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Particle bee algorithm for tower crane layout with material quantity supply and demand optimization

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ABSTRACT

The tower crane layout (TCL) problem, a typical construction site layout (CSL) problem, is currently used in a wide range of construction projects and site conditions. The tower crane is a key facility used in the vertical and horizontal transportation of materials, particularly heavy prefabrication units such as steel beams, ready-mixed concrete, prefabricated elements, and large-panel formwork. Matching the location of tower cranes to material supply and engineering demands is a combinatorial optimization issue within the TCL problem that is difficult to resolve. Swarm intelligence (SI) is a popular artificial intelligence technique that is used widely to resolve complex optimization problems. Various SI-based algorithms have been developed that emulate the collective behavior of animals such as honey bees (bee algorithm, BA) and birds (particle swarm optimization, PSO). This study applies the particle bee algorithm (PBA), a hybrid swarm algorithm that integrates the respective advantages of honey bee and bird swarms, to the TCL problem. The performances of PBA, BA, and PSO are compared in terms of their effectiveness in resolving a practical TCL problem in construction engineering. Results show that the PBA performs better than both the BA and PSO algorithms.

1. Introduction

Construction site layout (CSL) problems are interesting because they introduce the consideration of layout esthetics and usability qualities into the facility design process [1]. The CSL problem identifies a feasible location for a set of interrelated facilities that meets all design requirements and maximizes design quality in terms of design preferences while minimizing the total cost associated with interactions among these facilities.

Artificial intelligence (AI)-based algorithms have previously been applied to solve CSL problems. Elbeitagi and Hegazy [2] used a hybrid neural network to determine optimal site layout. Yeh [3] applied annealed neural networks to solve construction site-level CSL problems. Li and Love [4] and Osman et al. [5] used a genetic algorithm (GA) to solve site layout problems in unequally sized facilities. The objective functions of these algorithms work to optimize inter-facility interactions in terms of variables such as transportation costs and trip frequencies. Hegazy et al. [6] developed a comprehensive system for site layout planning based on GA. Elbeitagi et al. [7] presented a practical model for schedule-dependent site layout planning in construction that combined a knowledge-based system, fuzzy logic, and GA.

Tower crane layout (TCL), a typical CSL problem, is suited to a wide range of construction work assignments and site conditions. The tower crane is a key facility used in the vertical and horizontal transportation of materials, particularly heavy prefabrication units such as steel beams, ready-mixed concrete, prefabricated elements, and large-panel formwork [8].

In large construction projects, several cranes are often used to handle transportation tasks, particularly in situations in which a single crane cannot cover all demand and supply points and/or when the capacity of a single crane cannot meet construction-schedule needs. Many factors influence tower crane location [9]. Currently, locations are typically determined through trial and error based on site topography/shape and overall task-coverage requirements. The complex factors involved in crane location and the lack of quantitative references often leave managers with little choice but to rely on experience and/or instinct [9]. Zhang et al. [9] and Tam et al. [8] developed an analytical model to model the travel time of tower crane hooks. In determining the time required for a hook to travel from one position to another, they considered factors related to physical parameters such as the topographical layout, building tower layout, and adjacent environment, which are unique to each site. The proper positioning of tower cranes and related material supply and demand points is critical to overall work efficiency on a construction site. Ideally, a tower crane jib should reach and cover all sections of all buildings on a construction site in order to allow the transport of construction materials between all supply and demand points [8].

Many research studies that address the problem of optimizing the location and transportation time of tower cranes have been published. Zhang et al. [9] used a Monte Carlo simulation to optimize tower crane

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location, and Tam and Hoang et al. [8,10,11] developed an artificial neural network (ANN) model for predicting tower crane operations and a GA model for optimizing site facility layout. The problem of optimizing tower crane and material supply locations within a building construction site resembles the conventional facility location problem, with the exception that the former requires 3-D (dimensional) consideration of material transportation due to the hook movements of the tower crane. The focus of the aforementioned studies was on solving different optimization problems by applying the proposed algorithms under different constraints. Thus, the quality of the obtained solution is necessarily constrained by the capability of the algorithm used.

Swarm intelligence (SI) has been of increasing interest to research scientists in recent years. SI was defined by Bonabeau et al. [12] as any attempt to design algorithms or distributed problem-solving devices based on the collective behavior of social insect colonies or other animals. Bonabeau et al. [12] focused primarily on the social behavior of ants [13], fish [14], birds [15] and bees [16–18] etc. However, the term "swarm" can be applied more generally to refer to any restrained collection of interacting agents or individuals. Although bees swarming around a hive are a classical example of "swarm", swarms can easily be extended to other systems with similar architectures.

A few models have been developed to model the intelligent behaviors of honeybee swarms and applied to solve combinatorial type problems [16–22]. Pham et al. [16–18] presented an original bee algorithm (BA) and applied it to two standard functional optimization problems with two and six dimensions. Results demonstrated that BA is able to find solutions very close to the optimum, showing that BA generally outperformed GA. However, while BA [16–18] offers the potential to conduct global searches and uses a simpler mechanism in comparison with GA, its dependence on random search makes it relatively weak in local search activities and does not record past searching experiences during the optimization search process. For instance, a flock of birds may be thought of as a swarm whose individual agents are birds. Particle swarm optimization (PSO), which has become quite popular for many researchers recently [23], models the social behavior of birds [16–18]. PSO is potentially used in local searching, and records past searching experiences during the optimization search process. However, it converges early in highly discrete problems [24].

