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Dynamic construction site layout planning using max-min ant system

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ABSTRACT

Construction site layout planning (CSLP) is a dynamic multi-objective optimization (MOO) problem as there are different facilities employed in the different construction phases of a construction project. In this study, a new method using continuous dynamic searching scheme to guide the max-min ant system (MMAS) algorithm, which is one of the ant colony optimization (ACO) algorithms, to solve the dynamic CSLP problem under the two congruent objective functions of minimizing safety concerns and reducing construction cost is proposed. Using weighted sum method the MOO problem can be solved by the proposed MMAS method. An office building case was used to verify the capability of the proposed method to solve dynamic CSLP problem and the results are promising. The approach could be benchmarked by researchers using other advanced optimization algorithms to solve the same problem or expand the applications to other fields.

1. Introduction

An optimal construction site layout shall improve the productivity of a construction project and the safety level of a construction site. Therefore, an effective construction site layout planning (CSLP) is utmost important for the success of a construction project. CSLP problems can be broadly divided into static and dynamic ones. The major difference between the static and dynamic CSLP is the fact that whether the schedule intervals and the facilities involved in each of the schedule intervals are varied during construction progress. If the facilities serviced in the different construction phases in accordance with the requirements of the construction work during the whole progress of a construction project are the same, it is termed as static CSLP. However, the problems associated with the planning of a construction site layout with the consideration of changing site facilities and site space in different time intervals are termed as dynamic CSLP problem [1]. Literature reviews showed that most of the previous research works on CSLP heavily concentrated on the static CSLP problems [2–4]. This study attempts to propose a new method using continuous dynamic searching scheme to guide the max-min ant system (MMAS) algorithm, which is one of the ant colony optimization (ACO) algorithms, to solve the dynamic CSLP problem.

Literature reviews show that many models using artificial intelligence (AI), evolutionary algorithm (EA), swarm intelligence (SI), and computer-aided design (CAD) were developed to solve static CSLP problems. With regard to AI, Hamiani and Popescu [5] and Chau and Anson [6] proposed knowledge-base systems to solve CSLP problems. With the application of AI, the merit is that a search strategy and inference mechanism can be specified. Moreover, experts' knowledge can be elaborated, and thus heuristic judgment and experience of experts are transformed into knowledge base and the decision-making process to design site layout could be simulated with computer. However, the proposed AI systems need huge database to enhance its capability. Among the models using EA in solving CSLP problems, genetic algorithm (GA) is mostly used [3,7,8]. The merit of GA is its strong evolutionary process to find optimal solution by the operation of crossover, selection and mutation of parents' generation. But, the randomly generated initial generation in the beginning of the algorithm shall affect the solution quality because of the bad gene inherited from the parent generation. Moreover, the searching capability is reduced as GA does not rely on gradient or derivative information [9]. Ant colony optimization (ACO) algorithm, which is one of algorithms of SI, is recently employed to solve facility layout problem in construction site [10] and single layout problem in flexible manufacturing system [11]. Nevertheless the application of the ACO algorithm is still confined to solve static CSLP problem. Sadeghpour, Moselhi and Alkass [12] proposed a CAD-based model to solve construction site layout problem as CAD-based model could offer a very intuitionistic understanding of the whole construction site layout. Using CAD to solve CSLP, CAD always hybrid with other advanced optimization algorithm as CAD itself has no computational capability, albeit, it could give site planners an intuitionistic description of facility shapes and layout in the construction site. Kumar and Singh [13] tried to use CAD technique together with ACO algorithm to solve static CSLP problem. However, they did not consider the different time interval of the site plan.

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In practice, most of the CSLP problems are dynamic in nature. Up to now, there are few studies focusing on solving dynamic CSLP problems. Zouein and Tommelein [14] attempted to use linear programming (LP) to solve dynamic CSLP problem. For the nature of CSLP problem, which is not a linear problem, should not be modeled as a LP problem under the same constrains. CSLP problem should be modeled as quadratic assignment problem (QAP) [15]. Apart from LP, CAD [16] and GA [17,18] were also employed to solve dynamic CSLP problems but only under single objective function. Nevertheless, those methods do not employ dynamic search scheme to lead the algorithm to layout different facilities involved in the different time interval during the dynamic research.

In this study, the CSLP problem is modeled as QAP under two objective functions of minimizing the representative score of safety/environment concerns and the total handling cost of interaction flows between the facilities associated with the construction site layout. It is regarded as multi-objective optimization (MOO) problem. Furthermore, a continuous dynamic searching scheme is employed to lead the max-min ant system (MMAS), which is one of ACO algorithms, to solve the MOO problem using the weighted sum method. Dorigo and Stützle [19] and Duan [20] claimed that ACO algorithms performed better than other meta-heuristic algorithms such as GA, stimulated annealing, tabu search in solving QAP. Therefore, MMAS is employed in the proposed method to solve the CSLP problem. The following sections are organized in this manner: first the MMAS application procedure is introduced in Section 2. Second, the optimization process of assigning temporary facilities to free locations is introduced in Section 3. Third, using the case study of office building in Beijing, China to verify the capability of the proposed method to solve the dynamic CSLP problem is demonstrated in Section 4. Fourth, the results include the ratios of the parameters which shall affect the speed of convergence of the proposed method are discussed in Section 5 and finally conclusion is drawn.

2. Max-min Ant System

MMAS was firstly introduced by Stützle and Hoos [21] and then Stützle [22] applied it to solve QAP. The steps of the MMAS [22,23] adopted in this study to solve QAP are as follows:

Step 1. Define the heuristic information

The heuristic information of ACO algorithms are firstly defined in accordance with the characteristics of the problem that is yet to be solved, on a case-by-case basis. The different problems determined different heuristic information. This act makes ACO algorithms more applicable in solving real-world problems and increases its ability to find high-quality solutions to combinatorial optimization problems in a reasonable time [19]. The following equation (definition) of heuristic information defined by Stützle and Dorigo [24] is adopted in the proposed method using MMAS to solve the QAP in this study.

The heuristic information (η) of assigning facility i to location j is

$$\eta_{ij} = 1 / e_{ij} \tag{1}$$

Where $e_{ij}=f_i \cdot d_j$, the two vectors f_i and d_j represent the flow potential of facility i and the distance potential of location j respectively. They are calculated by the sum of the flows (closeness relationship) from facility i to all other facilities and the sum of the distances from location j to all other locations respectively. The lower the value of d_j, the more the central location is considered to be, and the higher the value of f_i, the more important the facility to be considered.

Step 2. Select assignment sequence for the facilities

The assignment sequence will determine the position of the facilities and the sequence for the facilities is selected in non-increasing order by the f_i.

