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A comparative study of several nature-inspired algorithms in steel deck floor system cost optimization

T Emanuel[1,2], Hadrian[1], D Prayogo[1] and F T Wong[1]

[1] Department of Civil Engineering, Petra Christian University, Surabaya, Indonesia

[2] Corresponding author: b11180015@john.petra.ac.id

Abstract. Steel deck floor systems can be considered as one of the main components of a structure. As technology advances, the role of optimization is used in many aspects of structural designs. Steel deck floor systems are one of many components that are usually optimized to look for its optimum cost but are still able to hold the structure. This study compares the performance of the particle swarm optimization (PSO), artificial bee colony (ABC), differential evolution (DE), and symbiotic organisms search (SOS), that categorized as nature-inspired algorithms, in the optimization of a steel deck floor system. The variables considered are the edge beams, interior beams, and the composite steel deck. The results show that the SOS gives the most optimum cost with a better average and a perfect success rate.

1. Introduction

Nowadays development in optimization plays a big role in civil engineering [1], especially in the design optimization of structures. Many aspects and elements of a structure can be optimized to attain the best solution to the design problem. By using optimization, efficiency in cost, selection of steel profiles, and even locations can be found. One of the components that can be optimized during a structural design is the steel deck floor system. As a typical section of the structure, steel deck floor system components such as beams, girders, decks as well as the slab itself, create thousands of possibilities of combinations that can suit the structure. In the construction industry, each steel deck floor system can be designed in a various combination that needs to be considered in the design process.

Many algorithms have been used to find the best solution for the composite and non-composite steel deck floor systems design, but still lack in variety of algorithms used [2]. To obtain more variety of the optimum combination that can be used, other algorithms are tested to attain the optimum solution. In this paper, four optimization nature-inspired algorithms are compared to obtain the optimum combination of steel deck floor systems based on the methods and standards of Canadian Standards [3].

2. Review of nature-inspired algorithms

Nature-inspired algorithms are inspired by nature-related or biological-related phenomena, such as the behavior of animals and the theory of evolution by Darwin. The algorithms in this study are the ones inspired by the evolution theory and the behavior of bees, birds, and fishes [4].

2.1. Particle Swarm Optimization (PSO)

Introduced by Kennedy and Eberhart in 1995 [5], the algorithm is inspired by the food searching behavior of birds or fishes. In the wild, these animals search for food in groups where each of their behavior affects the other member of the group. In the initialization step, randomly generated locations of particles are created. In the next iterations, the particles move using equation (1) as the velocity vector and will update the location through equation (2).

$$V_i(t+1) = Wv_i(t) + rand(0,1)C_1\big(xPbest(t) - x_i(t)\big) + rand(0,1)C_2(xGbest(t) - x_i(t)) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

where $v_i(t+1)$ is the velocity vector, W is the inertia weight, $v_i(t)$ is the initial velocity, C_1 is a cognitive parameter, C_2 is a social parameter, $xPbest(t)$is the location of personal best, $x_i(t)$ is the initial location, $xGbest(t)$ is the location of global best, and $x_i(t+1)$ is the new location of the particle.

2.2. *Artificial Bee Colony (ABC)*

This algorithm was introduced by Dervis Karaboga and Bahriye Basturk in 2005 [6]. The ABC algorithm was inspired by the unique behavior of honey bees, where they send three groups to find or look for food. The first group is called employed bees, where they come to the source depending on their experience or memory. The second group, which is the onlooker bees, where they just wait and see in the dance area before deciding where to go. The scout is the last group in the honey bees colony, they find their food randomly.

In the initialization stage, the scout bees discover new food locations randomly. In the employed bee stage, the employed bees visit a location and gather as many as they could. After that, they become just like scout bees where they look for new sources of food, then they give information they have to onlooker bees. In the onlooker bees stage, they choose one the best location (which has many sources of food) from many locations that employed bees gave them information about. In the scout bees stage, employed bees become scout bees to find a better location with equation (3) for food after the location before being abandoned. The ABC algorithm will stop after they find the best solution or when the iteration they have reached maximum iteration.

$$V_{ij} = X_{IJ} + rand(-1,1)(X_{ij} - X_{kj}) \quad (3)$$

where V_{ij} is a new location after onlooker bees stage, X_{ij} is food location at i, X_{kj} is food location at k.

