions to choose from while maximizing the benefits that can be gained from current resources. There have been many multi-objective algorithms developed for dealing with bi-objective problems like the time-cost tradeoff problem, including non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization (MOPSO) [2-7]. Several kinds of multi-objective optimization models have been developed incorporating one or more other factors such as quality, safety, environmental impact, and resource moment deviation into bi-objective models.

Deb and Jain [8] outlined a number of issues that multi-objective evolutionary algorithms (MOEAs) may face when solving multi-objective problems as follow: existence of a large number of nondominated solutions within the population due to the increase in objectives; complexity of diversity measurement and performance metrics; inefficiency of recombination operation; and difficult visualization of high-dimensional tradeoff front. Researchers have proposed various evolutionary algorithms, known as many-objective evolutionary algorithms, to overcome these obstacles. As an example, NSGA-III was developed by Deb and Jain [8] to address the inefficiencies of MOEAs in solving many-objective optimization problems, with the crowding distance concept being replaced by the reference point-based selection approach in NSGA-II.

MOSP has been studied in the literature by several authors, which are explained as follows:

1.1 Time-cost tradeoff models:

Due to the importance of total project time and total project cost for assessing a project's success, the time-cost tradeoff is the most common type of bi-objective optimization problem [9]. Generally, reducing construction project duration leads to additional costs due to more expensive resources being needed. Therefore, the efficiency of a construction project is greatly affected by the tradeoff between time and cost. Multi-objective optimization techniques are employed to determine the most effective method of minimizing the total project cost and duration. In order to resolve the construction time-cost tradeoff problem, Zhang and Li [10] proposed the MOPSO technique, which was incorporated with a combined methodology. Afshar et al. [11] developed a new Nondominated Archiving Ant Colony Optimization (NA-ACO) algorithm to solve the time–cost multi-objective optimization problems, using multi colony ant principals.

1.2 Time-cost-resource tradeoff models:

Previous studies have examined the linking of resource planning with time and cost optimization since resource utilization is closely related to the project's overall duration and cost [12]. Problems of resource allocation or resource leveling are commonly used in construction when scheduling resources. Peak resource demands are reduced through resource leveling, and period-to-period assignments are smoothed out while assuming an unlimited supply of resources. According to the resource allocation problem, resources are limited to a maximum value, and the objective is to allocate the available resources to project activities to reduce project duration [13]. Zahraie and Tavakolan [14] developed a multi-objective method to optimize total time, total cost, and the moments of resources, at the same time with NSGA-II. Moreover, in their study, fuzzy numbers were also utilized for direct cost and time to take into account managers' behavior when predicting cost and duration for a given activity. In order to consider resource constraints, Ghoddousi et al. [15] extended the general multi-mode resource-constrained project scheduling problem (MRCPSP) to a multi-mode resource-constrained discrete–time–cost–resource optimization model (MRC-DTCRO) while minimizing the time, cost, and resource moment deviation simultaneously.

1.3 Time-cost-environmental impact tradeoff models:

Few studies have considered environmental impact in MOSP. Marzouk et al. [16] developed a multi-objective optimization framework to address construction pollution. Three objective functions, representing project duration, cost, and pollution, were considered using evolutionary genetic algorithms within their framework. Building materials have environmental impacts at every stage of their life cycle, including manufacturing, construction, maintenance, and end-of-life. This issue was analyzed by Ozcan-Deniz et al. [17] by combining both lifecycle assessments and multi-objective optimization utilizing NSGA-II to evaluate the total GHG emissions. Cheng and Tran [18] presented opposition-based multiple-objective differential evolution to solve the time–cost–environment impact tradeoff problem. They proved the superiority of their algorithm over other techniques that had been previously applied to the time-cost-environmental impact tradeoff problems.

1.4 Time-cost-safety tradeoff models:

An essential objective of every construction project is to ensure construction safety. However, safety is rarely incorporated into construction schedules in the literature. Afshar and Dolabi [19] added safety risk to the time-cost tradeoff model and determined the Pareto-optimal solution using the multi-objective genetic algorithm. They stated that there are two types of safety risk assessment methods: activity-based and job-based. According to their argument, the safety risk assessment should employ an activity-based approach since the discrete time-cost tradeoff problem is activity-based. Furthermore, often, accurate safety data is not available during the planning process. So the qualitative safety risk assessment approaches would be more practical than quantitative methods. Based on these facts, they devised a qualitative activity-based safety risk method that could be applied to discrete frameworks for estimating safety risks.

1.5 Time-cost-quality tradeoff models:

El-Rayes and Kandil [20] introduced a modified multi-objective genetic algorithm to solve the time-cost-quality tradeoff (TCQT) optimization problem, in which the value of quality assigned to a specific execution mode was quantified. Afshar et al. [21] developed a multi colony ant algorithm to deal with TCQT. A colony of ants was allocated to each objective, and the ants within a colony were instructed to find the optimal solution for that objective.

1.6 Four objectives optimization models:

The scheduling of construction projects that addressed more than three objectives has been investigated in a few studies. Elbeltagi et al. [22] proposed a PSO-based scheduling model with a new evolutionary strategy using the Pareto-compromise solution, taking concurrently into account the four objectives of time, cost, resource utilization, and cash flow. Although the researchers optimized four objectives using a multi-objective PSO, they did not indicate whether this algorithm is appropriate or not for many-objective optimization problems. In cases with multiple competing objectives, finding non-dominated solutions is less likely, meaning that the multi-objective PSOs show less effectiveness [23]. Zheng [24] created a model based on a genetic algorithm to handle large-scale construction project scheduling while minimizing the total project time, cost, quality defect level, and environmental impact. A priori approach was applied to determine each objective's weight to convert the four-objective problem into a single-objective optimization. They considered a single objective by integrating four objectives, which was less helpful when solving many-objective optimization problems. Panwar and Jha [25] introduced an optimization model based on NSGA-III to determine the tradeoff between the four objectives of time, cost, resource moment, and environmental impact. They used the weighted sum method allowing the project team to make the optimal choice according to their priorities. In Sharma and Trivedi's [26] work, a latin hypercube sampling (LHS)-based NSGA-III model was developed to optimize time–cost–quality–safety tradeoffs in a multi-mode resource-constrained problem. They used LHS to generate a well-distributed parent population. Both quality indicators and activities were weighted using the AHP method and Fuzzy logic was applied to assess safety risks. In another study by Panwar and Jha [27] they proposed a many-objective optimization scheduling model based on NSGA-III that included time, cost, quality, and safety objectives. Due to intrinsic tradeoffs between time, cost, resource moment, environmental impact, safety, and quality, it would be challenging to identify the best construction alternatives that result in low overall costs, a short delivery period, limited fluctuation in resources, minimal environmental impact, proper safety risk score, and high quality in a real-world project. However, no study was found related to time-cost- resource moment-environmental impact-safety-quality tradeoff optimization. In the present study, this problem is addressed by developing a model that considers six objectives simultaneously. This framework is created based on NSDE-R, a recently developed many-objective optimization algorithm.

More objectives lead to a larger nondominated population (Pareto solutions) and decision-makers are responsible for finding the best compromise solution among the Pareto set of alternatives based on stakeholders' priorities. As a result, it makes sense to apply a Multi-Attribute Decision Making (MADM) approach. Generally, simple additive weighting [28] or technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [29] are used to arrive at the best compromise. However, simple additive weighting does not obey the requirement of each criterion being independent [30]. Thus, in this research, TOPSIS is used to find the best compromise solution.

This paper provides an NSDE-R-based optimization model for many-objective tradeoff in construction scheduling, employing TOPSIS to choose the final solution between a pool of nondominated solutions based on project team priorities. A pairwise comparison-based analytical hierarchy process (AHP) theory is also employed to assign the corresponding weight of each project objective.

The rest of the paper is organized as follows. In Section 2, the study begins with problem formulation. The NSDE-R based optimization model is developed in Section 3. Verification of the model is performed in Section 4. An analysis of a case study project is conducted numerically in Section 5. The results and discussion form Section 6. TOPSIS to determine the best compromise solution is decribed in Section 7. Results and discussion are provided in Section 8. Finally, in Section 9, the conclusions are derived.