To improve BA and PSO, Cheng and Lien [25] proposed a hybrid swarm algorithm called particle bee algorithm (PBA) that imitates a particular intelligent behavior of bird and honey bee swarms and integrates their advantages. The objective of this study is to formulate the design problem for a proposed hypothetical TCL case study involving locating tower cranes and associated material supply and demand points into a mixed-integer linear program to minimize the total operating cost.

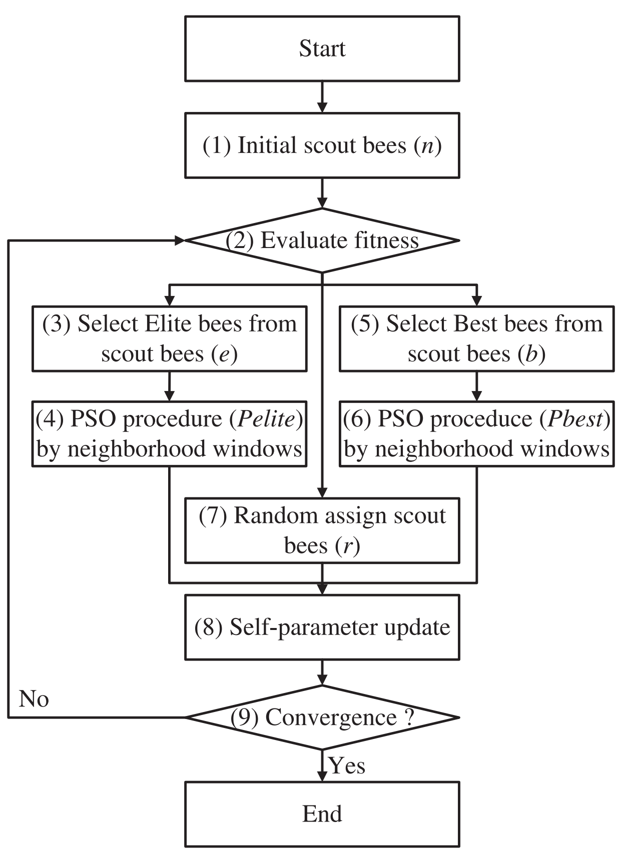

Fig. 1. Particle bee algorithm flowchart.

Table 1
Coordinates of crane points.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
X	45	65	65	45	51	60	70	70	60	51	42	42
Y	36	36	57	57	33	33	41	52	58	58	52	41
Z	30	30	30	30	30	30	30	30	30	30	30	30

2. Hybrid swarm algorithm particle bee algorithm (PBA)

The particle bee algorithm (PBA) that was proposed by Cheng and Lien [25] is based on the intelligent behaviors of bird and honeybee swarms. For improved BA local search ability, PSO global search ability and to seek records from past experience during the optimization search process, the study reconfigures the neighborhood dance search [16–18] as a PSO search [15]. Based on cooperation between bees (BA) and birds (PSO), the PBA improves BA neighborhood search using PSO search. Therefore, PBA employs no recruit bee searching around "elite" or "best" positions (as BA does). Instead, a PSO search is used for all elite and best bees. In other words, after PSO search, the number of "elite", "best" and "random" bees equals the number of scout bees.

In PBA, the particle bee colony contains four groups, namely (1) number of scout bees (n), (2) number of elite sites selected out of n visited sites (e), (3) number of best sites out of n visited sites (b), and (4) number of bees recruited for the other visited sites (r). The first half of the bee colony consists of elite bees, and the second half includes the best and random bees. The particle bee colony contains two parameters, i.e., number of iteration for elite bees by PSO (*Pelite*) and number of iteration for best bees by PSO (*Pbest*). PBA flowchart and steps are shown in Fig. 1 and below:

Step (1) Initialize scout bees.
PBA starts with n scout bees being randomly placed with respective positions and velocities in the search space.

Step (2) Evaluate fitness.
Start the loop and evaluate scout bee fitness.

Step (3) Select elite sites (e) from scout bees.
Elite sites are selected for each elite bee, whose total number is equal to half the number of scout bees.

Step (4) Elite bees initiate the PSO procedure by *Pelite* iteration for neighborhood-windows (NW).

Table 2
Coordinates of demand points.

	D1	D2	D3	D4	D5	D6	D7	D8	D9
X	34	34	51	60	76	76	60	51	43
Y	41	51	65	65	51	41	26	25	44
Z	15	15	15	15	15	15	15	15	15

Table 3
Coordinates of supply points.

	S1	S2	S3	S4	S5	S6	S7	S8	S9
X	73	83	87	73	55	35	22	36	55
Y	26	31	45	67	73	67	46	27	15
Z	2	2	1.5	1.5	1.5	0	0	1	1

In this step, new particle bees from elite and best bees are produced using Eq. (1). Elite and best bee velocity updates are performed as indicated in Eq. (2). This study further proposed a neighborhood-windows (NW) technique to improve PSO searching efficiency as shown in Eq. (3). Thus, after $x_{id}(t+1)$ is substituted into Eq. (1) and Eq. (2), the NW ensures PSO searching within the designated $x_{id\min}$ and $x_{id\max}$. In other words, if the sum of $x_{id}(t+1)$ exceeds $x_{id\min}$ or $x_{id\max}$ then $x_{id}(t+1)$ is limited to $x_{id\min}$ or $x_{id\max}$.

