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Research Article

Optimization in Construction Management Using Adaptive Opposition Slime Mould Algorithm

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The purpose of this research study is to solve a four-objective optimization problem in the construction industry using a hybrid model that combines the slime mould algorithm (SMA) with opposition-based learning. This hybrid model is known as the adaptive opposition slime mould algorithm (AOSMA). Two typical construction projects have introduced time, cost, quality, and safety trade-off (TCQS), which are the factors that have the greatest influence on the completion of a construction project and are represented by optimal results and obtained at Pareto, in order to better illustrate the potential of the proposed model. In order to compare AOSMA with a nondominated sorting genetic algorithm III (NSGA III), multiobjective particle swarm optimization (MOPSO), LHS-based NSGA III, and a hybrid model of MAWA (MAWA-TLBO, MAWA-GA, MAWA-AS, and MAWA-ACS-SGPU) and to assess the model's potential and viability, performance evaluation indexes are applied. To assist project managers in planning time, cost, quality, and safety for construction investment projects, this study creates a hybrid model.

1. Introduction

Investment in construction has been severely affected by the COVID-19 pandemic. Consequently, project efficiency has decreased, investment costs have increased, project implementation times have increased, and construction safety has become less stable. The construction industry in Vietnam faces particular challenges. Cost and time management, quality improvement, and safety risk reduction must be a top priority; and a combination of these aims is needed to achieve project efficiency, and the impact of safety on project costs is also essential [1].

The field of objective optimization has flourished due to the introduction of a variety of complex algorithms. The topic of time and cost trade-offs among those in this industry has been covered [2, 3]. Replaced with the problem of the time-cost-qualitytrade-off [4, 5] and time-cost-safetytrade-off [1], numerous writers have successfully used algorithms to resolve optimization issues with three trade-offs. Time, cost, resources, and cash flow [6]; time, cost, resources, and environmental effect [7]; and time-cost-quality-safety in construction projects [8] are the three examples of trade-offs. Due to the complexity rising as the number of competing objectives rises, this trade-off optimization problem is difficult [9].

The performance of the slime mould algorithm (SMA) in optimization technique was the primary aspect that influenced this research study [10]. By mimicking the foraging and movement patterns of the slime mould, SMA resolves the optimization problem. It can successfully find a hopeful and a global optimal solution. In contrast, SMA chooses two randomly chosen search agents from the entire population to determine future removals and rotations based on the best search agents, and SMA's ability to be exploited and explored is constrained by this characteristic. This study improves the exploration phase of optimization algorithms by using the opposition-based learning (OBL) technique [11]. The benefits of using the OBL idea have been examined for defining the transfer function and weights of the neural networks, developing potential solutions for evolutionary algorithms, and defining the reinforcement agent action policy.

AOSMA solely refers to merging techniques that address the same issue but vary in other respects, most notably performance. Many algorithms can be conceived of as assemblages of more basic components. Systemic issues are addressed using the AOSMA technique. The AOSMA has a great deal of possibilities for processing data in different forms rather than at random since algorithms address issues by form more than once rather than just once. It is demonstrated that AOSMA's capacity for exploration and exploitation is incredibly successful when compared to previous algorithms. Local optimization, however, was also applied in this work to efficiently highlight the shortcomings of AOSMA while concurrently optimizing a number of objectives. To effectively boost, the authors advise combining the SMA with more well-known methods.

The content of this article is divided into the following sections. In Section 2, a review of the literature is provided. Section 3 describes the challenges in calculating the TCQC components and the AOSMA. In Section 4, case studies and outcomes are displayed. The authors complete their research study in Section 5.

2. Literature Review

2.1. Slime Mould Algorithm. The slime mould algorithm is a fresh algorithm model that was presented in [10]. ANN and SMA are used to address the urban water demand [12]. X-ray chest image segmentation problems were solved using the SMA model with Whale optimization [13]. A hybrid SMA with a differential evolution strategy was presented in [14] to address the challenging optimization challenge. The SMA approach was used to determine the photovoltaic models' parameters [15]. As a result, the SMA approach is frequently used in a variety of industries. To make it simpler to comprehend the issue with the model, many authors from around the world have tried this algorithm. To help the project managers choose the best building projects, the SMA algorithm has not yet been used to optimize significant construction goals.

2.2. Trade-Off Optimization. Several approaches have been put forth to address the optimization issues. Many authors have used two-factor optimization simultaneously for the comprehensive and ideal research of many objectives starting with this problem [2, 3]. It is critical to strike a balance between time, money, and quality while implementing initiatives. Babu's method was employed during the construction of a cement factory, and it was shown to be effective [16]. The GA model was used to tackle the time-cost-quality problem [17], and applying optimization approaches to four concurrent goals, such as time-cost-quality-safety [8], time-cost-resources-flow, cost [6], and time-cost-resources-environment [7], is now a standard practice. So, it is getting more and more important to simultaneously optimize the four objectives, which shows the growing need for users and will help the project succeed overall. This shift from two-objective optimization to three-objective optimization lays the groundwork for future development, fresh avenues for investigation, and solutions to optimization-related issues.

The discrete time-cost trade-off problem is another important aspect of the building optimization problem (DTCTP). The DTCTP developments highlight the scheduled cost of the project by solving difficult and competitive issues [18]. The time-cost trade-off problem has drawn the interest of many academics over the past 40 years [19]. Many studies have been conducted on the time-cost trade-off in project networks [20]. The development of an association strategy for the DTCTP involved the use of genetic algorithms (GA), simulated annealing (SA), and quantum simulated annealing (QSA) techniques [21] and the budgeting and scheduling of large-scale projects using discrete swarm optimization [22]. Certain procedures are carried out more quickly when a project's time-cost proportion is favorable [23]. There is a brand-new discrete symbiotic search methodology introduced for large-scale DCOPs [24]. The main topics covered by the DTCTP are precision processes and benchmarking databases of construction industry factors.

2.3. Research Experience. In the area of construction management, the author has also conducted a considerable study on a wide range of problems connected to artificial intelligence. A metamodel optimization approach in conjunction with computer models was specially provided to address the energy consumption of buildings [25]. To lower the cost of establishing water distribution networks, the GWO-HHO is being researched [26]. Construction material cost optimization using the dragonfly-particle swarm optimization method [27, 28] has developed a game model for compensation in the contractor selection process. The author has published a large number of works on artificial intelligence studies in the area of construction management.

3. Methodology

The development based on this model is newly proposed in Figure 1 and Algorithm 1.

3.1. Declaration of Parameters and Generation of Population. In this study, a construction project's four concurrent optimization criteria, time, cost, quality, and safety, were applied. The necessary model's input parameters included project-specific data on labor relations, construction time, required cost, and assessments of the quality and safety standards for each individual task. Also established was the number of populations ($N = 100$), the maximum number of iterations ($T\_max = 200$), the value of lower and upper boundaries ($LB = -100$, $UB = 100$), and the number of decision variables ($D = 25$) and $\delta = 0.03$. The optimization algorithm carried out automatic calculations using the aforementioned parameters to determine the scenario of the best possible outcome for all the four concurrent factors. For

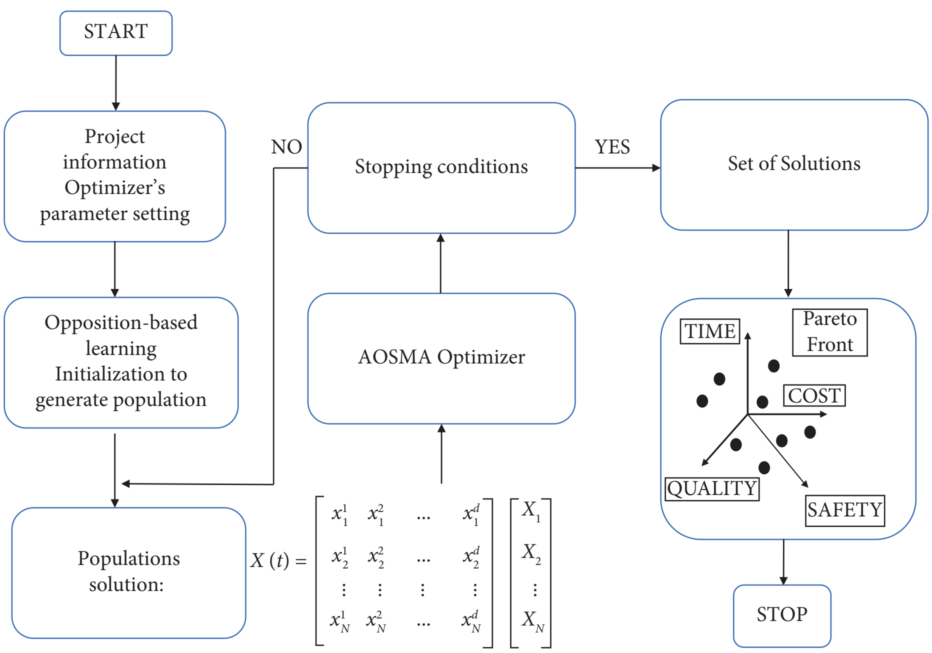

FIGURE 1: Flowchart of AOSMA.