Step 3. Assign facilities to a location

At each construction step, an ant k assigns the next unassigned facility i to a free location j in term of

$$j = \begin{cases} \arg\max_{l \in N_i^k} \{\tau_{ij}^{\alpha} [\eta_{ij}]^{\beta}\}, \text{If } q \leq q_0; \\ J, \qquad\qquad \text{Otherwise} \end{cases} \tag{2}$$

$$p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}]^{\beta}} \ \text{ if } j \in N_{\mathrm{i}}^k \tag{3}$$

Where τ_{ij} is the ants' pheromone information; η_{ij} is the heuristic information between facility i and location j; α, and β are the parameters that determine the relative influence of the pheromone information and the heuristic information respectively. q is a random variable uniformly distributed over [0,1] and q_0 is a parameter between [0,1]. If $q \le q_0$, the solution components which maximize τ_{ij}^{α} $[\eta_{ij}]^{\beta}$ among the feasible components will be chosen. Otherwise, the probability rule (Eq. (3)) is adopted. $\tau_{ij}(t)$ is the pheromone information at iteration t and this step is repeated until a complete solution is found. N_i^k is the feasible neighborhood of node i, that is, only those locations that are still free.

Step 4. Pheromone update

After all of the ants have found a solution in accordance with the following equation, the pheromone shall be updated.

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{best} \tag{4}$$

Where the parameter $\rho (0<\rho<1)$ is the persistence of the pheromone information such that $1-\rho$ represents the evaporation. ρ is used to avoid an unlimited accumulation of pheromone information, and allows the algorithm to ignore previous bad choices.

Here, $\Delta\tau_{ij}^{best}$ is defined as

$$\Delta\tau_{ij}^{best} = \begin{cases} 1 \Big/ F_{\Phi^{best}} \text{ if facility } i \text{ is assigned to location } j \text{ insolution } \Phi^{best} \\ 0 \quad \text{otherwise} \end{cases} \tag{5}$$

Where $F_{\Phi^{best}}$ is the objective function value of Φ^{best}.

After the pheromone is updated if $\tau_{ij} \rangle \tau_{\max}$, we set $\tau_{ij}=\tau_{\max}$; if $\tau_{ij} \langle \tau_{\min}$, we set $\tau_{ij}=\tau_{\min}$.

The advantages of using MMAS to solve QAP [23] are elaborated as follows:

First, it can exploit the best solution found during iteration. After each iteration only one ant will add pheromone and this ant may be the one which found the best solution in the current iteration (iteration-best ant) or the one which found the best solution from the beginning of the trial (global-best ant).

Second, it can avoid stagnation of the searching process as the range of possible pheromone trails on each solution component is limited to an interval $[\tau_{\min}, \tau_{\max}]$.

Third, the pheromone trials are initialized to the upper trial limit, by which a higher exploitation is provided at the beginning of the algorithm running.

3. Optimal Assignment of Temporary Facilities

Apart from the above-mentioned steps using MMAS, the optimization process also involves the following steps: first, identify the dynamic layout intervals and facilities serviced in each time interval in accordance with the project planning (we shall discuss in Section 4 via case study). Second, calculate the closeness relationship between the facilities (see Section 3.1). Third, define the multiple objective functions (see Section 3.2). Fourth, define the dynamic searching scheme (see Section 3.3) to guide the optimization algorithm to

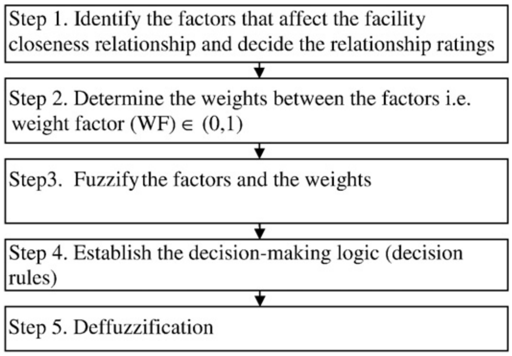

Fig. 1. The workflow of using fuzzy rule-based system to calculate the facility closeness relationship.

layout the same facilities serviced in the different dynamic time intervals. Having these four steps defined, MMAS is then employed to find locations for the facilities serviced in the different construction phases.

3.1. Facility closeness relationship

Effective placement of facilities within the site is significantly influenced by the movement of resources, or basically the interactions among the facilities. Such interactions are termed as the closeness (or proximity) relationship among the facilities [25]. The factors that affect the facility closeness relationship can be broadly divided into quantitative and qualitative factors and therefore, fuzzy rule-based system in facilities layout planning is needed [26,27]. The workflow of using fuzzy rule-based system [26] to calculate the facility closeness relationship is shown in Fig. 1.

For the first step, four quantitative factors, namely, material flows (MF), information flows (IF), personnel flows (PF) and equipment flows (EF) and two qualitative factors, namely, safety/environment concerns (SE) and users' preference (UP) are considered in the facility closeness relationship to illustrate the proposed method to solve CSLP problem in this study. According to [26–28], these six factors are defined as

- Material flows (MF): the flow of parts, raw materials, works-in-process and finished products between departments. The MF can be measured by unit per time unit.
- Information flows (IF): the communication (oral or reports) between facilities. IF can be measured via a survey of involved personnel and it can be expressed by the number of communications per time unit.
- Personnel flows (PF): the number of employees from one or both facilities that perform tasks from one facility to another.
- Equipment flows (EF): EF is defined by the number of material handling equipment (trucks, mixers, etc.) used to transfer materials between facilities.
- Safety/environment concerns (SE) represents the level of safety and environment hazards, measured by the safety concerns, which may arise when the two facilities are close to each other, and may affect site workers by increasing the likelihood of accidents, noise, uncomfortable temperature and pollution.
- Users' preference (UP) represents the project manager's desire to have the facilities close to or apart from each other.

Table 1
The 'if-then' rules for the interaction factors and their respective weight factors employed in the case study.

Interaction factor/ Weight factors (WF)	VL	L	M	H	VH
L	U	O	O	I	E
M	O	O	I	E	E
H	O	I	E	E	A

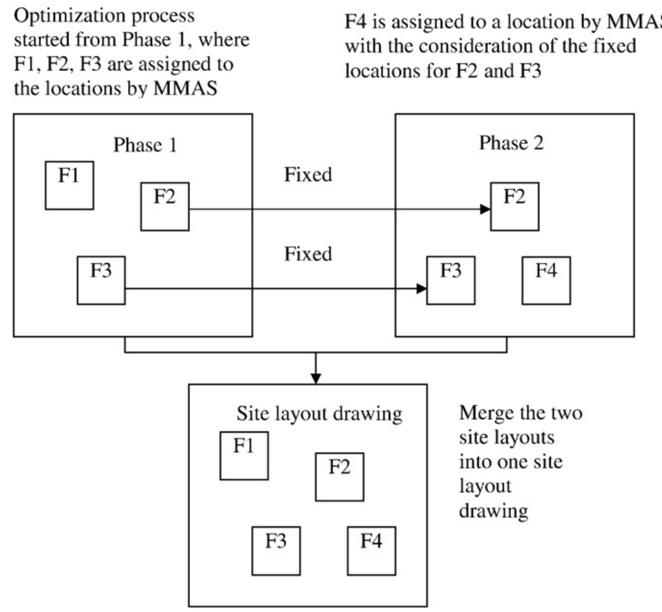

Fig. 2. Continuous dynamic searching scheme.