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{1}$$

where x_i is ith x and $i = 1$ to n; v_i is ith v; d is dimension in x_i or v and $d = 1$ to D; t is iteration; $x_{id}(t)$ is dth dimension in ith x and in t iteration; $v_{id}(t+1)$ is dth dimension in ith v and in $t+1$ iteration; $x_{id}(t+1)$ is dth dimension in ith x and in $t+1$ iteration; n is the number of particles.

$$v_{id}(t+1) = w \times v_{id}(t) + c_1 \times Rand \times [P_{id}(t) - x_{id}(t)] + c_2 \times Rand \times [G_d(t) - x_{id}(t)] \tag{2}$$

where v_{id}(t) is dth dimension in ith v and in t iteration; w is inertia weight and controls the magnitude of the old velocity $v_{id}(t)$ in the calculation of the new velocity; $P_{id}(t)$is dth dimension in ith local best particle and in t iteration; $G_d(t)$ is dth dimension global best particle in t iteration; c_1 and c_2 determine the significance of P_{id}(t) and G_d(t); *Rand* is a uniformly distributed real random number within the range 0 to 1. Furthermore, v_{id} at any time-step of the algorithm is constrained by parameters $v_{\max}$ and $v_{\min}$. The swarm is initialized by assigning each particle to a uniformly and randomly chosen position in the search space. Velocities are initialized randomly in the range $v_{\max}$ to $v_{\min}$. Particle velocities on each dimension are clamped to a maximum velocity $v_{\max}$. If the velocity of that dimension exceeds $v_{\max}$ or $v_{\min}$ (user-specified parameters), dimension velocity is limited to $v_{\max}$ or $v_{\min}$.

$$x_{id\,\min} \le x_{id}(t+1) \le x_{id\,\max} \tag{3}$$

where x_i is ith x and $i = 1$ to n; d is dimension in x_i and $d = 1$ to D; t is iteration; $x_{id}(t+1)$ is dth dimension in ith x and in $t+1$ iteration; n is the number of particles.

Step (5) Select best sites (b) from scout bees.
Best sites are selected for each best bee, the total number of which equals one-quarter of the number of scout bees.

Step (6) Best bees start the PSO procedure using the NW *Pbest* iteration.
In this step, new particle bees from elite and best bees are produced using Eq. (1). Elite and best bee velocity updates are acquired using Eq. (2). The NW technique improves PSO search efficiency, as shown in Eq. (3).

Step (7) Recruit random bees (r) for other visited sites.
The random bees in the population are assigned randomly around the search space scouting for new potential solutions. The total number of random bees is one-quarter of the number of scout bees.

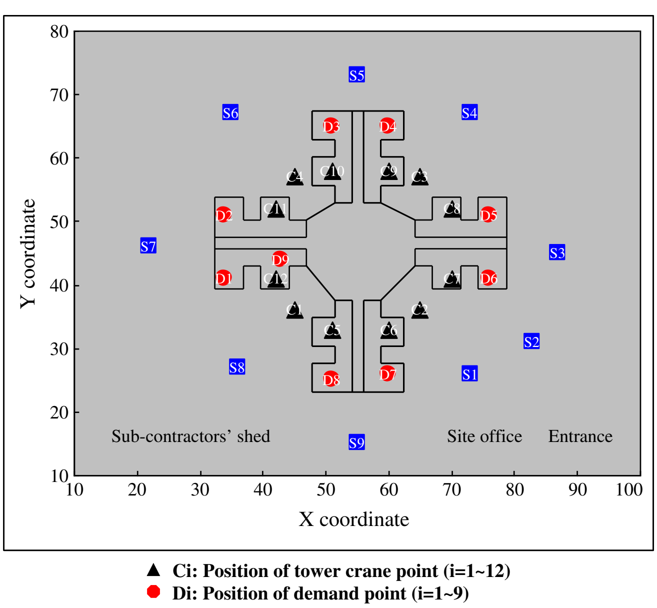

Fig. 2. A reference of tower crane layout.

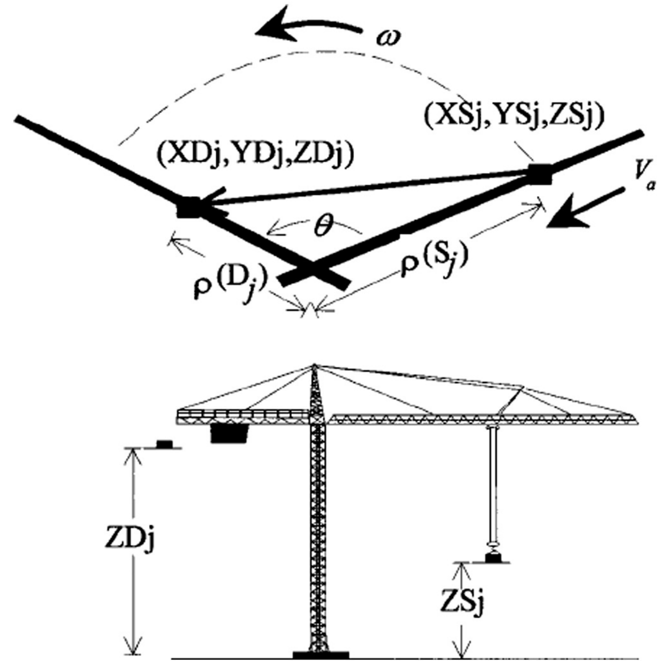

Fig. 3. Hook travel time.