Step 1: begin
Step 2: initialize all parameters needed N, d, T_Max, t, δ, LB, UB, and $X_{GB;}\ f_{GB}$
Step 3:$t \le T\_\mathrm{Max}$
Calculate $f(X) = [f(X_1), f(X_2), \ldots, f(X_N)]$
Sort $[\mathrm{Sort}_f, \mathrm{SortInd}_f] = \mathrm{sort}(f)$
Update $f_{LB} = f(\mathrm{Sort}_f(1))$ and $X_{LB} = X(\mathrm{SortInd}_f(1))$
Update $f_{LW} = f(\mathrm{Sort}_f(N))$
Update $f_{GB} = f(X_{GB})$

Update $W(\mathrm{SortInd}_f(i)) = \begin{cases} 1 + \mathrm{rand} & \log(f_{LB} - f(X_i)/f_{LB} - f_{LW} + 1), 1 \le i \le N/2 \\ 1 - \mathrm{rand} & \log(f_{LB} - f(X_i)/f_{LB} - f_{LW} + 1), N/2 < i \le N \end{cases}$

Update $b = \arctan\, h(-(t/T) + 1)$ and $c = 1 - t/T$
Step 4: $i = 1:N$
Create r_1 and r_2: random the range of [0, 1].
Create $p_i = \tan\mathrm{h}|f(X_i) - f_{GB}|, \forall i \in [1, N]$
Evaluate new slime $Xn_i(t) = X_{LB}(t) + V_b(\mathrm{W.X_{LB}(t)} - \mathrm{X}_B(t))$ if $r_1 \ge \delta$ and $r_2 < p_i$, $Xn_i(t) = V_c.X_i(t)$ if $r_1 \ge \delta$ and $r_2 \ge p_i$,
$Xn_i(t) = \mathrm{rand}(UB - LB) + LB$ if $r_1 < \delta$
Step 5: if $f(Xn_i) > f(X_i)$
Estimate $Xo_i^j(t) = \min(Xn_i(t)) + \max(Xn_i(t)) - Xn_i^j(t)$

Select $Xs_i(t) = \begin{cases} Xo_i(t), \text{ if } f(Xo_i(t)) < f(Xn_i(t)) \\ Xn_i(t), \text{ if } f(Xo_i(t)) \ge f(Xn_i(t)) \end{cases}$

Step 6: update $X_i(t+1) = \begin{cases} Xn_i(t), \text{ if } f(Xn_i(t)) \le f(X_i(t)) \\ Xs_i(t), \text{ if } f(Xn_i(t)) > f(X_i(t)) \end{cases}, \forall i \in [1, N]$

Step 7: stopping conditions, the best value of X_{GB} given

ALGORITHM 1: Pseudocode of AOSMA.

any evolutionary algorithm, creating the starting population is crucial.

3.2. Decision Variable

$$\text{Minimum amount of time} = \text{PCT} = \sum_{A\in \text{CP}} \text{ACT}_A, \quad (1)$$

where PCT is the total time and ACT_A is the key path activity's estimated time of completion (A).

$$\text{Minimum amount of cost} = \text{PCC} = \sum_A D.C + I.C \text{ per day} \times \text{PCT in days}, \quad (2)$$

where PCC is the total individual activity completion cost, $\sum_A D.C$ is the total direct cost, and I.C is the indirect cost.

$$\text{Maximum amout of quality} = \text{PQI} = \sum_{A=1}^{n} \text{wt}_A \sum_{k=1}^{K} \text{wt}_{A,k} x Q_{A,k}^{m}, \quad (3)$$

where $Q_{A,k}^{m}$ is the performance according to the quality index (k) for the activity (i), $wt_{A,k}$ is the activity's other indicators and the quality indicator's (k) weight (i), and wt_A is the relative relevance of the activity to other project activities.

$$\text{Minimum amout of safety} = \text{PSR} = \sum_{A=1}^{n} \text{ASR}_A, \quad (4)$$

where PSR is each activity's overall safety risk, i.e., activity safety risk (ASR) and ASR_A is the total of the three safety hazards (RL + RS + SR) (more explanation is in Supplementary Material (available here)).

3.3. Function of SMA.

At this moment (current iteration), t, slime mould N's position and fitness are stated as follows:

$$X(t) = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \vdots & \vdots \\ x_N^1 & x_N^2 & \cdots & x_N^d \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix}. \quad (5)$$

For updating the new location of the algorithm for $t = t + 1$, we have

$$X_i(t+1) = \begin{cases} X_{\text{LB}}(t) + V_b(\text{W}.X_A(t) - X_B(t)), & r_1 \ge \delta \text{ and } r_2 < p_i, \\ V_c.X_i(t), & r_1 \ge \delta \text{ and } r_2 \ge p, \forall i \in [1, N], \\ \text{rand}(\text{UB} - \text{LB}) + \text{LB}, & r_1 < \delta, \end{cases} \quad (6)$$

where

(i) X_{LB} stands for the current iteration and represents the local best

(ii) X_A and X_B represent the slime mould from present populations collected at random

(iii) W is the weight factor

(iv) V_b and V_c stand for the random velocity

$$\begin{aligned} b &= \text{arctan h}\left(-\left(\frac{t}{T}\right) + 1\right), \\ c &= 1 - \frac{t}{T}. \end{aligned} \quad (7)$$

(i) r_1 and r_2 stand for random [0; 1]

(ii) δ is the slime mold's fixed 0.03 initialization probability at a random search site

The weight W in iteration t is determined as follows:

$$W(\text{SortInd}_f(i)) = \begin{cases} 1 + \text{rand} \log\left(\dfrac{f_{\text{LB}} - f(X_i)}{f_{\text{LB}} - f_{LW}} + 1\right), & 1 \le i \le \dfrac{N}{2}, \\ 1 - \text{rand} \log\left(\dfrac{f_{\text{LB}} - f(X_i)}{f_{\text{LB}} - f_{LW}} + 1\right), & \dfrac{N}{2} < i \le N, \end{cases} \quad (8)$$

where

(i) Rand means random [0; 1]

(ii) f_{LB} means the local best fitness value

(iii) f_{LW} means the local worst fitness value

The function optimization and engineering design difficulty as indicated in [10] has been successfully explored and exploited by the SMA. The three cases based on updating rules are as follows:

(i) *Case 1.*$r_1 \geq \delta$ and $r_2 < p_i$:

$$Xn_i(t) = X_{LB}(t) + V_b \cdot (\text{W.X}_{\text{LB}}(t) - \text{X}_B(t)), \quad if\, r_1 \geq \delta \text{ and } r_2 < p_i. \tag{9}$$

(ii) *Case 2.*$r_1 \geq \delta$ and $r_2 \geq p_i$:

$$Xn_i(t) = V_c.X_i(t), \quad if\, r_1 \geq \delta \text{ and } r_2 \geq p_i. \tag{10}$$

(iii) *Case 3.*$r_1 < \delta$:

$$Xn_i(t) = \text{rand}(\text{UB} - \text{LB}) + \text{LB}, \text{ if } r_1 < \delta. \tag{11}$$

3.4. Opposition-Based Learning. In order to explore the search space and widen the search region after creating the initial population, the AOSMA applied the opposite to the process position at each iteration. The opposition-based learning vector for each vector is determined through equations (13)–(15).

$$Xo_i^j(t) = \min(Xn_i(t)) + \max(Xn_i(t)) - Xn_i^j(t), \tag{12}$$

$$Xs_i(t) = \begin{cases} Xo_i(t), & \text{if } f(Xo_i(t)) < f(Xn_i(t)), \\ Xn_i(t), & \text{if } f(Xo_i(t)) \geq f(Xn_i(t)), \end{cases} \tag{13}$$

$$X_i(t+1) = \begin{cases} Xn_i(t), & \text{if } f(Xn_i(t)) \leq f(X_i(t)) \\ Xs_i(t), & \text{if } f(Xn_i(t)) > f(X_i(t)) \end{cases}, \forall i \in [1, N]. \tag{14}$$

Using the opposition-based learning, which compares the present population and the opposing population simultaneously, speeds up the convergence.

3.5. Adaptive Decision Strategy. A proposed model is made based on the recent $f(Xn_i(t))$ and the previous $f(X_i(t))$ when the slime mould is pursuing a decedent nutrition path. When necessary, the adaptive choice uses OBL to supplement additional exploration. Oddly, the suggested AOSMA improves the effectiveness of SMA by using an adaptive judgment technique to determine whether OBL is required along the search trajectory.

3.6. Stopping Condition. When the halting condition is met, the optimization process is complete. Two often used stopping conditions are the number of objective function evaluations or the maximum number of repetitions. The proposed model made use of as many iterations as possible. When the algorithm's halting condition is met, the best solutions are shown.

4. Case Study and Results

To show how the proposed AOSMA outperforms previous algorithms in solving the issue of time-cost-quality-safety risk, the case study was undertaken [8, 29]. The LHS-NSGA-III procedure starts by creating an initial population based on an N-dimensional LHS and a collection of widely spaced-out M-dimensional reference points on a normalized hyperplane. A swarm intelligence program called MOPSO competes for solutions to issues involving objective optimization. It works particularly well in the project management sector [6, 30]. The reference point selection approach from the NSGA-II substitutes the idea of crowded distance in the NSGA III [31]. The first case study involved a building construction project in Gwalior, India, which included a total of 13 actions. There is a specific building scenario associated with each of these jobs. The second case study had 18 actions that were carried out in two to five different methods for each other, and it was drawn from multiple studies. One choice that has a high cost is one that minimizes time. To find the best balance between time, cost, safety, and quality, the Gantt path must be defined. To demonstrate the usefulness and prospective uses of this SMA, this project acted as a case study.

Tables 1 and 2 and Figure 2 provide the relevant information on TCQS for case 1 while Tables 3 and 4 and Figure 3 give the input parameter factors for case 2. Combining these two difficulties, the author uses the MATLAB's AOSMA method to identify examples at random that strike the ideal balance between the project's duration, cost, safety, and quality. The AOSMA-derived ideal findings are shown in this section.