In addition to the above-mentioned interaction factors, the weights between these factors or weight factors (WF) should be assigned to the facilities. Karry et al. [27] suggested the rating of interaction relationship can be ranged from absolutely important (A), especially important (E), important (I), ordinary (O), unimportant (U) to undesirable (X). (Note: In order to verify the proposed method, their corresponding rating settings are renamed as 243, 81, 27, 9, 3 and 1, in terms of project scale in the case study respectively). Having the quantitative and qualitative factors determined, the weight factor (WF) is then calculated.

In step 3, a family of fuzzy sets has been developed i.e. MF, IF, EF, PF, SE, UP, and they are limited to three membership functions i.e. low (L), medium (M) and high (H). The WF was developed in accordance with the experience of decision makers in this case study. The WF is fuzzified via a set of membership functions of very low (VL), low (L), medium (M), high (H) and very high (VH).

Step 4 is to establish the decision rules, in the form of 'if-then' rules to imitate the decision makers' decision processes with the

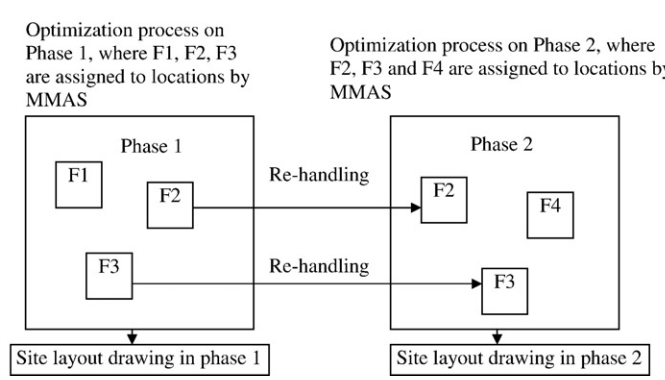

Fig. 3. Discrete dynamic searching scheme.

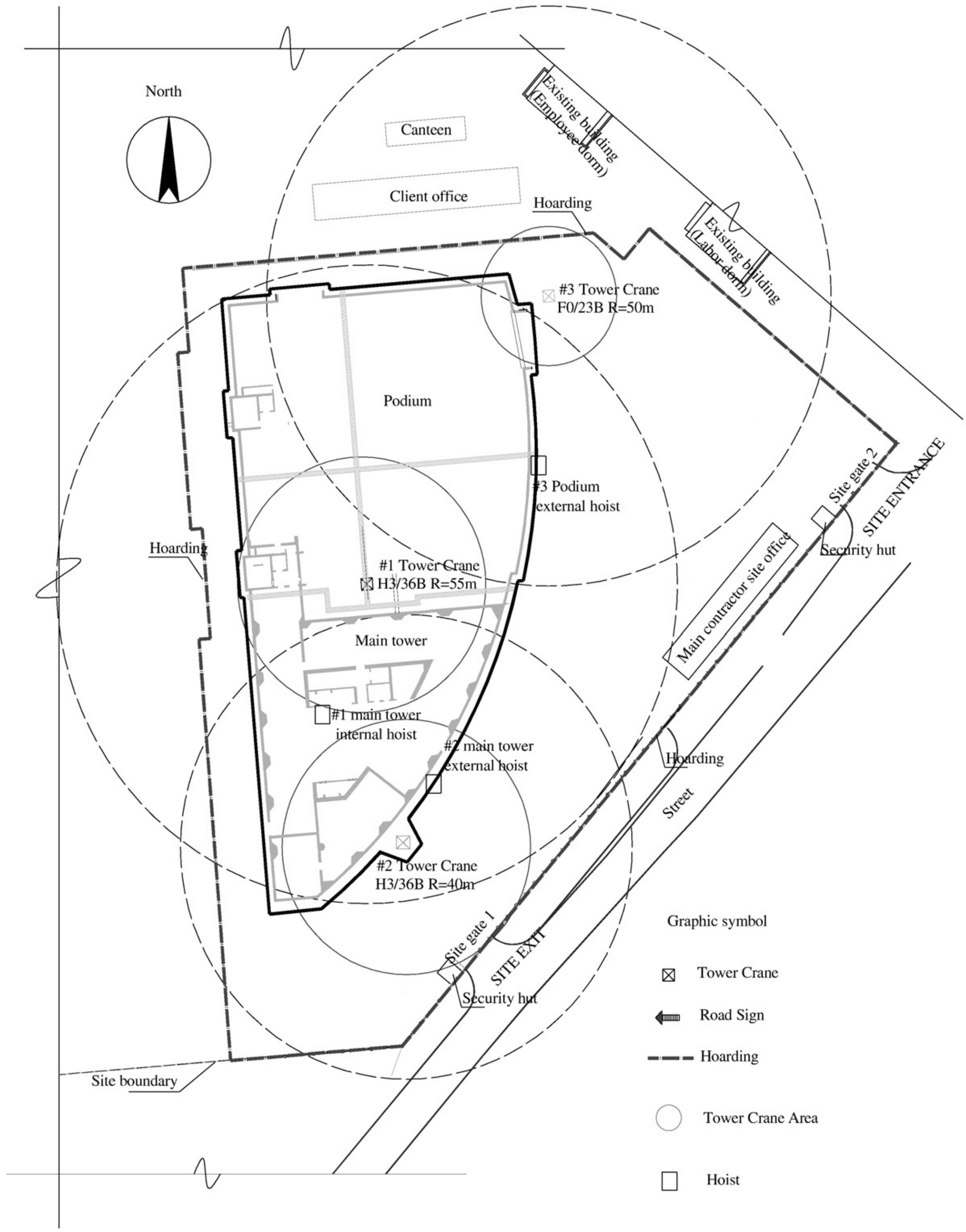

Fig. 4. The geographic condition of the construction site of the office building.

consideration of the membership functions of the fuzzy sets. In this case study, the 'if-then' rules for the interaction factors and their respective WF employed are shown in Table 1.

The if-then rule is employed (see Table 1), where A, E, I, O, U and X stand for absolutely importance, especially important, important, ordinary, unimportant and undesirable respectively. The if-then rule can be illustrated by an example: if one of the interaction factor (MF, IF, PF, EF, SE and UP) is L AND WF is VL, then the closeness rating is U.

Step 5 is diffuzification where the center of area method [29] is used to calculate the closeness relationship value of each pair of facilities as bellow:

$$R_o = \frac{\sum_i (\mu(R_i)^* R_i)}{\sum_i \mu(R_i)} \tag{6}$$

Table 2
The quantity of the facilities, the facility type and their dimensions.