Table 4
Parameter values used in the experiments.

PSO		BA		PBA	
n	100	n	100	n	100
w	0.9–0.7	e	$n/2$	e	$n/2$
v	$X_{\min}/10$–$X_{\max}/10$	b	$n/4$	b	$n/4$
		r	$n/4$	r	$n/4$
		n_1	2	w	0.9–0.7
		n_2	1	v	$X_{\min}/10$–$X_{\max}/10$
				Pelite	15
				Pbest	9

n = population size (colony size); w = inertia weight; v = limit of velocity; e = elite bee number; b = best bee number; r = random bee number; n_1 = elite bee neighborhood number; n_2 = best bee neighborhood number; *Pelite* = PSO iteration of elite bees; *Pbest* = PSO iteration of best bees.

Table 5
Parameter values used in single tower crane.

	CU	α	V_h	β	V_a	V_w	M	DY	IS	MS	MST	RS	LC	LA
Crane #1	1.92	1	60	0.25	53.3	7.57	1000	80	5000	500	10	2000	100	5

Step (8) Self-parameter-updating (SPU) for elite, best and random bees.
Furthermore, in order to prevent being trapped into a local optimum in high dimensional problems, this study proposed a solution, i.e., the self-parameter-updating (SPU) technique, the idea for which came from Karaboga [20]. Eq. (4) shows the SPU equation.

$$x_{id(new)} = x_{id(cur)} + 2 \times (Rand - 0.5) \times \left(x_{id(cur)} - x_{jk}\right) \tag{4}$$

$$j = \text{int}(Rand \times n) + 1 \tag{5}$$

$$k = int\ (Rand \times d) + 1 \tag{6}$$

where x_i is ith x and $i = 1$ to n; d is dimension in x_i and $d = 1$ to D; x_{id}(cur) is dth dimension in ith x and in current solution; x_{id}(new) is dth dimension in ith x and in new solution; $Rand$ is a uniformly distributed real random number within the range 0 to 1; j is the index of the solution chosen randomly from the colony as shown in Eq. (5), k is the index of the dimension chosen randomly from the dimension as shown in Eq. (6); n is the number of scout bees.
In step (8), after elite, best and random bees have been distributed based on fitness, fitnesses are checked to determine whether they are to be abandoned or memorized using Eq. (4). Therefore, if fitnesses of elite, best or random bees are both improved using Eq. (4) and improved over previous fitnesses, the new fitnesses are memorized. In step (3) through step (8), this differential recruitment is a key operation of the PBA.

Step (9) Convergence?
In this step, only the bee with the highest fitness will be selected to form the next bee population. These steps are repeated until the stop criterion is met and bees are selected to be abandoned or memorized.

In PBA, scout bees are used to classify both elite and best bees. Classification is controlled by scout bee fitness and optimized by control parameters called "*Pelite*" and "*Pbest*", which are important PBA control parameters. In PBA, the idea of *Pelite* for elite bees gives a higher potential to search optimization solutions. The idea of *Pbest* for best bees gives a second opportunity to search optimization solutions because luck continues to play a role in resource identification. Therefore, in this study, *Pelite* is always larger than *Pbest*. In a robust search process, exploration and exploitation processes must be carried out together. In PBA, while elite bees (*Pelite*) implement the exploitation process in the search space, best bees (*Pbest*) and random bees control this process.

Table 6
The result of three algorithms.

	Iteration	Mean	Worst	Best	Std
PBA	100	7.62E+05	8.92E+05	7.08E+05	6.64E+04
	300	7.34E+05	8.50E+05	6.21E+05	5.31E+04
	500	7.44E+05	8.28E+05	6.19E+05	5.63E+04
	1000	7.08E+05	8.12E+05	5.83E+05	6.28E+04
	5000	**7.03E+05**	8.55E+05	**5.41E+05**	5.99E+04
BA	100	9.52E+05	9.83E+05	9.10E+05	1.46E+04
	300	9.30E+05	9.56E+05	8.83E+05	1.64E+04
	500	9.17E+05	9.46E+05	**8.35E+05**	2.14E+04
	1000	9.12E+05	9.35E+05	9.03E+05	6.39E+03
	5000	**8.86E+05**	9.08E+05	8.59E+05	1.55E+04
PSO	100	9.29E+05	1.01E+06	8.90E+05	2.88E+04
	300	9.05E+05	1.00E+06	7.87E+05	4.25E+04
	500	8.84E+05	9.40E+05	8.24E+05	2.88E+04
	1000	8.82E+05	9.73E+05	7.91E+05	3.69E+04
	5000	**8.68E+05**	9.46E+05	**7.50E+05**	3.87E+04

Bold are the best Mean and best solution results of these mention algorithms.

