A Development of Optimization Model for Construction Site Layout Planning Using Genetic Algorithm

Chakrey Duong[1] and Vachara Peansupap[2*]

[1,2] *Department of Civil Engineering, Faculty of Engineering, Chulalongkorn University, Bangkok, THAILAND*
**Corresponding author; E-mail address: vachara.p@chula.ac.th*

Abstract

An effective construction site layout planning (CSPL) is essential to ensure site safety and enhance work efficiency. The primary task of CSPL process is to identify suitable location for temporary facilities (TFs) so that the safety and work efficiency can be improved. The problem of CSLP is generally formulated as an optimization problem, where a specific objective can be achieved with a set of constraints. Dealing with a large number of facilities, multiple tower cranes, and additional constraints can make the problem particularly challenging. In this study, a model is proposed to solve the problem of CSLP using Genetic Algorithm (GA). The model searches all free areas by using grid system to minimize the bias for facility location. In addition, the model can layout the location for tower cranes optimally. Flexibility of the model is increased by optimizing not only location for TFs, but also location for tower cranes. Moreover, this study investigated the effectiveness of closeness relationships on the developed model. A novel prototype was developed and tested to evaluate efficiency of the model. The results indicate that the proposed model can efficiently optimize the site layout for building projects. It can assist project managers in arranging facilities and tower cranes more effectively.

Keywords: genetic algorithm, site layout planning, optimization, tower crane, temporary facility

1. Introduction

Construction site layout planning (CSLP) is a crucial step in project planning, especially in limited space, such as in urban areas where land is scarce and expensive [1]. A well-developed site layout can improve work efficiency and ensure safety on construction sites. Although the importance of CSLP has been widely recognized, many contractors still overlook this process. Site layouts have been usually adjusted from previous plans based on personal experience, subjective opinion, and a first-come-first-served policy. These adjustments can lead to trial and error, ambiguity, inefficiency, and insufficient space [2]. A systematic approach has rarely been used for the process of CSLP [3].

Usually, building construction projects require temporary facilities (TFs) to support construction activities on site. These facilities includes, but are not limited to material storages, rebar fabrication and bending yards, residence facilities (e.g. site office), labor resting rooms, guardhouses, and haul roads, in order to support the various construction activities [4]. The primary task of CSLP is to position these facilities at the best location so that it can improve work performance on site. The problem of CSLP is usually formulated as facility location optimization problem, where specific objectives can be achieved with a set of constraints. The optimization process involves searching for optimal or nearly optimal facility location in available site spaces. There are two methods, namely facility-to-location and facility-to-site assignment, that can be used to model CSLP. Facility-to-location assignment method involves allocating a set of predetermined facilities to a set of predetermined locations, with the number of locations being equal or greater than the number of facilities. On the other hand, facility-to-site method assigns a set of predetermined facilities to all free areas on site [5].

Previous studies have employed both heuristic and exact methods to address the CSLP problems. Heuristic methods rely on algorithms that systematically try to achieve a predefined objective, meaning that the algorithms can find acceptable solutions within limited computing time [6]. Heuristic algorithms including Genetic Algorithm (GA) [7], Particle Swarm Optimization (PSO) [1] and Ant Colony Optimization (ACO) [8] have been commonly used to perform the optimization process. There are also some previous studies that have used exact methods such as simplex, branch and bound, and cutting plane algorithms to solve the CSLP problems. These methods can provide optimal solutions for both single or multi-objectives problems. However, they are not suitable for medium-sized nor large-sized projects [9].

2. Problem statement

Many CSLP models that have been developed in previous studies such as the studies by Osman [10], Lam, Ning [11], Papadaki and Chassiakos [5], and Hammad [12], used facility-to-location assignment as the method for assigning facilities to site area. Their models assumed that every pre-determined location can accommodate any pre-determined facilities, overlooking the size of facility which is a crucial aspect of a real construction site. Furthermore, this assumption restricts the model to search for solutions within given spaces as the locations have already been pre-determined.

Many CSLP models have been developed by previous scholars. Most of their approaches aim to minimize transportation cost or total travel distance by applying relative proximity weight between facilities. Proximity weight is a concept that is usually used to represent the relationship between a pair of TFs how close or far they should be positioned from each other [1]. The closeness relationship can be determined either based on subjective or objective judgement [13]. However, there are only limited studies that have examined the effectiveness of close relationships that deals with numerous large facilities and non-linear constraints.