2 Problem formulation

As described before, an activity in a construction project can be performed using a variety of methods. Each activity mode is different in terms of completion time, completion cost, resource utilization, environmental impact, safety risk score, and quality index due to variations in resource consumption. Hence, an appropriate execution mode must be designated for each project activity during the planning phase of the project. In this paper, the following input parameters for the optimization process are assumed: activity completion time (T), activity completion cost (C), activity resource requirement (R), activity environmental impact (EI), activity safety risk score (SR), and activity quality index (QI). Fig. 1 shows a construction project consisting of n activities represented by $\mathrm{Activity}_1$, $\mathrm{Activity}_2$,… $\mathrm{Activity}_\mathrm{n}$ which can be implemented using various execution modes indicated by EM_1, EM_2,… EM_m. Different alternatives of an activity consume a particular amount of labor resources (LR), material resources (MR), and equipment resources (ER). T, C, R, EI, SR, and QI values are determined according to the selected alternative for each activity. In this paper, the construction scheduling optimization model has the following objective function: (i) minimization of the project completion time (PCT), (ii) minimization of the project completion cost (PCC); (iii) minimization of the total resource moment (TRM); (iv) minimization of the total environmental impact (TEI); (v) minimization of the project safety risk (PSR); and (vi) maximization of the project quality index (PQI). This framework aims to develop a set of non-dominated solutions according to the mentioned six objective functions representing feasible schedules that meet the requirements of the project.

The six previously identified objectives are formulated as follows:

Objective 1: minimize project completion time (PCT)

The first objective is to minimize project makespan as an essential factor of construction projects. One of the critical path methodologies is the precedence diagramming method (PDM), by which project duration can be assessed [25]. Therefore, the time function is defined as the sum of the durations of all activities on the critical path while maintaining precedence relationships between activities.

$$PCT = \sum T_{i_{cp}}^{j} \tag{1}$$

where $T_{i_{cp}}^{j}$ is completion time corresponds to the jth alternative of ith activity on the critical path (cp).

Objective 2: minimize project completion cost (PCC)

The second objective of MOSP is to minimize the project's costs. Total project cost is a function of the sum of each activity's direct cost and total indirect cost. A project's costs are typically separated into direct and indirect costs. The cost of labor, materials, and equipment constitutes the direct cost specifically attributed to the execution of activities, while the indirect cost refers to overhead expenses and outage losses. Project completion cost is formulated as follow:

$$PCC = DC + IC \tag{2}$$

$$DC = \sum_{A} C_{i}^{j} \tag{3}$$

$$IC = C_{ic} \times PCT \tag{4}$$

where DC= total direct cost; IC= total indirect cost; C_i^j= performance cost of the jth mode of ith activity; C_{ic}= indirect cost per unit of time.

Objective 3: minimize total resource moment (TRM)

Resources should be allocated efficiently to prevent high resource fluctuations, periods of high utilization, and extra costs. Intense variations in resource levels of a project lead to (1) employment and firing of labors abruptly; (2) difficulties in attracting and retaining top-quality workers if employment is unstable; (3) disruptions in learning curve effects; and (4) need to maintain the unproductive level of workers on site, which keeps some workers idle during periods of low demand [31]. Besides, when resources from other sources are hired or shared across multiple projects, it is imperative to reduce the resource-utilization timeframe. With the minimum moment approach introduced by Panwar and Jha [25], both mentioned factors are minimized. In this method, the fluctuations in resources considering the resource histogram moments along the x-axis (M_x) is computed. In addition, calculating the y-moment (M_y) about the y-axis represents the resource utilization period. The sum of M_x and M_y is referred to as the double moment or total resource moment. Total resource moment is calculated as:

$$TRM = \sum_{A} M_x + M_y \tag{5}$$

where

$$M_x = \sum_{A} (R_k^t)^2 \tag{6}$$

$$M_y = \sum_{A} R_k^t \times t \tag{7}$$

where R_k^t indicates the utilization of resources k for a time period t.

Objective 4: minimize total environmental impact (TEI)

The environmental impact can be measured along the project's life cycle through metrics such as greenhouse gas (GHG) emissions, energy consumption, acidification, pollutants to air and water, etc. [32]. This study defines the environmental impact function as the sum of kg CO_2 equivalent produced by all activities. Total environmental impact is given by:

$$TEI = \sum_{A} EI_i^j \tag{8}$$

where EI_i^j indicates the environmental impact of operation of activity i in jth execution mode.

Objective 5: minimize project safety risk (PSR)

Construction is recognized as one of the most hazardous industries [33]. This study incorporates safety measures into the model through the calculation of project safety risk (PSR), which is the sum of each activity's safety risk score. Afshar and Dolabi [19] assessed the safety risks of each activity using a qualitative activity-based safety risk (QASR) method. The QASR can be proposed in the following steps: Step 1. Identification of major safety risks; Step 2. determination of likelihood and severity of safety risks; Step 3. Overall evaluation of safety risk score. On the basis of safety legislations such as Bureau of Labor Statistics (BLS), Occupational Health and Safety Administration (OSHA), Health and Safety Executive (HSE), and literature, the most probable safety risks related to the alternatives are identified first. In the second step, the probable likelihood and severity of identified safety risks are assessed based on expert judgment. In order to provide numerical input for the optimization model, qualitative risk evaluation must be quantified. Therefore, both likelihood and severity were rated on a 1–6 scale. Table 1, which is adapted from Cooke and Williams [34], illustrates a simple 6×6 matrix approach for assessing identified safety risks.

Based on reported ratings from the experts, the safety risk score of an identified risk is determined by multiplying its likelihood by its severity, as shown in the following equation:

$$S_{R_i}^j = \sum_{p=1}^{P} \left(L_p^j \times S_p^j\right)_i \tag{9}$$

Then PSR can be calculated by summation of obtained safety risk scores for each alternative. project safety risk is given by:

$$PSR = \sum_{A} S_{R_i}^{j} \tag{10}$$

where $S_{R_i}^{j}$ = safety risk score of jth execution mode of ith activity; P = total number of probable safety risks for the ith activity; L_p^j = likelihood of pth safety risk performing in jth execution mode; and S_p^j= severity of the pth safety risk in jth execution mode.

Objective 6: maximize project quality index (PQI)

Throughout the construction process, it is vital to employ adequate quality-control measures. Lack of quality of performance can lead to failures or defects in constructed facilities, which ultimately causes increases in construction costs and delays in the project. In order to quantify the construction quality, the impact of different strategies of performing activities on the quality of activities should be considered. The proportion of each activity's quality performance on the total quality level of the project should also be determined. Therefore, PQI is a function of the weighted sum of each activity's quality. In this formulation, an activity's weight implies its relative importance and contribution to the overall project's quality. The project quality index is formulated as follow:

$$PQI = \sum_{A} w_i \sum_{k=1}^{K} w_{i.k}^{j} \times q_{i.k}^{j} \tag{11}$$

where w_i = weight of ith activity; $w_{i.k}^{j}$ = weight of the kth quality indicator for jth execution mode of ith activity (indicates the relative importance and contribution of the quality indicator over the other activity indicator measures); and $q_{i.k}^{j}$ denotes the performance of the kth quality indicator value of the jth execution mode of the ith activity.

3 Development of NSDE-R based optimization model

Differential evolution (DE) [35, 36] algorithm is currently among the most popular evolutionary computation techniques used in a wide range of highly non-linear and complicated optimization problems. DE enables global optimization over a continuous domain with a stochastic population-based search approach. DE shifts its population towards global optimum utilizing mutation operators, crossover operators, and selection operators. The ability of DE in solving complex problems efficiently with relatively straightforward operations has motivated many researchers to develop multi-objective DE (MODE) techniques [37]. Applications of MODE-based algorithms in solving MOSPs are described in works by Cheng and Tran [38], Tran and Long [39], Tran et al. [40].

The literature demonstrates that MOEAs can find well-converged and well-diversified non-dominated solutions in a wide range of two- or three-objective optimization problems. Nevertheless, many real-world problems have multiple objectives, which require the detection of optimal solutions involving four or more objectives. Such problems are called many-objective optimization problems [41]. Since increasing the number of objectives in an optimization problem leads to an exponential increase in the population of subsets that are non-dominated, it might be a challenge for MOEAs to handle a large number of objectives. Creating new solutions for the next generation of an optimization process from a non-dominated population and preserving diversity in the Pareto solutions are some of the difficulties existing MOEAs may face in handling many-objective problems. In order to overcome these issues, several many-objective optimization algorithms have been developed in the last years.