Temporary facilities (facility number)	Number of facilities	Dimension of facilities (m^2)	Facility type (fixed = 1; non-fixed = 0)
Tool shed (F1)	1	100	0
Steel bar and half-finished products storage area (F2)	1	250	0
Molding board storage area (F3)	1	250	0
Steel structure elements storage area(F4)	1	250	0
Concrete elements storage area(F5)	1	250	0
Closed refuse house (F6)	1	100	0
Rebar bending yard (F7)	1	100	0
Electrical and mechanical (E&M) equipment and material storage area (F8)	1	100	0
#1 Tower Crane (F9)	1	60	1
#2Tower Crane (F10)	1	60	1
#3 Tower Crane (F11)	1	60	1
#1 Material Hoist (F12)	1	20	1
#2Material Hoist (F13)	1	20	1
#3 Material Hoist (F14)	1	20	1
Main contractor site office (F15)	1	180	1
Security hut at site entrance (F16)	1	9	1
Security hut at site exit (F17)	1	9	1

Where R_o is the final crisp rating of the activity, i is the rule that is used in the activity, R_i is the numerical rating of the activity of the rules and $\mu(R_i)$ is the membership value of R_i.

3.2. Multiple objective functions

Dynamic CSLP problems involve multiple objective functions, albeit, the multiple objective optimization (MOO) itself is also a problem. To verify the proposed method using MMAS to solve dynamic CSLP problem, two congruent objective functions are employed in the case study. The first objective function is minimizing the likelihood of accidents happened in order to improve the safety level. The second is minimizing the total handling cost between the facilities in order to reduce cost in the construction site. Thus, the first objective function (f_1) can be represented by minimizing the representative score of safety/environment concerns associated with the construction site layout (see Eq. (7)). The second objective function (f_2) can be represented by minimizing the total handling cost of interaction flows between the facilities associated with the construction site layout (see Eq. (8)). Hence, the multiple objective functions used to verify the proposed dynamic CSLP method in the case study can be mathematically defined as follows:

$$f_1 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{l=1}^{m} \sum_{k=1}^{m} S_{ij}\, d_{kl}\, x_{ik}\, x_{jl} \tag{7}$$

$$f_2 = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{l=1}^{m} \sum_{k=1}^{m} C_{ij}\, d_{kl}\, x_{ik}\, x_{jl} \tag{8}$$

Subject to the following constraints

$$\textstyle\sum_{i=1}^{n} x_{ik} = 1 \tag{9}$$

$$\textstyle\sum_{l=1}^{m} x_{jl} = 1 \tag{10}$$

$$\text{and } x \in \{0, 1\}. \tag{11}$$

Where S_{ij} in f_1 and C_{ij} in f_2 are the closeness relationship values for safety/environment concerns and the total handling cost of interaction flows (MF, IF, PF, EF, SE and UP) between facilities i and j respectively. d_{kl} is the distance between facilities k and l. x_{ik} means when facility i is assigned to location k and x_{jl} means when facility j is assigned to location l. n is the number of the facilities and m is the number of the locations. The constraint of x_{ik} will be a binary variable which takes value 1 if facility i is assigned to location k and 0 otherwise. The constraint of x_{jl} will be a binary variable which takes value 1 if facility j is assigned to location l and 0 otherwise. The two constraints guarantee one facility can be assigned to one location and one location can accommodate one facility. The location of each facility is then assigned and located in accordance with these constraints.

Since the multiple objective functions defined in this study are congruent, they can be transformed into single objective function using following equation:

$$f = w_1 \cdot f_1 + w_2 \cdot f_2 \tag{12}$$

Where, w_1 and w_2 are the weights of the two congruent objective functions respectively. This method is known as weighted sum method, which is a method scalarizing a set of objectives into a single objective by pre-multiplying each objective with a user-supplied weight [30] to solve MOO problems. The proposed method using MMAS to solve dynamic CSLP could then be used to find the solution using the single objective function.

3.3. Dynamic searching scheme

In order to solve the dynamic CSLP problem, the best site layout should suit the whole construction period with the consideration of the interactive relationships in the different construction phases, as well as the facilities used in each phase. Therefore, a continuous dynamic searching scheme [18], rather than a discrete dynamic searching scheme [31] is needed to find the minimum value for the objective functions during the whole construction period using the proposed MMAS algorithm. The basic difference between a continuous dynamic searching scheme and a discrete dynamic searching scheme is illustrated in Figs. 2 and 3 respectively.

Assume that there were four facilities (F1, F2, F3 and F4) required during two construction phases in a construction site where facilities F1, F2 and F3 were employed in Phase 1 and F2, F3 and F4 were employed in Phase 2 (see Figs. 2 and 3 respectively). The adoption of continuous dynamic searching scheme should be more favorable than the discrete searching scheme because the arrangement of the four facilities for the whole construction period can be positioned on a single site layout [32]. On the contrary, a re-handling cost i.e. more labor cost and time consumed is occurred when discrete dynamic searching scheme is used. Moreover, the increase in materials transportation flows shall lead to a decrease in the safety level at the construction site.

4. The Office Building Case Study

The data of the office building complex, which is located in Beijing, China as a landmark of the commercial business district (CBD) is used to verify the proposed method using MMAS for solving the dynamic CSLP problem. This office building complex is invested by a multinational enterprise and the building design is in accordance with the so-called 5A (building automation, office automation, communication automation, security automation and fire alarm automation) intelligent building grade. The entire construction site was separated into two main areas by the setting of the hoarding: the temporary living area and construction area (see Fig. 4). The temporary living area included client office, canteen, employee dormitory and labor dormitory were situated outside of the hoarding and the area inside the hoarding was the construction area.

