Using Biological Knowledge for Layout Optimization of Construction Site Temporary Facilities: A Case Study

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Abstract. In recent years, a number of studies have successfully transformed various models for biological collective behavior into intelligent optimization algorithms. These bio-inspired optimization techniques have been developed to provide better solutions than traditional methods to a variety of engineering problems. This paper attempts to apply and compare recent bio-inspired algorithms for determining the best layout of construction temporary facilities. To validate the performance of the proposed techniques, an actual building construction project was used as a test problem. Based on the obtained results, the performance of each bio-inspired algorithm is highlighted and discussed. This paper presents beneficial insights to decision-makers in the construction industry that are involved in handling optimization problems.

1 Introduction

Construction site layout planning (CSLP) has a significant effect on labor productivity; thus, it must be taken into early consideration in the planning stage [1]. The purpose of CSLP is to organize temporary facilities, including warehouses, batch plants, labor residences, and job offices in such a way as to maximize the design quality and satisfy the design requirements to minimize total costs of the interactions between such facilities [2]. Efficiency and effectiveness of production are significantly increased by an adequate site layout. However, CSLP problems are often so complex that determining the optimal solution using a “brute force” approach often requires huge computational time.

Bio-inspired optimization techniques have been widely investigated and applied to engineering optimization over the past four decades. These optimization techniques take inspiration and knowledge from natural biological processes and transform them into various simulation and optimization models. For instance, particle swarm optimization (PSO) simulates the social behavior of a bird flock moving to a preferred destination [3]. Another example of bio-inspired algorithms is the artificial bee colony (ABC), which represents a simulation of the foraging behavior of honey bees [4]. Some researchers have attempted to increase performance by combining bio-inspired algorithms with other methods to form a hybrid intelligence system [5,6].

Over the last two decades, bio-inspired algorithms have been employed to solve various CSLP problems. Different researchers have developed PSO applications to tackle the facility site layout problem [7,8] and a recent study has attempted to develop an ABC-based methodology to solve CSLP problems [9]. Many researchers have attempted to address CSLP problems; however, there is still scope for improving the solutions and finding new applications of bio-inspired algorithms. As it is challenging to develop the optimal solution in large projects, researchers need to investigate more advanced bio-inspired optimization techniques to solve more complex CSLP problems.

Symbiotic organisms search (SOS) is a bio-inspired algorithm proposed by Cheng and Prayogo [10] and, thus far, it has been employed in various engineering optimization studies [11-21]. This algorithm simulates mutualism, commensalism, and parasitism, which are biological collective behaviors occurring among living organisms in an ecosystem. Being a new algorithm, it is necessary to further examine and investigate its capacity for resolving various complex problems. Until now, only a small number of studies have examined the ability of the SOS to solve the CSLP and similar discrete problems. Thus, to examine the performance of SOS in resolving the CSLP problem, it is necessary to conduct additional further experiments and research.

This study implements the SOS algorithm in solving the CSLP problem. A real construction project case from Indonesia is employed to measure the performance and applicability of the SOS algorithm. A comparison of the robustness of its performance to other bio-inspired algorithms was conducted. SOS was then compared with PSO and ABC, which are well-established bio-inspired algorithms for performance benchmarking.

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2 Bio-inspired optimization techniques

2.1 Particle swarm optimization (PSO) and artificial bee colony (ABC) models

PSO mimics the movements of bird flocks flying together and schools of fish swimming together [3]. Each random solution of the problem in question in the PSO algorithm corresponds to a particle that moves in the search space. The particles employed in the PSO algorithm benefit from the social experience of the swarm as well as their own experience. The assumption is that such a situation represents a simulation of communication between organisms that move in unison. It is supposed that in the PSO algorithm, the social experience of the swarm and the individual experience of the particles correspond, respectively, to the concepts of global and local search. The movement of particles in PSO can be modeled as a mathematical equation as follows:

$$v_i = w \times v_i + rand(0,1) \times c_1 \times (x_{pbest} - x_i) + rand(0,1) \times c_2 \times (x_{gbest} - x_i) \quad (1)$$

where v_i is the velocity of i-th particle; w is the inertia weight parameter; c_1 is the cognitive factor parameter, c_2 is the social factor parameter; x_i represents the location coordinate of i-th particle; x_{pbest} is the location coordinate of pbest; x_{pbest} is the location coordinate of gbest; and $rand(0,1)$ represents uniform random generator with a range from 0 to 1.