4.1. Input Parameters

4.2. Optimisation Results Obtained Using the AOSMA

4.2.1. AOSMA Results for Case 1. Table 5 shows the AOSMA's convergence findings for TCQS in the Indian project, along with the optimum way to combine all four aspects at once to produce the greatest outcomes. To achieve successful project delivery, a talented project manager must recognize the ideal possibilities, such as finding the spots when multiple factors are balanced. The suggested approach generates 50 distinct optimal combinations in total to fulfil the specified project objectives. All of the numbers, including PCT from 160 to 226 days, PCC from 487310.30 to 795589.00 dollars, PQI from 0.819 to 0.917, and PSR from 182 to 207.23, are reflected in the results. The Gantt output are [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12] and [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 10]. In addition, there are cases where there are 02 to 03 results with the same PCT, but the values of the remaining 03 factors have differences and are uniformly different; for example, case PCT = 187 but (1) PCC = 492801.80, PQI = 0.819, PSR = 207.23 (2) PCC = 493690.97, PQI = 0.885,

Table 1: Specific activities method of case 1.

ID	Activities	Successors
1	Site clearance	2
2	Excavation	3
3	Footing	4
4	Formwork	5
5	Retaining wall	6
6	Basement	7
7	Slab	8
8	Exterior wall	9
9	Interior wall	13
10	Flooring	—
11	Exterior finish	—
12	Interior finish	—
13	Roof	10, 11, 12

Table 2: Data resources for case 1.

ID	Case	Time	Cost	SI $K=1$		SI $K=2$		SI $K=3$		Act. Weight	Ql $k=1$		Ql $k=2$		Ql $k=3$	
(i)	(n)	Days	$	RL L_{kmA}	RS S_{kmA}	RL L_{kmA}	RS S_{kmA}	RL L_{kmA}	RS S_{kmA}	(%) (wt_A)	IW $wt_{A,k}$	QP $Q^m_{A,k}$	IW $wt_{A,k}$	QP $Q^m_{A,k}$	IW $wt_{A,k}$	QP $Q^m_{A,k}$
1	1	8	10039.42	1	1	1	1	1	1	0.16	0.45	97	0.3	99	0.25	93
	2	8	9849.86	1	2	1	2	1	2			70		73		71
2	1	6	1082.13	3	3	1	1	3	2	0.164	0.2	94	0.35	91	0.45	89
	2	6	891.05	3	4	2	1	4	3			83		88		84
3	1	12	15545.67	3	2	4	2	3	2	0.19	0.3	95	0.45	94	0.25	95
	2	10	17039.34	2	2	3	3	3	2			85		87		89
4	1	5	562.13	3	5	2	1	2	2	0.133	0.35	89	0.35	92	0.3	94
	2	4	590.32	2	4	3	2	3	4			83		83		87
5	1	26	158,34.49	3	3	2	2	1	2	0.07	0.3	85	0.35	92	0.35	95
	2	16	17274.94	2	4	3	3	1	1			78		95		89
6	1	32	74124.65	2	3	4	5	3	3	0.057	0.4	99	0.3	78	0.3	94
	2	29	76345.78	3	4	4	6	4	4			90		85		88
	3	23	84312.34	4	5	5	6	3	3			85		90		86
7	1	22	32646.05	4	5	3	3	3	4	0.059	0.5	94	0.4	93	0.1	87
	2	11	29759.59	4	6	4	4	4	4			80		85		96
8	1	18	65959.52	2	3	2	4	2	3	0.043	0.4	90	0.5	78	0.1	73
	2	29	105296.94	2	2	3	3	1	2			85		90		94
	3	11	157433.42	2	2	3	2	2	3			90		95		95
9	1	37	58570.35	2	3	2	4	2	1	0.025	0.4	97	0.5	98	0.1	97
	2	21	59999.39	2	2	3	3	1	2			89		96		67
	3	32	57668.29	2	2	3	2	2	2			81		85		63
	4	17	63321.11	2	2	3	3	2	3			95		84		90
10	1	34	38411.50	2	3	2	4	2	1	0.02	0.45	85	0.45	90	0.1	78
	2	17	65326.48	2	2	3	3	1	2			88		92		90
	3	12	50214.22	2	2	3	2	2	3			78		84		93
11	1	9	12216.23	2	5	2	2	2	3	0.024	0.4	70	0.5	85	0.1	90
	2	12	3846.23	3	6	3	3	3	3			95		88		85
12	1	41	90219.78	1	2	2	3	1	3	0.022	0.4	70	0.5	85	0.1	90
	2	31	233034.50	2	3	3	3	2	3			95		88		85
13	1	23	127641.84	2	3	3	4	2	4	0.025	0.3	98	0.4	95	0.3	99
	2	24	81323.17	3	4	4	5	3	5			87		86		83

and PSR = 200.98. This gives a project manager many options, which is needed for improving the project and for bringing impact and feasibility to the optimal solution.

Figures 4–9 show the 2D plots of the balance between PCT and PCC, PCT and PQI, PCT and PSR, PCC and PQI, PCC and PSR, and PQI and PSR. Figures 10–13 show the 3D plots of TCQ trade-off, TCS trade-off, CQS trade-off, and QST trade-off.

For each of the 50 Pareto-optimal options, a value route map is shown in Figure 14. In the figure, the PCT, PCC, PQI,

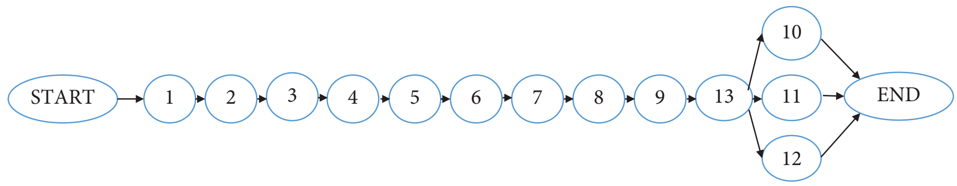

Figure 2: Case 1 network.

Table 3: Specific activities method of case 2.

Act	Successors
1	5, 6
2	10
3	13
4	14
5	7, 12
6	8, 9, 10
7	11
8	11
9	12
10	12, 14
11	17
12	15
13	16
14	16, 17
15	17
16	18
17	18
18	—

Table 4: Data resources for case 2.

Act	EM	*D* (days)	*C* ($)	*Wt*	Quality performance (*Qp*) and quality indicator (*K*)						*Sr*
					*K*1		*K*2		*K*3		
					Kwt	*Qp*	*Kwt*	*Qp*	*Kwt*	*Qp*	
	1	14	2400	0.03	50.00	100.00	30.00	96.00	20.00	98.00	12
	2	15	2150	0.03	50.00	90.00	30.00	89.00	20.00	89.00	9
1	3	16	1900	0.03	50.00	86.00	30.00	77.00	20.00	84.00	12
	4	21	1500	0.03	50.00	75.00	30.00	72.00	20.00	73.00	8
	5	24	1200	0.03	50.00	63.00	30.00	60.00	20.00	65.00	5
	1	15	3000	0.05	40.00	98.00	40.00	94.00	20.00	99.00	30
	2	18	2400	0.05	40.00	87.00	40.00	94.00	20.00	95.00	24
2	3	20	1800	0.05	40.00	81.00	40.00	92.00	20.00	85.00	20
	4	23	1500	0.05	40.00	77.00	40.00	72.00	20.00	70.00	20
	5	25	1000	0.05	40.00	60.00	40.00	66.00	20.00	59.00	18
	1	15	4500	0.08	70.00	100.00	15.00	97.00	15.00	98.00	20
3	2	22	4000	0.08	70.00	80.00	15.00	82.00	15.00	81.00	24
	3	33	3200	0.08	70.00	62.00	15.00	60.00	15.00	63.00	14
	1	12	45000	0.11	50.00	99.00	35.00	95.00	15.00	94.00	5
4	2	16	35000	0.11	50.00	74.00	35.00	71.00	15.00	76.00	5
	3	20	30000	0.11	50.00	59.00	35.00	63.00	15.00	64.00	4
	1	22	20000	0.1	60.00	100.00	20.00	97.00	20.00	99.00	12
5	2	24	17500	0.1	60.00	93.00	20.00	89.00	20.00	89.00	8
	3	28	15000	0.1	60.00	77.00	20.00	71.00	20.00	72.00	5
	4	30	10000	0.1	60.00	61.00	20.00	64.00	20.00	61.00	9
	1	14	40000	0.11	50.00	95.00	25.00	95.00	25.00	100.00	12
6	2	18	32000	0.11	50.00	76.00	25.00	74.00	25.00	79.00	5
	3	24	18000	0.11	50.00	59.00	25.00	62.00	25.00	68.00	9

Table 4: Continued.