Moreover, tower cranes are essential equipment for the vertical transportation, installation, and positioning of building components in high-rise buildings. Previously, the most studies of CSLP assumed that tower cranes have been predefined at pre-determined locations. There are also some previous scholars such as Tam, Tong [14], Birewar [15], and Wang, Zhang [16] that attempted to find the optimal locations for tower cranes, and material supply points while assuming that other types of TFs are positioned at pre-determined location, and ignoring the interaction between the tower cranes and TFs in terms of safety and work efficiency on site. This could limit the flexibility and capability of their models to search for locations in a way that represents the actual requirement of the construction site.

In this study, a model for CSLP is developed to search for nearly optimal solution for CSLP using GA and grid system. GA is employed to perform the optimization process that searches all free site areas to minimize the bias for facility location. Trapezoid shape is adopted for construction site, and rectangular shape for TFs. The study also investigates the effectiveness of closeness relationship value on the developed model. The model has been developed with an assumption that all facilities are not allowed to be relocated once the optimal site layout is found.

3. Literature review

The literature has been reviewed on the topic of success criteria for the CSLP, formulation of CSLP problems and optimization techniques. To ensure the success of CSLP, the there are some criteria that can be used as success indicators of site layout. Lam, Tang [17] and Lee [18] identified three key criteria that can ensure the success of site layout. These criteria include workflow, information flow, safety and environment. A well-developed site layout can ensure environmental and site safety, and facilitate the flow of material, equipment, information and personnel on the construction site [18].

The problem of CSLP is usually formulated as facility location optimization problem, where specific objectives can be achieved with a set of constraints. Construction site layout can be modeled either as a quadratic assignment problem (facility-to-location assignment) or as facility-to-site assignment problem [5]. Some related research assumed that the number of predetermined locations should be equal or greater than the number of predetermined facilities. The problem becomes an unequal area layout problem when some of predetermined locations are only able to accommodate some of the facilities. Both methods can be applied to solve equal-area CSLP or unequal-area CSLP depending on whether all locations can accommodate every predetermined facilities or not [5]. Many CSLP models that have been developed in previous studies such as the studies by Osman [10], Lam, Ning [11], Papadaki and Chassiakos [5], and Hammad [12] used facility-to-location assignment as the method for assigning facilities to construction site area. Using this method restricts the model to search for other better solutions as the locations have already been pre-determined. Moreover, most of the existing models in the literature used a rectangular shape to represent the construction site and ignored safety and environmental aspects, which is impractical and does not reflect real-life situations.

Selecting an appropriate technique for the optimization process is another important step in solving CSLP problem. Previous studies have solved the CSLP problems using two categories of optimization methods: Exact and Metaheuristic methods. Exact methods provide an optimal solution for the optimization of either single or multi-objective. These methods provide exact solution by putting a lot of mathematical effort [9]. An example of the studies that used exact method to solve the CSLP problem is by Easa and Hossain [4]. They used branch and bound approach and introduced linear programming model to optimize single objective site layout. Another example is a study conducted by Hammad, Rey [19]. They applied a cutting plane algorithm to minimize distance between facilities and used space discretization to analyze site space. However, these methods are not applicable for large-sized problems. On the other hand, heuristic methods use the algorithms that systematically try to achieve a predefined objective, meaning that the algorithms can find acceptable solutions within limited computing time [6]. These methods are more applicable to solve large size problems of CSLP. Heuristic algorithms including Genetic Algorithm (GA) [7], Particle Swarm Optimization (PSO) [1] and Ant Colony Optimization (ACO) [8] have been commonly used to perform the optimization process.

PSO is a stochastic optimization inspired by the social behavior of birds flocking or fish schooling. It aims to locate a favorable position for achieving specific objectives [20]. Zhang and Wang [21] proposed PSO-based model to solve an equal-area facility layout problem with space discretization. Their model used a priority-based particle solution representation and formulated the problem as a quadratic assignment problem. Benjaoran and Peansupap [1] also proposed a model using PSO to solve the problem. Their model was developed based on a grid system and aimed to minimize worker travel distances between facilities. However, the effectiveness of the closeness relationship parameter still needs to be investigated, as the results heavily rely on it.