3. Case study of the tower-crane-layout problem

3.1. Modeling of the multi-tower crane layout problem

3.1.1. A reference tower crane layout

In the past, project engineers considered site conditions, building structure, construction sequence, market conditions, and climate conditions in order to determine the tower crane layout (TCL) and the location of associated tower cranes, supply points, demand points, and supporting equipment. In this study, the TCL was modeled based on the minimum operation time cited in previous studies [10,11]. Tam and Hoang considered only a per-crane-operation-time cost of material operation flow and neglected other important cost factors such as rent, labor and, tower crane setup. Therefore, the current study extends their work by designing a TCL model that more practically reflects the actual conditions on a construction site. This study adopts and modifies a project as a reference [10] case study in order to determine optimal TCL with material quantity supply and demand through PSO, BA, and PBA. The project includes 12 potential tower crane locations, with the coordinates of each shown in Table 1. Furthermore, the project includes 9 supply points and 9 demand points, with coordinates shown, respectively, in Tables 2 and 3. Fig. 2 shows the completed site map for this project.

3.1.2. Objective function

In this study, the particle bee algorithm (PBA) was used to optimize the location of the tower crane. PBA was further used to optimize the

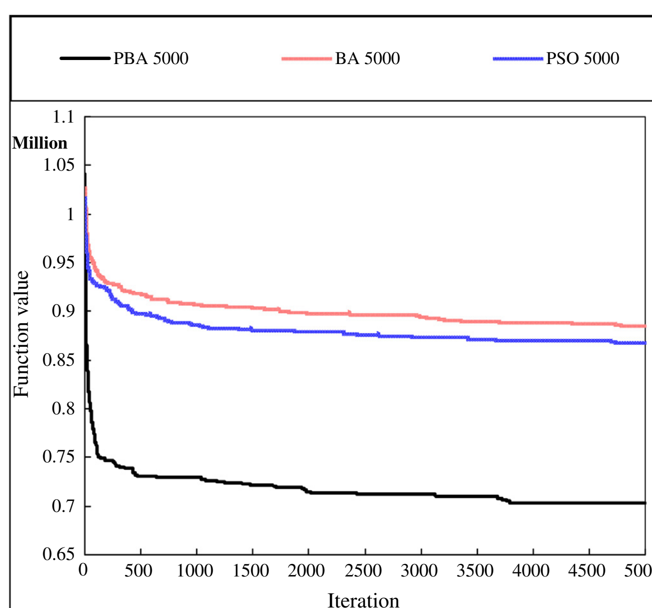

Fig. 4. Evolution of mean best values for single TCL problem.

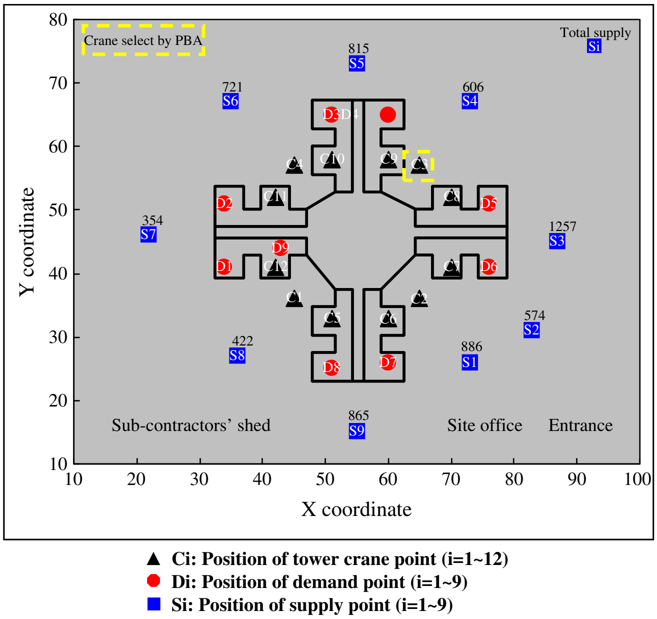

Fig. 5. PBA best single tower crane layout design.

operating distance and frequency between demand and supply points in terms of total operating costs based on the material requirements at demand and supply points. The objective function of the TCL problem was required to satisfy two requirements: (1) The function must be high only for those solutions with a high design preference and (2) The function must be high only for those solutions that satisfy the layout constraints. Therefore, this study was based on Ref. [10] and gives the total objective function as shown in Fig. 3 and Eq. (8). While the linear problem in Eq. (8) may be resolved using the mixed-integer-linear program (MILP) [10], using this program leaves many variables, including the tower crane position variable, and the supply to demand connecting variable, still to be optimized. Therefore, this study compares the performance of PBA against the abovementioned optimization methods in terms of accurately determining the variables in Eq. (8).

$$\text{Minimize}\, TC = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{o} T_i \times Q_{jk} \times CU_i + R + S + L \tag{8}$$

$$T_i = \max(T_{hi}, T_{vi}) + \beta \times \min(T_{hi}, T_{vi}) \tag{9}$$

$$T_{hi} = \max(T_{ai}, T_{wi})\alpha_i \times \min(T_{ai}, T_{wi}) \tag{10}$$

$$T_{vi} = |ZS_m - ZD_o|/V_{hi} \tag{11}$$

$$T_{ai} = |\rho(D_o) - \rho(S_m)|/V_{ai} \tag{12}$$

$$T_{wi} = \frac{1}{V_i} \times \arccos\left(\frac{l_p^2 - \rho(D_o)^2 - \rho(S_m)^2}{2 \times \rho(D_o) - \rho(S_m)}\right) \tag{13}$$