Act	EM	D (days)	C (\$)	Wt	Quality performance (Qp) and quality indicator (K)						Sr
					$K1$		$K2$		$K3$		
					Kwt	Qp	Kwt	Qp	Kwt	Qp	
7	1	9	30000	0.1	30.00	97.00	30.00	99.00	40.00	93.00	24
	2	15	24000	0.1	30.00	70.00	30.00	73.00	40.00	71.00	20
	3	18	22000	0.1	30.00	61.00	30.00	62.00	40.00	67.00	12
8	1	14	220	0.01	100.00	95.00	0.00	0.00	0.00	0.00	0
	2	15	215	0.01	100.00	83.00	0.00	0.00	0.00	0.00	0
	3	16	200	0.01	100.00	75.00	0.00	0.00	0.00	0.00	0
	4	21	208	0.01	100.00	68.00	0.00	0.00	0.00	0.00	0
	5	24	120	0.01	100.00	61.00	0.00	0.00	0.00	0.00	0
9	1	15	300	0.01	50.00	100.00	50.00	99.00	0.00	0.00	6
	2	18	240	0.01	50.00	97.00	50.00	92.00	0.00	0.00	4
	3	20	180	0.01	50.00	81.00	50.00	88.00	0.00	0.00	8
	4	23	150	0.01	50.00	71.00	50.00	75.00	0.00	0.00	3
	5	25	100	0.01	50.00	63.00	50.00	64.00	0.00	0.00	4
10	1	15	450	0.01	60.00	94.00	40.00	97.00	0.00	0.00	9
	2	22	400	0.01	60.00	79.00	40.00	83.00	0.00	0.00	12
	3	33	320	0.01	60.00	63.00	40.00	69.00	0.00	0.00	8
11	1	12	450	0.01	70.00	96.00	30.00	95.00	0.00	0.00	3
	2	16	350	0.01	70.00	72.00	30.00	75.00	0.00	0.00	5
	3	20	300	0.01	70.00	61.00	30.00	66.00	0.00	0.00	4
12	1	22	2000	0.02	50.00	99.00	35.00	98.00	15.00	95.00	30
	2	24	1750	0.02	50.00	89.00	35.00	85.00	15.00	87.00	36
	3	28	1500	0.02	50.00	70.00	35.00	71.00	15.00	79.00	24
	4	30	1000	0.02	50.00	62.00	35.00	61.00	15.00	63.00	20
13	1	14	4000	0.03	40.00	99.00	40.00	96.00	20.00	97.00	15
	2	18	3200	0.03	40.00	73.00	40.00	71.00	20.00	76.00	18
	3	24	1800	0.03	40.00	60.00	40.00	62.00	20.00	63.00	24
14	1	9	3000	0.01	80.00	100.00	10.00	95.00	10.00	98.00	16
	2	15	2400	0.01	80.00	79.00	10.00	82.00	10.00	81.00	15
	3	18	2200	0.01	80.00	63.00	10.00	67.00	20.00	66.00	16
15	1	16	3500	0.07	70.00	100.00	30.00	98.00	0.00	0.00	30
	2	12	4500	0.07	70.00	100.00	30.00	98.00	0.00	0.00	25
16	1	20	3000	0.03	30.00	97.00	30.00	96.00	40.00	98.00	10
	2	22	2000	0.03	30.00	89.00	30.00	85.00	40.00	87.00	3
	3	24	1750	0.03	30.00	81.00	30.00	79.00	40.00	78.00	6
	4	28	1500	0.03	30.00	72.00	30.00	73.00	40.00	74.00	8
	5	30	1000	0.03	30.00	67.00	30.00	60.00	40.00	62.00	6
17	1	14	4000	0.06	70.00	98.00	20.00	97.00	10.00	99.00	36
	2	18	3200	0.06	70.00	73.00	20.00	75.00	10.00	72.00	36
	3	24	1800	0.06	70.00	62.00	20.00	65.00	10.00	61.00	20
18	1	9	3000	0.05	30.00	98.00	45.00	99.00	25.00	94.00	20
	2	15	2400	0.05	30.00	75.00	45.00	77.00	25.00	71.00	18
	3	18	2200	0.05	30.00	63.00	45.00	66.00	25.00	67.00	12

and PSR values are displayed together with a straight line connecting the values on the horizontal axis and values between [0, 1] on the vertical axis. This value represents the impact on all activities from attempts at building construction.

4.2.2. AOSMA Results for Case 2. The convergence results for the other project's of AOSMA for TCQS, which generated the best optimal solutions, are shown in Table 6. It is crucial for a project manager to understand the best-case scenario in order to calculate the trade-off between objectives and prevent negative consequences on their project. The project must be finished in 100 days, at a minimum cost of \$101865, with an average quality rating of 84.78 and a safety rating of 195. These are the best values that the model's search skills can find.

Figures 15–20 show the 2D plots of the balance between PCT and PCC, PCT and PQI, PCT and PSR, PCC and PQI, PCC and PSR, and PQI and PSR. Figures 21–24 show the 3D plots of TCQ trade-off, TCS trade-off, CQS trade-off, and QST trade-off. The value path plot for the 20 Pareto-optimal solutions is shown in Figure 25.

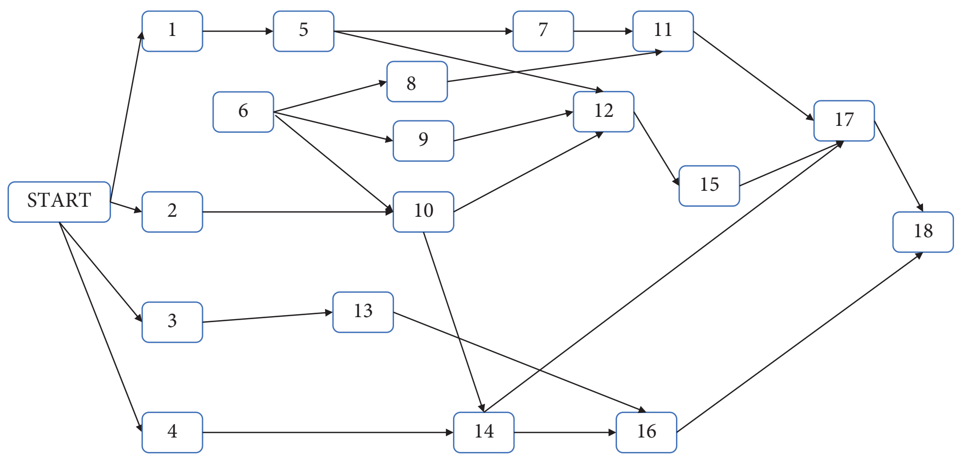

Figure 3: Case 2 network.

Table 5: Result Pareto-optimal solutions for case 1.

No.	Pareto-optimal of projects	PCT	PCC	PQI	PSR	Gant
1	[1, 1, 2, 2, 2, 3, 2, 3, 4, 3, 2, 2, 1]	160	795589.00	0.869	200.76	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
2	[1, 1, 2, 2, 2, 3, 2, 3, 4, 3, 1, 2, 2]	161	757640.73	0.864	202.99	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
3	[1, 1, 2, 1, 2, 3, 2, 3, 4, 3, 2, 2, 2]	162	749242.54	0.876	202.51	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
4	[1, 1, 1, 2, 2, 3, 2, 3, 4, 2, 1, 2, 2]	163	771259.32	0.880	200.14	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
5	[1, 1, 1, 2, 2, 3, 2, 3, 4, 3, 1, 2, 2]	163	756147.06	0.878	200.74	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
6	[1, 1, 2, 1, 2, 3, 2, 3, 4, 1, 2, 2, 1]	164	783758.49	0.880	197.87	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 10]
7	[1, 1, 1, 1, 2, 3, 2, 3, 4, 2, 1, 2, 2]	164	771231.13	0.890	198.38	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
8	[1, 1, 1, 1, 2, 3, 2, 3, 4, 3, 1, 2, 2]	164	756118.87	0.888	198.38	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
9	[1, 1, 1, 2, 2, 3, 2, 3, 4, 1, 1, 2, 1]	165	790663.01	0.882	196.10	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 10]
10	[1, 1, 1, 2, 2, 3, 2, 3, 2, 3, 2, 2, 1]	166	790774.01	0.884	197.23	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
11	[1, 1, 2, 2, 2, 3, 2, 1, 4, 3, 1, 2, 1]	167	712485.50	0.862	198.46	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
12	[1, 1, 2, 1, 2, 3, 2, 1, 4, 3, 2, 2, 1]	168	704087.31	0.874	200.98	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
13	[1, 1, 2, 1, 2, 3, 2, 1, 4, 2, 1, 2, 2]	169	681250.90	0.870	203.67	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
14	[1, 1, 2, 2, 2, 3, 2, 3, 4, 1, 1, 1, 1]	170	649341.96	0.865	196.70	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
15	[1, 1, 2, 1, 2, 3, 2, 3, 4, 1, 2, 1, 1]	171	640943.40	0.877	196.47	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
16	[1, 1, 2, 1, 2, 3, 2, 3, 4, 1, 2, 1, 2]	172	594625.10	0.875	200.79	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
17	[1, 1, 1, 2, 2, 3, 2, 3, 4, 1, 2, 1, 2]	173	593159.62	0.879	198.91	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
18	[1, 1, 1, 1, 2, 3, 2, 3, 4, 1, 2, 1, 2]	174	593131.43	0.889	198.55	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
19	[1, 1, 2, 2, 2, 3, 2, 3, 2, 1, 2, 1, 2]	175	591331.57	0.865	198.33	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
20	[1, 1, 2, 1, 2, 3, 2, 3, 2, 1, 2, 1, 2]	176	591303.38	0.875	199.96	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
21	[1, 1, 1, 1, 2, 3, 2, 3, 2, 1, 1, 1, 1]	177	644498.38	0.910	191.27	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
22	[1, 1, 2, 1, 2, 3, 2, 1, 4, 1, 2, 1, 1]	178	549469.50	0.869	199.24	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
23	[1, 1, 1, 1, 2, 1, 2, 3, 2, 1, 2, 2, 1]	179	768755.00	0.917	191.89	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 10]
24	[1, 1, 1, 1, 2, 3, 2, 1, 4, 1, 2, 1, 1]	180	547975.80	0.900	197.14	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
25	[1, 1, 1, 1, 2, 3, 2, 1, 4, 1, 2, 1, 2]	181	501657.20	0.900	203.36	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
26	[1, 1, 1, 1, 2, 1, 2, 3, 4, 1, 2, 1, 1]	182	629262.00	0.909	190.17	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
27	[1, 1, 1, 2, 2, 3, 1, 3, 4, 1, 1, 1, 1]	183	650734.75	0.885	189.05	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
28	[1, 1, 1, 1, 2, 3, 1, 3, 4, 1, 2, 1, 1]	184	642336.56	0.897	188.57	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
29	[1, 1, 1, 1, 2, 3, 1, 3, 4, 1, 2, 1, 2]	185	596017.89	0.895	193.14	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
30	[1, 1, 1, 1, 2, 1, 2, 3, 2, 1, 2, 1, 1]	186	625940.69	0.895	190.28	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
31	[1, 2, 2, 2, 2, 1, 2, 1, 4, 1, 2, 1, 2]	187	492801.80	0.819	207.23	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
32	[1, 1, 1, 1, 2, 2, 2, 1, 4, 1, 2, 1, 2]	187	493690.97	0.885	200.98	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
33	[1, 1, 2, 1, 2, 1, 2, 1, 4, 1, 2, 1, 2]	188	492963.51	0.872	200.96	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
34	[1, 1, 1, 2, 2, 1, 2, 1, 4, 1, 2, 1, 2]	189	491498.03	0.877	199.08	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
35	[1, 1, 1, 1, 2, 1, 2, 1, 4, 1, 1, 1, 2]	190	499839.84	0.884	196.83	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
36	[1, 1, 1, 2, 2, 1, 1, 3, 4, 3, 2, 1, 1]	192	643979.40	0.909	188.67	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
37	[1, 1, 1, 1, 2, 1, 1, 3, 4, 1, 1, 1, 1]	193	640518.87	0.913	183.81	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
38	[1, 1, 1, 1, 2, 3, 1, 1, 2, 1, 1, 1, 1]	195	555910.94	0.907	188.90	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]

