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RESEARCH ARTICLE

Charged System Search and Magnetic Charged System Search Algorithms for Construction Site Layout Planning Optimization

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Abstract

Construction site layout planning can be considered as an effort to place different temporary facilities in available site locations such that multiple objectives are satisfied as much as possible. With the extension of high-rise building construction and construction activities besides the lack of available spaces in construction sites, proper utilization of this resource has been highlighted because of its significant positive influences on direct cost, safety, and security of the site which consequently affects the total cost and schedule of the project. Thus the construction site layout planning is considered as one of the essential and important phases in construction projects. Site layout planning problem is an NP-Hard problem from the viewpoint of complexity. In this research, two prominent meta-heuristic algorithms, namely Charged System Search (CSS) and Magnetic Charged System Search (MCSS) are utilized to optimize the site layout planning problem. The obtained results of implementing these two algorithms for two different types of site space modeling are compared with the results of the Particle Swarm Optimization (PSO) algorithm and also those of the previous studies. The results illustrate the capability of the CSS and MCSS algorithms in solving the present problem.

Keywords

construction site layout planning, meta-heuristic optimization algorithms, charged system search, magnetic charged system search, particle swarm optimization

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1 Introduction

Construction site layout planning can be defined as an effort to place different temporary facilities in available site locations such that multiple objectives are satisfied as much as possible. The site layout can have a considerable effect on the constructions operations and should cover several involved constraints [1]. In construction projects, besides the required resources like materials, machinery, manpower and the construction project time and budget, available spaces are vital for placing the facilities and construction requirements transportations [2]. Due to the limitations of the construction site space as a resource, its management is necessary [3]. With the extension of high-rise building construction and construction activities besides the lack of available spaces in construction sites, proper utilization of this resource has been highlighted because of its significant positive influences on direct cost, safety, and security of the site which consequently effects on the total cost and schedule of the project. Therefore, it can be considered as the heart of productivity in construction projects [4][5][6]. In a construction project, contractors usually have the responsibility of an efficient site layout planning. This is considered as a complex task because of the numerous factors involved in such facilities, site surroundings, constraints and etc. [7]. An efficient construction site layout planning has to deal with many conflicting objectives and is a decision-making procedure [8]. Not paying attention to site layout planning will lead to inefficiency of the project, additional cost for material handling, reworking, further cost for setting up facility in dynamic sites, wasting time and creation of an unsafe site [9][4]. In recent decades, site layout planning problem has attracted researchers' attention and many researches were conducted on this issue.

Site layout planning problem is an NP-Hard problem from the viewpoint of complexity [10]. This means there is no recognized algorithm that is capable of finding the optimum solution in polynomial time [11]. By passing of time and science development, trial and error or applying experts' opinions have been replaced by optimization methods and researchers have proposed a wide range of techniques and methods to deal with these problems. Solution methods can be classified into general classes of heuristic, meta-heuristic, mathematical methods, knowledge base methods and etc. Research indicates that meta-heuristic methods are most the common and appropriate approach in this field [4]. A relative comparison between meta-heuristic methods indicates that the genetic, particle swarm and ant colony methods have found the most application in construction site layout planning [4].

The Genetic algorithm (GA) is a search procedure based on bio-evolutionary mechanisms. The initial idea of this method has been inspired by Darwin's evolution theory and is based on bio-inspired operators like mutation, crossover, inheritance and selection. Based on this algorithm, chromosomes of the population with superior capabilities have a greater chance of proliferation [12]. RazaviAlavi and AbouRizk [13] developed a framework that simultaneously considers both the site layout and construction plan to optimize their integrated model with use of genetic algorithm and simulation. In another paper, RazaviAlavi and AbouRizk [14] optimized their model considering both quality and quantity perspectives by using their proposed framework and with the help of GA and simulation. Xu et al. [15] tackled the problem with the risk of material transportation in a construction site from the outlook of site layout and minimized this risk with the use of their multi-objective simulation-based genetic algorithm. Song et al. [7] in their paper created a system to aid decision making on site layout of large-scale projects. This system utilizes multi-objective mathematical model and fuzzy simulation-based genetic algorithm to achieve optimized site layouts and also fuzzy TOPSIS method to measure achieved alternatives and select the prime one. Li and Love [16] optimized their model that had predetermined locations with unequal-areas by the use of this algorithm. Osman et al. [17] proposed a model by integrating graphical designing capabilities of computer-aided design (CAD) and the GA in construction site layout planning. Khalafallah et al. [9] with regard to their multi-objective model, dealt with the optimization of their model by the use of the multi-objective genetic algorithm (NSGA II). Adrian et al. [18] tackled this problem by comparison of different methods including GA. Cheung et al. [19] used a GA algorithm for optimizing arrangement of the facilities in a site pre-cast yard.