$$\rho(D_o) = \sqrt{(XD_o - XCr_i)^2 + (YD_o - YCr_i)^2} \tag{14}$$

$$\rho(S_m) = \sqrt{(XS_m - XCr_i)^2 + (YS_m - YCr_i)^2} \tag{15}$$

$$l_p\sqrt{(XD_o - XS_m)^2 + (YD_o - YS_m)^2} \tag{16}$$

$$R = \sum_i^n M_i \times (\operatorname{int}(DY_i/30) + 1) \tag{17}$$

$$S = \sum_i^n IS_i + MS_i \times MST_i + RSI_i \tag{18}$$

$$L = \sum_i^n LC_i \times LA_i \times DY_i \tag{19}$$

where TC is total cost; n is the number of crane; m is the number of supply points; o is the number of demand points; T_i is hook travel time by ith crane; T_{hi} is hook horizontal travel time by ith crane; Q_{jk} is quantity of material flow from S_j to D_k; CU_i is cost of material flow from S_j to D_k per unit quantity and unit time by ith crane (defined value is \$1.92 [10]); α_i is degree of coordination of hook movement in radial and tangential directions in horizontal plane by ith crane (defined value is 1 [9]); T_{vi} is hook vertical travel time by ith crane; V_{hi} is hoisting velocity of hook by ith crane (in this study setting the values are between 35 to 60 m/min [10]); β_i is the degree of coordination of hook movement in vertical and horizontal planes by ith crane (defined value is 0.25 [9]); T_{ai} is time for trolley radial movement by ith crane; V_{ai} is radial velocity of trolley by ith crane (in this study setting the values are between 33.1 to 53.3 m/min [10]); T_{wi} is time for trolley tangent movement by ith crane; l_i is distance between supply and demand points; Vw_i is slewing velocity of jib (in this study setting the values are between 2.8 to

Table 7
PBA best capacity of demand and supply points design.

		D1	D2	D3	D4	D5	D6	D7	D8	D9	Actual supply	Limit supply	Supply degree
C3	S1	237	0	0	208	0	231	96	0	114	886	1500	59%
	S2	154	0	111	0	0	0	82	227	0	574	1000	57%
	S3	97	151	0	179	264	0	0	314	252	1257	1500	84%
	S4	136	0	315	0	0	102	0	0	53	606	1000	61%
	S5	58	252	140	0	0	0	0	0	365	815	1500	54%
	S6	0	218	0	50	0	0	361	0	92	721	1000	72%
	S7	0	71	77	45	0	161	0	0	0	354	1500	24%
	S8	0	0	0	69	120	106	83	44	0	422	1000	42%
	S9	218	108	57	49	116	0	78	215	24	865	1500	58%
	Total										6500	11,500	57%
	Actual demand	900	800	700	600	500	600	700	800	900	6500		
	Limit demand	900	800	700	600	500	600	700	800	900	6500		

Table 8
Parameter values used in multi tower crane.

	CU	α	V_h	β	V_a	V_w	M	DY	IS	MS	MST	RS	LC	LA
Crane #1	1.92	1	60	0.25	53.3	7.57	1000	80	5000	500	10	2000	100	5
Crane #2	1.92	1	35	0.25	33.1	2.8	1000	80	5000	500	10	2000	100	5

7.57 rad/min [10]); $\rho(D_i)$ is horizontal distance from tower to demand point; $\rho(S_i)$ is horizontal distance from tower to supply point; $Cr_i(XCr_i, YCri, ZCr_i)$ is coordinate of tower crane; $D_i(XD_i, YD_i, ZD_i)$ is coordinate of demand point i; $S_i(XS_i, YS_i, ZS_i)$ is coordinate of supply point i; R is total rent cost; S is tower crane total setup cost; L is total labor cost; M_i is rent cost per month by ith crane (defined value is \$1000 [26]); DY_i is days of renting tower crane/labor work by ith crane (defined value is \$80 [26]); IS_i is tower crane initial setup cost (defined value is \$5000 [26]); MS_i is tower crane modified setup cost by ith crane (defined value is \$500 [26]); MST_i is modified setup times by ith crane (defined value is 10 [26]); RS_i is disassembly cost (defined value is \$2000 [26]); LC_i is labor cost per person by ith crane (defined value is \$100 [26]); LA_i is labor amount by ith crane (defined value is 5 person [26]).

Subject to

If actual supply capacities (i) > limit supply capacities (i) then $TC = TC + 40{,}000$.

If actual demand capacities (i) <> limit demand capacities (i) then $TC = TC + 40{,}000$.

Notice: the objective function limit of actual supply capacities should be smaller or equal to limit supply capacities. Besides, the objective function limit of actual demand capacities should be equal to limit demand capacities. The subject will give a penalty when objective function breaks the above rules.

3.2. Results and discussion for the single-tower crane problem

This study was adapted from 30 experimental runs. The values listed in Table 4 are the results of 100, 300, 500, 1000 and 5000 iterations using BA, PSO, and PBA. The parameter values used for the single tower crane design are listed in Table 5. Table 6 and Fig. 4 present the evolution of the TCL problem result. As seen in Table 6, the best mean fitness and best solution for PBA are, respectively, 7.03E+05 and 5.41E+05. These values are better than those obtained using either BA (8.86E+05 and 8.35E+05) or PSO (8.68E+05 and 7.50E+05). Thus, PBA obtained a better evolution result than either BA or PSO.