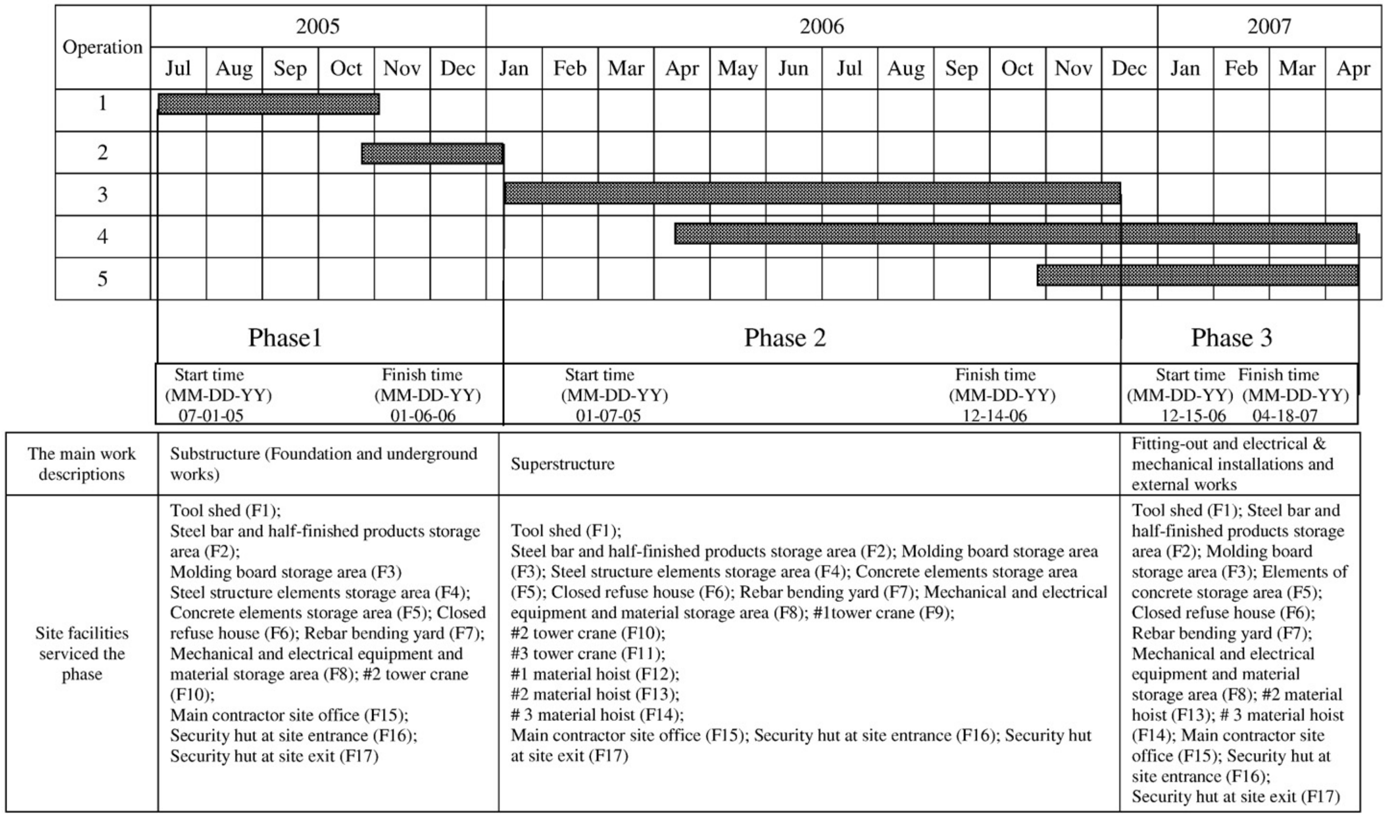

Fig. 5. The key dates and serviced site facilities in each construction phase. Note: Operation 1-Foundation, Operation 2-Undergroud woks, Operation 3-Superstructure, operation 4-Fitting out and electrical & mechanical (E&M) installations, Operation 5-External works.

4.1. Dynamic time interval and site facilities employed in each interval

In this case study, only the temporary facilities inside the construction area would be optimized using the proposed method. The facilities and their dimensions for all construction phases of the case study are shown in Table 2.

In many construction projects, factors such as hoisting capacity, temporary material areas, building layout, building site and surrounding constraints e.g. building height, unloading areas and lifting constraints of large building components shall affect the practitioners' decisions of assigning the locations for tower cranes and material hoists which are used to transport materials to the superstructure. In this case study the three tower cranes (F9, F10 and F11 of Table 2) and the three material hoists (F12, F13 and F14 of Table 2) were fixed in the locations (See Fig. 4) as experienced construction site planners usually fix these types of facilities first. Moreover, the locations of main gates are usually determined with the consideration of external transportation and the security huts, which are commonly assigned next to the main gates. For the security and safety, in this case study, one security hut (F16 of Table 2) is situated at the site entrance and the other security hut (F17 of Table 2) is situated at the site exit. The main contractor site office (F15 of Table 2) is located near to the main gate.

In order to verify the proposed method using MMAS to solve dynamic CSLP problem, the whole construction operation of this case study was triangulated into three construction phases instead of the original five construction phases, namely, the foundation construction phase, the underground section construction phase, the superstructure construction phase, the fitting-out and electrical and mechanical

Table 3
Parameters setting in MMAS.

Parameters	$\rho=0.5$						$\rho=0.7$						$\rho=0.9$					
	α	β	α	β	α	β	α	β	α	β	α	β	α	β	α	β	α	β
Setting value	2	1	2	2	1	2	2	1	2	2	1	2	2	1	2	2	1	2

Table 4
Assignment sequence of facilities in each construction phase.

Construction Phase	Assignment sequence of facilities (by facility number)
Phase 1	F6, F2, F4, F3, F1, F7, F8, F5
Phase 2	F6, F5, F4, F8, F7, F3, F1, F2
Phase 3	F6, F5, F2, F3, F1, F7, F8

Table 5
The optimal results via MMAS in phase 1.

Parameters setting		Convergence Status within 100 steps	Representative scores of f	Layout no.
$\rho=0.5$	$\alpha=2$ $\beta=1$	Y	36205	1
	$\alpha=2$ $\beta=2$	Y	36738	2
	$\alpha=1$ $\beta=2$	N	N/A	N/A
$\rho=0.7$	$\alpha=2$ $\beta=1$	Y	35892	3
	$\alpha=2$ $\beta=2$	Y	37058	4
	$\alpha=1$ $\beta=2$	N	N/A	N/A
$\rho=0.9$	$\alpha=2$ $\beta=1$	Y	35598	5
	$\alpha=2$ $\beta=2$	Y	36838	6
	$\alpha=1$ $\beta=2$	N	N/A	N/A

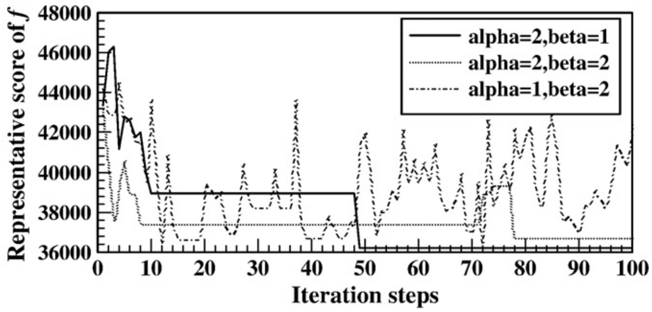

Fig. 6. Optimization process under the parameter setting of $\rho=0.5$ in phase 1.

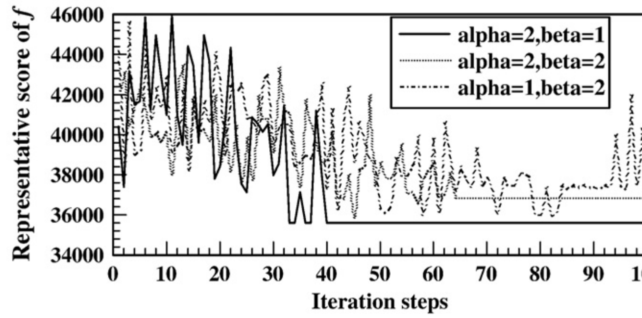

Fig. 8. Optimization process under the parameter setting of $\rho=0.9$ in phase 1.

(E&M) installations phase, and the external works employed by the main contractor in the original site layout plan. For the site facilities employed and their corresponding start time and finish time in each construction phase are shown in Fig. 5.

The triangulation was based on the amount of facilities used and their corresponding time serviced. Since there was only one tower crane employed in the original foundation phase, so the first two phases (foundation and underground section construction) of the original site layout plan could be merged into one phase, namely, foundation and underground works (Phase 1) in this case study. Moreover, there was little time overlapped between the underground section construction phase and the superstructure construction phase, in which 17 facilities involved. The execution of the fitting-out and E&M installations depends on the progress of the superstructure construction phase. The overlapped time between the original superstructure construction phase and fitting-out and E&M installations phase was approximately eight months and these two phases were merged into one phase, namely, superstructure (Phase 2) in this case study. For the external works, all the temporary facilities involved in the construction operation are cleared up, therefore, the remaining fitting-out works and E&M installations and external works were merged into Phase 3 in this case study.