Swarm intelligence of creatures is one of the basics that is used in meta-heuristic algorithms and its application has been started from many years ago. Ant colony algorithm mimics ants social behaviour for finding food and was introduced by Dorigo [20]. Researchers have recognized that ants find the shortest path toward food source by utilizing a chemical called Pheromone that they lay out while moving [21]. Lam et al. [10] in their paper first tackled with calculating closeness relationships between facilities and then optimized his model with the help of the ant colony algorithm. Ning et al. [22], optimized their semi-dynamic multi-objective model by using Max-Min ant system that is one of the ant colony algorithm's version. Ning et al. [23] in another research designed a decision-making model for site layout planning and also used the Max-Min ant system in their model for optimization of the multi-objective model and eventually prioritized their discovered Pareto-front by use of the TOPSIS methods.

The particle swarm optimization algorithm (PSO) originally was proposed by Kennedy and Eberhart on the basis of social movement in a bird or fish flock [24]. Zhang and Wang [25], optimized their single-objective predetermined unequal-area model by the use of particle swarm algorithm. Lien and Cheng [26] achieved a new hybrid algorithm named particle-bee algorithm (PBA) by combining artificial bee colony algorithm (ABC) and Particle Swarm optimization algorithm (PSO). Then they implemented this new algorithm on their model and attained better solutions rather than each of the other employed methods separately. The multi-objective version of this algorithm, MOPSO has been also utilized in the site layout problem. Xu and Li [27] minimized the site costs and maximized the facilities' distance from hazardous facilities simultaneously and dealt with solving their model by the multi-objective version of particle swarm algorithm.

Mathematical optimization methods were introduced firstly in industrial engineering to optimize the layout of facilities. Because of the complexity of these methods especially in large-scale projects, their application in construction site layout projects is confined to [28]. Hammad et al. [29] optimized the site layout of their multi-objective model using mixed integer nonlinear programming (MINLP) in order to minimize the noise pollution caused by construction project operations besides considering other factors like costs, social effects and etc. Hammad et al. [1] discretized the available continuous space of the construction site into a collection of discrete locations by using a cutting plane method and afterwards optimized their model considering travel obstacles like transportation cost with the help of a mixed integer programming model. Huang and Wong [30], formulated their phased layout model as a binary-mixed-integer-linear programming (BMILP) and thereupon solved it by using the branch-and-bound method and commercial software package LINGO.

Besides the aforementioned algorithms, several other algorithms have been used in construction site layout optimization. For example, Abune'meh et al. [3] proposed a methodology which puts under consideration hazard sources and components vulnerability in a construction site and thereupon dealt with optimization of their model with the goal of minimizing the total risk using a differential evolution algorithm. Ning et al. [8] proposed an intuitionistic fuzzy model which takes into account several qualitative objectives that are difficult to be quantified with focus on developing a method that facilitates choosing the paramount site layout created by optimization models. Yahya and Saka [31], used artificial bee colony algorithm (ABC) with

Levy flights for optimization of their multi-objective model in the case of Construction site layout planning. Andayesh and Sadeghpour [32] utilized an algorithm, named minimization of total potential energy method (MTPE), in their fully dynamic model to find the optimum solution of the model. Kaveh et al. [33] employed Colliding Bodies Optimization (CBO) algorithm to discover the optimal location of temporary facilities in two different benchmark problems. In another paper, Kaveh et al. [34] used Non-dominated Sorting Colliding Bodies Optimization (NSCBO) algorithm in a multi-objective problem and ranked the obtained layouts by using Data Envelopment Analysis (DEA) method. Tabu search (TS) [35], Harmony Search (HS) [36], Annealed Neural Network (ANN) [11], [37] are also some of the other methods used in this subject.

The purpose of this paper is to implement two recently developed meta-heuristic algorithms, Charged System Search (CSS) and Magnetic Charged System Search algorithms (MCSS) in the field of construction site layout optimization. These meta-heuristics are explained in the next section. In section 3, the efficiency and applicability of the utilized algorithms are examined and the results obtained by CSS, MCSS and PSO are compared. Finally, in section 4 the concluding remarks are provided.

2 Employed meta-heuristic algorithms

2.1 Charged system search algorithm

Charged system search algorithm (CSS) is introduced by Kaveh and Talatahari [38], and the following explanations are originated from this reference. This algorithm is based on Coulomb and Newton's law of Physics and the movement law from Newtonian mechanics. In this approach, each solution candidate that is consisted of some decision variables is considered as a charged particle (CP). Each charged particle is under the influence of other particles' electric field. The magnitude of the force applied to this particle and the state of its movement is interpreted by using the electrical and Newtonian mechanics laws respectively [39]. The basis of these particles movement is that a particle with good results has to apply a greater force than a worse particle. The steps of this algorithm is briefly described in the following:

2.1.1 Step 1. Initialization

The initial locations of the particles are set up randomly in the search space with the following formula:

$$x_{i,j}^{0} = x_{i,\min} + rand.\left(x_{i,\max} - x_{i,\min}\right), \quad i = 1,2,...,n \tag{1}$$

Where $x_{i,j}^{0}$ determines the initial value of the i^{th} variable for the j^{th} particle; $x_{i,min}$ and $x_{i,max}$ are the minimum and maximum allowed value for the i^{th} variable; and *rand* is a random number in the range of [0,1].