2.3. *Differential Evolution (DE)*

Introduced by Rainer Storn and Kenneth Price as a technical report in 1997 [7], the algorithm working principle is summarized in a four-stage cycle. The first stage is the initialization stage. In this stage, the population, x, for each generation is generated into an NP D-dimensional parameter vector based on the upper bound and the lower bound limits that have been set before.

The second stage is called the mutation stage. The vectors generated are "mutated" and combined one to another to create a new vector called the mutant vector, v. Three vectors are chosen at random and two of those vectors are multiplied by factor F, where the value varies from 0 to 2 and then added to the other last vector. The process is defined in equation (4).

$$v_{i,G} = x_{ri1,G} + F(x_{ri2,G} - x_{ri3,G}) \quad (4)$$

The third stage, the crossover stage, is the process of increasing the diversity of the population through the creation of a new vector, the trial vector, u. The vector is a product of the mutant vector combined with the initially generated vector. The variable CR is determined between the number equal to 0 until less than 1. If a random number between 0 and 1 is generated, *randb(j)*, is less than the variable CR, a mutant vector value will enter the trial population, else a value in the initial vector enters the trial population. The forming of the trial vector is defined in equation (5).

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & if\ (randb(j) \leq CR)\ or\ j = rnbr(i) \\ x_{ji,G} & if\ (randb(j) > CR)\ and\ j \neq rnbr\ (i) \end{cases} \quad (5)$$

The last stage is the selection stage. The process in this stage is to compare between the trial vector and the initially generated vector by the greedy criterion. The vector with a better value after the selection enters the next generation vector.

2.4. Symbiotic Organisms Search (SOS)

This algorithm was introduced by Cheng and Prayogo in 2014 [8]. Symbiotic organisms search (SOS) comes from an inspiration of symbiotic relationships within organisms. This relation contains three symbioses, namely, mutualism phase, commensalism phase, and parasitism phase. In the mutualism phase, organisms will work beneficially together to improve their survival quality, just like bees and flowers. In this phase, the organisms (X_i and X_j), will be renewed using equations (6) and (7), only if the resulting new organism is better.

$$X_{inew} = X_i + rand(0,1)(X_{best} - X_{average}\ round(1 + rand)) \quad (6)$$

$$X_{jnew} = X_j + rand(0,1)(X_{best} - X_{average}\ round(1 + rand)) \quad (7)$$

$$X_{average} = \frac{Xi + Xj}{2} \quad (8)$$

where X_{best} is the global best, (X_{best}-$X_{average}$*round(1+*rand*)) represents the mutualistic between organisms to increase the quality of survival in life.

In the commensalism phase, two organisms will react to each other, in which one organism will get the benefit, but the other organism will not get any effect from the first organism (advantages or disadvantages) just like remora fish and sharks. In this phase, the organism X_i is calculated using X_i and X_j and updated using equation (9), only if the resulting new organism is better than before.

$$X_{inew} = X_i + rand(-1,1)(X_{best} - X_j) \quad (9)$$

From this equation, (X_{best} - X_j) represents a beneficial symbiotic relationship to improve survival quality. In the parasitism phase, two organisms have a relationship together, which one of them is harmed by the other organism. In this phase, X_i will produce artificial parasite organisms and be compared to X_j. If the result value of X_j is worse than X_i, it replaces organism X_j.

3. Optimization of steel deck system problem

The main goal of the study is to minimize the cost of a steel deck floor system without violating any constraints that have been set, that is, the moment, web crippling, deflection, total factored load, shear of each of the components. The problem to be optimized is defined in Figure 1.

Symbol *W* in Figure 1 is the width of the steel floor and also stands for the length of the south and north edge beams (girders). Symbol *L* is the length of the steel floor and also stands for the length of interior beams and the length of east and west edge beam. Symbol A is to show the section of the steel deck.

Constraints violated will cause a penalty added to the objective function. A set of variables to be optimized by the algorithms are [2].

$$\mathbf{x} = \{x_1, x_2, x_3, x_4, x_5, x_6\} \quad (10)$$

where x_1 is the selection of steel deck and the slab thickness, x_2 is the selection of interior beam, x_3 is the selection of east edge beam, x_4 is the selection of west edge beam, x_5 is the selection of south edge beam (girder), x_6 is the selection of north edge beam (girder).