4.2. Optimization process using MMAS

In the optimization process using MMAS, the ants, which depend on pheromone and heuristic information between the free locations, choose a solution step by step with the consideration of updated pheromone. The key parameters of MMAS are the persistence of the pheromone trails (ρ), relative influences of the pheromone information (α) and the heuristic information (β). In order to investigate the capability of the proposed MMAS in solving the dynamic CSLP problem and the impact caused by the parameter settings, three sets of parameters ($\alpha=2$, $\beta=1$ or $\alpha=2$, $\beta=2$ or $\alpha=1$, $\beta=2$ with $\rho=0.5$; $\alpha=2$, $\beta=1$ or $\alpha=2$, $\beta=2$ or $\alpha=1$, $\beta=2$ with $\rho=0.7$; $\alpha=2$, $\beta=1$ or $\alpha=2$, $\beta=2$ or $\alpha=1$, $\beta=2$ with $\rho=0.9$) were tested in this case study (see Table 3).

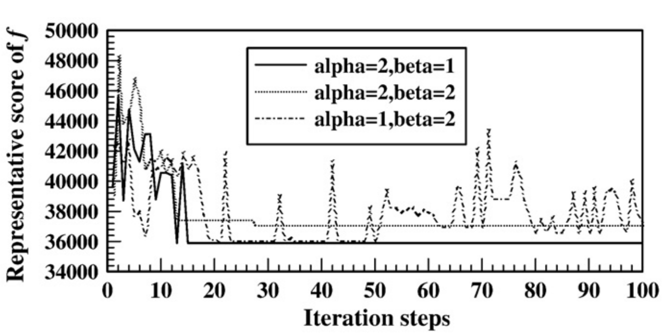

Fig. 7. Optimization process under the parameter setting of $\rho=0.7$ in phase 1.

In the process of solving dynamic CSLP problem, project managers or planners will position the key facilities, which influence the construction methods and sequences, with higher interactions to the other facilities first and then they will assign the remaining facilities in the available space that are left over. When applying the proposed method using MMAS to find optimal locations of the facilities for further evaluation, the assignment sequence of the facilities should be determined in accordance with the interaction flows to the other facilities in descending order, which mimics the practitioners assigning the facilities to locations in reality. The assignment sequences of the facilities adopted in this case study is shown in Table 4.

Having the heuristic parameters of MMAS defined (step 1 in Section 2) and the assignment sequence of the facilities determined (step 2 in Section 2), the proposed method using MMAS with the adoption of the continuous searching scheme shall find the corresponding locations of the assigned facilities (step 3 and step 4 in Section 2). The above-mentioned steps were then applied to the office building case study; the results are discussed in the following section.

5. Discussion of the Results

In this case study, the heuristic parameters of MMAS had already been defined and the assignment sequence of the facilities was determined. Following the continuous dynamic searching scheme using MMAS, the locations of the eight temporary facilities of Phase 1 were assigned correspondingly. The convergence criteria adopted in the MMAS is dual convergence criteria. Firstly, fixed number of

Table 6
The representative score for *f* in the construction duration.

Layout no.	Representative scores of *f* in each construction phase			Total representative score
	Phase 1	Phase 2	Phase 3	
Original layout	50266	91956	53280	195502
1	36205	74850	41483	152538 (22%)
2	36738	75217	38983	150893 (23%)
3	35892	74087	40763	150742 (23%)
4	37058	74383	37611	149052 (24%)
5	35598	72744	39790	148132 (24%)
6	36838	76933	40792	154563 (21%)

Note: the value in the bracket is the reduction rate for *f* after compared with the original layout.

Table 7
The representative score for f_1 and f_2 in the construction duration.

Layout no.	Representative scores for f_1 and f_2 in each construction phase						Sum of the representative score for f_1, f_2	
	Phase 1		Phase 2		Phase 3			
	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
Original layout	61861	39983	106070	79436	65040	42851	232971	162270
1	43944	29342	84448	66338	50951	33088	179343 (23%)	128768 (21%)
2	44370	29970	84902	66628	48327	30696	177599 (24%)	127294 (22%)
3	43787	28891	83663	65596	50727	31928	178177 (24%)	126415 (22%)
4	45749	29350	84157	65715	46095	30088	176001 (24%)	125153 (23%)
5	43182	28872	81479	64998	49222	31425	173883 (25%)	125295 (23%)
6	50324	33322	86278	68647	50728	31980	187330 (20%)	133949 (17%)

Note: the value in the bracket is the reduction rate for f_1 and f_2 after compared with the original layout.

generation reached. Secondly, if best-so-far solution fluctuates within a small defined range within the fixed generation number. In the study, the number of generation is set to 100. Under the three sets of parameter settings, the convergence status within 100 iteration steps and the total representative scores of weighted sum of multiple objective functions (see Eq. (12)) in the construction phase 1 are shown in Table 5.

In order to find the "consistent rule" of how ρ, α and β could affect the convergence speed (within 100 iteration steps), the optimization processes under the three parameter settings of this case study are illustrated from Figs. 6 to 8 respectively.

In Figs. 6 to 8, the x-axis stands for 100 iteration steps and the y-axis is the value (representative score) of multiple objective functions transformed into a single objective function (see Eq. (12)). These figures show the fact that the parameter variations strongly affect the convergence speed of single objective function. Under the parameter settings of $\alpha=2$, $\beta=1$ and $\alpha=2$, $\beta=2$, the convergence happened within100 iteration steps no matter which value of $\rho=0.5$, 0.7 or 0.9 was adopted. However, there was no convergence within the 100 iteration steps when the parameters setting of $\alpha=1$, $\beta=2$ under the $\rho=0.5$, $\rho=0.7$, $\rho=0.9$. From the results, the ratio between α and β (α/β) was recognized as the key determinant to the convergence speed of the results.