Fig. 5 shows the optimal location alternative for the single tower crane, with the best tower crane location shown at C3. Table 7 shows the optimal design for demand and supply point capacities. As seen in Fig. 5 and Table 7, supply points S1 through S6 are closest to C3 and are thus associated with higher degrees of supply completion (886, 574, 1257, 606, 815, and 721, respectively) than S7 through S9 (354, 422, and 865, respectively), which are relatively more remote from C3. C8 was the best tower crane location identified in Ref. [11]. C3 and C8 are located very near one another. The prioritized supply points for Ref. [11] were points 1, 2, and 5, all of which are in close proximity to C8. Thus, this study obtained a solution very similar to Ref. [11]. Furthermore, the results demonstrate that PBA not only optimizes the tower crane location but also minimizes operating costs in line with demand and supply point capacity requirements.

3.3. Results and discussion for the multi-tower crane problem

In order to compare the cost inferences made for the single-tower-crane and multi-tower-crane problems in terms of the costs of rent, labor, and crane setup, this study also adapted the multi-tower-crane study from 30 experimental runs. The values listed in Table 4 are the results of 100, 300, 500, 1000 and 5000 iterations using BA, PSO, and PBA. The parameter values used for the single tower crane design are listed in Table 8. Table 9 and Fig. 6 present the evolution of the TCL problem result. As seen in Table 9, the best mean fitness and best solution for PBA are, respectively, 1.20E+06 and 1.03E+06, which are better than those obtained by either BA (1.43E+06 and 1.39E+06) or PSO (1.38E+06 and 1.30E+06). These results show that PBA obtained an evolution result that is better than either BA or PSO.

Fig. 7 shows the optimal location alternative for the multi-tower cranes, with the best tower crane locations shown at C5 and C9.

Table 9
The result of three algorithms.

	Iteration	Mean	Worst	Best	Std
PBA	100	1.34E+06	1.45E+06	1.22E+06	5.03E+04
	300	1.29E+06	1.44E+06	1.20E+06	6.77E+04
	500	1.27E+06	1.38E+06	1.07E+06	7.41E+04
	1000	1.23E+06	1.35E+06	1.07E+06	6.69E+04
	5000	**1.20E+06**	1.36E+06	1.06E+06	6.46E+04
	10,000	1.21E+06	1.28E+06	**1.03E+06**	5.55E+04
BA	100	1.51E+06	1.54E+06	1.48E+06	1.53E+04
	300	1.49E+06	1.52E+06	1.45E+06	1.59E+04
	500	1.48E+06	1.51E+06	1.45E+06	1.48E+04
	1000	1.46E+06	1.49E+06	1.43E+06	1.40E+05
	5000	1.44E+06	1.48E+06	**1.39E+06**	5.68E+05
	10,000	**1.43E+06**	1.46E+06	1.40E+06	1.66E+04
PSO	100	1.46E+06	1.55E+06	1.39E+06	3.64E+04
	300	1.44E+06	1.51E+06	1.39E+06	3.61E+04
	500	1.42E+06	1.51E+06	1.35E+06	4.00E+04
	1000	1.41E+06	1.46E+06	1.36E+06	2.67E+04
	5000	**1.38E+06**	1.47E+06	**1.30E+06**	4.42E+04
	10,000	1.39E+06	1.47E+06	1.31E+06	4.21E+04

Bold are the best Mean and best solution results of these mention algorithms.

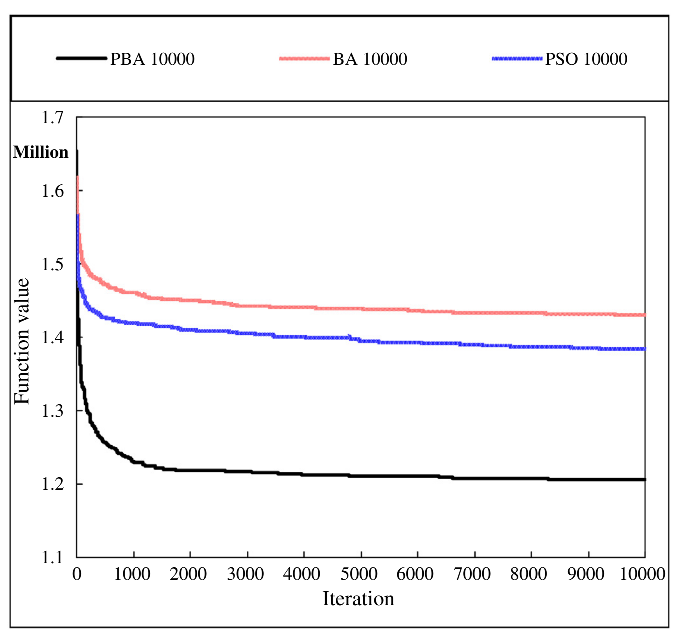

Fig. 6. Evolution of mean best values for multi TCL problem.

