Conjoining MMAS to GA to Solve Construction Site Layout Planning Problem

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Abstract: An optimal construction site layout planning (CSLP) is vital for project management. It can reduce the transportation flows and thus the costs of a project. Genetic algorithm (GA) is the most used algorithm to solve site layout problems, but randomly generated initial population in GA will decrease solution quality. Max-min ant system (MMAS) can offer a better initial population than the randomly generated initial population at the beginning of GA. In this study, a modified GA (MMAS-GA) formed by conjoining MMAS to the step of initialization of GA is proposed to solve CSLP problems. In order to reveal the computational capability of MMAS-GA to solve CSLP problems, the results of MMAS-GA and traditional GA are compared by solving an equal-area CSLP problem. The results showed that the proposed MMAS-GA algorithm provided a better optimal solution under the objective function of minimizing the transportation flows between the site facilities. The proposed MMAS-GA algorithm could assist project managers and planners to design optimal construction site layout, and thus to reduce construction costs.

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Introduction

Construction site layout planning (CSLP) is an optimization problem. It can be defined as a number of predetermined facilities n being assigned to a number of predetermined free locations m, where $m \geqslant n$. In real construction operations, it is common for site managers or planners to put the tower crane or material hoist in a "reasonable" location to fulfill requirements such as efficient material transportation, and then assign the rest of the facilities to other free locations by their own experience. Although experienced site managers will consider the construction method, safety, and convenience to the construction operations, work flows or costs caused by the transportation of materials and equipment cannot be fully taken into account by pure experience. From the studies in the manufacturing industry, materials handling costs can be reduced by 20–60% if the facility layout is appropriately planned (Lam et al. 2005). Therefore, it is necessary to properly lay out the facilities, which affect the resource flows of a construction site.

In this study, the max-min ant system-genetic algorithm (MMAS-GA) algorithm is proposed to solve an equal-area CSLP problem. CSLP is regarded as a nondeterministic polynomial-time hard problem, which is considered as one of the hardest optimization problems. Up to now, a CSLP problem can be modeled as an equal-area CSLP (Cheung et al. 2002; Li and Love 1998) and unequal-area CSLP problem (Li and Love 2000; Zouein et al. 2002). If each of the predetermined free locations is capable of accommodating any of the facilities, then the CSLP problem can be modeled as an equal-area CSLP problem. If some of the predetermined free locations are only able to accommodate some of the facilities, then the problem becomes an unequal-area CSLP problem (Li and Love 2000). In this study, the objective function of the case study was minimizing the transportation flows among facilities. The results showed that the proposed MMAS-GA algorithm remarkably outperformed the traditional GA under the objective function of minimizing the transportation flows between the site facilities.

Algorithms and Techniques Applied to Construction Site Layout

Algorithms applied to CSLP can be broadly classified into artificial intelligence (AI), evolutionary algorithm (EA) and swarm intelligence (SI). For AI, Hamiani (1987) developed a knowledge-based expert system to locate temporary support facilities on construction site. Yeh (1995) proposed annealed neural network (NN) model to solve CSLP problems. The model merged features of simulated annealing (SA) and the Hopfield NN. Tam et al. (2002) proposed a nonstructural fuzzy decision support system, which integrated experts' judgment into computer decision modeling. Elbeltagi and Hegazy (2001) and Zhang et al. (2002) proposed a hybrid AI-based system to solve CSLP problems. GA belongs to EA, which is mostly used algorithm in CSLP. There are many studies on GA to solve CSLP problems, such as Hegazy and Elbeltagi (1999); Zouein et al. (2002) applied GA to solve the unequal-size CSLP problem. Mawdesley et al. (2002) tested the GA's application on the two cases to prove the efficiency of the model. Besides, ant colony optimization (ACO) algorithm, which

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is one of the algorithms of SI, is used for CSLP recently. The application of ACO algorithm to solve CSLP problems was started from 2006. Samdani et al. (2006) and Lam et al. (2007) applied ACO algorithm to solve static CSLP problems.

On top of these advanced optimization methods were applied to CSLP, computer-aided design (CAD) based models offer a very intuitive understanding of the whole CSLP. In order to build up a user-support friendly system with the utilization of the user's experience, knowledge, and the consideration of a number of conditions, such as safety and security, Sadeghpour et al. (2004) proposed a CAD-based model to solve CSLP problems. In order to solve dynamic CSLP problems, Ma et al. (2005) introduced a four-dimensional (4D) integrated site planning system which integrated schedules, three-dimensional (3D) models, resources and site spaces together with 4D CAD technology to provide 4D graphical visualization capability for CSLP.