Singh [8] proposed a method for solving the problem of unequal temporary facility using ACO algorithm, inspired by the foraging behavior of real ants. Their model considered facility shapes such as triangular and elliptical shapes, and natural obstacles. Lam, Ning [11] employed also ACO to solve the problem of planning the layout of a construction site in a hypothetical project of medium size. Their study used fuzzy reasoning and the entropy technique to determine the proximity between various facilities. Although ACO has been successfully applied to solve the problems, its coding process is complex. ACO method of representing problems is appropriate for the assignment problem, in which discrete locations are predetermined, and solutions are encoded using permutation sequences [1].

GA has been widely recognized as a useful optimization tool for solving the problems of CSLP [17]. GA is a type of computational model that imitates the principle of evolution proposed by John Holland in 1975 [22]. He converted the principles of evolution into a computational algorithm. Today, GA is generally regarded as a problem optimizer and has been applied in many different research areas. It mimics an evolutionary process by encoding potential solutions as an initial population of parents or chromosomes. It then generates a new population of offspring through genetic operators, which include selection, crossover, and mutation. Selection involves choosing the fittest parents for reproduction, while crossover involves combining two parent chromosomes to create a new offspring. Mutation introduces small changes to the offspring's gene. Through these mechanisms, GA is able to iteratively refine potential solutions until an optimal solution is found [23]. There are several reasons that make GA more suitable for CSLP problems. First, the concept is easy to use and understand. Any optimization problem can be described by chromosome encoding. Second, GA is one of the most popular metaheuristic methods that can solve hard NP problems effectively because of their ability to escape from local optima during the optimization process [5]. Third, GA has a mechanism that can handle constraints better than other metaheuristic methods such as PSO and Discrete PSO [24].

4. Methodology

In order to develop the model, several modules including input module, constraint module and objective function module are described in this section. Furthermore, the optimization process facilitated by the use of GA is detailed in this section.

4.1 Input Module:

The input module serves as an important component of the optimization model. It provides the initial data that is required to run the optimization. Several assumptions required for the model are described as follows:

A two-dimensional grid: grid system is employed to present the shape of construction sites, TFs and buildings in this study. Trapezoid shape and a grid unit of 1m x 1m are adopted for construction site shape. TFs are presented in a rectangular shape as shown in Fig. 1.

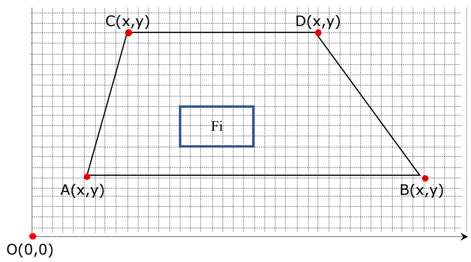

Fig. 1 Representation of construction site and facility shape

Predetermined facilities: Some facilities must be placed in predetermined locations and should not be moved during the construction period. These facilities are modeled as rectangular, with their dimensions and center coordinates serving as inputs for the optimization.

A set of predefined-center coordinates of facilities will serve as potential solutions for initial population in the optimization process. The dimensions of facilities and working radius of tower cranes will be used as input for constraint and objective function calculation.

4.2 Constraint module

4.2.1 Site boundary

Site boundary constraint ensures that all TFs are placed within the site boundary. This constraint can be done by allowing every corner point of rectangular facility to be inside a trapezoid as shown in Fig. 2. To work out such constraint, Eq. (1) is applied as follows:

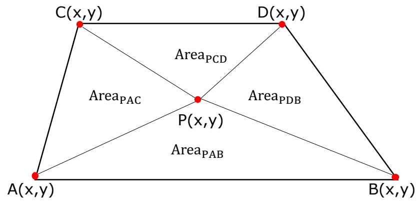

Fig. 2 Criteria for point P inside trapezoid

$$\mathrm{Area}_{PAC} + Area_{PCD} + Area_{PDB} + Area_{PAB} = Area_{ABDC} \quad (1)$$

4.2.2 Non-overlapping constraint

Non-overlapping constraint allows the algorithm to find a location for a facility where it does not overlap with another as shown in Fig. 3. Eq. (2), (3) and (4) are applied for non-overlapping constraint in the optimization engine [25].