ABC represents an optimization technique that corresponds to the swarm behavior of honey bees in collecting food [4]. At first, ABC begins with the initialization of food sources randomly containing the candidate solutions. Once the food source is determined, the algorithm will enter the “employed bee phase”. At this stage, employed bees will modify candidate solutions by looking for other solutions around them. The quality of the food source, measured by the objective value, is shared with the onlooker bees through the waggle dance as can be seen in Eq. (2). At the “onlooker bee phase”, the solution generated by the employed bees will be randomly selected with a certain probability in correspondence with the quality of the solution. Onlooker bees will then re-modify the solution based on information from employed bees. At the “scout bee phase”, employed bees will turn into scout bees to find new alternative solutions if the solution is not improved at any given time interval. ABC terminates the optimization process after achieving a predefined objective value or reaching a maximum number of generations:

$$new\_food_i = food_i + rand(-1,1) \times (food_i - food_j) \quad (2)$$

where $food_i$ is the i-th food source; new_food_i is the modified version of $food_i$ after the bee’s searching; and $rand(-1,1)$ represents uniform random generator with a range from –1 to 1.

2.2 Symbiotic organisms search (SOS)

Cheng and Prayogo [10] initially developed the SOS optimization method based on symbiotic relationships among living organisms. Its initial application was to solve continuous optimization problems [10]. The main mechanisms of the SOS searching process are mutualism, commensalism, and parasitism phases, which are inspired by the three well-known symbioses.

The “mutualism phase” modifies the organisms using the following equations:

$$new\_O_i = O_i + rand(0,1) \times [O_{best} - (1 + round(rand(0,1)) \times (O_i + O_j)/2] \quad (3)$$

$$new\_O_j = O_j + rand(0,1) \times [O_{best} - (1 + round(rand(0,1)) \times (O_i + O_j)/2] \quad (4)$$

where O_i and O_j are the i-th and j-th organism vectors, respectively, such that $i \neq j$; O_{best} is the best organism in the current iteration; new_O_i and new_O_j are the modified solutions for O_i and O_j after conducting the symbiosis.

The “commensalism phase” modifies the organisms using the following equation:

$$new\_O_i = O_i + rand(-1,1) \times (O_{best} - O_j) \quad (5)$$

The “parasitism phase” modifies the organisms using the following equation:

$$O_{par} = F \times O_i + (1 - F) \times (rand(0,1) \times (ub - lb) + lb) \quad (6)$$

where O_{par} represents the parasite that competes to eliminate the host O_j; u_b and l_b denote the upper and lower bounds of the given problem, respectively; and F and $(1 - F)$ are the binary random matrix and its inverse, respectively.

3 Formulation of objective function of CSLP problem

The purpose of CSLP is to plan and organize a number of facilities (n) into a number of locations (m). In this case, costs related to the flow between facilities are linear in regard to the distance traveled by the construction workers [22]. The CSLP problem can be viewed as a quadratic assignment problem (QAP), which is categorized as a non-polynomial hard (NP-hard) problem. Due to its combinatorial complexity, the exhaustive solution for reasonably sized layout problems is not possible [2]. To illustrate, the layout alternatives for n facilities can be up to $n!$. Even in cases of a small n, this is still an enormous number. For example, the number of alternatives for 10 facilities is higher than 3,628,000 and it is a 12-digit number for 15 facilities.