In the previous studies, majority of the research works are focused on the improvement of the algorithm capabilities and technology to solve CSLP problems. It means that algorithm capability and technological improvement are the key determinants to find a good construction site layout, thus to improve the management level of the project. This study aims to propose a new heuristic algorithm MMAS-GA, which is a hybrid optimization algorithm by conjoining MMAS to GA. GA is the mostly used algorithm to solve site layout problems (Elbeltagi and Hegazy 2001; Hegazy and Elbeltagi 1999; Li and Love 2000; Osman et al. 2003), as it has the merit of strong evolutionary process to find optimal solutions by the operations of crossover, selection, and mutation of parent generation. But, the randomly generated initial population at the beginning of the algorithm will affect the solution quality. It is because the bad genes could be inherited from the parent generation for the subsequent operations of selection, crossover, and mutation, which depend on the parent generation. As an alternative to the randomly generated initial population, it is likely to be advantageous to begin the GA with a population of high performance candidate solutions (Yang and Nygard 1993). In order to generate better initial parent generation, MMAS is adopted in this study. As MMAS makes use of heuristic information and pheromone to improve the search capability, and thus improve the quality of solution.

Genetic Algorithm

GA is mostly used optimal algorithm, which is based on a biological metaphor to solve CSLP problems (Li and Love 1998, 2000). GA views learning as a competition among a population of evolving candidate solutions. A "fitness" function is used to evaluate each solution and decide whether it will contribute to the next generation of solutions. Then, through operations analogous to gene transfer in sexual reproduction, the algorithm creates a new population of candidate solutions (Luger 2002). GA is a globe optimal algorithm and can be applied to find near optimal solution to a problem which may have many solutions. The search process of GA can be performed under many types of fitness function, which can be discrete or continuous, linear or nonlinear.

According to Falkenauer (1998), after defining the fitness function, the following steps of GA are applied to a problem.

Encoding

The search space of all possible solutions of the problem is mapped onto a set of finite strings over a finite (usually small) alphabet, such that each point in the search space is represented by a string, which is called chromosome. The GA will work with these chromosomes, rather than the solutions themselves.

Initialization

An initial population of solutions is selected. The first generation is usually selected at random. Unlike standard optimization techniques, a GA performs a parallel search over a set of points in the search space, thus lessening the probability of being trapped in a local optimum.

Selection

A proportion of the existing population is selected through a fitness-based process. i.e., individuals are selected randomly. The probability of an individual being selected is increasing with fitness functions. GA is thus essentially a stochastic optimization technique.

Crossover

The basic operator for producing new chromosomes is called crossover in GA. Crossover produces new individuals that have some parts of both parents' genetic materials. Crossover operator is not necessarily performed on all strings in the population. Instead, it is applied with a probability when the pairs are chosen for breeding.

Mutation

The operator of mutation proceeds by performing a random modification on an individual. It can be defined as one performing the small possible random modification of an individual. The mutation operator is commonly defined as the flip of one or (rarely) more bits in the chromosome.

Termination

The optimization process started at initialization and can be iterated until termination condition has been reached. The common conditions are: (1) fixed number of generation reached; (2) the generated solution satisfy the requirement of objective function; and (3) the average value of solution or best-so-far solution fluctuates within a small defined range.

Max-Min Ant System-Genetic Algorithm

In this research, the MMAS-GA (conjoining MMAS in the initialization step of GA) is proposed to solve the CSLP problem. In the initialization step of GA, the first generation is usually selected at random and then being used as parent generation to reproduce offset. Owing to the randomness, there is a possibility of inherited bad genes and thus influence the quality of offset, and finally the optimal solution. The proposed MMAS-GA aims to improve the quality of the first population of GA by employing MMAS, which is one of the ACO algorithms and first being applied to solve the traveling salesman problem by Stützle and Hoos (1997,1998). ACO algorithms are population-based, general search technique for the solution of difficult combinatorial problems. It was inspired by the pheromone trail laying behavior of real ant colonies (Stützle 2005).

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Table 1. Work Flows between the Site Facilities