Also, the initial velocities of charged particles are zero.

$$v_{i,j}^{0} = 0, \quad i = 1,2,...,n \tag{2}$$

2.1.2 Step 2. Calculation of the particle's charge

Each generated particle has the q_i charge so an electrical field is created in its surrounding space. The amount of this charge is calculated according to the fitness value and quality of the particles as follows:

$$q_i = \frac{fit(i) - fit_{worst}}{fit_{best} - fit_{worst}}, \quad i = 1,2,...,n \tag{3}$$

Where $fit(i)$ is equal to the value of the objective function of particle i ; fit_{best} and fit_{worst} are respectively the best and worst values of the objective function of all particles since the current iteration; and n is the number of all charged particles.

2.1.3 Step 3. Particles ranking

In this stage according to the objective function value, particles are ranked in ascending order in the case of minimization problems.

2.1.4 Step 4. Saving in memory

A memory is considered to store the best CPs location and their related objective function values. It causes an enhancement in the algorithm's performance without an increment in calculation time by leading other CPs to best CPs founded so far.

2.1.5 Step 5. Calculation of the electrical forces applied to the particles

In this algorithm, each CP is considered as a sphere with radius "R" that the charge is uniformly spread on it. The size of the radius can be obtained by the following equation according to the dimensions of the search area or is considered unit.

$$R = 0.1 \times \max\left(\left\{x_{i.\max} - x_{i.\min} \middle| i = 1,2,...,n\right\}\right) \tag{4}$$

The distance between two charged particles is defined by the following equation:

$$r_{ij} = \frac{\left\|X_i - X_j\right\|}{\left\|\frac{\left(X_i + X_j\right)}{2} - B_{best}\right\| + \varepsilon} \tag{5}$$

Where X_i and X_j are the location of the i^{th} and j^{th} particles; X_{best} is the location of the best particle among the population; ε and is a small positive number.

The probability of attracting each CP toward the others is determined by the following formula:

$$p_{i,j} = \begin{cases} 1 & \dfrac{fit(i) - fit(best)}{fit(j) - fit(i)} > rand \vee fit(j) > fit(i) \\ 0 & else \end{cases} \tag{6}$$

Finally, the resultant force that is being applied to each CP is calculated by the following formula:

$$F_j = q_i \sum_{i,i\neq j}\left(\frac{q_i}{R^3} r_{ij}.i_1 + \frac{q_i}{r_{ij}^2}.i_2\right) p_{ij}\left(X_i - X_j\right)$$

$$\begin{cases} j = 1,2,\ldots,n \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < R \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq R \end{cases} \quad (7)$$

Where F_j is equal to the resultant forces applied to the j^{th} particle.

2.1.6 Step 6. Updating the locations and velocities of the particles

The new location and velocity of each CP after applying the electrical forces are calculated as follows:

$$X_{j,new} = rand_{j1}.k_a.\frac{F_j}{m_j}.\Delta t^2 + rand_{j2}.k_v.V_{j,old}.\Delta t + X_{j,old} \quad (8)$$

$$X_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t} \quad (9)$$

Where k_a is the coefficient of acceleration and k_v is the coefficient of velocity; $rand_{j1}$ and $rand_{j2}$ are two random numbers that are distributed uniformly in the range of [0,1]; is the mass of the j^{th} particle that is equal to q_j; and Δt is the time step that is considered unit.

The two coefficients k_a and k_v control the influences of the previous velocity and applied resultant force to a particle respectively. These coefficients are calculated as follows:

$$k_a = 0.5\left(1 + iter / iter_{\max}\right) \quad (10)$$

$$k_v = 0.5\left(1 - iter / iter_{\max}\right) \quad (11)$$

Where "*iter*" is the algorithm's current iteration and "$iter_{\max}$" is equal to the number of all considered iterations.

2.1.7 Step 7. Termination of the search

The process of CSS algorithm is repeated from step 2 until a termination criterion, is satisfied, such as predetermined iteration number.

The process of this algorithm is briefly presented in the flowchart of Fig. 1.

2.2 Magnetic charged system search algorithm

Magnetic charged system search algorithm is the improved version of the CSS algorithm that was introduced by Kaveh et al. [40]. This algorithm is so similar to the CSS algorithm but also has some changes in it. These changes include adding magnetic forces beside employing electrical forces in MCSS algorithm process. Therefore, the new algorithm has more similarities to the nature of charged particle's movement.

As in physics laws, due to the movement of a charged particle, magnetic induction occurs. This magnetic field causes the creation of a magnetic force towards particles that is calculated by the following formula:

$$F_B = qv \times B \quad (12)$$

Where q is the amount of the particle's charge; B is the magnetic field intensity and v is the velocity of the particle's movement in the magnetic field.

When the particle moves at the velocity of v, in addition to the applied electrical force between particles, the magnetic force that is applied to the particle. Thereupon the total magnitude of the forces applying to the particle can be obtained by the following formula:

$$F_B = qv \times B + qE = q.\left(v \times B + E\right) \quad (13)$$

From the perspective of optimization, this additional force causes more recorded information about the movement of the charged particles that eventually causes the improvement of this algorithm's performance in comparison to the CSS algorithm.