The objective function of the CSLP problem used in this study is determined by the distance traveled by the construction workers and can be modeled as follows:

$$min\ TD = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} f_{ik} d_{jl} x_{ij} x_{kl} \quad (7)$$

such that:

$$\sum_{j=1}^{n} x_{ij} = 1,\ i = 1,2,3,...,n \tag{8}$$

$$\sum_{i=1}^{n} x_{ij} = 1,\ j = 1,2,3,...,n \tag{9}$$

$$x_{ij} \in \{0,1\},\ i = 1,2,3,...,n,\ j = 1,2,3,...,n \tag{10}$$

where *TD* represents the objective function; *n* represents the number of locations and facilities; f_{ik} represents the number of trips made between facilities *i* and *j*; d_{jl} represents the distances between facilities *i* and *j*; and x_{ij} and x_{kl} represent the values from the assignment matrix that shows the relationship between facilities and locations.

4 Optimization of CSLP problem using bio-inspired algorithms

The optimization of the CSLP problem by bio-inspired algorithms is divided into four main steps:

Step 1. Parameter initialization: The objective function and project information, such as the distance between locations and traveling frequency between facilities, were defined. In addition, the parameter setting for each algorithm was determined before the search process began and included the population size, iteration number, and other algorithm-specific parameters.

Step 2. Initialization of random candidate solutions: The population of candidate solutions was initialized randomly at the beginning. The candidate solutions should be in the form of permutation numbers that represent the placement of facilities at locations. Because the algorithms are using continuous-based solutions, a procedure for changing the representation of solutions from continuous-based values to sequence-based is needed. The location–facility relationship is formed by using the index value from sorting the continuous value in ascending order. Representation of this solution is used to solve the problem of determining the facility layout. An example of a transformation process from a continuous-based solution to a sequence-based model can be illustrated by Table 1.

Table 1. Solution transformation from continuous-based to sequence-based

Location	Facility (continuous-based)	Facility (sequence-based)
1	0.28	2
2	0.35	3
3	0.78	5
4	0.48	4
5	0.03	1

Step 3. Optimization process by bio-inspired algorithm: For each bio-inspired algorithm, the optimization process is repeated with search operator simulations that mimic the patterns from nature. The search simulation in ABC involves the bee colony (employed bee, onlooker bee, scout bee) foraging behavior concept. The search simulation in the PSO is based on the concept of particles movement that refers to cognitive and social aspects in accordance to their swarm. SOS search simulation involves biological interaction between organisms in the mutualism, commensalism, and parasitism phases.

Step 4. Stopping criterion: The optimization process continues until the stopping criterion is met.

5 Case Study

This paper employed a construction site layout for a high-rise building construction project in Surabaya, Indonesia [17]. Based on the project information, there are 32 types of temporary facilities. Nevertheless, after further inspection, not all temporary facilities are actively used. Additionally, there are some facilities that are not routinely visited by the construction personnel at the current time of observation. In this study, the elimination of inactive facilities resulted in a total of 10 temporary facilities to be considered for the optimization process. Location for facility placement can be seen in Fig. 1. The corresponding facilities used in this study are:

A. Batching plant
B. Site office
C. Formwork shop
D. Site gate, permanently located at location #4
E. Guard house, permanently located at location #5
F. GRC fabrication shop
G. Contractor office
H. Rebar storage yard
I. Rebar fabrication shop 1
J. Rebar fabrication shop 2

Fig. 1. Construction site layout plan for the employed project.

The traveling distance between locations is shown in Table 2 and the traveling frequency of construction workers between facilities in a typical day is shown in Table 3.