Site facilities	Facility number	Closeness index of work flow between facilities									Sum of closeness index
		1	2	3	4	5	6	7	8	9	
Refuse chute	1	0.0	3.1[a]	0.8[a]	0.6[a]	0.6[a]	0.9[a]	1.7[a]	0.4[a]	0.4[a]	8.5[b]
			6.2[c]	2.2[c]	2.3[c]	2.3[c]	2.4[c]	4.2[c]	2.7[c]	2.5[c]	24.8[d]
			9.3[e]	3.6[e]	4.0[e]	3.9[e]	3.9[e]	6.7[e]	5.0[e]	4.5[e]	40.9[f]
Debris storage area	2	3.1[a]	0.0	2.1[a]	1.9[a]	1.5[a]	1.5[a]	3.2[a]	1.2[a]	1.2[a]	15.7[b]
		6.2[c]		4.0[c]	4.3[c]	3.6[c]	3.6[c]	5.5[c]	3.1[c]	3.2[c]	33.5[d]
		9.3[e]		5.9[e]	6.6[e]	5.7[e]	5.7[e]	7.7[e]	4.9[e]	5.2[e]	51.0[f]
Rebar bending yard	3	0.8[a]	2.1[a]	0.0	1.6[a]	1.9[a]	1.2[a]	3.6[a]	5.2[a]	1.9[a]	18.3[b]
		2.2[c]	4.0[c]		4.1[c]	3.8[c]	3.9[c]	6.2[c]	7.2[c]	3.9[c]	35.3[d]
		3.6[e]	5.9[e]		6.7[e]	5.7[e]	6.5[e]	8.8[e]	9.2[e]	6.0[e]	52.4[f]
Carpentry workshop and store	4	0.6[a]	1.9[a]	1.6[a]	0.0	1.8[a]	2.1[a]	3.1[a]	5.1[a]	1.9[a]	18.1[b]
		2.3[c]	4.3[c]	4.1[c]		4.5[c]	4.7[c]	5.2[c]	7.2[c]	3.8[c]	36.1[d]
		4.0[e]	6.6[e]	6.7[e]		7.2[e]	7.3[e]	7.3[e]	9.3[e]	5.7[e]	54.1[f]
Labor hut	5	0.6[a]	1.5[a]	1.9[a]	1.8[a]	0.0	2.2[a]	2.3[a]	1.5[a]	2.3[a]	14.1 [b]
		2.3[c]	3.6[c]	3.8[c]	4.5[c]		4.7[c]	4.2[c]	4.1[c]	4.3[c]	31.5 [d]
		3.9[e]	5.7[e]	5.7[e]	7.2[e]		7.2[e]	6.1[e]	6.6[e]	6.20[e]	48.6 [f]
Materials storage area	6	0.9[a]	3.2[a]	1.2[a]	2.1[a]	2.2[a]	0.0	3.6[a]	4.5[a]	2.5[a]	18.5 [b]
		2.4[c]	5.5[c]	3.9[c]	4.7[c]	4.7[c]		5.8[c]	6.7[c]	4.8[c]	36.6 [d]
		3.9[e]	7.7[e]	6.5[e]	7.3[e]	7.2[e]		8.0[e]	9.0[e]	7.1[e]	54.7 [f]
Main gate	7	1.7[a]	3.2[a]	3.6[a]	3.1[a]	2.3[a]	3.6[a]	0.0	2.5[a]	2.0[a]	22.0 [b]
		4.2[c]	5.5[c]	6.2[c]	5.2[c]	4.2[c]	5.8[c]		5.2[c]	5.5[c]	41.8 [d]
		6.7[e]	7.7[e]	8.8[e]	7.3[e]	6.1[e]	8.0[e]		7.9[e]	8.9[e]	61.4 [f]
Materials hoist	8	0.4[a]	1.2[a]	5.2[a]	5.1[a]	1.5[a]	4.5[a]	2.5[a]	0.0	1.5[a]	21.9 [b]
		2.7[c]	3.1[c]	7.2[c]	7.2[c]	4.1[c]	6.7[c]	5.2[c]		3.6[c]	39.8 [d]
		5.0[e]	4.9[e]	9.2[e]	9.3[e]	6.6[e]	9.0[e]	7.9[e]		5.7[e]	57.6 [f]
Site office	9	0.4[a]	1.2[a]	1.9[a]	1.9[a]	2.3[a]	2.5[a]	2.0[a]	1.5[a]	0.0	13.7[b]
		2.5[c]	3.2[c]	3.9[c]	3.8[c]	4.3[c]	4.8[c]	5.5[c]	3.6[c]		31.6[d]
		4.5[e]	5.2[e]	6.0[e]	5.7[e]	6.2[e]	7.1[e]	8.9[e]	5.7[e]		49.3[f]

[a]Closeness index between facilities under lower bound.
[b]Sum of closeness indices between one facility to the other facilities under lower bound.
[c]Closeness index between facilities under mean bound.
[d]Sum of closeness indices between one facility to the other facilities under mean bound.
[e]Closeness index between facilities under upper bound.
[f]Sum of closeness indices between one facility to the other facilities under upper bound.

Construction of Solutions by Max-Min Ant System

MMAS is metaheuristic, a set of algorithm concepts that can be used to define heuristic methods, which is applicable to a wide set of different problems (Dorigo and Stützle 2004). In MMAS, the assignment sequence for facilities which is determined by flows between facilities. According to Stützle and Hoos (1997), at each construction step, ant k randomly chooses a facility i to the free location j with a probability given by

$$p_{ij}^{k}(t)=[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}/\sum_{l\in N_i^k}[\tau_{il}(t)]^{\alpha}\cdot[\eta_{il}]^{\beta} \quad \text{if } j\in N_i^k \tag{1}$$

where $\tau_{ij}(t)$=pheromone trail at iteration t; η_{ij}=heuristic information between facility i and location j; and α and β=parameters that determine the relative influence of the pheromone strength and the heuristic information respectively. N_i^k is the feasible neighborhood of node i, that is, only those locations that are still free. Note that $\sum_{l\in N_i^k}p_{ij}(t)=1$.