The amount of the magnetic force applies to each particle is obtained through the following formula:

$$F_{Bj} = q_j \sum_{i,i\neq j}\left(\frac{I_i}{R^3} r_{ij}.z_1 + \frac{I_i}{r_{ij}^2}.z_2\right) pm_{ji}\left(X_i - X_j\right)$$

$$\begin{cases} z_1 = 1, z_2 = 0 \Leftrightarrow r_{ij} < R \\ z_1 = 0, z_2 = 1 \Leftrightarrow r_{ij} < R \\ j = 1,2,\ldots,n \end{cases} \quad (14)$$

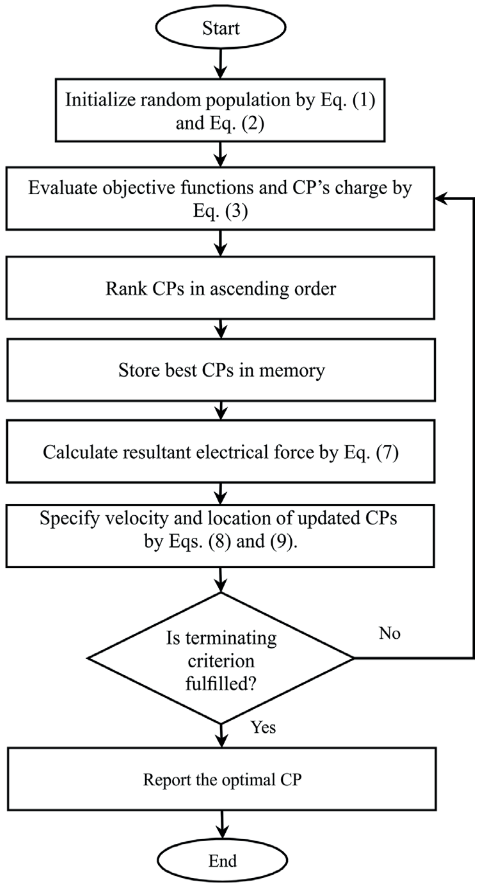

Fig. 1 Flowchart of the CSS algorithm [38]

Where in this formula, the value of q_j is equal to the j^{th} particle charge value; value of R is equal to the influence radius of the j^{th} particle; $r_{i,j}$ is the distance between two particles i and j; and pm_{ji} indicates the magnetic influence probability of i^{th} particle on j^{th} particle and it is achieved as follows:

$$pm_{ji} = \begin{cases} 1 \Leftrightarrow fit(i) > fit(j), \\ 0 \Leftrightarrow else, \end{cases} \tag{15}$$

Where $fit(i)$ and $fit(j)$ are indicators of the objective function for two particles i and j, respectively. Also in the aforementioned formula, the value of I_i is determined by the following expression:

$$I_i = \frac{q_{i,k} - q_{i,k-1}}{q_{i,k} + \varepsilon} \tag{16}$$

Where $q_{i,k}$ and $q_{i,k-1}$ are the charges of the i^{th} particle in iterations k and k–1 respectively; moreoveris ε is a small positive amount that prevents the denominator from becoming zero.

Hence by the combination of the two electrical and magnetic forces, the total force applies to each particle is obtained from the following formula:

$$F_j = F_{B,j} + F_{E,j} = q_j \sum \left(\frac{I_i}{r_{ij}} pm_{ji} + \left(\frac{q_i}{a^3} r_{ij}.w_1 + \frac{q_i}{r_{ij}^2}.w_2 \right).p_{ji} \right) \left(X_i - X_j \right)$$
$$\begin{cases} w_1 = 1, w_2 = 0 \Leftrightarrow r_{ij} < R \\ w_1 = 0, w_2 = 1 \Leftrightarrow r_{ij} \geq R \\ j = 1, 2, \ldots, n \end{cases} \tag{17}$$

Other stages of this algorithm are the same as the CSS algorithm, therefore their explanations have abstained.

A complete description of the PSO, CSS, and MCSS can be for in Kaveh [41].

3 Implementation of the CSS and MCSS in construction site layout planning problem

In the previous sections, CSS and MCSS optimization algorithms were investigated and also their steps and mechanism were explained. In this section, these algorithms are applied in two different types of site space modelling, i.e. Case 1: site with discrete spaces (predetermined locations), and Case 2: site with continues spaces. Eventually, results are compared with each other, a powerful algorithm (PSO) and previous studies. Implementation of this study was performed in MATLAB.R2016a.

3.1 Construction site layout planning problem in site with discrete areas

The first problem is a medium-sized project that is taken from Lam et al. [10]. This chosen construction site is a hypothetical seven-story concrete school building. The aim of the study is to assign 9 facilities to 13 predetermined locations. Site enclosure and the position of the predetermined locations are illustrated in Fig. 2. Specifications of the facilities

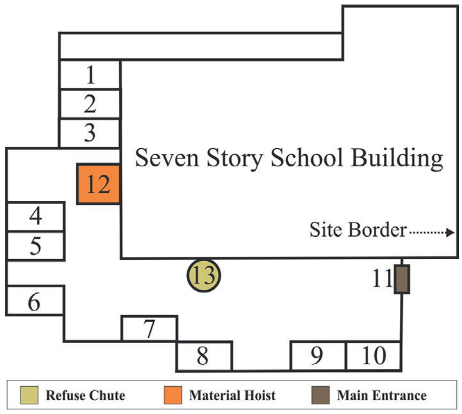

Fig. 2 A construction site and the predetermined locations

Table 1 Facilities of the first case

Status	Facility Name	Index
-	Site office	1
-	Waste deposit	2
-	Rebar bending yard	3
-	Carpentry workshop	4
-	Workers' restroom	5
-	Material storage	6
Fixed	Main entrance	7
Fixed	Material hoist	8
Fixed	Refuse chute	9

are shown in Table 1. The main entrance of the site, material hoist and refuse chute are assumed as fixed facilities and their locations will not move during the project.