Table 2. Distance between locations (in meters)

	1	2	3	4	5	6	7	8	9	10
1	0	139	156	33	39	49	138	170	174	150
2	139	0	19	106	100	112	128	160	165	188
3	156	19	0	125	119	131	112	144	148	207
4	33	106	125	0	12	23	111	143	147	123
5	39	100	119	12	0	12	99	131	135	111
6	49	112	131	23	12	0	89	121	125	101
7	138	128	112	111	99	89	0	32	36	104
8	170	160	144	143	131	121	32	0	9	42
9	174	165	148	147	135	125	36	9	0	102
10	150	188	207	123	111	101	104	42	102	0

Table 3. Traveling frequency of construction workers between facilities

	A	B	C	D	E	F	G	H	I	J
A	0	10	8	9	3	9	0	0	0	0
B	10	0	8	12	8	9	11	5	0	1
C	8	8	0	4	3	8	0	0	0	0
D	9	12	4	0	6	15	10	10	8	5
E	3	8	3	6	0	9	5	3	2	1
F	9	9	8	15	9	0	0	0	0	0
G	0	11	0	10	5	0	0	7	7	10
H	0	5	0	10	3	0	7	0	25	27
I	0	0	0	8	2	0	7	25	0	16
J	0	1	0	5	1	0	10	27	16	0

A total of 25 simulations were conducted to ensure each algorithm's consistent performance. The final traveling distances from each simulation were recorded to obtain the mean, standard deviation, best, and worst. The parameter setting of each method was set as shown in Table 4. Each bio-inspired algorithm used the same value of population size (*popSize*) and maximum number of iterations (*maxIter*), which are 50 and 20, respectively. The additional parameter setting for PSO is suggested by Kennedy and Eberhart [3] while the value of *limit* parameter for ABC is determined to 10 which is a half value of *maxIter*.

Table 4. Parameter setting for each bio-inspired algorithm

PSO	ABC	SOS
popSize = 50 *maxIter* = 20 w = 0.4-0.9 $c_1 = 2$ $c_2 = 2$	*popSize* = 50 *maxIter* = 20 *Limit* = 10	*popSize* = 50 *maxIter* = 20

Table 5 shows the average, best, worst, and standard deviation results after the simulations of each algorithm. It appears that the three bio-inspired algorithms are capable of finding the best value of 39,184 m. However, only SOS can produce the best value on every trial, which is shown from the fact that the average value is equal to the best value of 39,184 m and the standard deviation is 0. The worst performing algorithm in this case is the PSO, with an average value, standard deviation, and the worst value higher than the other two methods. Additionally, using the layout from SOS might save a total traveling distance of 4,132 m in comparison to the original project facility layout as seen in Table 6.

Table 5. Mean, standard deviation, best, and worst after 30 simulations (in meters)

Algorithm	Mean	Standard Deviation	Best	Worst
PSO	41829.20	2447.10	39184	46128
ABC	41390.56	1736.57	39184	44972
SOS	39184	0	39184	39184

Table 6. Comparison of layout plan between original layout and layout after optimization by bio-inspired algorithms

Location	Original Layout	Best Layout after Optimization by SOS and Other Algorithms
1	A	F
2	B	A
3	C	C
4	D	D
5	E	E
6	F	B
7	G	H
8	H	J
9	I	I
10	J	G
Objective value (in meters)	43,316	39,184

6 Conclusion

This research applies SOS in determining the CSLP for the traveling distance of construction project workers from temporary facilities. One case study was used to test the performance of SOS adopted from the layout of a multi-story building project in Surabaya. On this occasion, PSO and ABC were appointed as a comparison. The results analysis shows that SOS has high searching accuracy in each case when compared with other algorithms. This is evident from the solutions produced by SOS that have been the most optimal. On the other hand, SOS is able to consistently produce optimal solutions when compared with other algorithms. SOS is able to produce the average value and the smallest standard deviation among other algorithms from the results of 30 simulations. A good optimization algorithm usually has the ability to search for new global search areas that have the potential to have optimal solutions (known as "exploration capability") as well as the ability to investigate the best local solutions within a particular search area (known as "exploitation capability"). The balance of the SOS search scheme is divided into exploration capability (mutualism phase and commensalism phase) and the ability of exploitation (parasitism phase), which can make SOS superior compared with other metaheuristic methods. In addition, through the parasitism phase, SOS is also capable of eliminating inferior solutions. This makes SOS one of the potential alternative methods to deal with various problems in the field of facility layout optimization.

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