Update of Pheromone Trails

After all ants have constructed a solution, the pheromone trails are updated in accordance with the following equation:

$$\tau_{ij}(t+1)=\rho\cdot\tau_{ij}(t)+\Delta\tau_{ij}^{\text{best}} \tag{2}$$

where $\rho(0<\rho<1)$=persistence of the pheromone trail. Here, $\Delta\tau_{ij}^{\text{best}}$ is defined as

$$\Delta\tau_{ij}^{\text{best}}=\begin{cases}1/J_{\Phi^{\text{best}}} & \text{if facility } i \text{ is assigned to location } j \text{ in solution } \Phi^{\text{best}}\\ 0 & \text{otherwise}\end{cases} \tag{3}$$

where $J_{\Phi^{\text{best}}}$=objective function value of Φ^{best}. If after the pheromone update we have $\tau_{ij}>\tau_{\max}$, we set $\tau_{ij}=\tau_{\max}$; if $\tau_{ij}<\tau_{\min}$, we set $\tau_{ij}=\tau_{\min}$.

Proposed Mathematical Model

A mathematical model for solving the equal-size CSLP which involves fuzzy logic (Zadeh 1965) for analyzing the collected data are proposed. It can assist construction managers and planners to optimize the CSLP.

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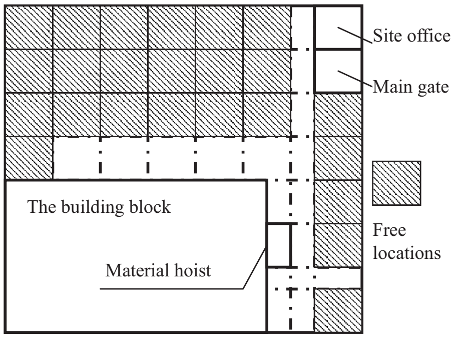

Fig. 1. Simplified layout of the hypothetical construction site

Closeness Indices of the Site Facilities

In order to minimize the transportation of work flows, a closeness index (C_f) is used to show the closeness relation between the facilities. The work flows include transportation of materials, equipment, etc. from one facility to the other. The higher the frequency of the transportation of work flows between facilities, the closer the distance from the facilities to the others. A preset 9-point rating scale (9 indicates that the facilities should be arranged as closely as possible and 1 means that the facilities should be far away from the other facilities) is used to show the closeness between the facilities (see Table 1).

In reality, exact values of parameters cannot always be generated due to vague, imprecise and uncertain problems solved. Fuzzy arithmetic is a useful tool to handle these problems with uncertain and imprecise parameters. As a specific crisp value of these uncertain parameters cannot fully cover the whole spectrum of possible values, the triangular fuzzy number is adopted. The following triangular fuzzy number (Hanss 1999) is used for the C_f in this study

$$C_f = \begin{cases} C_u = C_m + \sigma(\text{upper bound}) \\ C_m(\text{medium bound}) \\ C_l = C_m - \sigma(\text{lower bound}) \end{cases} \tag{4}$$

where C_m=mean value ($\Sigma C_i/n$) and σ is the standard deviation ($\sqrt{\Sigma(C_i - C_m)^2/n}$) of the collected C_f.

Objective Function

A CSLP problem can be modeled as a quadratic assignment problem (Domschke and Krispin 1997). The objective function of this study is to minimize the transportation of work flows between the site facilities, for which depends mainly on two attributes: the closeness index of work flow (C_{ij}) between the site facilities and the distance (d) between the site locations. The objective function of CSLP problem can be defined as follows:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{l=1}^{n} \sum_{k=1}^{n} C_{ij} d_{kl} x_{ik} x_{jl} \tag{5}$$

Subject to the following constraints

$$\sum_{i=1}^{n} x_{ij} = 1 \tag{6}$$

$$\sum_{j=1}^{n} x_{ij} = 1 \tag{7}$$

and

$$x \in \{0,1\} \tag{8}$$

The location of each facility is then assigned and located in accordance with these constraints, where C_{ij} is the closeness index of work flow between facilities i and j and d_{kl} is the distance between facilities k and l. x_{ik} and x_{jl} means when facility i is assigned to location k and facility j is assigned to location l respectively. The constraint of x_{ij} will be a binary variable which takes Value 1 if facility i is assigned to location j and 0 otherwise.

Table 2. Parameters Set in MMAS-GA

Algorithm	Parameters	Value
MMAS-GA	Number of ants	20.00
	Influence coefficient of pheromone strength α	3.00
	Influence coefficient of heuristic information β	3.00
	Crossover rate	0.90
	Mutation rate	0.01

Table 3. Assignment Sequences of Facilities under Different Bounds

Bounds of C_f	Assignment sequence of facilities (by facility number of Table 1)
Lower	6-3-4-2-5-1
Medium	6-4-3-2-5-1
Upper	6-4-3-2-5-1

Case Study

Hypothetical Site

A hypothetical construction site extracted from a 6-story reinforced concrete administration building for the application of the proposed MMAS-GA compared to the traditional GA to solve an equal-area CSLP problem. It is assumed that: (1) the geometric layout of available locations is predetermined and fixed and (2) each of the predeterminants is further considered to be capable of accommodating the largest one among the facilities.

