Contents lists available at **SCCE**

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Optimization of Construction Projects Time-Cost-Quality-Environment Trade-off Problem Using Adaptive Selection Slime Mold Algorithm

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https://doi.org/10.22115/SCCE.2023.390042.1622

ARTICLE INFO

Article history:
Received: 15 March 2023
Revised: 29 May 2023
Accepted: 10 June 2023

Keywords:
Adaptive selection slime mold algorithm;
Data envelopment analysis;
Time-cost-quality-environmental trade-off Problem;
Tournament Selection.

ABSTRACT

In order to address optimization problems, artificial intelligence (AI) is employed in the construction industry, which aids in the growth and popularization of AI. This study utilizes a Hybrid algorithm called Adaptive Selection Slime Mold Algorithm (ASSMA), which combines the Tournament Selection (TS) and Slime Mould Algorithm (SMA) to address the four-factor optimization problem in projects. This combination will improve the original algorithm's performance, speed up result finding and achieve good convergence via Pareto Front. Hence, efficient resource management must be comprehended in order to optimize the time, cost, quality and environmental impact trade-off (TCQE). Case studies are used to illustrate the capabilities of the new model, and ASSMA results are compared to those of the data envelopment analysis (DEA) method used by the previous researcher. To improve the suggested model's superiority and effectiveness, it is compared to the multiple-target swarm algorithm (MOPSO), multi-objective artificial bee colony (MOABC) and non-dominant sort genetic algorithm (NSGA-II). Based on the overall results, it is clear that the ASSMA model illustrates diversification and offers a robust and convincing optimal solution for readers to understand the potential of the proposed model.

How to cite this article: Son PVH, Khoi, LNQ. Optimization of construction projects time-cost-quality-environment trade-off problem using adaptive selection slime mold algorithm. J Soft Comput Civ Eng 2024;8(1):107–125. https://doi.org/10.22115/SCCE.2023.390042.1622

1. Introduction

The project's influencing factors present managers with ongoing difficulties. The three criteria of time, cost, and quality are consistently what decide whether a project will succeed (TCQ). Yet, a variety of other factors could also be relevant which is the environmental impact (EI) in construction projects. It is vital to optimize the TCQE impact since the bulk of competing components cannot be coordinated simultaneously to accomplish a project.

The need to execute environmental protection both inside and beyond the project's boundaries is a requirement for the building sector. Projects that lessen pollution have recently attracted the interest of many project managers. Misuse of resources causes damage to the surrounding environment, the climate, and even the land on the construction site. Environmental pollution removal is examined by [1]. Wang et al. [2] also emphasized environmental preservation techniques due to the fact that this problem has been overlooked and quantified inaccurately. External factors are commonly ignored by project managers. In this article, the importance of environmental factors in construction projects is emphasized.

Several unique or hybrid algorithms are used in the development of optimization between objectives, or stronger ones are developed. Initial foundation construction involved time and cost optimization [3]. Researchers have made substantial progress in employing these strategies to handle the three optimization challenges of TCQ [4], as well as time, cost, and safety (TCS) [5]. Using algorithmic models for concurrent three-factor optimization, numerous researchs have provided compelling data. Performance is increased to previously unheard-of levels with the use of time-cost-quality-safety (TCQS) optimization [6], yielding a wide range of standout effects. Pareto's ability to converge also has a wider range of possibilities. In a project involving infrastructure, this study uses TCQE's concurrent four-factor optimization (ASSMA). But when complexity grows and the objectives of the search space change, this problem has come up against several obstacles.

Artificial intelligence (AI), sometimes referred to as augmented intelligence, appears to be a transformative technique that employs robots to complete jobs intelligently, successfully, and effectively. This is one of the techniques that combines human strengths in a way that, it seems, makes it possible to accomplish the project in a way that neither robots nor people acting alone can. By incorporating AI concepts, any knowledge might be standardized and made freely available to customers, empowering them to make the best choice possible while considering both the available facts and verified evidence. Since several generations ago, deep learning technology has been employed successfully in a variety of industries, including construction management. In truth, the emergence of complex systems like skyscrapers from the distant past has brought machine learning approaches to the forefront of the industry. You more than anyone else are experiencing the development and deployment of AI in the construction industry, including the use of sophisticated algorithms, big data, and deep learning machines that have revolutionized production efficiency. Support vector machines (SVM) were used in the study to forecast ground vibration during blasting activities at the Bakhtiari Dam in Iran [7]. By combining the Multivariate Adaptive Regression Splines (MARS) and Escaping Bird Search optimization technique (EBS), this study seeks to create a model for estimating the bearing capacity of geogrid-reinforced stone columns [8]. The natural logarithm, secant hyperbolic, tangent hyperbolic, exponential, and sinusoidal inner functions were used to create five models for this investigation [9]. For calculating the compressive strength of hollow concrete block masonry prisms, artificial intelligence algorithms such as neural networks (ANN), combinatorial methods of group data handling (GMDH-Combi), and gene expression programming (GEP) are proposed in this study [10].

To enhance the algorithm's performance, [11] introduced SMA. The SMA's main purpose is best served during the exploration and exploitation phases in order to find the best potential solution. The fact that SMA is led by two randomly chosen search agents who decide a course to take before changing it later to seek the best results limits its ability to explore and exploit new areas. The feature of TS resides in the random selection to choose the best candidate, therefore it is particularly ideal for linking with SMA, according to a proposal made by [12] to improve the SMA algorithm. The original approach is enhanced by this combination, which also lowers algorithmic risks, speeds up the process of finding answers, and provides superior convergence via the Pareto front.

The ASSMA approach is used to address systemic problems. While some problems cannot be addressed randomly, it is at least possible to offer solutions that are within the algorithm's allowable limits. Algorithms are developed to solve issues repeatedly rather than just once. ASSMA is very good at handling a variety of problems, such as: (1) Determining the "minimum distance" when there is no practical method to accomplish so; (2) Analyzing a large amount of data; (3) Utilizing the same steps per time; and (4) Computing several likely be considered.