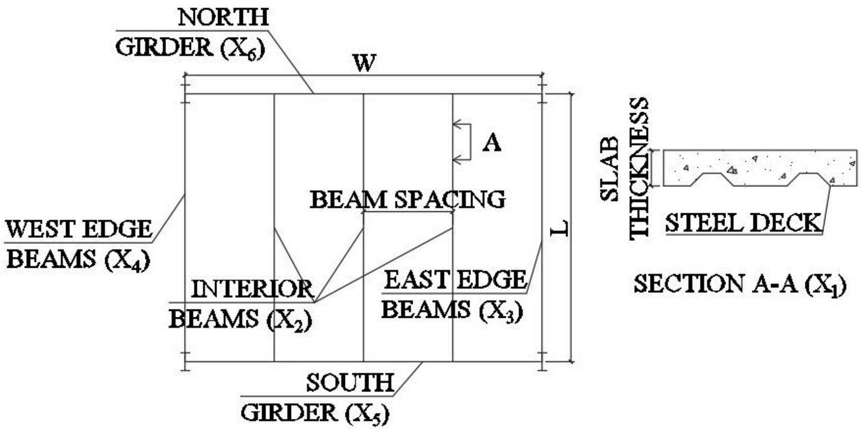

Figure 1. Steel floor system configuration [1].

The numbers obtained as variables refer to the list of steel deck and slab thickness and steel beam profiles used [3]. To minimize the variables needed for the design, the objective function is defined as below.

$$f_{cost} = c_1x_1 + c_2x_2 + c_3x_3 + c_4x_4 + c_5x_5 + c_6x_6 \tag{11}$$

Equation (11) represents the optimized total cost where c_1 represents the cost for the steel deck and concrete slab combination, while c_2, c_3, c_4, c_5, and c_6 represent the cost for the beams. The costs are taken based on the price listed in Table 1 [2]. This objective function is subjected to a set of design constraints as follows:

$g1$: Moment (steel deck), $Mf_{max(+)}/Mr_{(+)} \leq 1.0$ (12)

$g2$: Moment (steel deck), $Mf_{max(-)}/Mr_{(-)} \leq 1.0$ (13)

$g3$: Web Crippling (steel deck), $Rf_{int}/Br_{int} \leq 1.0$ (14)

$g4$: Web Crippling (steel deck), $Rf_{ext}/Br_{ext} \leq 1.0$ (15)

$g5$: Deflection (steel deck and slab), $\Delta L / \Delta adm \leq 1.0$ (Construction) (16)

$g6$: Deflection (steel deck and slab), $\Delta L / \Delta adm \leq 1.0$ (Cured) (17)

$g7$: Total Factored Load (slab), $wf_{max}/wr \leq 1.0$ (18)

$g8$: Moment (girders and beams), $Mf_{max}/Mr \leq 1.0$ (19)

$g9$: Shear (girders and beams), $Vf_{max}/Vr \leq 1.0$ (20)

$g10$: Deflection (girders and beams), $\Delta L / \Delta adm \leq 1.0$ (21)

$g11$: Floor acceleration limit (walking), $(ap/g) / (a0/g) \leq 1.0$ (22)

Where:

- $M_{fmax(+)}$ is the maximum positive factored moment
- $Mr_{(+)}$ is the positive resisting moment
- $M_{fmax(-)}$ is the maximum negative factored moment
- $Mr_{(-)}$ is the negative resisting moment
- Rf_{int} is the factored interior loads
- Br_{int} is the interior factored bearing resistance
- Rf_{ext} is the factored end loads
- Br_{ext} is the end factored bearing resistance

- *ΔL* is the deflection
- *Δadm* is the allowable deflection
- wf_{max} is the total factored load
- *wr* is the service load
- Vf_{max} is the maximum factored shear
- *Vr* is the resisting shear force
- (*ap /g*) is the vertical peak acceleration ratio [8]
- (*a0 /g*) is the tolerance limit acceleration ratio [8]

Table 1. Prices for components of steel deck floor system [2].

Components	Price $
Steel	2.86 per kg
Steel Deck	2.25 per kg
Steel Deck (Installation)	5.40 per m^2
Concrete	131 per m^3
Concrete (Installation)	5.40 per m^2

4. Optimization procedure

In this paper, four metaheuristic algorithms are used to optimize the cost of a steel deck floor system, namely the PSO, ABC, DE, and SOS. These four algorithms were used to find the optimum cost by optimizing the choice of the beams, girders, steel deck, and slab height selection. Algorithms and calculations were coded in MATLAB R2019a. Optimization processes of the steel deck floor system are presented in a flowchart in Figure 2.

Calculations of the bending moment, shear, displacement, and vibration are used as constraints of the optimization. When a constraint is violated, a penalty to the objective function where the total cost is calculated is given.