This paper uses NSDE-R developed by Reddy and Dulikravich [42] to solve the proposed MOSP. This algorithm utilizes a reference point-based non-dominated sorting approach. A set of reference points evenly distributed throughout the objective function space allows for diversity preservation. NSDE-R has never been applied to the MOSP before this study.

As discussed previously, construction projects are composed of several activities that can be implemented by one or more methods. With a MOSP, various activity alternatives are combined optimally to meet the project's objectives simultaneously. Resources used by these alternatives (materials, equipment, labor) affect how these activities are performed. It is a tedious task to determine which combinations of execution modes should be used in a particular project since numerous activities and their execution modes should be regarded in scheduling process. The proposed framework is designed to provide a set of Pareto-optimal solutions, taking into account the most suitable alternatives for the overall project activities while considering all project objectives.

Initially, the NSDE-R starts with a randomly generated population set P_t known as the initial or parent population, having N members and a set of reference points, R. In this study, the reference points are distributed uniformly through objective function space. In each generation, the algorithm then selects three members and applies the mutation operator. It creates the offspring population, O, with size N. After that, the parent population and offspring population are combined and normalized. Following this, each individual within the combined population, C, is linked to the nearest reference point. The best N individuals from the combined population will be selected through an environmental selection procedure. This promotes both diversity of solutions and facilitation of convergence in generations.

The following sections explain the NSDE-R algorithm in detail.

Step 1. Population initialization and evaluation: Initializing the population is the first step of any evolutionary algorithm. Each individual in the population is generated using input data of the project, such as the number of activities, activity relationships, and the number of available execution modes for each activity. Every individual represents a solution to the MOSP. A population with N individuals can be generated as follows:

$$X_{i.j} = LB_j + rand[0.1] \times \left(UB_j - LB_j\right). \quad (i = 1. \dots . N; j = 1. \dots . D) \tag{12}$$

where $X_{i.j}$ is the jth decision variable of ith individual in the initial population; LB_j and UB_j denote the lower and upper bounds of the jth decision variable, respectively. In this study, LB_j and UB_j are considered to be 0 and 1, respectively. The $rand[a.b]$ is a function that represents a uniformly distributed random number between a and b. D is the number of decision variables of the problem, which is equal to the total number of activities in the project. In this model, the candidate solution can be represented as a vector with D elements as follow:

$$S_i = \left[s_{i.1}. s_{i.2}. \dots . s_{i.j}. \dots . s_{i.D}\right] \tag{13}$$

where S_i represents a set of feasible execution modes for all activities. Consider jth activity, which can be performed in M_j modes, then $s_{i.j}$ is an integer number in the range $\left[1. M_j\right]$ that refers to a selected execution mode for activity j. Since the original version of DE uses real numbers as the decision variable to perform its operations, a function is used to convert real numbers to integer values in the feasible range to determine the execution mode of activities as follow:

$$s_{i.j} = min\{Floor(1 + X_{i.j} \times M_j). M_j\} \tag{14}$$

where the $Floor$ function rounds a real number to the nearest integer that is less than or equal to it. To illustrate solution vector formation, we simply assume that a project consists of n activities that can all be completed using three different alternatives. A vector solution is shown in Fig. 2. This solution suggests execution modes of 3, 1, 3, 2, 1, and 2 to execute activities from 1 to n, respectively. Based on each activity's execution mode, respective values for objective functions are calculated using Eqs. (1-11).

Step 2. DE Operations to create offspring population: In the traditional DE algorithm for each individual i in parent population P, three unique parents are randomly chosen to perform mutation and crossover to create offspring. The most commonly used mutation operator in DE algorithms is the "rand/1/bin" (R1B) [35] given by:

$$\vec{V}_i = \vec{X}_{r_1} + F(\vec{X}_{r_2} - \vec{X}_{r_3}) \tag{15}$$

where $\vec{V}_i = [v_{i.1}. \dots . v_{i.D}]$ and $r_1. r_2. r_3 \in \{1. \dots . N\}$ are randomly selected, subjected to: $r_1 \neq r_2 \neq r_3 \neq i$. The F value controls the scaling of the difference between two randomly selected parents. Parent r_3 is considered a donor parent. In the R1B method, an individual of the population is randomly chosen as the donor vector.

The mutated vector and the ith individual of the current population are then subjected to crossover operation. The offspring o is then created as bellow:

$$o_j = \begin{cases} v_j & if\ rand \leq C_r \vee j = j_{rand} \\ x_{i.j} & otherwise \end{cases} \Bigg|_{j=1.\dots.D} \tag{16}$$

where $C_r \in [0.1]$ determines the probability of crossover and j_{rand} is a randomly chosen index from $\{1. \dots . D\}$ that ensures trail vector O_i differs from its target X_i at least one parameter.

Step 3. Nondominated sorting of combined population: A combined population of size $2N$ was created by merging child and parent population. In this step, these solutions are divided into nondominated fronts $(F_1 . F_2 . \dots . F_n)$ using a nondominated sorting approach.

Step 4. Generation of new population: In order to create a new population for the next generation, an intermediate population S_t is then preserved from the sorted fronts $(F_1 . F_2 . \dots . F_n)$ until $S_t \geq N$. In case the number of solutions of S_t equals N ($|S_t| = N$), then no further operations are required and S_t becomes the new generation (P_{t+1}). Whereas, if $|S_t| \geq N$ at first, members from the first $l -$ 1 nondominated fronts are added to S_t and remaining $K(N - |S_t|)$ required solutions are picked from front F_l based on the maximum diversity. Within NSDE-R, diversity is achieved by a reference point (Z_s)-based approach. According to this method, initially, each individual's objective value is normalized. Then H number of reference points (Z_r) are constructed on a normalized hyperplane. H is calculated as follow:

$$H = \binom{M + d - 1}{d} = \frac{(M + d - 1)!}{(M - 1)!\, d!} \tag{17}$$

where M is the number of objectives in the optimization problem, and d is the number of divisions desired in each objective axis in the normalized hyperplane. All individuals in S_t are then associated with a single reference point. Then, with niche counting strategy, the required K individuals for the next generation are selected from F_l to fill the vacant population of P_{t+1}. Fig. 2 shows the procedure of progressing from one generation to the next in NSDE-R. This process is iterative, and it continues until the stopping criterion is met. Some stopping criteria include the maximum number of generations, maximum number of function evaluations, or achieved convergence of solutions. At the end of the optimization process, construction planners are provided with Pareto-optimal solutions as a final solution set.

4 Verification of the model

To verify and evaluate the effectiveness of the proposed model, two types of optimization problems from the literature are chosen. Based on the proposed framework, these problems are analyzed, and the outcomes are assessed by comparison with reported findings in the literature. The first case study is a time-cost optimization problem taken from Feng et al. [9]. This case study presented a construction project with eighteen activities, each of which could be executed in several execution modes. The use of different optimization algorithms for finding a tradeoff between time and cost has been offered in previous studies [43, 44]. As shown in Table 2, the proposed model provides good performance and acceptable solutions similar and even better than the others with a considerably less number of function evaluation. The second example is a time-cost-environmental impact analysis taken from Ozcan-Deniz et al. [17]. The results from the developed model were compared with the literature results in Table 3. To make a comparison, only those results obtained by the model developed by Ozcan-Deniz [17] and the minimum solution derived from the proposed model are shown in this table. As can be seen, the proposed model offers more promising solutions than the method investigated in the literature. Therefore, the results confirm the model's applicability to the MOSP.

5 Case study

An analysis of a case study project is conducted numerically to demonstrate how effective the many-objective scheduling model for the six-objective optimization problems is. The case data was first presented by Ozcan-Deniz et al. [17] to investigate construction time–cost–environmental impact tradeoff analysis. This case study presents a zero-net-energy residential house construction project with 11 activities, each of which can be performed in several execution modes. According to the permutation theory, there are 9216 ways to complete this project, and each must be examined. So the complexity of the problem renders mathematical approaches useless. This large space of options is searched via an optimization module to provide optimal solutions. Originally, the optimization model from literature considered the three objectives of time, cost, and environmental impact and neglected the influence of resources, safety, and quality in the scheduling procedure. The resources data was taken from the study of Panwar and Jha [25]. Safety and quality are incorporated in the present study as the fifth and sixth objectives, respectively, to explain the advantages of integrating all six factors in a single optimization model. Since the detailed information of this case study is not available, and there is no MOSP example in the literature in which six objectives are involved, the risk score and quality index values of each execution mode are assumed by the authors in this paper. This assumption does not compromise the legitimacy of the proposed framework because the alternatives' information is project-specific and can be defined by the user of the model as input. Activities, associated execution modes, and successors with data of duration, cost, resources, and environmental impact of each alternative are presented in Table 4. Corresponding safety risk score (potential likelihood and severity of identified safety risks) and identified quality indicators with respective weight and quality performance percentage of each option are also shown in Table 5. The proposed model is practically implemented to the mentioned case study project utilizing the MATLAB R2018b.