ASSMA's ability to explore and exploit is demonstrated quite successfully when compared to previous algorithms. Local optimization, which was employed to synchronously optimize the four objectives in this study, however, also effectively illustrated the shortcomings of ASSMA at the same time. In order to refine the model in a useful way and use it to address optimization difficulties affecting the construction sector as well as other socioeconomic domains, the authors advise integrating the SMA model with more widely used methodologies. The authors will keep researching and experimenting to broaden the model and incorporate new ideas so that the study article can be improved in the future because the research's main emphasis has both numerous advantages and disadvantages.

The ability of ASSMA to derive the ideal circumstances for TCQE analysis from the aforementioned basis is discussed in this paper. The rest of this article is divided into the following sections. A literature review is presented in Section 2. SMA methodology is explained in Section 3. Case study and results are presented in Section 4. Research implications are presented in Section 5. Limitations and future research have been shown in Section 6 and 7. In Section 8, the authors finally wrap up their research.

2. Literature review

This section demonstrates how other people's literature reviews, particularly those for research in a similar topic, can be a very beneficial method to comprehend how it functions.

2.1. TCQE trade-off

Tiwari and Johari [13], and Zahraie and Tavakolan [14] illustrated the vital of time - cost building projects. Khang and Myint [15] employed Babu's strategy to build a cement plant, and they attested to its effectiveness. The TC trade-off was expanded to include TCQ [16], TCS trade-off optimization models [17], and more. The GA model was utilized by [18] to address the issues of TCQ. The TCQ issue has also been effectively solved using further evolutionary hybridization techniques [19–21]. In order to show the four-objective optimization phase, [22] were used. In a project with limited resources [23], use the DEA method and TCQE. The multi-opposition aim disparity development was used by [17] to improve the time-cost-quality tradeoffs of building projects. The need for optimization techniques is growing as a result of the aforementioned foundations, and successful project completion depends on making the most of the algorithm's capabilities.

2.2. Hybrid slime mold algorithm

In 2020, Li et al. [11] released the SMA with many new and improved features. In order to address the issue of urban water demand. Zubaidi et al. [24] employed ANN along with SMA. By combining the SMA with Whale optimization, Abdel-Basset et al. [25] were able to solve the chest X-ray image segmentation problem. Liu et al. [26] endorsed the SMA on quantum rotation gates. For the purpose of solving the complete optimization problem, Houssein et al. [27] presented a hybrid SMA approach with a differential evolution algorithm. Using a hybrid model that incorporates the slime mould algorithm (SMA) and opposition-based learning, research study's objective is to resolve a four-objective optimization problem in the construction sector [28]. The adaptive opposition slime mold method (AOSMA), which is proposed in this paper, is a hybrid model for TCQS trade-off optimization in construction building in India [29]. Optimizing time, cost, and quality trade-off problems (TCQT) using the slime mold algorithm model [30].

3. Methodology ASSMA for TCQE tradeoff

In Figure 1, the ASSMA procedure for resolving TCQC issues is depicted. It includes a flowchart for the model's execution, a full explanation, and a step-by-step evolutionary process.

3.1. Initialization

The proposed model's input parameters are project-specific data, including linkages between particular activities, construction times, costs per activity, assessments of quality metrics, and environmental impact factors. Authors also establish the number of populations, the maximum number of iterations, the lowest and highest boundaries of variables, and so forth.

3.2. Slime mold algorithm

The position and fitness of N slime molds at this iteration are shown in the diagram below:

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

$$f(X) = [f(X_1), f(X_2), \dots, f(X_N)] \tag{2}$$

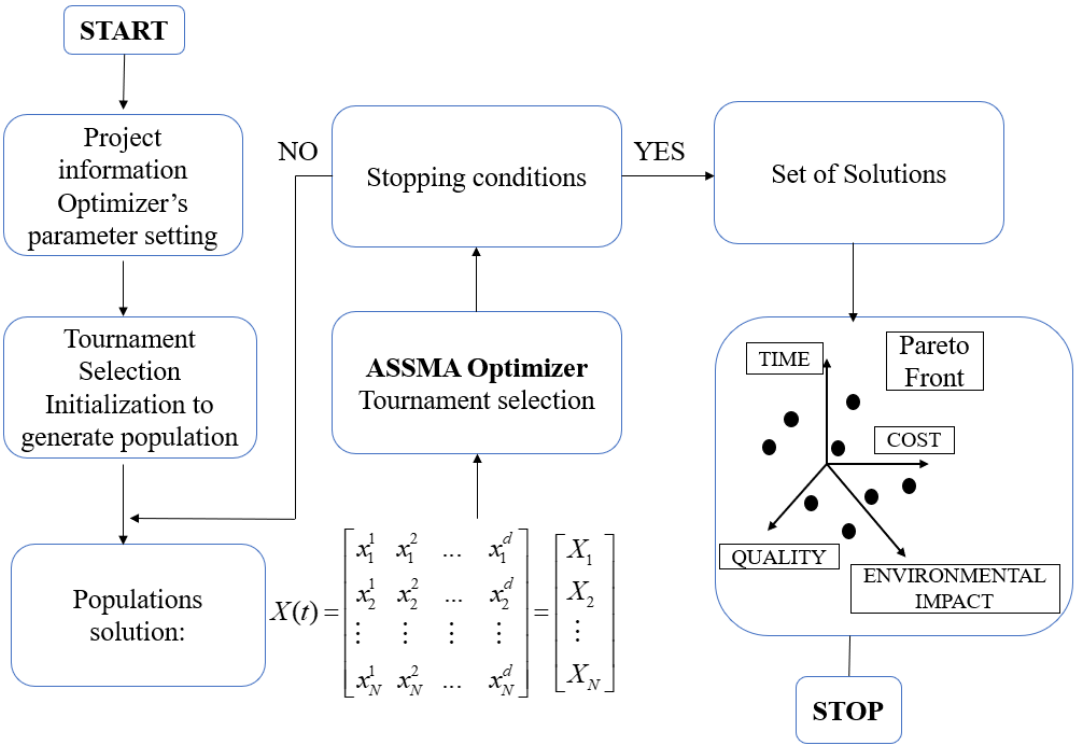

Fig. 1. Flowchart of ASSM.