The whole project consists of foundation, structural works, external works, and building service installation. Nine essential facilities are considered in order to simplify the complexity of the CSLP problem in this case study. Referring to Table 1, the facilities are: (1) refuse chute; (2) debris storage area; (3) reinforcement bending yard; (4) carpentry workshop and store; (5) labor hut; (6) materials storage area; (7) main gate; (8) material hoist; and (9) site office. There are three fixed facilities (site office,

Table 4. Encode the Initial Generation in MMAS-GA

	Chromosomes					
Layout	1	2	3	4	5	6
1	2	5	24	19	12	15
2	24	15	14	9	2	6
⋮	⋮	⋮	⋮	⋮	⋮	⋮
20	24	23	12	15	16	17

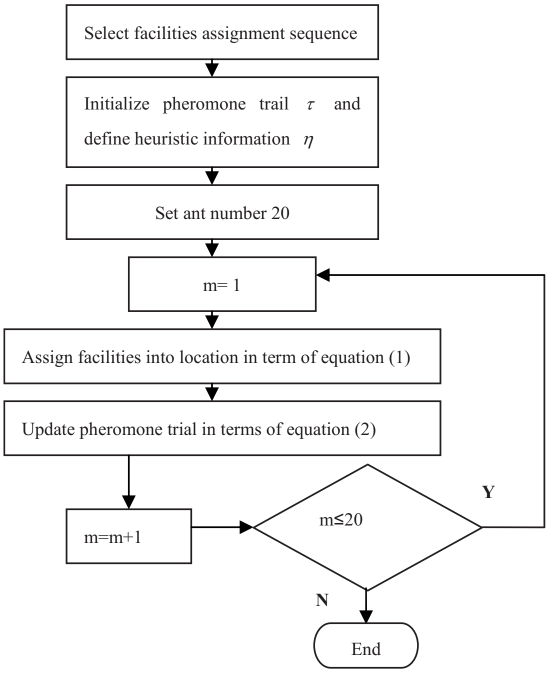

Fig. 2. Steps of MMAS to generate the initial population of the proposed MMAS-GA model

material hoist, and main gate) in the construction site. The location of main gate is usually predetermined in terms of external transportation system. Site office is always near the main gate for the safety of the working staff. The materials hoist is used for the transportation of materials to the superstructure and its location is dependent on the structural element to which it is tied, and thus site planners always freeze this facility in a certain location. Based on the above reasons, site office, main gate, and material hoist are predetermined by the planner. The simplified layout of the hypothetical construction site is showed in Fig. 1.

In Fig. 1, any location on the construction site can be specified and identified by coordinating the gravity center of each location and each location is a square with size 2×2. Thus, the d between the locations is defined as the Euclidean distance between gravity centers of locations. After applying the triangular fuzzy numbers [Eq. (4)], the triangular fuzzy closeness indices (lower bound, mean bound, upper bound) of work flows are shown in Table 1.

Table 5. Pseudocode of Single-Point Crossover Operation in MMAS-GA

Step	Function
1	Determine the maximum iteration number, N, of crossover operation
2	Pick two individuals from this generation to crossover
3	**If** $p_{\text{rand}} < p_c$, p_{rand} is a real number between 0 and 1 and p_c is crossover rate, **then**
4	Determine the crossover point
5	Deduce the new individual, which is deduced by exchanging the left part and right part of string in the two individuals on the crossover point
6	Finish crossover operation in one iteration
7	**If** the iteration number reaches N, **then** output the new generation of solutions
8	**If** iteration number does not reach N, **then** go to step 2

Table 6. Pseudocode of Mutation Operation in MMAS-GA

Step	Function
1	For each individual in the generation
2	**If** $p_{\text{rand}} < p_m$, p_{rand} is a real number between 0 and 1 and p_m is mutation rate, **then**
3	Determine the mutation point
4	Determine the mutation value $m_$value
5	Change the component of string in mutation point to mutation value
6	Output the new generation of solution

Application of Max-Min Ant System-Genetic Algorithm and Genetic Algorithm to Solve Site Layout Planning Problem

In order to investigate the efficiency of the proposed algorithm, MMAS-GA and traditional GA were tested on the same computer with Intel Pentium 4, CPU 2.4 GHz.

Specifications of Max-Min Ant System-Genetic Algorithm

The parameters set in MMAS-GA are shown in Table 2. The sequence of assigned facilities should be done before the first step of solution construction in MMAS-GA. In order to adopt the proposed MMAS-GA to solve the CSLP problem, the assignment sequence for the facilities was sorted out in nonincreasing order by the sum of C_f instead of random assignment sequence. Based on the sum of C_f in Table 1 (see the last column), the assignment sequences of the facilities under different bounds are shown in Table 3.

The real values of GA's encoding are adopted to represent the solution. For example, one generation of MMAS-GA can be represented as per Table 4. The steps of the MMAS proposed in this study is used to generate the initial population in this case study are shown in Fig. 2. After encoding and generating the initial population, the operations of selection, crossover and mutation are applied as follows.