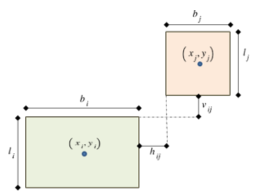

Fig. 3 Non-overlapping objects

$$0.5(\mathrm{b}_i + b_j) + h_{ij} - |x_i - x_j| \le 0 \quad \text{(horizontal range)} \quad (2)$$

$$0.5(l_i + l_j) + v_{ij} - |y_i - y_j| \le 0 \quad \text{(vertical range)} \quad (3)$$

$$\mathrm{Min}\left(0.5(b_i + b_j) + h_{ij} - |x_i - x_j|,\ 0.5(l_i + l_j) + v_{ij} - |y_i - y_j|\right) \le 0 \quad (4)$$

(x_i, y_i) and (x_j, y_j) are center coordinates of facility i and facility j, b_i represents the breadth of facility i, l_i represent the length of facility i, h_{ij}, v_{ij} represents the perpendicular distance between nearest edge of facility i and facility j in horizontal and vertical range respectively.

4.2.3 Tower crane reachability

Tower crane is usually located at an optimized location for the entire period of the construction. Processing facilities including, but not limited to material storage, laydown area and rebar fabrication and bending yard that serve as material supply points, must be positioned within tower crane's coverage area to avoid rehandling of material transportation. This constraint can be worked out by applying Eq. (5).

$$\sqrt{(x_i - TX_t)^2 + (y_i - TY_t)^2} - R \le 0 \quad (5)$$

Moreover, radius of tower crane or crane boom should be able to reach every corner of building known as demand points. For building (j) and tower crane (t) with reachable radius R, this constraint is mathematically expressed as in Eq. (6) [25].

$$\sqrt{(FCX_i - TX_t)^2 + (FCY_i - TY_t)^2} - R \le 0 \quad (6)$$

(FCX_i, FCY_i) are the farthest corner coordinates of building or facility (j) from center point of tower crane (t), (TX_t, TY_t) represent center coordinates of tower crane (t).

4.2.4 Safety for flammable and accommodating facilities

Facilities that store flammable materials and accommodating facilities, including but not limited to site office, labor resting room, and first aid room, shall be positioned beyond the envelope of tower crane to avoid any case of falling objects that may lead to injury of personnel. This constraint can be satisfied by applying Eq. (7) below:

$$\sqrt{(FCX_i - TX_t)^2 + (FCY_i - TY_t)^2} - R \ge 0 \quad (7)$$

4.2.5 Collision avoidance

If more than two tower cranes are used for the site operations, there is a potential that collision between the cranes occurs. To minimize this risk, a geometric constraint is introduced as shown in Eq. (8) below:

$$\sqrt{(TX_{ti} - TX_{tj})^2 + (TY_{ti} - TY_{tj})^2} \ge Max(R_i, R_j) \quad (8)$$

(TX_{ti}, TY_{ti}) and (TX_{tj}, TY_{tj}) are the center coordinates of tower crane (i) and tower crane (j). R_i, R_j represent the working radius of tower crane (i) and tower crane (j) respectively.

4.3 Objective function

The objective of the proposed model is to minimize the total distance between facilities. The function is descripted as fitness function for the optimization [23], which is mathematically expressed as in Eq. (9).

$$Fval = Min\left(\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} d_{ij} C_{ij}\right) \quad (9)$$

The distance between facility i and facility j is calculated by the following Eq. (10):

$$d_{ij} = \sqrt{(X_j - X_i)^2 + (Y_j - Y_i)^2} \quad (10)$$

n represents the total number of facilities including fixed and temporary facilities, tower cranes, and buildings. $(X_i, Y_i), (X_j, Y_j)$ are center coordinates of facility i and facility j respectively. C represents the total closeness relationship matrix in terms of material and equipment flow (C_{MEF}), safety and environment (C_{SE}), and movement of personnel and information flow (C_{mpi}). Therefore, the total closeness relationship is expressed by Eq. (11).

$$C = C_{MEF} + C_{SE} + C_{MPI} \quad (11)$$

In each criteria, the closeness relationship between a pair of facilities is rated based 6 degrees as shown in **Table 1** [3].