On the following iteration (t + 1), the SMA's location of the slime mold is updated:

$$X_i(t+1) = \begin{cases} X_{LB}(t) + V_b(W.X_A(t) - X_B(t))r_1 \geq \delta and r_2 < p_i \\ V_c.X_i(t) r_1 \geq \delta and r_2 \geq p \\ rand(UB - LB) + LB r_1 < \delta \end{cases}, \forall i \in [1, N] \tag{3}$$

where:

- X_{LB}: local slime for the at iteration
- X_A and X_B: random slime mold from populations
- W: the weight component
- V_b ; V_c: the random of V
- r_1 ;r_2: random between 0 and 1.
- δ: at a random search position (=0.03)

The algorithm's upper bound is represented by the Pi coefficient:

$$p_i = tan\,h|f(X_i) - f_{GB}|, \forall i \in [1, N] \tag{4}$$

where:

- $f(X_i)$: the value of fitness *i*th slime mold X_i,
- f_{GB}: the global best position's Eq. (5) global best fitness value X_{GB}

$$f_{GB} = f(X_{GB}) \tag{5}$$

The following definition describes the weight for N slime molds in iteration:

$$W(SortInd_f(i)) = \begin{cases} 1 + rand\ log(\frac{f_{LB}-f(X_i)}{f_{LB}-f_{LW}}+1) 1 \le i \le \frac{N}{2} \\ 1 - rand\ log(\frac{f_{LB}-f(X_i)}{f_{LB}-f_{LW}}+1) \frac{N}{2} < i \le N \end{cases} \quad (6)$$

Where:

- Rand: random between 0 and 1
- f_{LB}: the local best fitness value
- f_{LW}: the local worst fitness value
- f_{LB} and f_{LW} are identified from f given in Eq.(2).

To lessen the problem, organize the fitness values in the following manner:

$$[Sort_f, SortInd_f] = sort(f) \quad (7)$$

The Vb and Vc were distributed in the intervals [-b,b] and [-c,c]:

$$b = \text{arctan h}(-(\frac{t}{T})+1) \quad (8)$$

$$c = 1 - \frac{t}{T} \quad (9)$$

where:

- T: maximum iteration

3.3. TS

TS chooses at random among the existing populations, then chooses the contending population with the highest fitness. The TS process is composed of the two steps of sampling and selection. As illustrated in Figure 2, N populations of tournaments are required to create all individuals in the following generation because 7, 4 and 3 are widely used tournament sizes.

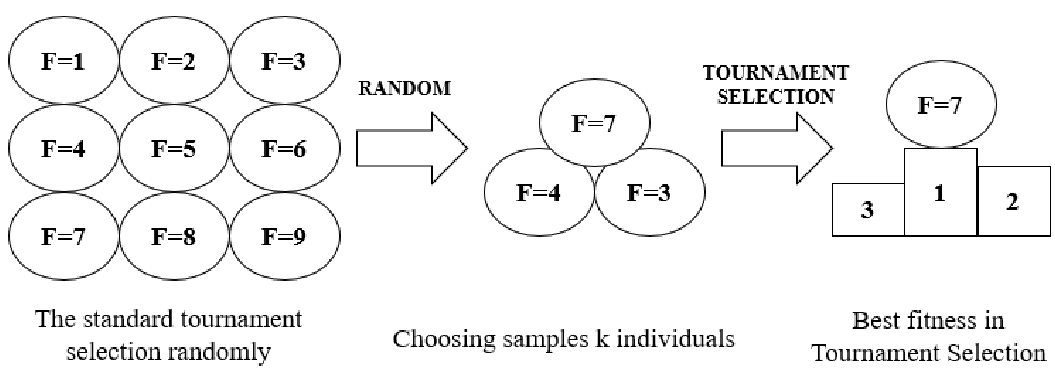

Fig. 2. Simulation of Tournament Selection.

TS has outstanding features compared to other selection modes, specifically: (i) It is simple to alter the selection pressure, (ii) Straightforward to code, (iii) No prearrangement of populations is required and is particularly time-complicated. The selection criteria of TS, which combines sample and selection, necessitates a great deal of focus on various samples as well as various selections.

Under the implicit assumption that the population is entirely diversified:

$$N^{-k}((N-j+1)^k-(N-j)^k) \quad (10)$$

In order to define the worst person to be placed first, they invented the cumulative fitness distribution. S(fj) stands for the number of people with fitness values fj or lower:

$$(\frac{S(fj)}{N})^k-(\frac{S(f_{j-1})}{N})^k \quad (11)$$

The likelihood of one participant not being sampled in one tournament was computed as 1-N1 by [25]:

$$N(\frac{N}{N-1})^{-ky} \quad (12)$$

where y is the sum of all competitions required to produce a new generation.

$$1-((\frac{N-1}{N})^N)^{\frac{y}{N}k} \quad (13)$$

$$1-(1-\frac{(\frac{\sum_{i=1}^{j}|S_i|}{N})^k-(\frac{\sum_{i=1}^{j-1}|S_i|}{N})^k}{|S_j|})^y \quad (14)$$

where $|S_j|$ is the number of programs of the same j^{th} rank.

3.4. Stopping conditions

Setting the maximum number of iterations allows us to establish the halting circumstances. The best solutions will produce results if the halting condition of the model is satisfied. As a result, project managers can start to select the finest values and solutions for construction projects.

3.5. Adaptive selection slime mold algorithm

The straightforward inspiration, limited number of regulating parameters, and adaptive exploratory behavior of this algorithm are mostly responsible for its success. Yet like other meta-heuristics, it has some restrictions and is subject to inevitable flaws. The authors advise using the tournament selection (TS) method to circumvent the SMA's drawbacks. Our hybrid algorithm tries to address the SMA's weaknesses by enhancing convergence from random to best candidate selection. This combination improves the original strategy, while also reducing algorithmic risks, accelerating the search for solutions, and delivering superior convergence via the Pareto front.