Since α and β are the parameters of relative influence of the pheromone strength and the heuristic information respectively, the relative influence of the pheromone strength which dominated in the searching process makes the convergence happened early. With the dominated status of pheromones on the searching trails, the heavily accumulated pheromones would bias the choice of ants strongly. In such a manner, more and more following ants would choose the same trail, and thus the convergence happened

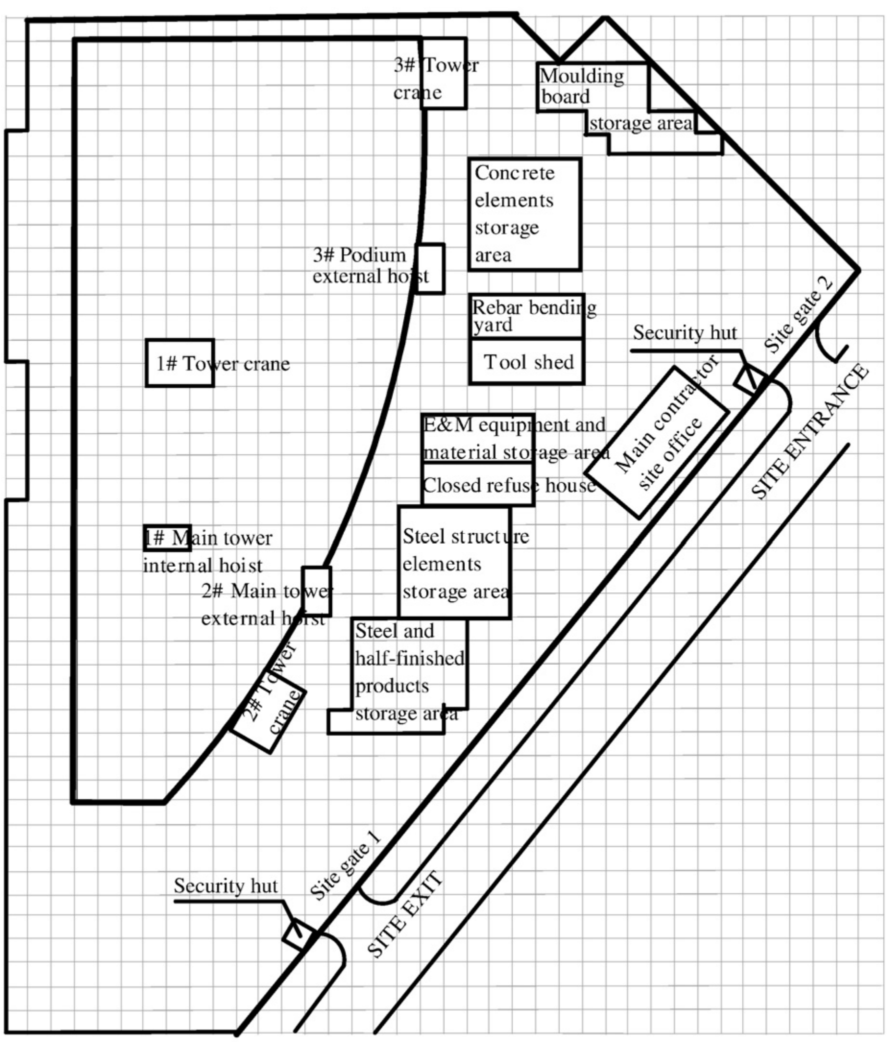

Fig. 9. Optimal layout of layout no.4.

consequently. Conversely, when the pheromone strength lost its dominant status during the searching process, i.e. the ratio between α and β was getting smaller and smaller, the influence of pheromone strength would not be used as the indicator of choice. In this circumstance, the convergence speed would decrease, and the convergence would be postponed.

To what extent of the ratio between α and β shall affect the speed of convergence is worth studying. From Figs. 6 to 8, the convergence speeds under the parameter settings of $\alpha=2$, $\beta=1$ were faster than that with the parameter settings of $\alpha=2$, $\beta=2$. The larger the ratios between α and β, the faster the convergence speeds under the parameters of $\rho=0.5$, $\rho=0.7$ and $\rho=0.9$. Thus the convergence speed under the parameters of $\alpha=2$, $\beta=1$ happened earlier than that under the parameter of $\alpha=2$, $\beta=2$. Correspondingly, there was no convergence when the ratio between α and β was smaller than 1 within the typical 100 running steps in this case study.

Using the continuous dynamic searching scheme for Phase 2 and Phase 3, the locations for facilities serviced in construction Phase 2 (From F1 to F8 of Table 2) and construction phase 3 (From F1 to F3 and from F5 to F8 of Table 2) were determined. Since all of them are in single site layout, therefore re-handling cost could be avoided. The representative scores for single objective function in construction Phase 2 and construction Phase 3 was calculated. The representative scores for f in the all construction phases are documented in Table 6.

In Table 6, the site layout plan candidates (Layout No. 1 to No. 6 of Table 6) were generated by the proposed method using MMAS. After the optimization by MMAS, the total representative scores (f) for the six alternatives are reduced from 21% to 24% compared with the original layout in the case study. The biggest reduction rate among the six alternatives is 24%. Thus, layout no.4 and layout 5 are the best layouts among the six layout plan candidates. However, what's the impact of the six alternatives on improving the safety level and reducing the construction cost, the reduction rate for minimizing the likelihood of accidents happened (f_1) and minimizing the total handling cost (f_2) are shown in Table 7.

In Table 7, the reduction rates of f_1 for the layout no.4 and layout no.5 are 24% and 25% respectively. The reduction rates of f_2 for layout no.4 and layout no.5 are all 23%. From the above reduction rates for layout no.4 and layout no.5, the layout no.5 is better than layout no.4, but not too much. In order to find the most satisfied layout plan, the layout no.4 and layout no.5 are drawn in Figs. 9 and 10 to compare as their reduction rates are near to each other. The original site layout is shown in Fig. 11.

First, layout no.4 (Fig. 9) and layout no.5 (Fig. 10) are compared with the original layout (Fig. 11). In the original layout, all the facility, with the exception of the tool shed, were arranged in front of office building. The tool shed in the original layout was located at the back of office building, as such, caused an inconvenience to the labors. From