6 Results and discussion

The developed MOSP is applied to the six-objective case study project. Based on the fact that the parameter configuration influences the performance of metaheuristics, a tuning procedure was performed on the parameters of the optimization algorithm, including population size, number of generations, scaling factor, and crossover probability. These parameters were set in accordance with the literature, and the trials were run by varying those parameters. Performance metrics of multi-objective algorithms differ from those of single-objective algorithms. There may not be a unique optimal solution when considering all objective functions in the multi-objective case. Hence, different approaches are needed for comparing the performance of each test of the proposed algorithm. Several performance indicators (e.g., number of Pareto solutions, diversification metric, spacing metric, mean ideal distance, and spread of non-dominant solution) are available in the literature to assess the quality of the Pareto fronts estimated by multi-objective optimization algorithms [45]. These indicators are widely available in several references, so they are not discussed here for the sake of brevity. A detailed explanation of these methods and their formulation may be found in [45, 46]. In this case, the best possible combination of mentioned parameters set as follow: population size = 100, number of generations = 200, scaling factor = 1~2, crossover probability = 0.8. A total of 65 unique optimal combinations of activity alternatives were acquired that satisfied the desired project objectives. Project objectives such as total duration of the project, cost, resource moment, environmental impact, safety risk score, and quality index were determined for these 65 project implementation alternatives. The total completion time of the project varied from a minimum of 83 days to a maximum of 122 days. Although 65 Pareto optimal solutions have been found, only 38 solutions are presented for different project durations. The alternative combinations and the numerical values of the objectives for these 38 solutions are shown in Table 6. In order to examine the behavior of each objective with respect to the project completion time, tradeoff graphs for the obtained results are shown in Fig. 3. The parallel coordinate plot system has been used to visualize all six objectives at a time. Fig. 4 shows the plot for the parallel coordinates of the obtained Pareto optimal solutions from the proposed model. Objective labels are placed along the horizontal axis, and normalized values of the objectives appear along the vertical axis. It can be concluded that the proposed model produced a suitable distribution of solutions in the solution space since it spread the Pareto-optimal solutions over the entire vertical axis.

7 TOPSIS to determine the best compromise solution

A Pareto optimal solution that best meets the decision maker's preferences should be determined at the end of a multi-objective optimization process. Therefore, in multi-objective optimization, the interaction between the decision-maker and the optimization algorithm is critical. Indeed, it is impossible to rank Pareto optimal solutions globally. The proposed framework offers several optimal solutions while optimizing the specified objectives simultaneously, allowing the project team to choose the final solution according to their priorities. Different approaches have been proposed for selecting a single Pareto solution out of a collection. In this paper, TOPSIS introduced by Hwang and Yoon [29] is used to rank the Pareto solutions obtained by NSDE-R. According to the weight assigned to each objective function by decision-makers, TOPSIS determines the best compromise solution, which is the closest to positive ideal solution (S^+) and furthest from negative ideal solution (S^-) in the Pareto set. The TOPSIS process for determining the best compromise solution is presented as follows:

Step 1. Input S and W, where the element s_{ij} represents the jth objective value of the ith alternative (that is, S is composed of the Pareto solutions) and w_j corresponds to the weight of the jth objective, and W must satisfy $\sum_{j=1}^{n} w_j = 1$.

Step 2. S is then normalized to be $\check{S}$ according to the following equation:

$$\check{s}_{ij} = \frac{s_{ij}}{\sqrt{\sum_{i=1}^{\tau} s_{ij}^2}} \quad for\ i = 1.2. \dots . \tau\ and\ j = 1.2. \dots . n \tag{18}$$

Step 3. Weighted normalized decision matrix $\hat{S}$ is calculated using the following equation:

$$\hat{s}_{ij} = w_j \times \check{s}_{ij} \quad \text{for } i = 1.2. \dots . \tau \text{ and } j = 1.2. \dots . n \tag{19}$$

Step 4. Best alternative (S^+) and worst alternative (S^-) are determined as follow:

$$S^+ = \{ (max(\hat{s}_{ij}) \mid j \in J_-). (min(\hat{s}_{ij}) \mid j \in J_+) \mid i = 1.2. \dots . \tau \}, \text{ and}$$

$$S^- = \{ (min(\hat{s}_{ij}) \mid j \in J_-). (max(\hat{s}_{ij}) \mid j \in J_+) \mid i = 1.2. \dots . \tau \}. \tag{20}$$

Step 5. The separation measures h_i^+ and h_i^- for each alternative are then calculated. The separation measure h_i^+ from S^+ is given by:

$$h_i^+ = \sqrt{\sum_{j=1}^{n} (\hat{s}_{ij} - s_j^+)^2} \text{ for } i = 1.2. \dots . \tau \tag{21}$$

The separation measure h_i^- from S^- is:

$$h_i^- = \sqrt{\sum_{j=1}^{n} (\hat{s}_{ij} - s_j^-)^2} \quad \text{for } i = 1.2. \dots . \tau \tag{22}$$

Step 6. Relative closeness H_i for each Pareto solution is calculated according to the following equation:

$$H_i = \frac{h_i^-}{h_i^+ + h_i^-} \quad \text{for } i = 1.2. \dots . \tau \tag{20}$$

where $0 < H_i < 1$.

Step 7. Select the best compromise solution whose relative closeness H_i is the closest to 1.

Three scenarios are analyzed using the proposed approach. The analytical hierarchy process (AHP) has been used to set the weight value for each objective. Table 7 shows the weight assigned to each objective and the final solutions obtained by TOPSIS.

8 Conclusion

In response to rapid technological developments and growing stakeholder demands, tradeoff strategies are needed between project goals. Construction projects involve important and interdependent performance factors, including time, cost, resources, impact on the environment, safety, and quality. Integrating all objectives into a single scheduling optimization model and making compromises between them can be considered as an approach to improve the effectiveness of construction project planning. As the number of activities, their alternatives, and the number of objectives of the project increases, the MOSP becomes exponentially more complex to solve. Previous studies have mainly focused on two or three objectives. Although a few studies have attempted to optimize four objectives simultaneously in recent years, none of them have considered the simultaneous effect of six objectives in an optimization model. In order to achieve the tradeoff between time, cost, resource moment, environmental impact, safety, and quality, which are considered as significant factors for construction projects, an NSDE-R-based optimization model was developed. Two case studies from the literature were analyzed to validate the proposed optimization model, and the results proved the superiority of the proposed model over previous models available in the literature. Also, a case study was used to demonstrate the model's applicability. In order to determine the best compromise solution based on the priorities of project team members, a TOPSIS based approach was employed. Besides AHP method was used to determine the weight of each objective. As a result, all stakeholders will benefit if decision-makers use this integrated model in the planning phase of the project.

References

1. Kaveh A. "Advances in Metaheuristic Algorithms for Optimal Design of Structures". 3 ed,pp 1-881, Springer International Publishing,(2020).
2. Fallah-Mehdipour E, Haddad OB, Tabari MMR, Mariño MA. "Extraction of decision alternatives in construction management projects: Application and adaptation of NSGA-II and MOPSO". Expert Systems with Applications,39(3),pp 2794-803(2012).