The step by step and the flowchart for solving optimization problems of the proposed ASSMA algorithm is as follows in Figure 3:

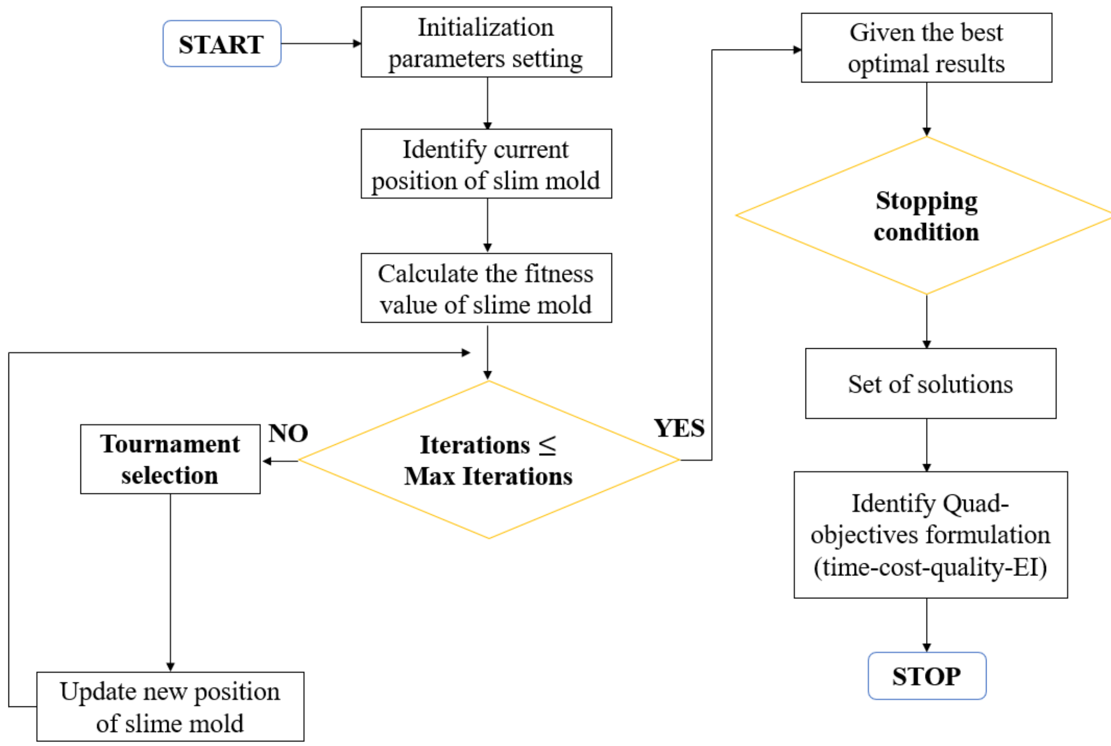

Fig. 3. Step by step of ASSMA.

4. Case study and results

Case studies related to the rural water pipeline project (Project 1) and "future house USA" in China (Project 2) demonstrates the superiority of the ASSMA compared to the author's results. In project management, there are two categories of DEA. Using a particular set of inputs and outcomes, the first kind evaluates the efficacy of various projects. The second category consists of initiatives that choose project portfolios and rank several initiatives before making an investment. The study concentrated on the Project 1, which has eight activities and eight distinct construction scenarios, as illustrated in Table 1 includes a list of the project's particular activities resources. The project 1 is expected to have 823544 outcomes in total, which will cause differences in TCQE. Also, Project 2 illustrates 11 activities with many cases in each activity which have shown in Table 2 which provide 9216 options to deliver the project.

The project's contractor and the employer's representative have provided estimates of the resources needed for each activity and the time needed to complete each activity for each execution method. Based on the price of input resources and the time required to complete an activity, the cost of each execution method was also determined. Since changes in the quantity of consumable resources and the duration of an activity have an impact on the activity's quality level, other execution modes' quality fluctuates with changes in their duration and resource usage. The environmental impact of the project operations has been assessed taking into account seven different factors. These factors include contaminating the soil, causing erosion and sedimentation, contaminating the surface and groundwater, contaminating the air and dust, destroying plant species and habitats, and making noise.

Table 1
Project 1's data.

Activity Number	*Predecessors*	Case	Time	Cost	Quality	Environmental Impact
1	-	1	19	788	0.8	0.3
2	1	1	11	701	0.78	0.36
		2	20	1384	0.8	0.44
		3	20	1195	0.83	0.64
		4	11	777	0.82	0.44
		5	18	1025	0.84	0.52
		6	20	666	0.87	0.64
		7	11	591	0.88	0.48
3	2	1	5	652	0.74	0.2
		2	9	1082	0.8	0.3
		3	14	1017	0.83	0.4
		4	5	1205	0.9	0.5
		5	5	791	0.82	0.4
		6	20	802	0.85	0.5
		7	11	1233	0.92	0.5
4	1,2	1	14	969	0.77	0.27
		2	12	1128	0.8	0.4
		3	19	613	0.83	0.47
		4	8	668	0.86	0.53
		5	18	578	0.85	0.4
		6	16	678	0.88	0.53
		7	13	718	0.9	0.53
5	3	1	13	1389	0.76	0.45
		2	19	1021	0.8	0.6
		3	6	1150	0.75	0.45
		4	19	666	0.85	0.6
		5	11	572	0.86	0.6
		6	10	1062	0.82	0.45
		7	14	1121	0.92	0.6
6	4,5	1	10	1330	0.78	0.3
		2	12	1129	0.8	0.4
		3	15	975	0.81	0.5
		4	5	932	0.82	0.6
		5	5	1123	0.82	0.4
		6	13	1200	0.83	0.6
		7	12	1185	0.84	0.6
7	6	1	7	842	0.82	0.4
		2	5	626	0.8	0.5
		3	13	1302	0.81	0.5
		4	12	1089	0.84	0.6
		5	8	1334	0.83	0.5
		6	10	752	0.83	0.6
		7	10	955	0.87	0.6
8	7	1	8	804	0.82	0.3
		2	16	904	0.8	0.35
		3	6	1280	0.74	0.35
		4	8	655	0.76	0.5
		5	10	972	0.81	0.3
		6	16	863	0.75	0.44
		7	14	596	0.77	0.44

Table 2
Project 2's data.