The purpose of this problem is to minimize the interactions between the facilities and it is expressed as:

$$\begin{aligned} &Minimize \quad TI = \sum_{i=1}^{n}\sum_{i=1}^{n}\sum_{i=1}^{n}\sum_{i=1}^{n} x_{ik} \times x_{jl} \times CR_{ij} \times d_{kl} \\ &Subjected\ to \quad = \sum_{i=1}^{n} x_{ij} = 1, \quad \sum_{j=1}^{n} x_{ij} = 1, \end{aligned} \tag{18}$$

When the i^{th} facility is assigned to the k^{th} location, $x^{i,k}$ = 1, otherwise it is equal to 0 ; $x_{i,l}$ has a similar context; The n is number of facilities; The CR_{ij} shows the closeness relationships between facilities i and j ; and d_{kl} shows the distance between locations k and l . Thus the above formula calculates the interactions between the facilities.

The distance between predetermined locations is calculated and presented in Table 2 and closeness relationships between facilities is prepared in Table 3.

3.1.1 Results and discussion for the first case

In order to evaluate the performance of mentioned algorithms, CSS and MCSS, their comparison with the PSO algorithm and also to achieve acceptable statistical results, this problem is solved independently 20 times and with 100 iterations to obtain the optimum result. The statistic results of these 20 independent solutions are shown in Fig. 3. As it is clear intuitively from the picture, the MCSS algorithm diagram is lower than the CSS and PSO algorithms in most points which indicates its higher performance. More expansive results such as the best result, average, the worst result, and the standard deviation for each of the methods are shown in the Table 4. By comparing these results, it is clear that the CSS and MCSS algorithms have gained a better average, worst result and standard deviation than the PSO algorithm, however their best results are the same as that of the PSO algorithm. This demonstrates that the CSS and MCSS algorithms have not only more capability in discovering better solutions but they also have more stability in their optimization process with regard to their lower standard deviation. Comparison of the CSS and MCSS algorithms' results is a confirmation for the improvements of the CSS algorithm by adding magnetic impacts in the MCSS algorithm that is obviously noticed from decreasing the average of the objective function and standard deviation.

Table 2 Distances between facilities in the first case

Location number		Location number												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
	1	0	1	2	6	7	9	12	14	16	17	13	4	9
	2	1	0	1	5	6	8	11	13	15	16	12	3	8
	3	2	1	0	4	5	7	10	12	14	15	11	2	7
	4	6	5	4	0	1	3	7	9	11	12	9	2	5
	5	7	6	5	1	0	2	6	8	10	11	8	3	4
	6	9	8	7	3	2	0	3	5	7	8	8	5	4
	7	12	11	10	7	6	3	0	2	4	5	7	6	3
	8	14	13	12	9	8	5	2	0	2	3	5	8	3
	9	16	15	14	11	10	7	4	2	0	1	3	11	6
	10	17	16	15	12	11	8	5	3	1	0	2	12	7
	11	13	12	11	9	8	8	7	5	3	2	0	9	5
	12	4	3	2	2	3	5	6	8	11	12	9	0	4
	13	9	8	7	5	4	4	3	3	6	7	5	4	0

Table 3 Closeness relationships among the facilities for the first case

Facility Number		Facility Number								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	1	0	3.11	4.79	4.94	5.15	5.41	6.34	3.48	2.55
	2	3.11	0	3.69	3.71	3.7	3.36	4.42	3.07	2.85
	3	4.79	3.69	0	4.27	4	4.4	5.65	6.26	2.03
	4	4.94	3.71	4.27	0	4.51	4.58	5.14	6.2	2.24
	5	5.15	3.7	4	4.51	0	4.99	4.39	4.13	2.48
	6	5.41	3.36	4.4	4.58	4.99	0	5.24	6.2	2.65
	7	6.34	4.42	5.65	5.14	4.39	5.24	0	4.62	3.75
	8	3.48	3.07	6.26	6.2	4.13	2.6	4.62	0	2.37
	9	2.55	5.85	2.03	2.24	2.48	2.65	3.75	3.37	0

Table 4 Statistical results after 20 runs for the first case

Algorithm	PSO	CSS	MCSS
Best result	843.94	843.94	843.94
Average	846.40	846.15	845.19
Worst result	852.44	851.14	851.14
Std. dev	1.87	1.82	1.68