3. Kaveh A, Moghanni RM, Javadi SM. "Ground motion record selection using multi-objective optimization algorithms: A comparative study". Periodica Polytechnica Civil Engineering,63(3),pp 812-22(2019).
4. Kaveh A, Massoudi M. "Multi-objective optimization of structures using charged system search". Scientia Iranica,21(6),pp 45-60(2014).
5. Kaveh A, Fahimi-Farzam M, Kalateh-Ahani M. "Performance-based multi-objective optimal design of steel frame structures: nonlinear dynamic procedure". Scientia Iranica,22(2),pp 373-87(2015).
6. Kaveh A, Vazirinia Y. "Smart-home electrical energy scheduling system using multi-objective antlion optimizer and evidential reasoning". Scientia Iranica,27(1),pp 177-201(2020).
7. Kaveh A, Ilchi Ghazaan M. "A new VPS-based algorithm for multi-objective optimization problems". Engineering with Computers,36(3),pp 1029-40(2020).
8. Deb K, Jain H. "An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints". IEEE transactions on evolutionary computation,18(4),pp 577-601(2013).
9. Feng C-W, Liu L, Burns SA. "Using genetic algorithms to solve construction time-cost trade-off problems". Journal of computing in civil engineering,11(3),pp 184-9(1997).
10. Zhang H, Li H. "Multi-objective particle swarm optimization for construction time-cost tradeoff problems". Construction Management and Economics,28(1),pp 75-88(2010).
11. Afshar A, Ziaraty AK, Kaveh A, Sharifi F. "Nondominated archiving multicolony ant algorithm in time–cost trade-off optimization". Journal of Construction Engineering and Management,135(7),pp 668-74(2009).
12. Senouci AB, Eldin NN. "Use of genetic algorithms in resource scheduling of construction projects". Journal of construction engineering and management,130(6),pp 869-77(2004).
13. Chan W-T, Chua DK, Kannan G. "Construction resource scheduling with genetic algorithms". Journal of construction engineering and management,122(2),pp 125-32(1996).
14. Zahraie B, Tavakolan M. "Stochastic time-cost-resource utilization optimization using nondominated sorting genetic algorithm and discrete fuzzy sets". Journal of construction engineering and management,135(11),pp 62-71(2009).
15. Ghoddousi P, Eshtehardian E, Jooybanpour S, Javanmardi A. "Multi-mode resource-constrained discrete time–cost-resource optimization in project scheduling using non-dominated sorting genetic algorithm". Automation in construction,30,pp 216-27(2013).
16. Marzouk M, Madany M, Abou-Zied A, El-said M. "Handling construction pollutions using multi-objective optimization". Construction management and economics,26(10),pp 1113-25(2008).
17. Ozcan-Deniz G, Zhu Y, Ceron V. "Time, cost, and environmental impact analysis on construction operation optimization using genetic algorithms". Journal of management in engineering,28(3),pp 265-72(2012).
18. Cheng M-Y, Tran D-H. "Opposition-based multiple-objective differential evolution to solve the time–cost–environment impact trade-off problem in construction projects". Journal of Computing in Civil Engineering,29(5),pp 1-10(2015).
19. Afshar A, Zolfaghar Dolabi H. "Multi-objective optimization of time-cost-safety using genetic algorithm". Iran University of Science & Technology,4(4),pp 433-50(2014).
20. El-Rayes K, Kandil A. "Time-cost-quality trade-off analysis for highway construction". Journal of construction Engineering and Management,131(4),pp 477-86(2005).
21. Afshar A, Kaveh A, Shoghli O. "Multi-objective optimization of time-cost-quality using multi-colony ant algorithm".pp 113-24(2007).
22. Elbeltagi E, Ammar M, Sanad H, Kassab M. "Overall multiobjective optimization of construction projects scheduling using particle swarm". Engineering, Construction and Architectural Management,pp 265-82(2016).
23. Köppen M, Yoshida K, editors. Substitute distance assignments in NSGA-II for handling many-objective optimization problems. International Conference on Evolutionary Multi-Criterion Optimization,pp 727-41, Springer,(2007).

24. Zheng H, editor The bi-level optimization research for time-cost-quality-environment trade-off scheduling problem and its application to a construction project. Proceedings of the Tenth International Conference on Management Science and Engineering Management,pp 745-53, Springer,(2017).

25. Panwar A, Jha KN. "A many-objective optimization model for construction scheduling". Construction management and economics,37(12),pp 727-39(2019).

26. Sharma K, Trivedi MK. "Latin hypercube sampling-based NSGA-III optimization model for multimode resource constrained time–cost–quality–safety trade-off in construction projects". International Journal of Construction Management,pp 1-11(2020).

27. Panwar A, Jha KN. "Integrating Quality and Safety in Construction Scheduling Time-Cost Trade-Off Model". Journal of Construction Engineering and Management,147(2),pp 1-15(2021).

28. Churchman CW, Ackoff RL. "An approximate measure of value". Journal of the Operations Research Society of America,2(2),pp 172-87(1954).

29. Hwang C-L, Yoon K. "Methods for multiple attribute decision making". Multiple attribute decision making,pp 58-191, Springer,(1981).

30. Farmer TA. "Testing the robustness of multiattribute utility theory in an applied setting". Decision Sciences,18(2),pp 178-93(1987).

31. Hegazy T. "Computer-based construction project management: Pearson new international edition",pp 1-405, Pearson Higher Ed,(2013).

32. Ozcan-Deniz G, Zhu Y. "Using a life cycle assessment approach for optimizing multi-objectives in construction projects". Computing in Civil Engineering,pp 177-85,(2013).

33. Patel D, Kikani K, Jha K. "Hazard assessment using consistent fuzzy preference relations approach". Journal of Construction Engineering and Management,142(12),pp 1-10(2016).

34. Cooke B, Williams P. "Construction planning, programming and control",pp 1-363, John Wiley & Sons,(2013).

35. Storn R, Price K. "Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces". Journal of global optimization,11(4),pp 341-59(1997).

36. Price K, Storn RM, Lampinen JA. "Differential evolution: a practical approach to global optimization",pp 1-543, Springer Science & Business Media,(2006).

37. Das S, Suganthan PN. "Differential evolution: A survey of the state-of-the-art". IEEE transactions on evolutionary computation,15(1),pp 4-31(2010).

38. Cheng M-Y, Tran D-H. "Two-phase differential evolution for the multiobjective optimization of time–cost tradeoffs in resource-constrained construction projects". IEEE Transactions on Engineering Management,61(3),pp 450-61(2014).

39. Tran DH, Long LD. "Project scheduling with time, cost and risk trade-off using adaptive multiple objective differential evolution". Engineering, Construction and Architectural Management,pp 623-38(2018).

40. Tran D-H, Cheng M-Y, Cao M-T. "Hybrid multiple objective artificial bee colony with differential evolution for the time–cost–quality tradeoff problem". Knowledge-Based Systems,74,pp 176-86(2015).

41. Coello CAC, Lamont GB. "Applications of multi-objective evolutionary algorithms",pp 1-791, World Scientific,(2004).

42. Reddy SR, Dulikravich GS. "Many-objective differential evolution optimization based on reference points: NSDE-R". Structural and Multidisciplinary Optimization,60(4),pp 1455-73(2019).

43. Kalhor E, Khanzadi M, Eshtehardian E, Afshar A. "Stochastic time–cost optimization using non-dominated archiving ant colony approach". Automation in Construction,20(8),pp 1193-203(2011).

44. Elbeltagi E, Hegazy T, Grierson D. "Comparison among five evolutionary-based optimization algorithms". Advanced engineering informatics,19(1),pp 43-53(2005).

45. Audet C, Bigeon J, Cartier D, Le Digabel S, Salomon L. "Performance indicators in multiobjective optimization". European journal of operational research,pp 1-50(2020).

46. Maghsoudlou H, Afshar-Nadjafi B, Niaki STA. "A multi-objective invasive weeds optimization algorithm for solving multi-skill multi-mode resource constrained project scheduling problem". Computers & Chemical Engineering,88,pp 157-69(2016).
47. Zheng DX, Ng ST, Kumaraswamy MM. "Applying Pareto ranking and niche formation to genetic algorithm-based multiobjective time–cost optimization". Journal of Construction Engineering and Management,131(1),pp 81-91(2005).
48. Zhang Y, Thomas Ng S. "An ant colony system based decision support system for construction time-cost optimization". Journal of Civil Engineering and Management,18(4),pp 580-9(2012).