Selection

The fitness of each solution (layout) in MMAS-GA can be evaluated by the objective function. Proportional selection is implemented by the Roulette wheel technique (Martorell et al. 2000) in the selection operation.

Crossover

Single-point crossover is adopted in crossover operation and the pseudocode of single-point crossover operation is shown as per Table 5.

Table 7. Pseudocode of Last Step to Avoid Bad Solution in MMAS-GA

Step	Function
1	From each component in the string
2	**If** the component does not equal to 0 and there are components that are the same, **then**
3	Change the value of components until there are no same components in the string
4	Output the new generation of solution

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Table 8. Parameters Set in Traditional GA

Algorithm	Parameters	Value
GA	Initial population	20.00
	Crossover rate p_c	0.90
	Mutation rate p_m	0.01

Mutation

The pseudocode of mutation operation is shown in Table 6. In order to transform the bad solution into good solution due to the real value encoding, crossover and mutation operations, the following operation of avoiding bad solution in the proposed MMAS-GA is shown in Table 7.

Specifications of Genetic Algorithm

In order to compare the efficiency of the proposed MMAS-GA to the traditional GA, the parameters set in the traditional GA are as per Table 8. The real values of encoding are adopted to represent the solution. The fitness of each solution (layout) in traditional GA can be evaluated by the objective function. The initial generation in traditional GA is randomly generated. In this case study, there are three fixed facilities and the locations for the other six facilities are randomly generated. Thus, there are 24^6 different arrangements and the initial population is set to 20. For example, one solution in the initial generation can be represented as per Table 9. The steps of selection, crossover, mutation and bad solutions transform step are the same to the procedure of the proposed MMAS-GA model.

Comparison of the Results of Max-Min Ant System-Genetic Algorithm and Genetic Algorithm

The optimal results of the proposed MMAS-GA and GA under different bounds in terms of steps, optimal algorithm used, optimal site layout candidates, optimal work flow and reduction to the results of GA are recorded in Table 10. The optimal construction site layout of A, B, C, D, E, and F are shown from Figs. 3–8 respectively.

The optimal construction site layout candidates of A, B, C, D, E, and F can be chosen by the construction managers or planners in accordance with their experiences and personal preference. The searching process (see Figs. 9–11) and coverage of the solution space (see Fig. 12–14) of the proposed MMAS-GA and GA under different bounds are shown respectively.

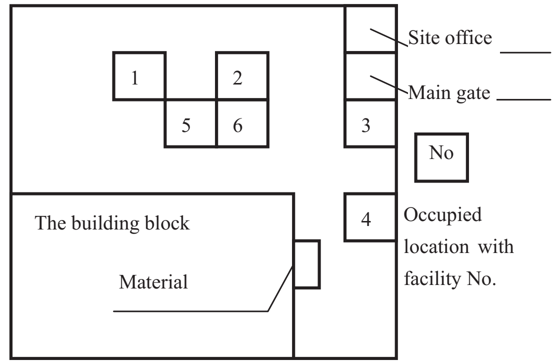

Fig. 3. Optimal construction site layout candidate A

The Figs. 9–11 illustrated searching process in reference to the objective function value of the proposed MMAS-GA and GA along the 100 steps. After MMAS was applied to find initial populations in the proposed MMAS-GA model, the solution quality was improved, i.e., the reduction from traditional GA were 159.69, 612.90, and 616.30 for lower bound, medium bound, and upper bound respectively (see Table 10). From the viewpoint of step, the proposed MMAS-GA got into convergence earlier than GA, as the searching space was smaller. In order to make clear of the searching space of two algorithms, Figs. 12–14 are drawn to show the convergences of the proposed MMAS-GA and GA under lower bound, medium bound, and upper bound respectively. The searching space of GA was wider than the proposed MMAS-GA, as the randomly generated initial population in GA increased the searching space, while decreased the computational capability of GA. In the proposed model, the initial population generation was generated by the MMAS and then the quality of parents' population, offset and final the optimal solutions were increased. The smaller searching space of the proposed MMAS-GA accelerated the convergence speed, which is an important index to evaluate the capability of an algorithm.

In general, an algorithm selects an optimal solution from a large number of candidate solutions. The algorithm shall generate different regions of search space and not emphasize on a limited

Table 9. Representation of Initial Generation in Traditional GA

Number of location	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Number of facilities	0	0	6	5	0	4	0	0	3	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0

Table 10. Optimal Solution of GA and MMAS-GA under Different Bounds

Closeness index	Step	Optimal algorithm used	Optimal site layout candidates	Optimal work flow	Reduction to the results of GA
Lower bound	100.00	GA	A	857.99	0
	100.00	MMAS-GA	B	698.30	159.69
Medium bound	100.00	GA	C	2,063.10	0
	100.00	MMAS-GA	D	1,450.20	612.90
Upper bound	100.00	GA	E	2,818.80	0
	100.00	MMAS-GA	F	2,202.50	616.30