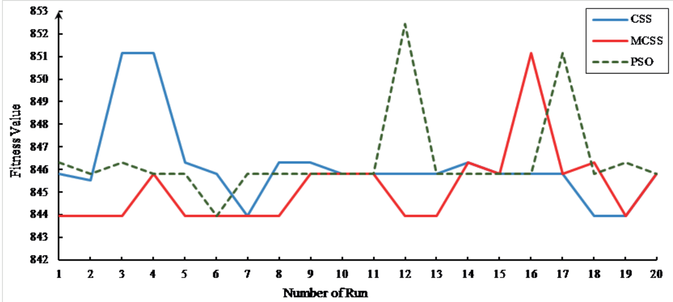

Fig. 3 The comparison of algorithms for 20 runs of the first case

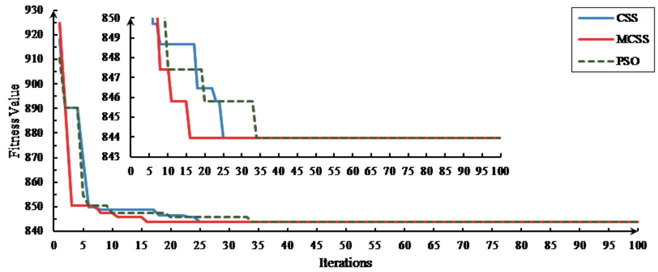

Fig. 4 The convergence curves of the three regarded algorithms in the first case

The trend of convergence and achieving the optimum solution is the other criterion which is considered for comparing the methods. These convergence curves for the PSO, CSS, and MCSS are presented in Fig. 4. The MCSS algorithm is better than the two other algorithms in the convergence speed and obtained result. The results are achieved sooner than the PSO and CSS algorithms, in 16th iterations.

Therefore, the statistical results of the algorithms and also the investigated convergence histories are both confirmations for the superiority of the MCSS.

Fig. 5 shows the found optimum layout, for which the magnitude of the corresponding objective function is 843.94. A comparison between the best-obtained results in this study and those obtained by other researchers is presented in Table 5.

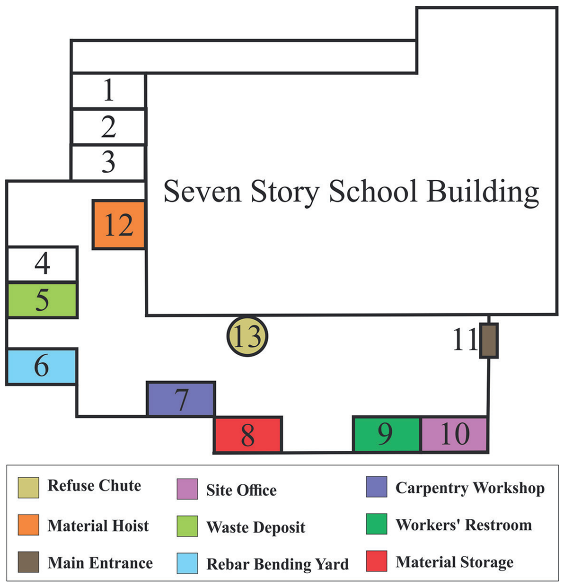

Fig. 5 The optimum layout for the first case

Table 5 Comparison of the attained results with previous studies for the first case

	Algorithm	MCSS*	CSS*	PSO*	ACO [10]
Location Number	Facility 1	10	10	10	9
	Facility 2	5	5	5	8
	Facility 3	6	6	6	4
	Facility 4	7	7	7	7
	Facility 5	9	9	9	5
	Facility 6	8	8	8	6
	Facility 7	11	11	11	11
	Facility 8	12	12	12	12
	Facility 9	13	13	13	13
Fitness Value		843.94	843.94	843.94	853.93

*Present Study

3.2 Construction site layout planning with continues space

In order to test and evaluate the CSS and MCSS algorithms for continues space models, a multi-story parking site layout optimization is chosen from [9]. Dimensions and forms of the surrounding of the site are shown in Fig. 6. The dimensions of the under-construction building and required facilities, positions. and dimensions of the tower crane and the site entrance are shown in Tables 6 and 7.

Establishment of these temporary facilities in the site space should be such that the cost of transportation between facilities and material handling, to be the least. This cost is calculated by the formulas (19) and (20).

$$Minimalize \sum_{i=1}^{I-1} \sum_{j=i+1}^{I} \left(C_{ij} \times d_{ij}\right) \tag{19}$$

$$d_{ij} = \sqrt{\left(X_i - X_j\right)^2 + \left(Y_i - Y_j\right)^2} \tag{20}$$

Where d_{ij} is the Euclidean distance between facilities i and j, C_{ij} is the cost of travel between facilities i and j, and this cost is provided in Table 8.