5. Test problems and results

The metaheuristic algorithms are compared to optimize the steel deck floor system problem. In the problem shown in Figure 2 [2], the width, W, and length, L, of the floor used is decided to determine the length of the beams. Additional live and dead load, additional uniform live load and dead load to the edge beams can be added, as well as the number of the internal beams (one set as a minimum) so the steel deck composite floor has two spans. The beam selection used in the optimization is based on the Canadian Institute of Steel Construction (2016) with a density of 7850 kg/m3 [3], while the steel deck composite slab and steel deck itself were chosen from the Canam® Steel deck catalog (PC3615, PC3623, PC2432). The slab thickness that can be used and chosen randomly in the optimization are 90, 100, 115, 125, 140. 150. 165, 190, and 200 mm. A selection of normal density (2400 kg/m3) or lightweight (1840 kg/m3) concrete can be chosen. The following choice of selection is based on past research of Poitras G, et al [2].

In this case, the inputs are set as shown in Table 2 [2] to be optimized by the metaheuristic algorithms. There are two types of input cases that are used as examples to show which algorithm shows the best optimization. From the data in Table 2, the dead load was combined with the self-weight of the component such as beam, steel deck, and concrete. The live load was combined too as well as dead load. Table 3 are the parameter settings used in the algorithms.

Table 4 is the results of all algorithms used based on the algorithm that was run 30 times with consideration of function evaluation of each algorithm. The PSO, ABC, and DE use 1000 iteration, while the SOS only use 250 iterations as the algorithm has 4 function evaluations. Each algorithm used 20 populations. The combination of each steel deck profile and beams optimized are shown in Table 5 based on Canam® Steel deck catalog and Canadian Institute of Steel Construction (2016) [3]. The run can be said successful if the run passes all the constraints and no penalty is added.

The convergence graph shown in Figure 3 shows that the SOS produces a better convergence over the other algorithms. SOS, DE, and ABC have the highest success rate where the optimized costs satisfy the constraints given, while the PSO has one output that violates the constraint. Even though SOS, DE, and ABC have the same success rate, the standard deviation obtained by the SOS is the lowest of the three, which is $8.35. From this case, SOS performed as the best algorithm to optimize the problem and PSO performed the worst with the lowest success rate and the highest standard deviation from the other three. Another algorithm that has tried to solve the problem successfully such as HS and PDO [10], still performs under SOS with the optimum cost produced is $7149.

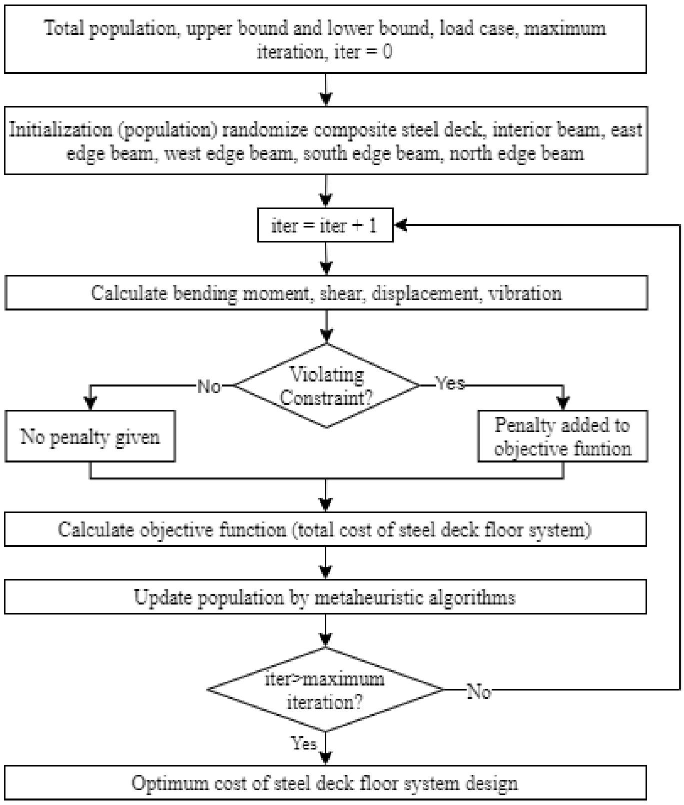

Figure 2. Flow chart of steel deck floor system optimization.

Table 2. Configuration of load and parameters [2].