Activity Number	Successors	Case	Time	Cost	Quality	Environmental Impact
1	2	1	28	1865	0.920	1728.86
		2	28	1810	0.78	2938.36
2	3	1	13	790	0.86	317.66
		2	15	741	0.77	399.34
3	4	1	28	1590	0.63	9541.15
		2	22	1436	0.61	9715.51
4	5	1	9	1371	0.74	9647.65
		2	12	723	0.76	9822.01
5	6	1	17	731	0.89	15790.3
		2	25	846	0.87	15964.7
6	7	1	17	1086	0.79	9152.52
		2	28	1427	0.82	35518.3
		3	9	1291	0.8	35518.3
7	11	1	17	1061	0.69	4152.23
		2	27	1054	0.72	4164.16
		3	28	862	0.7	15056.4
		4	30	1882	0.73	15062.4
8	End	1	4	1983	0.85	118.59
		2	17	975	0.88	544.3
		3	4	1963	0.84	3030.66
9	End	1	18	1870	0.9	4219.17
		2	10	1042	0.91	61163.9
10	End	1	4	1046	0.58	256.03
		2	9	1166	0.6	256.03
11	8, 9, 10	1	23	1939	0.61	12871.7
		2	4	1213	0.63	6747.33

4.1. Optimization results obtained using the ASSMA

Using the same input parameters as Table 3's population size (N), maximum generation (T), number of decision variables (D), parameter, lower bound (LB), and upper bound (UB), authors applied ASSMA to the two projects. To prevent issues with duplication and randomization during optimization, authors repeated the experiment 20 times.

Table 3
ASSMA parameters.

Input	Notation	Value (Project 1/Project 2)
Number of populations	N	100/100
Maximum iteration	T	200/200
Number of decision variables	D	25/25
δ parameter	δ	0.03/0.03
Lower boundary	LB	-100/-100
Upper boundary	UB	100/100

Table 4
Result Pareto optimal solutions.

No	Number of Project	Pareto-optimal of projects	Time	Cost	Quality	Environmental Impact	Gant	Iteration (1/200)
BEST TIME								
1	1	1 7 4 2 3 4 2 3	57	7700	0.81	0.45	1 2 3 5 6 7 8	50
2		1 1 4 1 3 5 2 1	59	7366	0.81	0.39	1 2 3 5 6 7 8	42
1	2	1 1 2 1 1 3 1 1 2 2 2	129	13949	0.77	145156.33	1 2 3 4 5 6 7 9 11	34
2		2 1 2 1 1 3 1 3 2 1 2	129	13754	0.76	149227.9	1 2 3 4 5 6 7 9 11	5
BEST COST								
1	1	1 1 1 6 5 4 2 7	70	5545	0.81	0.44	1 2 3 5 6 7 8	45
2		1 6 5 3 5 3 2 7	89	5627	0.82	0.48	1 2 3 5 6 7 8	10
1	2	2 2 2 2 1 1 3 2 2 1 2	160	11665	0.75	131585.94	1 2 3 4 5 6 7 8 11	14
2		2 2 2 2 2 1 3 2 2 1 2	168	11780	0.75	131760.3	1 2 3 4 5 6 7 8 11	31
BEST QUALITY								
1	1	1 6 4 7 7 4 4 1	83	7323	0.86	0.51	1 2 3 5 6 7 8	19
2		1 7 4 6 7 6 7 5	82	7510	0.86	0.49	1 2 3 5 6 7 8	37
1	2	1 1 1 2 1 2 2 2 2 2 2	174	12576	0.78	145593.97	1 2 3 4 5 6 7 8 11	24
2		1 1 1 2 1 2 4 2 2 2 2	177	13404	0.78	156492.18	1 2 3 4 5 6 7 8 11	43
BEST ENVIRONMENTAL IMPACT								
1	1	1 1 1 5 6 1 1 1	70	6757	0.80	0.34	1 2 3 5 6 7 8	16
2		1 1 1 1 6 1 1 2	78	7248	0.79	0.33	1 2 3 5 6 7 8	7
1	2	1 1 1 1 1 1 1 1 1 1 2	151	14606	0.77	61671.48	1 2 3 4 5 6 7 9 11	18
2		1 1 1 1 1 1 2 1 1 1 2	161	14599	0.77	61683.41	1 2 3 4 5 6 7 9 11	14

Table 4 displays the convergence findings from the ASSMA of time, cost, quality, and environmental effect, which produced the best optimal solutions. To manage a project successfully, it is of utmost importance that a project manager must know the best-case scenario to avoid adverse effects on their project by calculating the trade-off between objectives. Futhermore, for Project 1, Figures 4, 5, 6, 7 have been shown the best three-dimension TCQE trade-off and Figure 8, 9, 10, 11 for in Project 2. The solutions found utilizing the ASSMA were more uniformly and broadly distributed in terms of project optimization performance. The AOSMA also effectively demonstrated how time, money, quality, and environmental impact relate to one another. The ASSMA has better optimization performance in every situation where convergent solutions existed. The convergence results from the ASSMA for time, cost, quality, and environment in building projects are displayed for readers, along with the optimum combination of 04 factors to take into account simultaneously for the best outcomes. A good project manager must identify the ideal scenarios, such as the points of equilibrium between various factors, in order to ensure the project's successful completion.

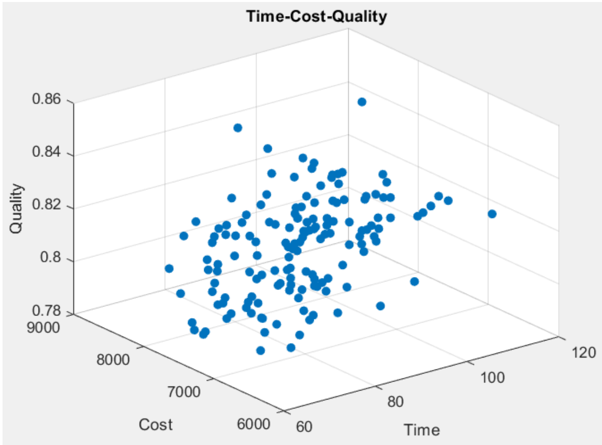

Fig. 4. Best TCQ trade-off (Project 1).