Figure Caption List

Fig. 1. Input data for the optimization model

Fig. 2. NSDE-R- based optimization model flowchart

Fig. 3. Obtained Pareto optimal solutions shown for each objective with respect to the project completion time

Fig. 4. Six-objective coordinate plot

Table 1. Safety risk rating system adapted from [34]

Likelihood		Severity	
Level description	Score	Level description	Score
Remote	1	Minor injury	1
Unlikely	2	Illness	2
Possible	3	Accident	3
Likely	4	Reportable injury	4
Probable	5	Major injury	5
Highly probable	6	Fatality	6

Table 2. Comparison of results for two-objective optimization problems

Study	Zheng et al **[47]**		Afshar et al [11]		Zhang and Ng **[48]**		Proposed model	
Optimization algorithm	MAWA-GA		NA-ACO		ACS-SGPU		NSDE-R	
Objective	Time (days)	Cost ($)	Time (days)	Cost ($)	Time (days)	Cost ($)	Time (days)	Cost ($)
Solution								
1	100	287720	100	283320	100	285400	100	283320
2	101	284020	101	279820	101	282508	101	279820
3	104	280020	104	276320	104	277200	104	276320
4	110	273720	110	271270	110	273165	110	271270
Number of function evaluation	25000		12300		2000		1500	

Table 3. Comparison of results for three objective optimization problem

Study	Ozcan-Deniz et al **[17]**			Proposed model			
Solution	Time (days)	Cost ($)	EI (CO_2-eq)	Time (days)	Cost ($)	EI (CO_2-eq)	Execution modes
1	83	758768	164173	83	741430	163830	2,2,2,2,2,3,4,1,2,2,1
2	87	713714	147150	87	585090	131170	2,2,1,2,2,1,4,1,2,2,2
3	87	713765	146022	87	585150	131080	2,1,1,2,2,1,4,1,2,2,2
4	88	705409	145767	88	592530	120440	2,2,2,2,2,1,2,1,2,2,2
5	90	608776	130381	89	586370	120270	2,2,1,2,2,1,2,1,2,2,2
6	92	627709	126217	92	476470	80520	2,2,2,2,2,1,4,1,1,2,1
7	93	587667	97689	93	470310	80346	2,2,1,2,2,1,4,1,1,2,1
8	95	533065	89779	95	421710	74222	2,2,1,2,2,1,4,1,1,2,2
9	98	495348	68582	97	423000	63323	2,2,1,2,2,1,2,1,1,2,2
10	99	428887	77051	99	418350	74222	2,2,2,1,2,1,4,1,1,2,2
11	99	478885	71069	99	419770	72756	1,1,1,2,1,1,4,1,1,2,2
12	106	422029	77045	106	411350	62975	2,2,1,1,1,1,2,1,1,2,2
13	106	428741	62190	106	411530	61683	1,1,1,1,1,1,2,1,1,2,2
14	107	424867	74465	107	405450	72832	1,2,1,1,2,1,3,1,1,2,2
15	111	422924	73001	111	403390	72576	1,1,1,1,1,1,3,1,1,2,2
Average	96.07	556703.6	103372.07	95.93	490126.67	92149.67	-

Table 4. Activities and available options

ID	Activity	Successors	Alt.	Time (days)	Cost ($)	Resource (Units)	EI (CO_2-eq)
1	Site work	2	1	4	5039.71	4	1728.86
			2	4	4924.93	5	2938.36
2	Excavation	3	1	2	360.71	6	317.66
			2	2	297.05	6	399.34
3	Footing	4	1	6	84232.67	20	9541.15
			2	5	90392.28	28	9715.51
4	Stem wall	5	1	13	76650.79	24	9647.65
			2	8	86174.94	28	9822.01
5	Slab	6	1	11	14636.05	21	15790.29
			2	7	16758.59	25	15964.65
6	Exterior wall	7	1	6	25959.52	12	9152.52
			2	14	65399.94	16	35518.33
			3	5	127542.4	20	35518.33
7	Interior wall	11	1	18	27970.53	6	4152.23
			2	10	35650.22	10	4164.16
			3	15	27508.21	12	15056.4
			4	8	34365.99	16	15062.37
8	Flooring	–	1	16	28341.6	10	118.59
			2	12	45616.48	8	544.3
			3	8	36554.88	8	3030.66
9	Exterior finish	–	1	31	69659.78	12	4219.17
			2	23	233034.5	8	61163.85
10	Interior finish	–	1	3	4006.8	6	256.03
			2	4	1746.55	10	256.03
11	Roof	8,9,10	1	21	117851.8	10	12871.66
			2	23	69253.17	6	6747.33

Table 5. Safety and quality data

ID	Alt.	Safety risk score		Act. W	Quality performance (Q_p and quality indicator (K)					
		Likelihood	Severity		$K=1$		$K=2$		$K=3$	
					k_1	q_1	k_2	q_2	k_3	q_3
1	1	2	2	0.12	20	98	70	99	10	95

	2	2	3	0.12	20	81	70	83	10	79
2	1	3	3	0.11	10	97	80	94	10	96
	2	4	4	0.11	10	86	80	78	10	84
3	1	3	5	0.15	35	97	35	93	30	91
	2	4	6	0.15	35	78	35	85	30	79
4	1	2	5	0.1	40	99	30	90	30	94
	2	3	6	0.1	40	83	30	75	30	82
5	1	3	4	0.08	60	81	20	84	20	77
	2	2	5	0.08	60	96	20	92	20	95
6	1	4	5	0.11	45	63	20	71	35	60
	2	1	5	0.11	45	99	20	95	35	92
	3	3	5	0.11	45	80	20	83	35	75
7	1	1	3	0.07	40	79	20	74	40	63
	2	2	2	0.07	40	98	20	96	40	89
	3	1	4	0.07	40	64	20	66	40	51
	4	3	4	0.07	40	88	20	82	40	75
8	1	2	5	0.05	60	82	30	74	10	81
	2	2	4	0.05	60	93	30	87	10	90
	3	3	5	0.05	60	71	30	62	10	69
9	1	2	2	0.09	65	81	10	79	25	83
	2	3	3	0.09	65	99	10	98	25	99
10	1	1	2	0.06	70	94	5	92	25	97
	2	1	3	0.06	70	83	5	78	25	85
11	1	3	6	0.06	50	96	20	99	30	91
	2	4	5	0.06	50	84	20	86	30	80

Table 6. Obtained Pareto optimal solutions of case study project

Solution	PCT	PCC	TRM	TEI	PSR	PQI	Execution modes
1	83	743750	79416	163750	133	86.64	2,1,2,2,2,3,4,1,2,1,1
2	84	659560	71590	136600	134	87.45	1,1,2,2,2,1,4,2,2,1,1
3	85	650960	73527	137720	135	85.07	2,2,1,2,2,1,4,2,2,2,1
4	86	658590	73082	125700	127	87.63	1,1,2,2,2,1,2,2,2,2,1
5	87	635040	79437	126310	122	87.01	2,1,1,2,2,1,2,1,2,2,1
6	88	609920	68772	119660	136	85.27	1,2,2,2,2,1,2,2,2,2,2
7	89	597030	62433	121890	126	88.42	1,1,1,2,2,1,2,3,2,1,2
8	90	634816	75672	138740	124	89.67	1,1,1,1,2,1,4,3,2,1,1
9	91	591360	70877	132610	137	85.71	1,1,1,2,1,1,4,3,2,2,2
10	92	578000	81358	129700	121	89.49	1,1,1,1,2,1,4,1,2,1,2
11	93	584430	80195	118800	124	87.12	1,1,1,2,1,1,2,1,2,2,2
12	94	543010	87643	99722	117	88.84	1,1,1,2,2,3,4,2,1,1,2