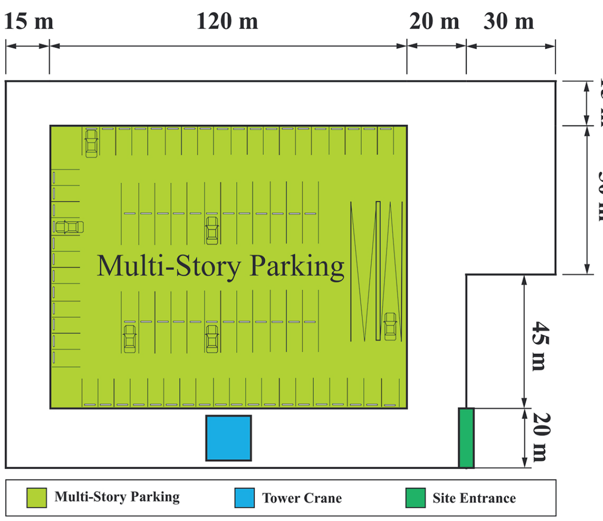

Fig. 6 Site surrounding and parking building

Table 6 Dimensions of the facilities

Index	Facility Name	Length	Width
1	Machinery parking	20	20
2	Office 1	20	5
3	Office 2	20	5
4	Office 3	20	5
5	Office 4	20	5
6	Workshop	5	4
7	Storage 1	6	5
8	Storage 2	4	5
9	Electrical generator	2	2
10	W.C.	5	6
11	Firefighting equipment	3	3
12	Storage of inflammable material	3	3
13	Multi-story parking	120	95
14	Tower crane	15	15
15	Site entrance	-	-

Table 7 Position coordinates of the fixed components

Name	Coordinate x	Coordinate y
Multi-story parking	75	67.5
Tower crane	75	10
Site entrance	155	10

Table 8 Travel cost between facilities

		Facility number														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Facility number	1	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	2	4	0	-	-	-	-	-	-	-	-	-	-	-	-	-
	3	4	7.5	0	-	-	-	-	-	-	-	-	-	-	-	-
	4	4	7.5	7.5	0	-	-	-	-	-	-	-	-	-	-	-
	5	4	5.5	5.5	2.5	0	-	-	-	-	-	-	-	-	-	-
	6	1.5	1	1	1	1	0	-	-	-	-	-	-	-	-	-
	7	1.5	1	1	1	1	9.5	0	-	-	-	-	-	-	-	-
	8	1.5	1	1	1	1	9.5	6.5	0	-	-	-	-	-	-	-
	9	1.5	2	1	3	3	3	3	3	0	-	-	-	-	-	-
	10	1.5	7.5	7.5	7.5	7.5	6.5	6.5	6.5	1	0	-	-	-	-	-
	11	1.5	1	1	1	1	1	1	1	1	1	0	-	-	-	-
	12	1.5	1	1	1	1	3.5	1	1	3.5	1	1	0	-	-	-
	13	1.5	3.5	3.5	3.5	3.5	6.5	4.5	4.5	5.5	3	1	4.5	0	-	-
	14	0	7.5	5.5	7.5	7.5	9.5	9.5	9.5	0	0	1	4.5	5	0	-
	15	1.5	0	0	0	0	3	7	7	0	0	0	1	0	0	0

3.2.1 Results and discussion for the second case

As mentioned above, this case is another type of space modeling problem. Therefore, to investigate the performance of the CSS and MCSS algorithms and gain trustful statistical results, the problem is required to be solved several times similar to the former case. Thus, this problem has been solved 20 times independently and with 2500 iterations per each one by the CSS, MCSS, and PSO. These results are shown in Fig. 7 separately. As it is obvious, the CSS and MCSS algorithms have shown better performances than the PSO algorithm, similar to the previous problem. In Table 9, the annotated statistical results found by these algorithms are also provided.

Table 9 demonstrates the best-found layout by the CSS algorithm and its objective function is 8992.10, that is better than the result found by PSO algorithm with the objective function value is equal to 9374.67. This superiority is also clear in average. The average of the CSS and PSO are 11059.65 and 12383.93 respectively. The most successful method that was implemented for Case 2 was MCSS algorithm with the objective function as 8566.45 that was the best result. This achievement is also obvious in the averages. Another strength of the MCSS algorithm is its low value of standard deviation that is a sign of good stability in discovering the results. In Fig. 8, the convergence trends of the three algorithms PSO, CSS, and MCSS to reach to the optimum result are illustrated. As can be seen, the MCSS algorithm has found layouts with lower cost in similar number of iterations compared to the other algorithms and by continuing its exploration, the most optimum layout has been discovered in further iterations. This achievement is gained sooner than the PSO and CSS, in 1487th iterations.