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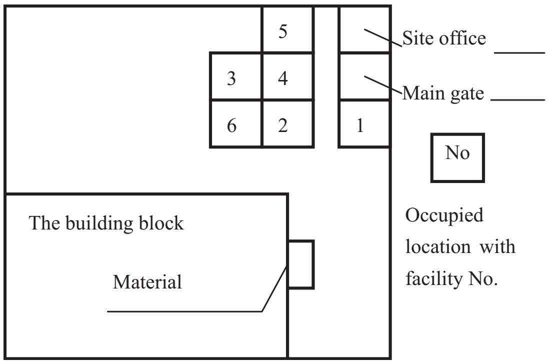

Fig. 4. Optimal construction site layout candidate B

search space too early. The balance between two aspects will improve the convergence of an algorithm and thus the capability of that algorithm. If the algorithm convergence speed is low, more steps are needed to find an optimal result, and thus decrease the algorithm's capability of searching. On the contrary, when an algorithm convergence speed is high, the algorithm will focus on a small region of search space too early. In this case study, convergence speed is higher in the proposed MMAS-GA and the overall steps to find optimal solutions are fewer than the steps consumed by GA to get optimal results. Therefore, the proposed MMAS-GA can deliver better solutions than those of GA.

Conclusions

In order to evaluate the capabilities of the proposed MMAS-GA model and the traditional GA to solve an equal-area CSLP problem, a government project was adopted as the hypothetical construction site for comparison. The comparison was made under the objective function of minimizing the transportation flows between the site facilities. The results showed that the flows of the traditional GA were reduced of 159.69, 612.90, and 616.30 by the proposed MMAS-GA under lower, medium and upper bound respectively (see Table 10). The convergence of MMAS-GA was happened earlier than convergence of traditional GA (see Figs. 9–11). The reason is that the coverage of solution space of the proposed MMAS-GA is much smaller than that of GA (see Figs. 12–14).

Both the proposed MMAS-GA and traditional GA are intelligent bionic optimization and globe optimization. Moreover, both of them also have the principles of self-organization and self-adaptation. With the exception of the resemblance, the proposed MMAS-GA and the traditional GA also have their own characters. The early convergence of the proposed MMAS-GA shall