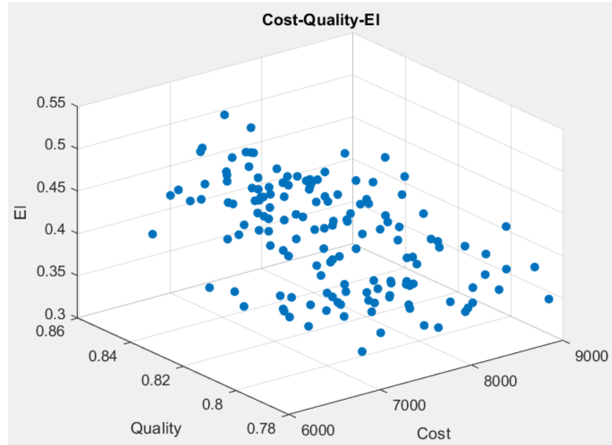

Fig. 5. Best CQEI trade-off (Project 1).

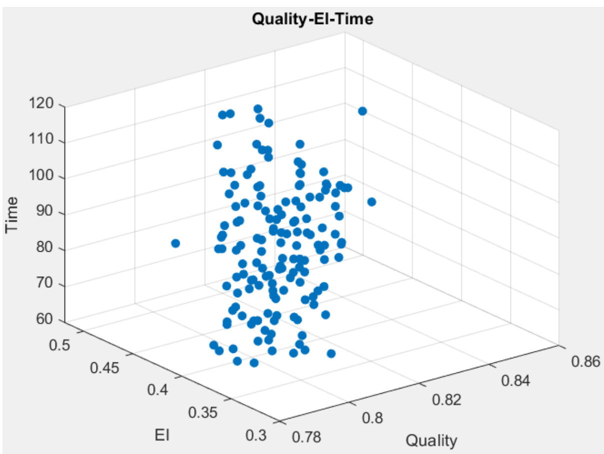

Fig. 6. Best QTEI trade-off (Project 1).

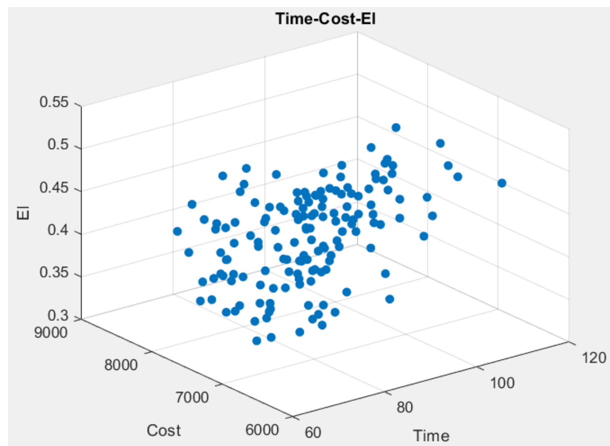

Fig. 7. Best EICT trade-off (Project 1).

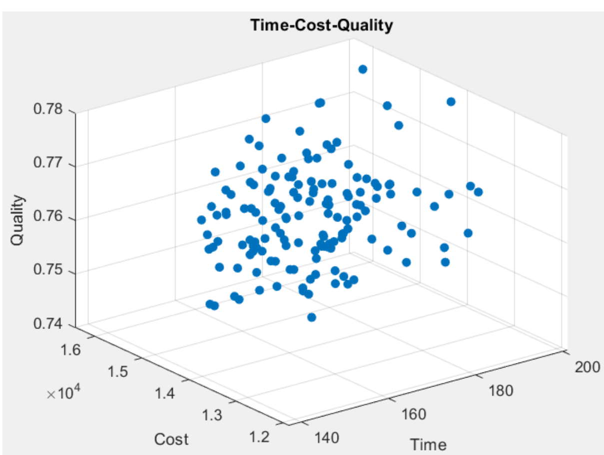

Fig. 8. Best TCQ trade-off (Project 2).

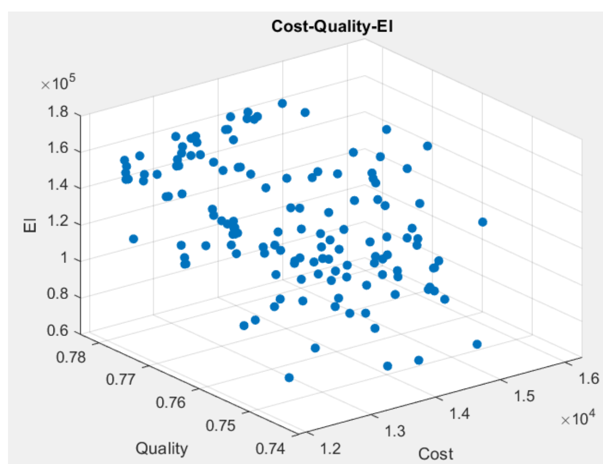

Fig. 9. Best CQEI trade-off (Project 2).

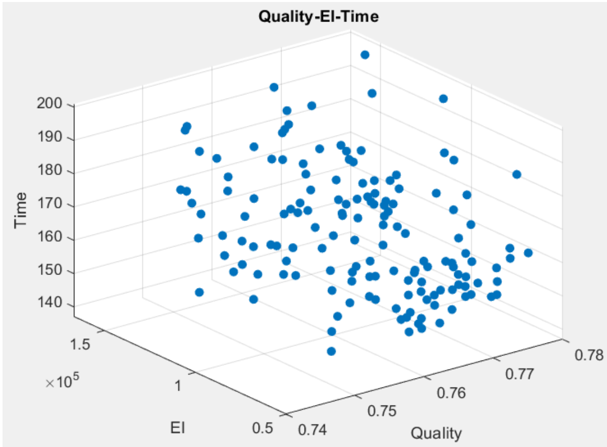

Fig. 10. Best QTEI trade-off (Project 2).