Table 5: Continued.

No.	Pareto-optimal of projects	PCT	PCC	PQI	PSR	Gant
39	[1, 1, 1, 1, 2, 2, 1, 1, 4, 1, 1, 1, 1]	197	551266.10	0.907	189.11	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
40	[1, 1, 1, 1, 2, 2, 1, 1, 2, 1, 1, 1, 1]	201	547944.38	0.907	188.29	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
41	[1, 1, 2, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1]	202	547216.92	0.895	188.27	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
42	[1, 1, 2, 1, 2, 1, 2, 1, 3, 1, 2, 1, 2]	203	487310.30	0.869	198.11	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
43	[1, 1, 1, 2, 2, 1, 1, 1, 2, 1, 2, 1, 2]	204	491062.77	0.899	193.85	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
44	[1, 1, 1, 2, 2, 1, 1, 3, 3, 1, 1, 1, 1]	207	634894.24	0.902	182.00	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
45	[1, 1, 1, 2, 2, 1, 1, 1, 3, 1, 2, 1, 1]	214	535050.34	0.900	186.93	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
46	[1, 1, 1, 2, 2, 1, 1, 1, 3, 1, 1, 1, 2]	215	497101.67	0.894	189.61	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
47	[1, 1, 1, 1, 2, 1, 1, 2, 3, 1, 1, 1, 1]	226	582729.57	0.909	182.40	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]
48	[1, 1, 1, 1, 2, 1, 1, 2, 3, 3, 2, 1, 1]	226	586161.90	0.909	184.85	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 13, 12]

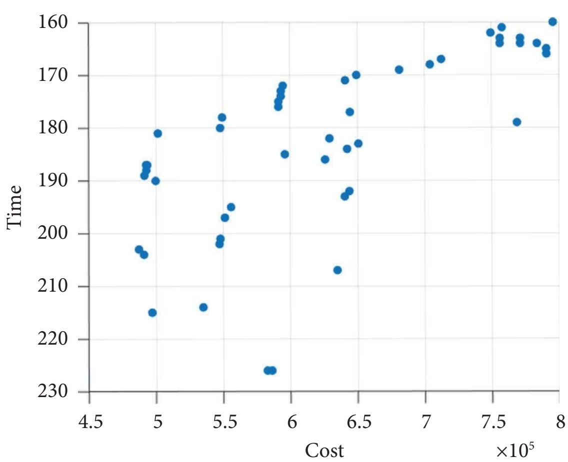

Figure 4: Time-cost trade-off.

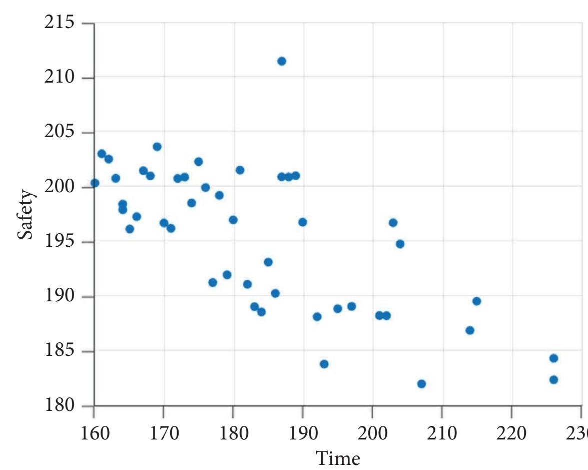

Figure 6: Time-safety trade-off.

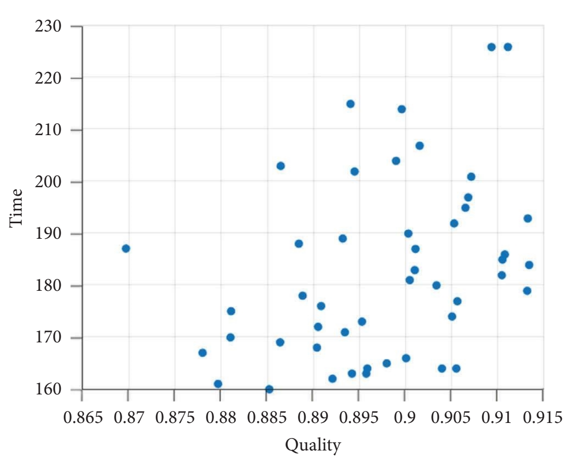

Figure 5: Time-quality trade-off.

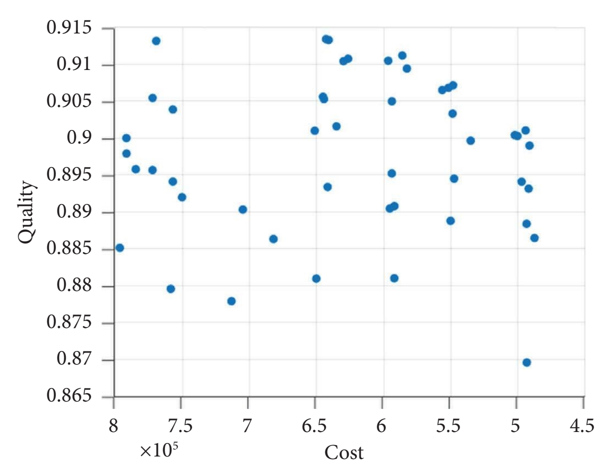

Figure 7: Cost-quality trade-off.

4.3. Comparison Results Obtained between the AOSMA and LHS-Based NSGA III. The same dataset, $N = 100$ and T Max = 200, is used by both the AOSMA and LHS-based NSGA III in order to compare the performance and to obtain the output from the model. As a result, in Tables 7 and 8, the AOSMA model's solution produces quicker and more accurate results than the LHS-based NSGA III solution. To get these outcomes, the authors suggested combining the OBL method with the SMA to boost the hybrid model's performance by extensively disseminating and updating new locations to enhance the data mining ability. The AOSMA model has demonstrated the comprehensiveness of the methodology, and the project managers want to discover solutions in a short time, with low costs and reduced accident risk while still achieving quality.

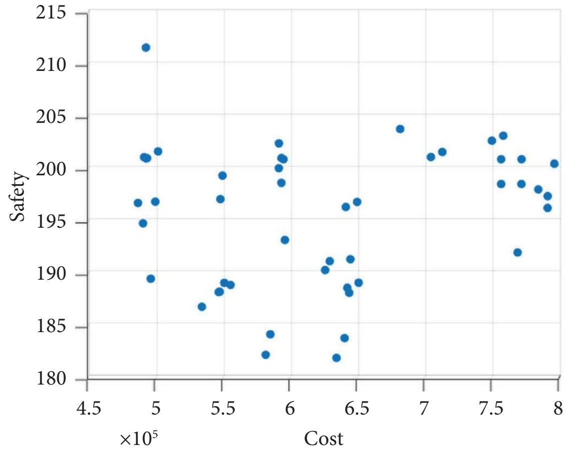

FIGURE 8: Cost-safety trade-off.

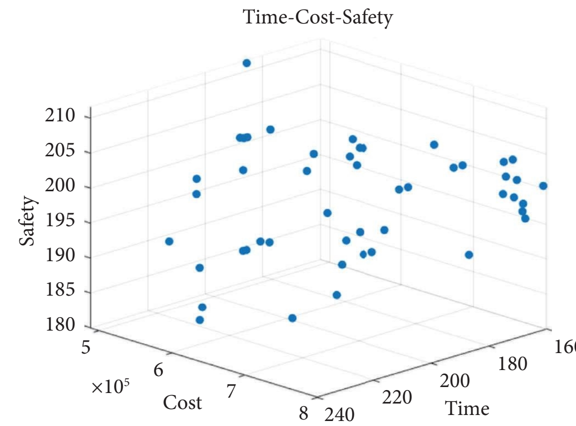

FIGURE 11: Time-cost-safety trade-off.