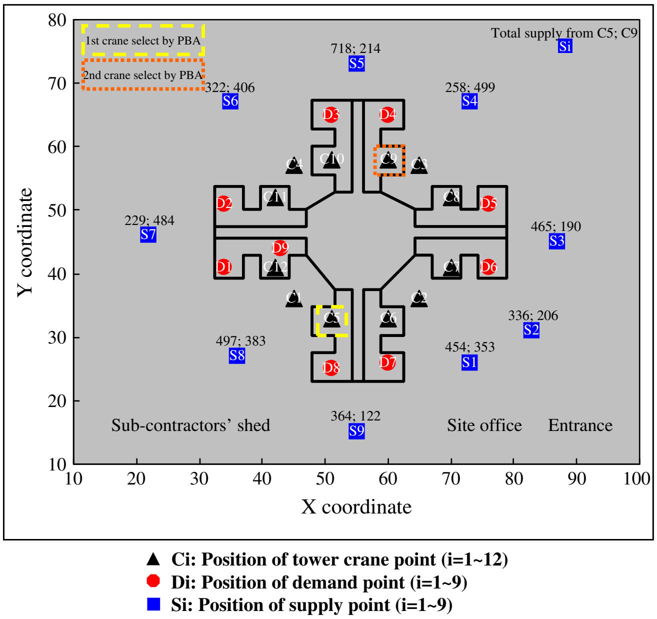

Fig. 7. PBA best multi tower crane layout design.

Table 10 shows the optimal design for demand and supply point capacities. Fig. 7 and Table 10 show that supply points S1, S2, and S7 through S9 are all close to location C5. Supply points S1, S2, S8, and S9 are associated with higher degrees of supply completion (454, 336, 497, and 364, respectively), while supply point S7 (229) is not. Furthermore, supply points S3 through S6 are all close to location C9, with supply points S4 and S6 associated with higher degrees of supply completion (499 and 406, respectively) and supply points S3 and S5 (190 and 214, respectively) associated with lower degrees. This result shows that while the PBA is able to optimize the tower crane location, the algorithm does not minimize the operating costs related to demand and supply point capacities in high-dimensional problems (the dimension in this case study is 164). Nevertheless, the single tower crane is the best overall choice in terms of total operation cost in this proposed practical TCL when rent, labor and, crane setup costs are factored into cost considerations.

4. Conclusion and recommendation

4.1. Conclusion

This study compared the relative performance of the particle bee algorithm (PBA), particle swarm optimization (PSO), and bee algorithm (BA) in resolving a proposed hypothetical tower crane layout (TCL) problem. Results show that the PBA performed better than the other two algorithms. In the single-tower crane design section, the best mean fitness and best solution for PBA were 7.03E+05 and 5.41E+05, respectively, which were better than the solutions obtained by BA (8.86E+05 and 8.35E+05) and PSO (8.68E+05 and 7.50E+05). This result shows that the PBA not only optimizes the location of the tower crane but also minimizes the operating costs for the demand and supply point capacities. In the multi-tower crane design section, the best mean fitness and best solution for PBA were 1.20E+06 and 1.03E+06, respectively, which were better than the solutions obtained by BA (1.43E+06 and 1.39E+06) and PSO (1.38E+06 and 1.30E+06). This result indicates that although the PBA performs well in optimizing the location of tower cranes, the algorithm is unable to minimize operating costs for the demand and supply point capacities for high-dimensional problems. From the perspective of total operation cost, the single-tower crane is the overall best choice in this practical case study when rent, labor and, crane setup costs are factored into cost considerations.

4.2. Recommendation

Factors considered in the alternative approach to tower-crane layout design and device selection include the maximum carrying load of crane hooks and the maximum radius of the crane. This study assumes that the selected tower crane is able to handle the maximum weight of materials and covers the entire work area and thus ignores maximum material weight and the maximum radius of the crane as optimization design factors. Nevertheless, these issues are practical tower crane layout problems faced on the construction site and may be interesting topics for future research.

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Table 10
PBA best capacity of demand and supply points design.

		D1	D2	D3	D4	D5	D6	D7	D8	D9	Actual supply	Limit supply	Supply degree
C5	S1	0	0	0	5	71	127	148	0	103	454	750	61%
	S2	119	66	0	0	20	0	0	0	131	336	500	67%
	S3	430	0	0	35	0	0	0	0	0	465	750	62%
	S4	0	88	170	0	0	0	0	0	0	258	500	52%
	S5	0	204	0	183	0	0	0	206	125	718	750	96%
	S6	0	0	54	129	89	0	0	50	0	322	500	64%
	S7	0	19	101	64	0	0	0	0	45	229	750	31%
	S8	39	27	0	0	166	78	0	107	80	497	500	99%
	S9	0	0	111	61	0	0	0	161	31	364	750	49%
	Total										3643	5750	63%
C9	S1	118	127	0	0	0	0	37	0	71	353	750	47%
	S2	40	0	0	10	17	0	139	0	0	206	500	41%
	S3	0	18	0	0	0	0	0	93	79	190	750	25%
	S4	0	0	140	0	0	139	91	129	0	499	500	100%
	S5	21	0	65	21	0	73	34	0	0	214	750	29%
	S6	133	26	46	0	0	0	92	0	109	406	500	81%
	S7	0	225	13	26	56	0	125	0	39	484	750	65%
	S8	0	0	0	47	81	114	0	54	87	383	500	77%
	S9	0	0	0	19	0	69	34	0	0	122	750	16%
	Total										2857	5750	50%
Actual demand		900	800	700	600	500	600	700	800	900	6500		
Limit demand		900	800	700	600	500	600	700	800	900	6500		

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