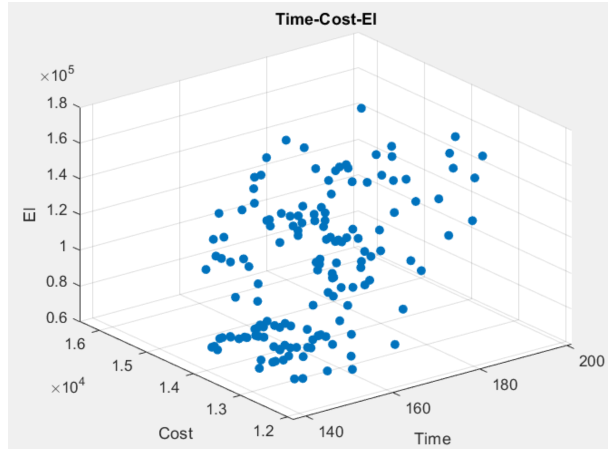

Fig. 11. Best EICT trade-off (Project 2).

Figures 12 and 13 for Project 1 and Project 2 respectively display the value path graph for the best-optimized TCQE solutions produced from Pareto. On the horizontal axis are displayed all four objectives. The normalized objective function values are indicated on the vertical axis of each objective. The obtained Pareto-optimal solutions are represented by 20 lines combining the values of various objective functions. Given that the Pareto optimal solutions are dispersed across the entire vertical axis, the proposed model can be regarded as effective in identifying a variety of solutions. Most lines exhibit a significant variation in slope between two successive axes of an objective function; it follows that the proposed model is also effective at identifying good tradeoff nondominated solutions.

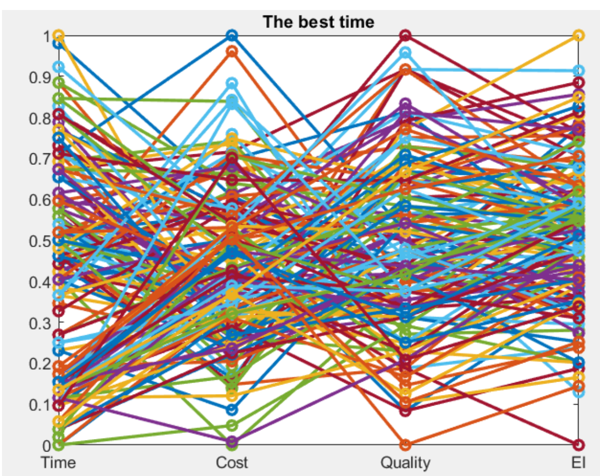

Fig. 12. Value path for best time (Project 1).

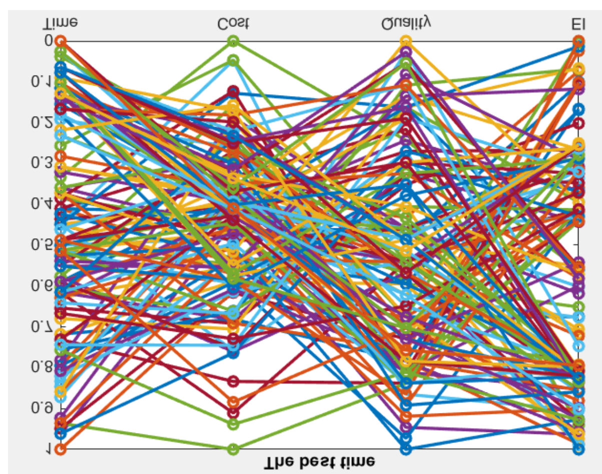

Fig. 13. Value path for best time (Project 2).

4.2. Contrasting the optimization outcomes produced by DEA and ASSMA

The tradeoffs between the DEA and the suggested model are compared in Table 5. The TS approach is paired with the SMA to help it expand exploration in a new search region and choose the best optima to deliver the best goals within the model's capabilities. The SMA has a characteristic that is widely and evenly distributed in a search space. This combination leads to exploitation by selecting search agents, then randomizing good value candidates, and finally using TS to identify the best candidate to update the new position of slime mold at time. The DEA mathematical model makes it possible to measure the effectiveness of an activity in relation to desired and undesirable effects by using various execution mechanisms. Due to a large number of output data, ASSMA has proven the convergence ability that the model brings. As a result, the searchability of the model has easily led to the desired results. To solve the aforementioned problem, ASSMA mostly employed Matlab R2019b.

Table 5
Comparison of the outcomes between DEA and ASSMA.

Sayyid and Mohammad, 2020					**Proposed model**				
DEA					**ASSMA**				
Case	**Time**	**Cost**	**Quality**	**Environmental Impact**	**Case**	**Time**	**Cost**	**Quality**	**Environmental Impact**
Project 1									
1 4 5 6 3 5 2 1	59	6737	0.81	0.42	1 7 4 2 3 4 2 3	57	7700	0.81	0.45
1 7 1 5 5 4 1 7	72	5551	0.81	0.43	1 1 1 6 5 4 2 7	70	5545	0.81	0.44
1 6 7 6 7 4 7 1	87	7177	0.86	0.51	1 7 4 6 7 6 7 5	82	7510	0.86	0.49
1 4 1 1 1 1 2 5	73	7503	0.79	0.35	1 1 1 5 6 1 1 1	70	6757	0.80	0.34
Project 2									
2 1 2 1 1 3 1 1 2 2 2	129	13894	0.76	146365.83	2 1 2 1 1 3 1 3 2 1 2	129	13754	0.76	149227.9
2 1 2 2 1 1 3 2 2 1 2	158	11714	0.76	131504.26	2 2 2 2 1 1 3 2 2 1 2	160	11665	0.75	131585.94
1 1 1 2 1 2 4 2 1 2 2	178	14232	0.78	99547.5	1 1 1 2 1 2 2 2 2 2 2	174	12576	0.78	145593.97
1 1 1 1 1 1 1 1 1 2 2	151	14726	0.77	61671.48	1 1 1 1 1 1 1 1 1 1 2	151	14606	0.77	61671.48

4.3. Comparing the evaluation indicators of the ASSMA than DEA with IDMU and ADMU

The inertia factor w is specified in the MOPSO model to be between 0.3 and 0.7, while the learning factors c1 and c2 are also set to 2. In NSGA-II, the probability for constant mutation and crossover are set to 0.5 and 0.9, respectively. MOABC has established the upper limit at 30.