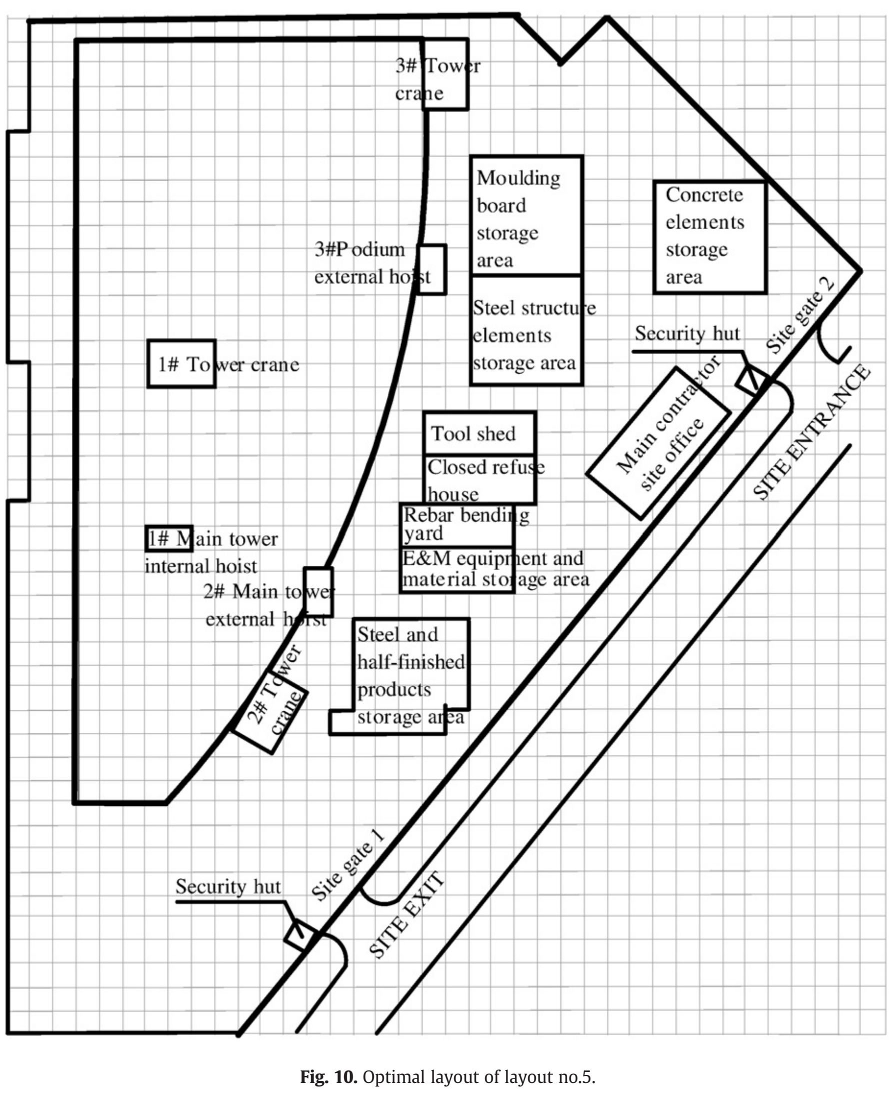

Fig. 10. Optimal layout of layout no.5.

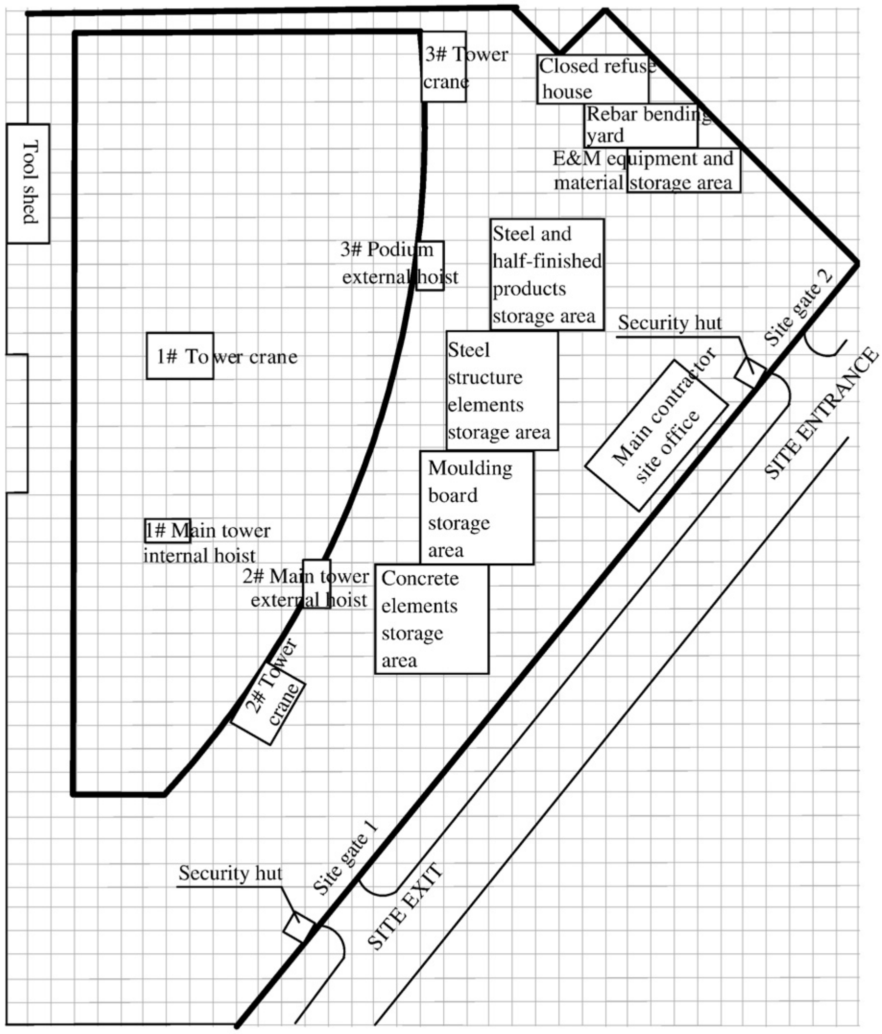

Fig. 11. The original layout of the case study.

the aspect of location of tool shed. Layout no. 4 and layout no 5 are much better than the original layout. Moreover, in the original layout, the closed refuse house, the rebar bending yard and the E&M equipment material storage area were put on the north-east of the hoarding. The frequent transference of waste materials to the closed refuse house could increase the likelihood of accidents. Also, the danger of the bended rebar being transported to the work area on the opposite side of the rebar bending yard would be increased. At the same time, the frequent handling of waste materials and bended rebar would decrease the work productivity because the laborers would waste too much time transporting. Second, select the better layout from layout no.4 and layout no.5. In layout no.4 and layout no.5, all the facilities were located in front of office building. Moreover, there was haul road between the facilities in both layouts, such as E&M equipment and material storage area and steel and half-finished products storage area in layout no.5, rebar bending yard and concrete elements storage area in layout no.4. The haul road will increase the flexibility of material handling at the construction site. In layout no.4, steel and half-finished products storage area and steel structure elements storage area were put next to each other. Such arrangement could bring convenience for the labor to transport the steel products between the two facilities with cross the haul road, thus increase the safety of work environment. From this point, layout no.4 is better than layout no.5. Furthermore, the adoption of layout no.4 could reduce the likelihood of accidents happened (f_1) and the total handling cost (f_2) by 24% and 23% respectively compared with the original layout.

6. Conclusion

CSLP problem is a dynamic MOO problem in reality. In order to enhance the congruent objectives of improving the safety level and reducing the construction cost, the two objective functions of minimizing safety concerns and minimizing the total handling cost are considered in this study. The method using MMAS under the guidance of continuous dynamic searching scheme was proposed to solve the MOO of the dynamic CSLP problem via weighted sum method, and the results show that the safety level is improved and the construction cost is reduced. The weighted sum method is generally used in solving multi-objective functions. It is because the easily used method could find the overall solution for the two objective functions. However, the limitation for the method is the overall solution may cover the solution quality for each objective function. In this study, apart from the newly proposed application of using MMAS to solve the dynamic MOO problem, other merits include the same approach could be adopted by other researchers using advanced algorithms, which had already solved the static CSLP problems and expand their applications to solve dynamic CSLP problems. Moreover, using fuzzy rule-based system in layout planning takes both the qualitative and quantitative factors involved in the interaction flows between the facilities into consideration. Furthermore, the ratio between α and β is identified as the key determinant to the convergence speed using MMAS and thus the optimal solution found. The results showed that the larger the ratio between α and β, the faster the convergence speed. The results verified the capability of the proposed method using MMAS under the guidance of the continuous dynamic searching scheme to solve dynamic CSLP problems.

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