13	95	474040	97027	68156	114	88.13	1,1,1,2,2,1,2,1,1,1,1
14	96	532860	86193	92520	119	85.92	2,1,1,2,2,3,2,3,1,2,2
15	97	580950	76971	120260	129	83.78	2,2,1,2,2,1,1,1,2,1,2
16	98	585380	74502	121540	120	88.64	1,1,1,1,1,1,2,3,2,1,2
17	99	563830	110050	94348	102	90.59	1,1,1,1,2,3,2,1,1,2,1
18	100	481670	98464	69617	106	88.06	2,1,1,1,2,1,2,2,1,1,1
19	101	529470	105205	105850	105	91.5	1,1,1,2,2,2,4,2,1,1,1
20	102	577450	76140	122910	120	85.56	2,1,1,1,2,1,1,3,2,2,2
21	103	513480	112159	94522	99	91.82	1,1,1,2,2,2,2,1,1,1,1
22	104	418460	99902	75494	124	85.53	1,1,1,1,1,1,4,3,1,2,2
23	105	462500	110659	89607	104	88.4	2,1,1,2,2,2,2,1,1,2,2
24	106	519940	114768	105670	97	92.89	1,1,1,1,2,2,4,2,1,1,1
25	107	415980	98426	75662	113	85.82	1,1,1,1,2,1,3,3,1,1,2
26	108	501580	124966	95557	94	90.51	2,1,1,1,2,2,2,1,1,2,1
27	109	421470	95725	65967	125	81.44	2,1,1,2,1,1,1,3,1,2,2
28	110	455350	117044	88224	93	92.48	1,1,1,1,2,2,2,1,1,1,2
29	111	405650	116580	72576	110	85.2	1,1,1,1,1,1,3,1,1,1,2
30	112	451950	124752	98947	103	90.45	1,1,1,1,1,2,4,1,1,1,2
31	113	472210	108233	88812	99	89.39	1,1,1,2,2,2,1,2,1,2,2
32	114	412060	104252	64584	115	84.83	1,1,1,1,1,1,1,3,1,2,2
33	115	447150	126214	99198	100	88.43	1,2,1,1,2,2,3,1,1,1,2
34	116	511290	122964	94762	89	91.51	1,1,1,1,2,2,1,2,1,2,1
35	117	452820	123195	88212	103	87.68	1,1,1,2,1,2,1,1,1,2,2
36	118	453560	113302	91205	105	88.06	1,2,1,1,2,2,1,3,1,2,2
37	119	442770	136404	99023	103	86.58	1,2,1,1,1,2,3,1,1,2,2
38	122	445550	129682	88037	94	89.75	1,1,1,1,1,2,1,1,1,1,2

Table 7. Optimal solutions with respect to the considered project scenarios

Scenario	Objective weight						Time (days)	Cost ($)	RM	EI (CO_2-eq)	Safety score	Quality (%)	Execution modes
	PCT	PCC	TRM	TEI	TSR	TQI							
1	0.456	0.086	0.034	0.054	0.242	0.129	87	635040	79437	126310	122	87.01	2,1,1,2,2,1,2,1,2,2,1
2	0.051	0.601	0.135	0.072	0.042	0.1	107	415980	98426	75662	113	85.82	1,1,1,1,2,1,3,3,1,1,2
3	0.073	0.06	0.085	0.03	0.316	0.436	116	511290	122964	94762	89	91.51	1,1,1,1,2,2,1,2,1,2,1