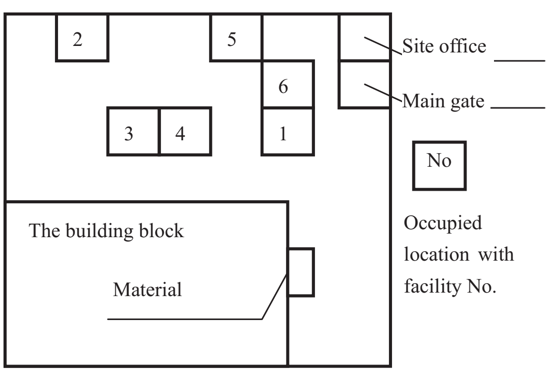

Fig. 5. Optimal construction site layout candidate C

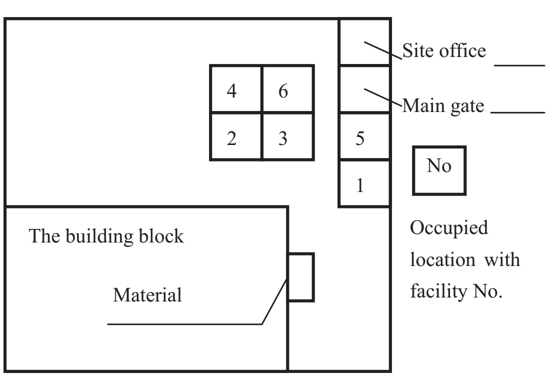

Fig. 6. Optimal construction site layout candidate D

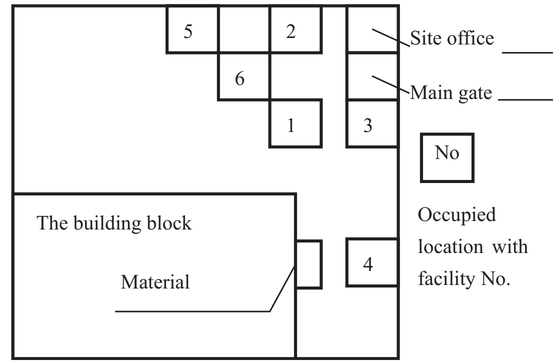

Fig. 7. Optimal construction site layout candidate E

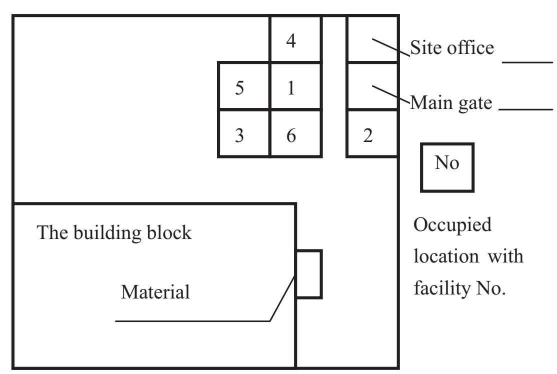

Fig. 8. Optimal construction site layout candidate F

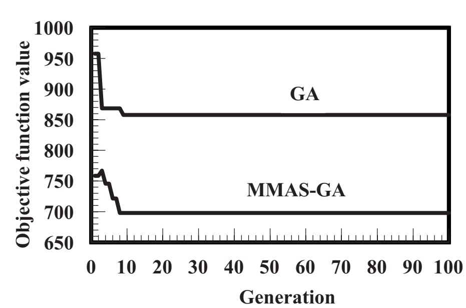

Fig. 9. Convergence of objective function value under the lower bound

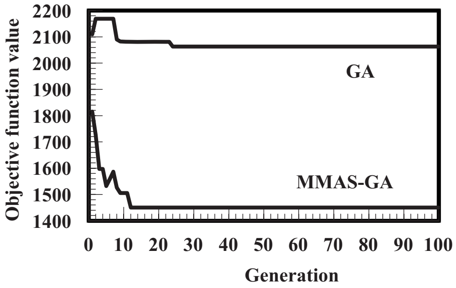

Fig. 10. Convergence of objective function value under the medium bound

improve the efficiency of algorithm. The reason leads to early convergence of the proposed MMAS-GA is due to smaller coverage of solution space. The smaller coverage of solution space will lose the search space of optimal solution. The advantage of MMAS-GA is to make use of heuristic and pheromone information to make early convergence by reducing searching space of optimal solution. The operations of crossover and mutation of GA are to keep the diversity of possible solutions, so the balance between convergence and searching space of solution can foster a good optimization capability of the proposed MMAS-GA. Conjoining MMAS to the initialization of GA can magnify the computational capability of GA for better solving the CSLP problem. Although the proposed MMAS-GA model is only validated by a case study only, it could be the new direction for future research of optimization problems in construction management field.

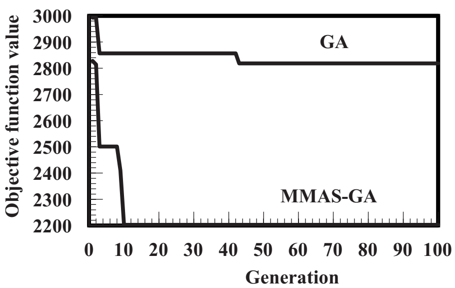

Fig. 11. Convergence of objective function value under the upper bound

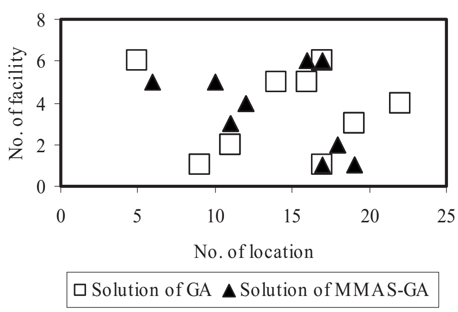

Fig. 12. Coverage of solution space of GA and MMAS-GA under the lower bound

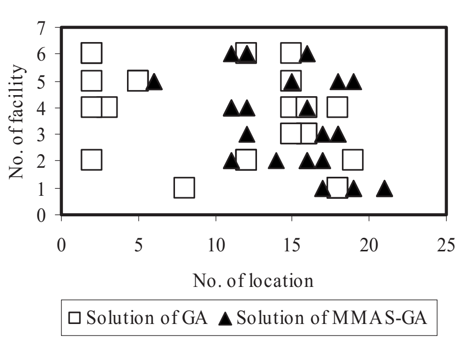

Fig. 13. Coverage of solution space of GA and MMAS-GA under the medium bound

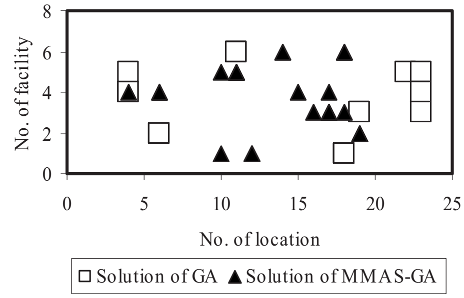

Fig. 14. Coverage of solution space of GA and MMAS-GA under the upper bound

Acknowledgments

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Notation

The following symbols are used in this paper:

C_{ij} = closeness index of work flow between facilities i and j;
d_{kl} = distance between facilities k and l;
$J_{\Phi^{\text{best}}}$ = objective function value of Φ^{best};
N_i^k = feasible neighborhood of ant k of node i;
$p_{ij}^k(t)$ = probability of ant k chooses facility i to the free location j at iteration t;
α = parameter that determines the relative influence of the pheromone strength;
β = parameter that determines the relative influence of the heuristic information;
$\Delta\tau_{ij}^{\text{best}}$ = incremental pheromone trial;
η_{ij} = heuristic information between facility i and location j;
ρ = persistence of the pheromone trail;
$\tau_{ij}(t)$ = pheromone trail between facility i and location j at iteration t; and
Φ^{best} = best solution at iteration.

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