Size (mm)	Dead Load (kN/m^2)	Live Load (kN/m^2)	Additional Uniform Dead Load (kN/m)	Additional Uniform Live Load (kN/m)
W = 8000 L = 6000	1.6	4.8	10 (North Beam) 6 (South Beam) 4 (West Beam) 6 (East Beam)	14 (North Beam) 4 (West Beam)
W = 10000 L = 8000	2.0	2.4	16 (North Beam 16 (North Beam) 10 (West Beam) 10 (West Beam)	9.6 (North Beam) 9.6 (South Beam) 6 (West Beam) 6 (East Beam)

Table 3. Parameter settings of algorithms.

PSO	DE	SOS	ABC
n = 20	n = 20	n = 20	nPop (Colony Size) = 20
c1 = 2	F = 0.2 – 0.8		nOnlooker (Number of Onlooker Bees) = 20
c2 = 2	pCR = 0.2		L (Trial Limit) = 72
w = 0.5			a = 1

Table 4. Optimization results from 30 trials, 1000 iterations, 20 populations.

Variables	PSO	ABC	DE	SOS
x_1	2	3	2	2
x_2	239	218	239	239
x_3	204	219	204	204
x_4	203	214	203	203
x_5	185	200	185	185
x_6	127	125	127	127
Best ($)	6119.90	7466.34	6119.90	6119.90
Average ($)	6451.46	8749.06	6154.22	6121.42
Worst ($)	11714.06	9672.02	6485.98	6165.66
Stdev ($)	1019.44	659.68	85.56	8.35
Median ($)	6257.18	8959.88	6119.98	6119.90
Success Rate (%)	96.67	100	100	100

Table 5. Profile of steel deck and beam.

Variables	PSO	ABC	DE	SOS
x_1	PC 3615 90 mm slab 0.76 mm deck	PC3615 90 mm slab 0.91 mm deck	PC 3615 90 mm slab 0.76 mm deck	PC3615 90 mm slab 0.76 mm deck
x_2	4-W150×18	4-W250×25	4-W150×18	4-W150×18
x_3	W310×21	W250×22	W310×21	W310×21
x_4	W310×24	W250×45	W310×24	W310×24
x_5	W260×33	W310×39	W260×33	W360×33
x_6	W530×66	W530×72	W530×66	W530×66

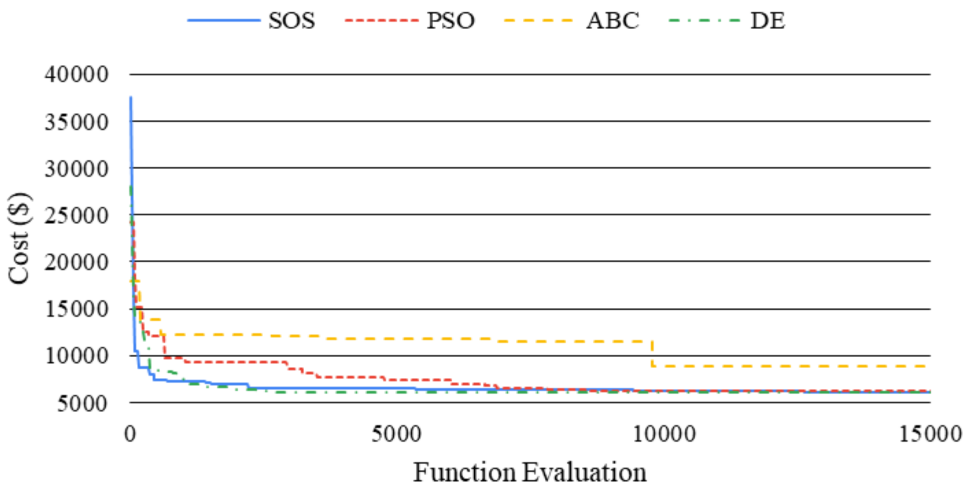

Figure 3. Convergence graph of steel deck floor system cost.

6. Conclusions

The research compared the four algorithms, that is, the PSO, ABC, DE, and SOS, to optimize the cost of a steel deck floor system. The choice of the beams, girders, deck, and slab is taken as the variables. Using 30 trials with 1000 iterations each, the optimum cost obtained is $6119.90. The three algorithms, that is, the PSO, DE, and SOS obtained the optimum cost of the problem. However, the SOS shows the best performance due to the average and success rate of the algorithm, while the ABC, unfortunately, performed the worst with obtaining only $7466.34 as the optimum cost.

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