- Number of Solutions (NS): the solutions of pareto
- Spacing: a measure of how Pareto front solutions differ in their separation
- Mean Ideal Distances (MID): Convergence speed of the Pareto front solution
- Spread of nondominant solution (SNS): the overall options of pareto
- Quality Metric (QM): identified Pareto optimum solutions
- Diversity: extending Pareto-optimal solutions
- Hypervolume (HV): where solutions are located in the objective space.
- Epsilon (E): a measure of a solution set's unsatisfactoriness in relation to the most well-known Pareto front.
- Computional time (CT): how long it takes to build a Pareto-optimal front.

Table 6
The criteria for the ASSMA's review.

Algorithms	NS	Spacing	MID	SNS	QM	Diversity	HypE	E	CT
Project 1									
MOPSO	29	0.56	1.79	69726	0.76	0.72	0.69	1.45	181
NSGA-II	30	0.49	1.84	71935	0.83	0.79	0.75	1.49	169
MOABC	30	0.44	1.87	75369	0.91	0.81	0.83	1.36	172
ASSMA	**33**	**0.38**	**1.97**	**81366**	**0.95**	**0.85**	**0.90**	**1.25**	**145**
Project 2									
MOPSO	32	0.52	1.81	69898	085	0.69	0.67	1.42	169
NSGA-II	33	0.48	1.86	74563	0.87	0.78	0.72	1.50	179
MOABC	35	0.45	1.90	75553	0.90	0.82	0.81	1.39	167
ASSMA	**38**	**0.42**	**1.95**	**79214**	**0.93**	**0.84**	**0.88**	**1.29**	**152**

[23] claim that they employed DEA based on ideal decision-making units (IDMU) to gauge IDMU's best possible relative effectiveness and DEA based on anti-ideal decision-making units (ADMU) to gauge ADMU's worst possible relative outcome. These two distinct efficacy assessments may lead to different inferences. From this ranking, it is possible to determine which activities are most important for effective optimization of results, which is one of the methods that has potential for future growth. The ASSMA model selects search agents at random from the total population to choose the best search agents' next course of action, efficiently utilizing exploration and exploitation abilities to produce a perfect or nearly ideal result. Many studies conducted internationally reveal that the measures listed in Table 6 make up the bulk of performance evaluation indicators used to rate the model's quality. The ASSMA is suggested above the DEA when conducting an evaluation since it provides a wider variety of fresh ideas. Also, the two models exhibit the greatest capacity for adjusting to a changing environment.

5. Research implications

Project manager must be able to identify the risk factors that will affect the project's time, cost, quality, and environment. Finding ways to accomplish projects with the least amount of time, cost and environmental impact while attaining the highest degree of quality is one of the issues facing the construction industry as a whole. To build the greatest database possible and ensure future projects are successful, project managers must anticipate various scenarios for each individual building activity.

Further analysis of the outcomes provided in Table 5 reveals that the suggested ASSMA model has greater evaluation of quality indicators, shorter data processing times, and superior convergence ability when compared to earlier algorithms. The author focuses on identifying the case among the cases that has the greatest outcomes across all criteria; in particular, the findings found utilizing the ASSMA model have better values. The author also uses quality assessment index approaches to compare the suggested model with the prior model in order to give a framework for examining and comparing the efficacy and performance of the model. Both projects in Table 6 are higher in any index when compared to MOPSO, MOABC, and NSGA-II. On the basis of this, it can be concluded that the ASSMA model is functional and that there is enough time to pinpoint the ideal solutions in order to obtain a very high likelihood of project completion without delay while still achieving the best outcomes.

The SMA had not yet been invented or used significantly in the building sector, only in the fields of biology and computer science. In this work, the author tackled the subject of applying this ASSMA to the construction sector in order to provide a novel research topic. The results show that the ASSMA model has great potential for development, but it also has several drawbacks. In order to mitigate the model's flaws, the author will keep advancing and improving it in upcoming investigations. Future implementations of the suggested model combined with these kinds of techniques will be possible from development bases like these by creating an application that runs on top of the current model that project managers or enterprises apply to the work being done.

6. Limitations

The authors will discuss several issues with this hybrid model as well as the numerous limitations of this study. (1) The Slime Mold Algorithm Model is mostly employed in the disciplines of biotechnology and information technology; it is not yet focused on the construction industry, specifically construction management. The authors introduce this cutting-edge hybrid model into the field in an effort to provide a brand-new area of study. (2) Due to its simplicity and sparse usage of parameters, the original Slime mold algorithm processes data faster than the comparison algorithms. The hybrid algorithm creates more code and is more complex because it incorporates multiple unique algorithms. (3) The authors will keep working to develop and refine the model in following studies in an effort to reduce its flaws.

7. Directions for future research

Further research can be applied for future implementation of the hybrid algorithm model for additional improvement. We extend the multi-objective optimization model to consider the crucial factors necessary to produce the best results for project managers. Multi-objective problems can be used in construction, logistics, and other industries to increase the model’s applicability to each new subject.

8. Conclusions

Promoting the business demands more attention due to the influencing factors that the construction industry must deal with, such as delays in development, excessive costs, poor quality, and the environment. As a result, the authors have proposed an approach that makes use of databases and artificial intelligence, or more specifically, expert knowledge software, to solve problems and reach smart judgments.

The adaptive selection slime mold algorithm model is a systematic framework that this study offers in order to handle the issues of time, cost, quality, and EI as well as to promote efficiency, scalability, and application. The model is based on the behavioral characteristics of slime mold and connected with well-known techniques of TS in order to correct the limitations of the SMA model and handle the activity-on-node network of the building. A metamodel of the ASSMA is used to meet the system's overall flexibility needs. Case studies of complex construction have been shown.

The performance indicators show that the objective functions frequently receive bigger benefit values than necessary. Performance metrics related to optimization are less likely to suffer a negative effect. This further exemplifies how taking into account particular benefits and co-benefits can drastically affect the range of alternatives. When assessing this association model, multi-objective optimization should be applied.

Declaration of competing interest

There’s no conflict of interests exist

Acknowledgments

We warmly acknowledge the time and resources offered by Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for this effort.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

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