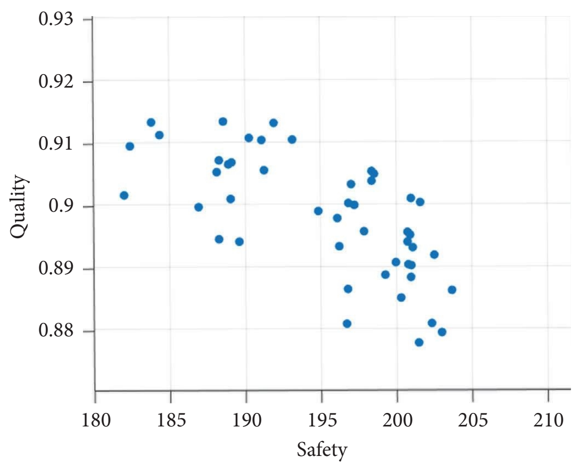

FIGURE 9: Quality-safety trade-off.

FIGURE 12: Cost-quality-safety trade-off.

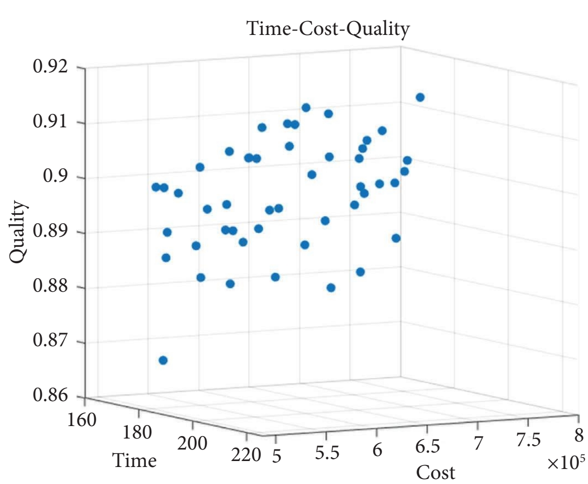

FIGURE 10: Time-cost-quality trade-off.

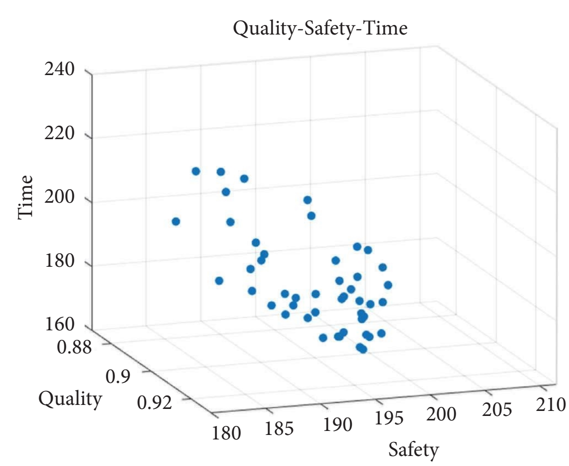

FIGURE 13: Quality-safety-time trade-off.

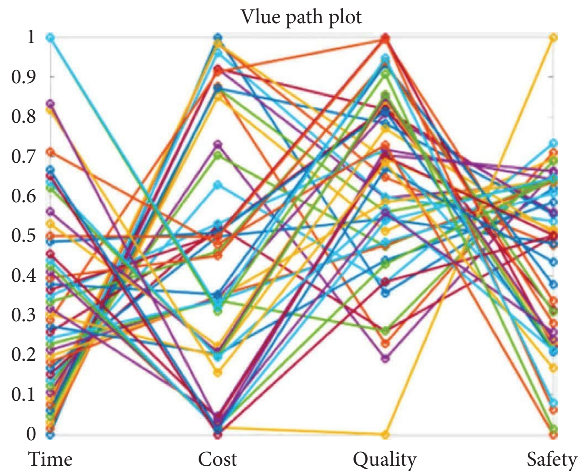

Figure 14: Value path plot of AOSMA for case 1.

Table 6: Result Pareto-optimal solutions for case 2.

No.	Pareto-optimal of projects	PCT	PCC	PQI	PSR
Best time					
1	[1, 4, 2, 3, 1, 1, 2, 2, 1, 1, 3, 1, 2, 3, 2, 5, 1, 1]	100	143065	75.27	274
	[1, 2, 3, 1, 1, 1, 2, 3, 1, 1, 2, 1, 3, 2, 2, 1, 1, 1]	100	159000	79.48	279
Best cost					
2	[4, 5, 3, 3, 4, 3, 3, 2, 1, 1, 3, 4, 3, 2, 2, 5, 3, 2]	141	101865	60.04	221
	[5, 4, 3, 3, 4, 3, 3, 3, 3, 1, 2, 4, 3, 3, 1, 5, 2, 3]	150	101980	60.15	239
Best quality					
3	[2, 1, 1, 1, 2, 1, 1, 5, 1, 1, 1, 1, 3, 1, 2, 1, 1, 1]	101	164770	84.46	287
	3, 1, 1, 1, 2, 1, 1, 1, 3, 1, 1, 1, 1, 2, 1, 3, 1, 1]	111	163850	84.78	283
Best safety					
4	[5, 5, 3, 1, 3, 2, 3, 2, 2, 1, 1, 4, 1, 2, 1, 2, 3, 3]	148	137655	68.13	195
	[4, 5, 3, 1, 3, 2, 3, 3, 2, 3, 1, 4, 1, 3, 2, 5, 3, 3]	156	137610	67.19	196

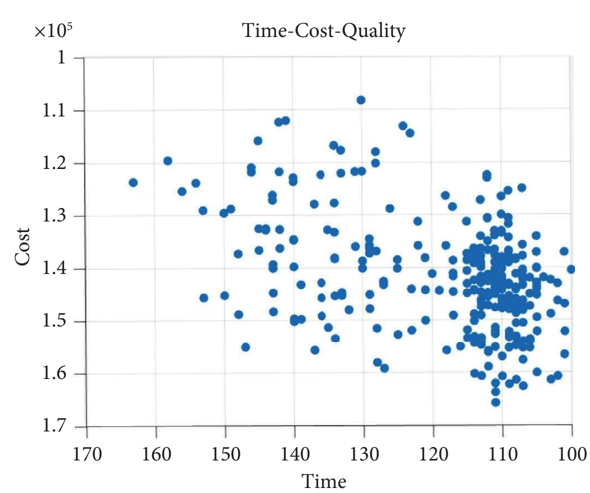

Figure 15: Time-cost trade-off.

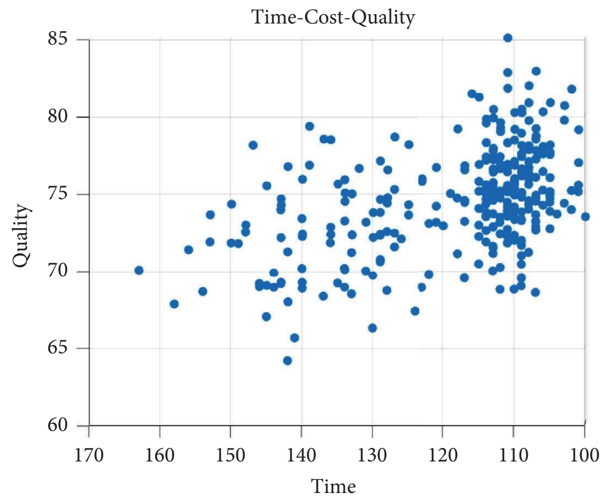

Figure 16: Time-quality trade-off.

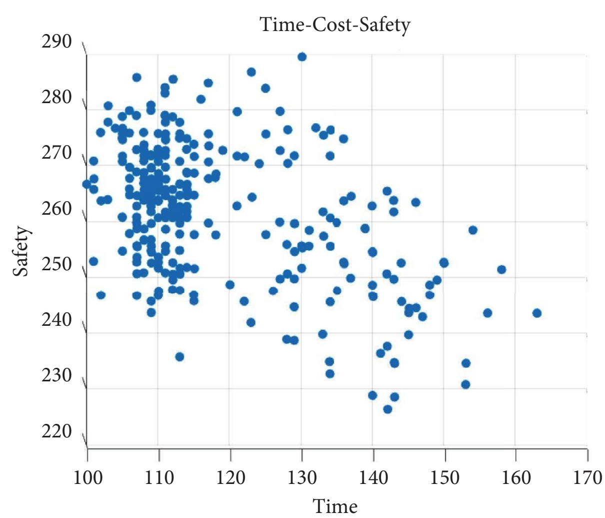

Figure 17: Time-safety trade-off.

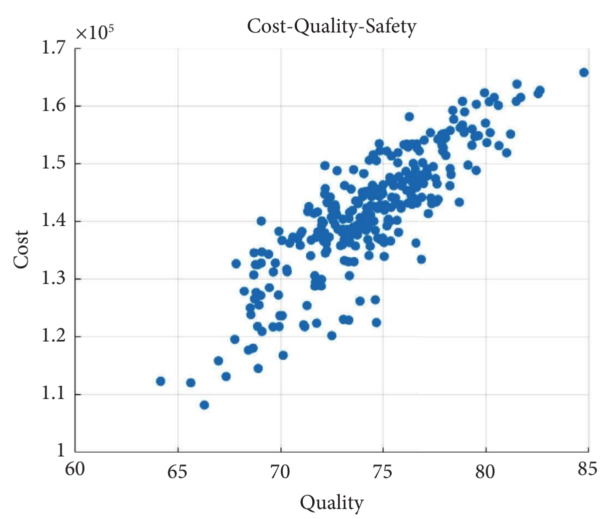

Figure 18: Cost-quality trade-off.