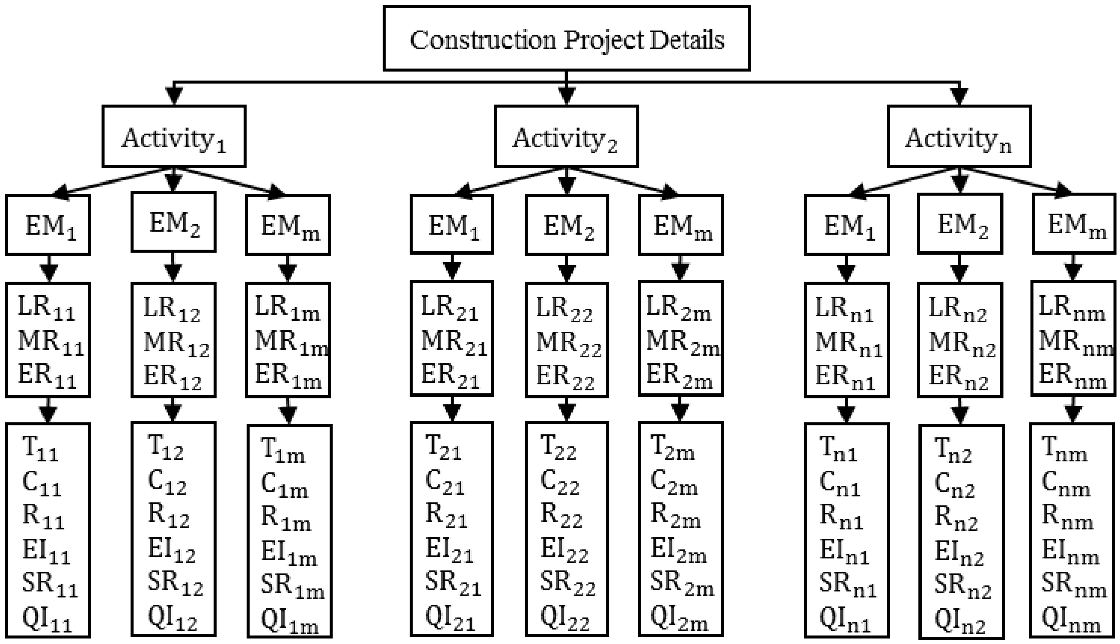

Fig. 1. Input data for the optimization model

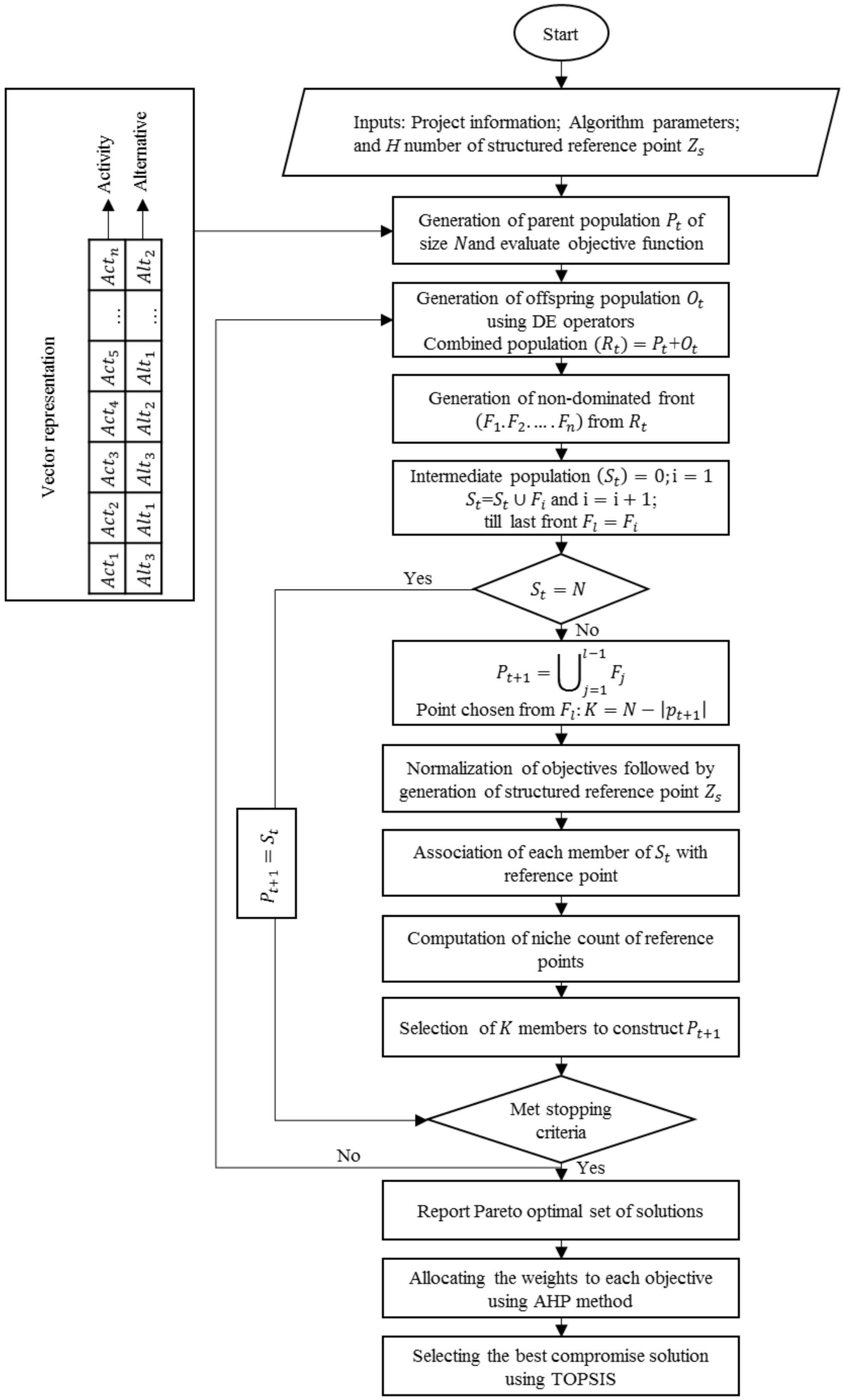

Fig. 2. NSDE-R- based optimization model flowchart

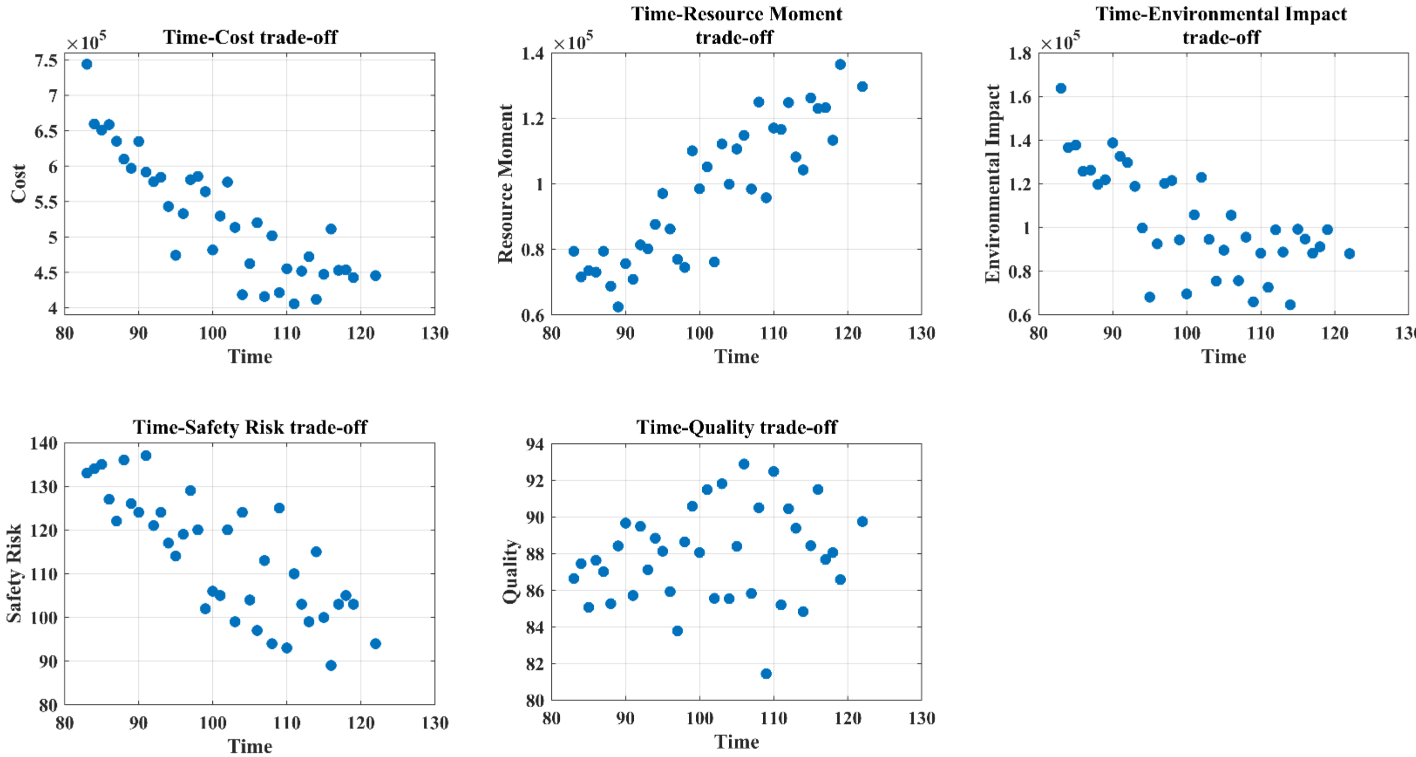

Fig. 3. Obtained Pareto optimal solutions for each objective with respect to the project completion time

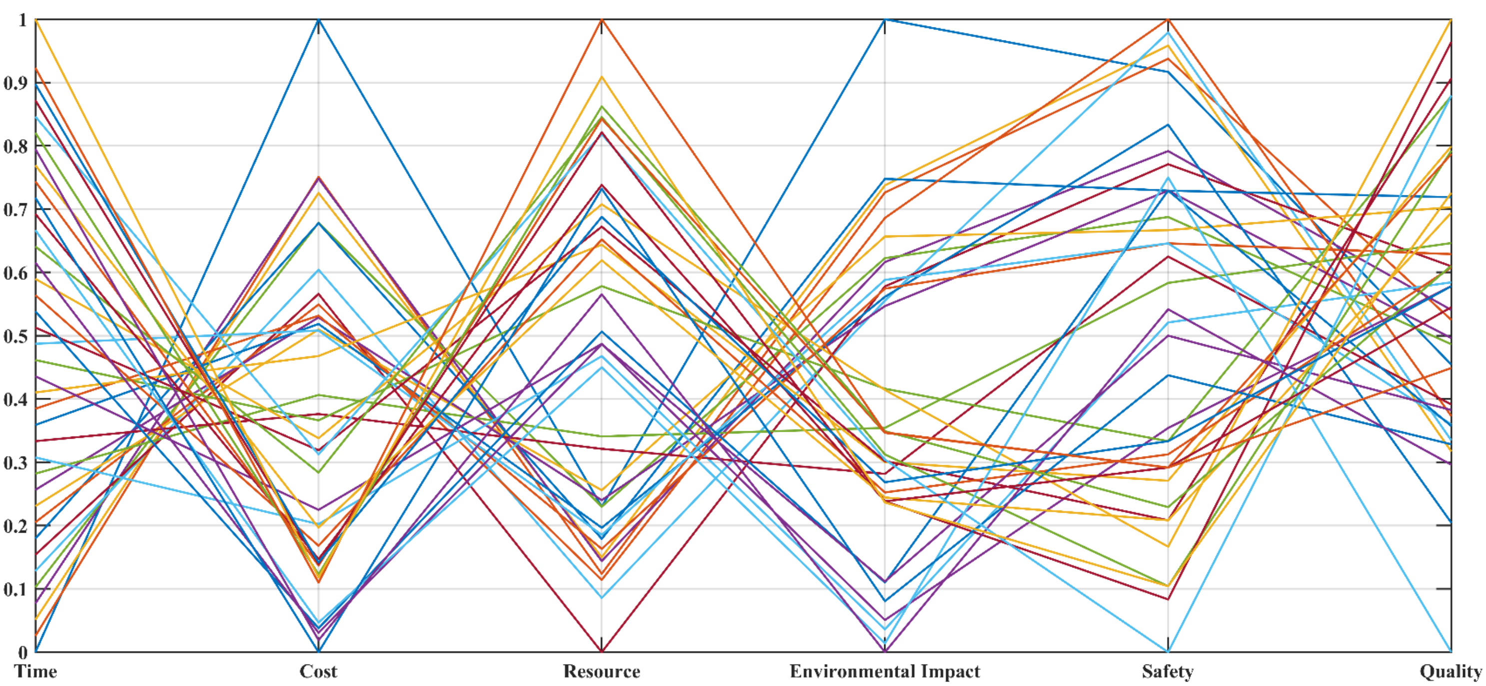

Fig. 4. Six-objective coordinate plot

Biographies

Ali Kaveh was born in 1948 in Tabriz, Iran. After graduation from the Department of Civil Engineering at the University of Tabriz in 1969, he continued his studies on Structures at Imperial College of Science and Technology at London University and received his MSc, DIC, and Ph.D. degrees in 1970 and 1974, respectively. He then joined Iran University of Science and Technology. Professor Kaveh is the author of 670 papers published in international journals and 170 papers presented at national and international conferences. He has authored 23 books in Persian and 14 books in English published by Wiley, Research Studies Press, American Mechanical Society, and Springer.

Farivar Rajabi is an MSc student in the Construction Engineering and Management program of the School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran. He also received his BSc degree in Civil Engineering from Iran University of Science and Technology, Tehran, Iran. His research interests include construction project management and building information modeling.

Sajjad Mirvalad is an Assistant Professor at the School of Civil Engineering specializing in Construction Engineering and Management at Iran University of Science and Technology, Tehran, Iran. He received his Ph.D. in Civil Engineering from Concordia University, Montreal, Canada, in 2014. His area of research focuses on sustainable development, construction technology, and concrete materials.