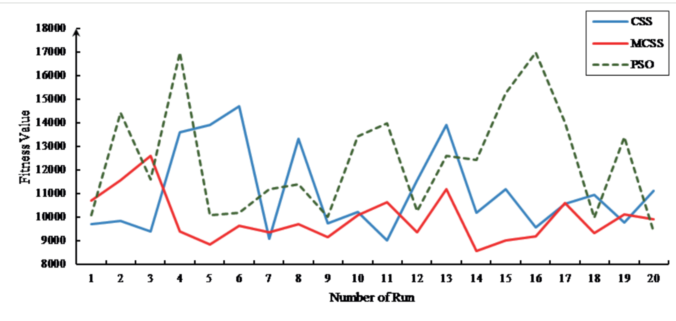

Fig. 7 The comparison of algorithms for 20 runs of the second case

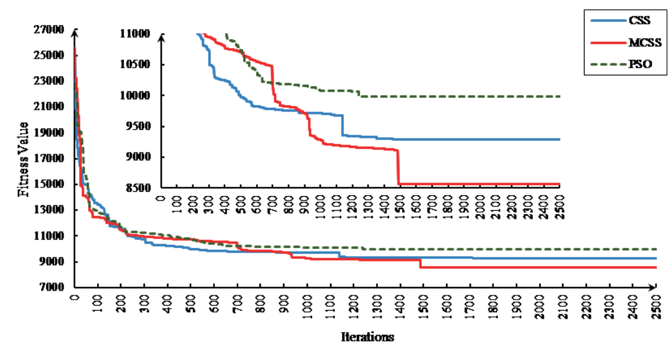

Fig. 8 The convergence curves of the three considered algorithms in the second case

The eventual CP that has objective function value equal to 8566.45, is presented in Fig. 9. In this figure, two variables are assigned to each facility. The first coordination is relevant to X and the second one is relevant to Y directions.

Table 9 Statistical results after 20 runs for the second case

Algorithm	PSO	CSS	MCSS
Best result	9374.67	8992.10	8566.45
Average	12383.93	11059.65	9942.87
Worst result	16983.87	14717.16	12611.54
Std. dev	2296.83	1776.99	990.18

Table 10 Comparison of the results with previous studies for the second problem

Algorithm	MCSS*	CSS*	PSO*	WOA [42]	GA [9]	CBO [42]
Fitness Value	8566.45	8992.10	9374.67	9049.2	9651	10605

*Present Study

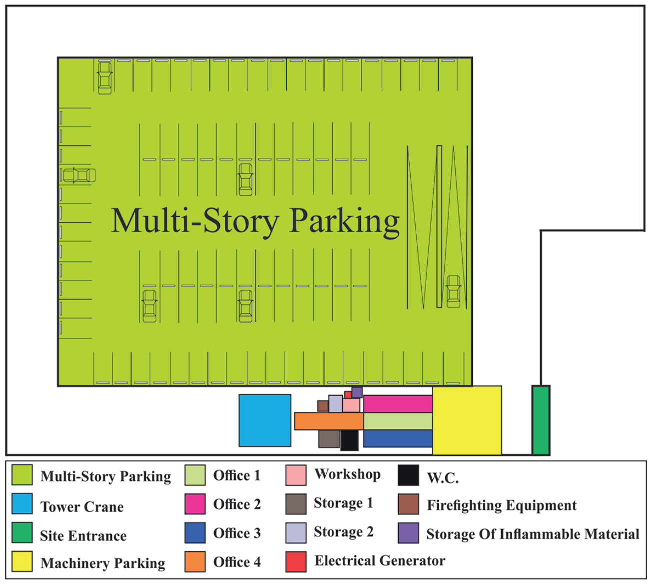

Fig. 10 The optimum layout found by the MCSS algorithm for the second case

The graphical representation of this CP is shown in Fig. 10. In this layout, in addition to twelve facilities of the problem, site borders, parking building, tower crane and the site entrance are illustrated. A comparison between the best-obtained results in this study and results that are obtained by other researchers is presented in Table 10.

4 Concluding remarks

Construction site layout planning and design is an essential and important stage in management and planning of construction projects and it is considered as an NP-hard problem which its complexity raises exponentially. In this context, many meta-heuristic algorithms have been utilized. In this study, for the first time two powerful meta-heuristic algorithms, CSS and MCSS have been used for construction site layout planning optimization.

133.6	10	113.6	9.8	113.6	14.8	113.6	4.8	93.6	9.8	100.0	14.4	93.6	4.7	95.5	14.8	99.1	17.4	99.5	4.3	91.8	14.2	101.7	18.1
Facility 1		**Facility 2**		**Facility 3**		**Facility 4**		**Facility 5**		**Facility 6**		**Facility 7**		**Facility 8**		**Facility 9**		**Facility 10**		**Facility 11**		**Facility 12**	

Fig. 9 Coordinates of the optimum CP found by the MCSS algorithm

Charged System Search algorithm (CSS) was introduced by Kaveh and Talatahari in [38]. This algorithm is based on Coulomb and Newton's law of Physics. Magnetic Charged System Search algorithm (MCSS) is the improved and full-fledged version of the CSS algorithm that was introduced by Kaveh et al. in 2013 [40]. In the MCSS algorithm, in addition to the electrical forces, magnetic forces are employed in the search process.

With regard to different types of space modeling and considered problems, the MCSS algorithm showed more capability to discover optimum solutions rather than the PSO and CSS algorithms. Also due to its lower value of standard deviations, MCSS has higher stability in the process of optimization. This superiority can also be seen from the convergence curves. Another noteworthy point was that the difference of the solution of the MCSS from those of the other algorithms in second case, which indicates high strength of the MCSS when high amount of calculations is involved.

The comparison of the results found in this paper with those of the previous studies, illustrates the correctness of the presented method. This comparison also shows the competitiveness of the utilized meta-heuristic algorithms with other methods in this applicable context.

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