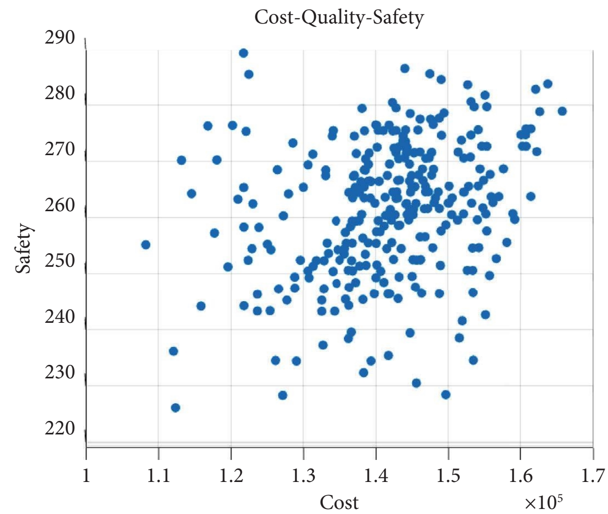

Figure 19: Cost-safety trade-off.

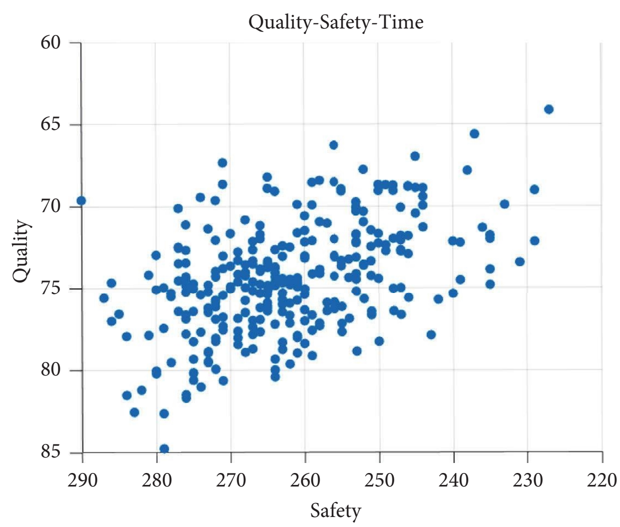

Figure 20: Quality-safety trade-off.

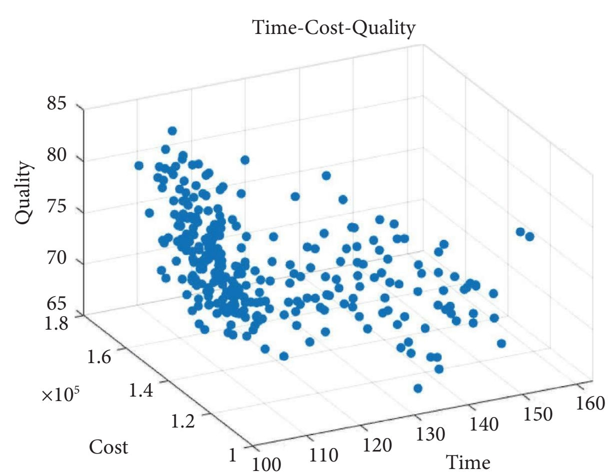

Figure 21: Time-cost-quality trade-off.

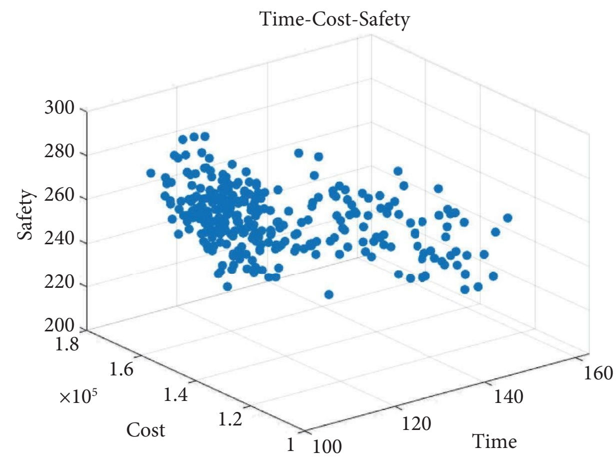

Figure 22: Time-cost-safety trade-off.

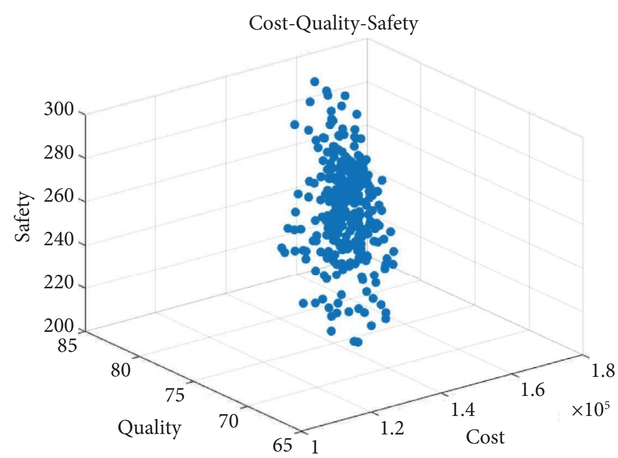

Figure 23: Cost-quality-safety trade-off.

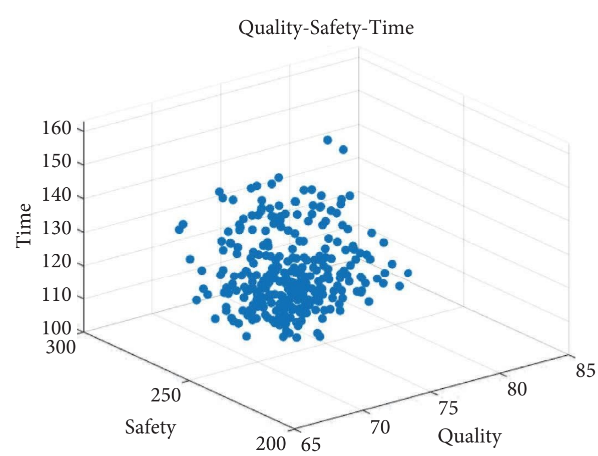

Figure 24: Quality-safety-time trade-off.

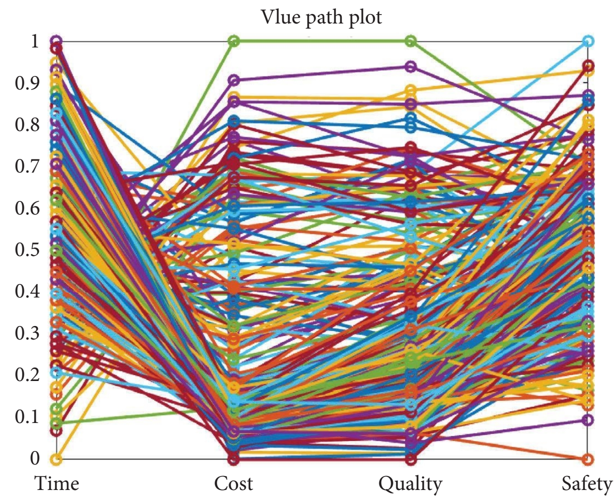

FIGURE 25: Value path plot of AOSMA for case 2.

TABLE 7: LHS-based NSGA III and AOSMA result comparison for case 1.

ID	LHS-based NSGA III				Adaptive opposition slime mould algorithm			
	PCT	PCC	PQI	PSR	PCT	PCC	PQI	PSR
1	160	795589.00	0.869	200.76	160	795589.00	0.869	200.76
2	—	—	—	—	161	757640.73	0.864	202.99
3	—	—	—	—	162	749242.54	0.876	202.51
4	163	783786.30	0.869	200.96	—	—	—	—
	—	—	—	—	163	771259.32	0.880	200.14
	—	—	—	—	163	756147.06	0.878	200.74
5	164	792267.30	0.869	199.64	—	—	—	—
	—	—	—	—	164	783758.49	0.880	197.87
	—	—	—	—	164	771231.13	0.890	198.38
	—	—	—	—	164	756118.87	0.888	198.38
6	165	792239.10	0.877	197.99	—	—	—	—
	—	—	—	—	165	790663.01	0.882	196.10
7	166	787622.50	0.869	199.19	—	—	—	—
	—	—	—	—	166	790774.01	0.884	197.23
8	—	—	—	—	167	712485.50	0.862	198.46
9	168	780246.80	0.840	202.51	—	—	—	—
	—	—	—	—	168	704087.31	0.874	200.98
10	—	—	—	—	169	681250.90	0.870	203.67
11	—	—	—	—	170	649341.96	0.865	196.70
12	171	640943.40	0.877	196.47	171	640943.40	0.877	196.47
13	—	—	—	—	172	594625.10	0.875	200.79
	173	639260.20	0.869	198.69	—	—	—	—
14	—	—	—	—	173	593159.62	0.879	198.91
	174	604.724.70	0.892	202.55	—	—	—	—
15	—	—	—	—	174	593131.43	0.889	198.55
	175	637432.10	0.833	199.67	—	—	—	—
16	—	—	—	—	175	591331.57	0.865	198.33
17	—	—	—	—	176	591303.38	0.875	199.96
18	177	636128.00	0.909	193.25	—	—	—	—
	—	—	—	—	177	644498.38	0.910	191.27
19	178	549469.50	0.869	199.24	178	549469.50	0.869	199.24
20	179	768755.00	0.917	191.89	179	768755.00	0.917	191.89
21	180	547975.80	0.900	197.14	180	547975.80	0.900	197.14
22	181	501657.20	0.900	203.36	181	501657.20	0.900	203.36
23	182	629262.00	0.909	190.17	182	629262.00	0.909	190.17
24	—	—	—	—	183	650734.75	0.885	189.05

Table 7: Continued.

ID	LHS-based NSGA III				Adaptive opposition slime mould algorithm			
	PCT	PCC	PQI	PSR	PCT	PCC	PQI	PSR
25	184	627434.00	0.877	191.15	—	—	—	—
	—	—	—	—	184	642336.56	0.897	188.57
26	—	—	—	—	185	596017.89	0.895	193.14
27	—	—	—	—	186	625940.69	0.895	190.28
28	187	492801.80	0.819	207.23	187	492801.80	0.819	207.23
	—	—	—	—	187	493690.97	0.885	200.98
29	188	537991.70	0.833	200.87	—	—	—	—
	—	—	—	—	188	492963.51	0.872	200.96
30	189	536526.20	0.854	200.42	—	—	—	—
	—	—	—	—	189	491498.03	0.877	199.08
31	190	536306.90	0.854	200.93	—	—	—	—
	—	—	—	—	190	499839.84	0.884	196.83
32	192	643979.40	0.909	188.67	192	643979.40	0.909	188.67
33	193	625858.50	0.900	191.30	—	—	—	—
	—	—	—	—	193	640518.87	0.913	183.81
34	195	624911.80	0.869	191.28	—	—	—	—
	—	—	—	—	195	555910.94	0.907	188.90
35	197	578181.60	0.909	194.99	—	—	—	—
	—	—	—	—	197	551266.10	0.907	189.11
36	201	534166.90	0.862	196.74	—	—	—	—
	—	—	—	—	201	547944.38	0.907	188.29
37	202	533629.00	0.869	191.89	—	—	—	—
	—	—	—	—	202	547216.92	0.895	188.27
38	203	487310.30	0.869	198.11	203	487310.30	0.869	198.11
39	204	531945.80	0.862	194.11	—	—	—	—
	—	—	—	—	204	491062.77	0.899	193.85
40	207	638326.60	0.900	185.52	—	—	—	—
	—	—	—	—	207	634894.24	0.902	182.00
41	214	546852.70	0.900	188.29	—	—	—	—
	—	—	—	—	214	535050.34	0.900	186.93
42	215	500534.00	0.892	194.51	—	—	—	—
	—	—	—	—	215	497101.67	0.894	189.61
43	226	586161.90	0.909	184.85	226	586161.90	0.909	184.85
	—	—	—	—	226	582729.57	0.909	182.40

Table 8: LHS-based NSGA III and AOSMA result comparison for case 2.

Optimisation algorithm objectives solutions	Proposed model							
	NSGA III				AOSMA			
	PCT	PCC	PQI	PSR	PCT	PCC	PQI	PSR
1	100	169820	97.63	285	100	143065	75.27	274
2	145	100865	67.63	226	141	101865	60.04	221
3	104	168820	97.63	290	101	164770	84.46	287
4	144	138655	77.49	190	148	137655	68.13	195

Table 9: Comparison of AOSMA with other algorithms.

Algorithms	SM	Sp	DM	HV	CT
MOPSO	0.45	0.577	0.74	0.75	158
NSGA III	0.44	0.539	0.79	0.77	162
LHS-based NSGA III	0.36	0.532	0.81	0.84	169
AOSMA	**0.36**	**0.519**	**0.86**	**0.88**	**153**

The meaning of the bold values represent the AOSMA model's greatest evaluation.

Table 10: Comparison of different algorithms and AOSMA.

No. of runs	MAWA-TLBO		MAWA-GA		MAWA-AS		MAWA-ACS-SGPU		AOSMA	
	Time (days)	Cost ($)	Time (days)	Cost ($)	Time (days)	Cost ($)	Time (days)	Cost ($)	Time (days)	Cost ($)
1	100	283420	100	287720	100	286670	100	285400	**100**	**288250**
2	101	281200	101	284020	101	284300	101	282508	**101**	**291615**
3	104	277170	104	280020	104	277265	104	277200	**104**	**280408**
4	110	273470	110	273720	110	272265	110	273165	**110**	**280320**
Populations	40		50		50		10		**50**	
Number of iterations	70		500		400		200		**100**	
Number of evaluation	5,640		25,000		20,000		2,000		**5,000**	

The meaning of the bold values represent the AOSMA model's greatest evaluation.

4.4. Comparing the Evaluation between AOSMA and MOPSO, NSGA III, and LHS-Based NSGA III

4.4.1. Comparing the AOSMA with Those of Other Algorithms for Case 1. The performance of AOSMA was assessed by using the quality indicators, which evaluated the diversity of solutions along the Pareto front and convergence to Pareto-optimality using [7, 32]. The performance of the suggested AOSMA can be measured using the following parameters listed, which were found to be satisfactory:

(i) Spacing metric (SM)

$$\mathrm{SM} = \frac{\sum_{i=1}^{n-1}\left|d_i - \overline{d}\right|}{(n-1)\overline{d}}. \tag{15}$$

(ii) Spread (Sp)

$$\mathrm{SP} = \frac{\sum_{i=1}^{k} d\left(E_1,\Omega\right) + \sum_{x\in\Omega}\left|d\left(X,\Omega\right) - \overline{d}\right|}{\sum_{i=1}^{k} d\left(E_1,\Omega\right) + \left(|\Omega| - k\right)\overline{d}}. \tag{16}$$

(iii) Diversification metric (DM)

$$\mathrm{DM} = \sqrt{\left(\frac{\max\left(f_{1i}\right) - \min\left(f_{1i}\right)}{f_1^{\text{nadir}} - f_1^{\text{best}}}\right)^2 + \left(\frac{\max\left(f_{2i}\right) - \min\left(f_{2i}\right)}{f_2^{\text{nadir}} - f_2^{\text{best}}}\right)^2 + \left(\frac{\max\left(f_{3i}\right) - \min\left(f_{3i}\right)}{f_3^{\text{nadir}} - f_3^{\text{best}}}\right)^2}. \tag{17}$$

(iv) Hypervolume (HV):

$$\mathrm{HV} = \bigcup_{i=1}^{|\Omega|} v_i. \tag{18}$$

(v) Computational time (CT): measures the time to generate a Pareto-optimal front.

As a comparison to the LHS-based NSGA III, MOPSO, and NSGA III, the AOSMA performed better on a number of parameters (SM, Sp, DM, HV, and CT and Table 9). As a result, the suggested model performs well across a wide range of performance evaluation metrics; specifically, AOSMA achieved the best results for the CT indicator.

4.4.2. Comparing the AOSMA with Those of Other Algorithms for Case 2. Table 10 for case 2 compares AOSMA, MAWA-TLBO, MAWA-GA, MAWA-AS, and MAWA-ACS-SGPU [33]. The AOSMA model used a population of 50, a maximum of 100 iterations, and a total of 5,000 assessments. The optimal outcomes provided by AOSMA outperform those of the previous algorithms despite the population size and loop being average compared to other models. In addition to offering solutions that are less expensive than MAWA-TLBO, MAWA-GA, and MAWA-AS, the emerging model also addresses the complicated problems. However, it still has limitations when compared to the MAWA-ACS-SGPU model. Sensitivity analysis is used to look at the effects of various inputs on the output parameters.

5. Conclusion

The authors suggested changing the original SMA algorithm to AOSMA in order to better prepare for project completion problems and take into account characteristics specific to the construction sector. Finding the optimal Pareto solutions will be made easier by combining the proposed model with the OBL approach. The AOSMA is used in this combination to balance and improve the convergence of the algorithm by proposing to apply it to two construction projects in the research study to demonstrate its superiority and efficiency and the model's potential in finding optimal solutions, including minimizing time, cost, and safety while maximizing the project quality in construction projects.

The aforementioned findings demonstrate that the AOSMA model successfully resolves the issue of simultaneously optimizing the four objectives and identifies the Pareto-optimal solutions in the test runs. The initiative delivered noticeably positive results and had no impact on the objectives specified. In this way, the proposed model is also put to the test by looking at the performance of the proposed project as it is widely derived from the AOSMA findings and contrasting it with the outcomes of the comparative algorithm models to be analogous to MAWA's hybrid models, NSGA III, LHS-based NSGA III, and MOPSO's. In contrast to the previous algorithms, the AOSMA model exhibits diversity, uniform distribution, and a higher level of result satisfaction.

6. Directions for Future Research

The AOSMA model's development demonstrates improved exploration and exploitation since it achieves a better convergence than other contemporary techniques. For its superiority and viability, it is advised to continue combining the SMA model with various techniques so that it can be contrasted with other beneficial and competitive development models to address the optimization problems. Furthermore, the implementation of 04-factor optimization in the construction sector is still relatively new, particularly the implementation of new goals to address issues in the building. Therefore, subsequent research studies should keep applying optimization of newer elements to diversify in the construction area or enhance by optimizing 05 targets at once to increase the optimization problem's quality in the 4.0 era. Every topic has a positive and a negative side; thus, in the studies that follow, the author will continue to research and try numerous approaches in an effort to provide readers with a useful example.

Data Availability

The data used to support the findings of the study can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

The authors provide the supplementary material to show more details of how to calculate fuzzy of safety elements. (*Supplementary Materials*)

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