Table 1 Proximity weights used for closeness relationships

Desired relationship	Proximity weight
Absolutely necessary (A)	$6^5 = 7776$
Especially important (E)	$6^4 = 1296$
Important (I)	$6^3 = 216$
Ordinary closeness (O)	$6^2 = 36$
Unimportant (U)	$6^1 = 6$
Undesirable (X)	$6^0 = 1$

4.4 Genetic Algorithm for facility location optimization

Genetic algorithm (GA) is employed for the optimization process in this study. Solution encoding is an important issue in GA as it represents a solution to the problem. Center coordinates of temporary facilities including tower cranes are regarded as gene variables, and these gene variables are encoded into a chromosome. Each encoded chromosome of gene variables represents a potential solution. This encoding method is called value encoding in which each gene represents the center coordinate value of facility. Let n be the number of temporary facilities including tower cranes, then solution to the problem will be represented in a chromosome length of 2n as shown in **Table 2**.

Table 2 Encoded chromosome of gene variables

x1	y1	x2	y2	x3	y3	…	…	xn	yn

xi, yi are the decision variables, and must be the value within the site boundary of ABCD, for i = 1, 2, 3,..., n. The GA engine will search for these variables that satisfy the predefined constraints.

To reduce searching time for feasible solutions, several chromosomes that fulfill the constraints are required to initialize the algorithm. A wide range of the chromosomes called initial population can help to ensure diversity in the gene pool, promoting exploration of different solutions and avoiding premature convergence to local solutions. Fig. 4 illustrates the optimization process of GA inspired by Holland [22].

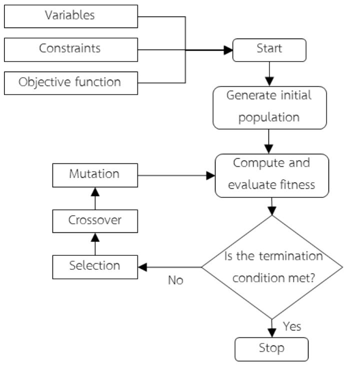

Fig. 4 Optimization process of GA

Once the initial populations are generated, they will be evaluated based on fitness value calculated from the fitness function. Chromosomes that have better performance have higher chance of getting selected for reproduction. selection is a process that chromosomes are selected from the population to be parents for the next process. Tournament selection method is employed for this study. The tournament selection chooses a k number of random individuals from the population and copy the best individual from this group for reproduction, and repeat N times [26]. N is the number of potential solution or population size. Once parents are selected, the crossover operator is used to generate two offspring. Similar to the process of nature, crossover produces new individuals that have some genes from both parents. The present study uses two-point crossover. A two-point crossover selects two random points on chromosomes and the genes of each chromosome (parents) are exchanged at these points. Through selection and crossover, some good genes may be randomly lost. To prevent this, mutation is applied to bring back these genes for the offspring with the probability of mutation *p(mut)* [23]. Mutation It is a process of randomly modifying genes in a chromosome which is essential to the convergence of global optima. It helps the algorithm escape the local optima. In this study, power mutation with *p(mut)* = 0.4 is applied as it is suitable for the problem that has integer variables. A new generation is created after mutation. The performance of each chromosome in the new generation is evaluated based on the fitness value, and this process repeats until the termination condition is satisfied. The maximum number of generations is used as termination condition in this study.

5. Prototype testing

The GA toolbox in MATLAB is utilized to run the optimization. A set of constraints and objective function are saved as function files. Then, a set of codes called "Algorithm" has been written to import the data input from Spreadsheet, and to run the optimization. All files that are required to run the optimization must be saved in the same folder where MATLAB can look for them in the current working dictionary.

A prototype has been developed and tested to evaluate model. 10 temporary facilities (F1-F10) will be located by GA and 9 facilities (F11-F17, B1 and B2) are fixed at predetermined locations. Facilities with their dimensions and coordinates are illustrated in **Table 3**.

The prototype is attempted to run the algorithm 10 times by increasing 100 generations in each run. it is observed that the fitness value dropped significantly from generation 1 to generation 400 as shown in Fig. 6. However, the graph started to fluctuate after 400 generations. This is because GA is a stochastic algorithm; therefore, the solution may be slightly different when it nearly reaches the optimal.

Total closeness relationships are calculated from Eq. (11). The prototype is tested to evaluate the efficiency of the model and the effectiveness of closeness relationship. The relationship between material storage (F7) and building 1 (B1) is selected for investigation. This relationship obtained highest score of 23328 among others as shown in Fig. 5. This relationship value was obtained by summing up 7776 for c_{MEF}, 7776 for c_{SE}, and 7776 for c_{mpi}. This value may vary because the proximity degree is assessed based on user's preference.

ID	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	B1	B2
F1	0	1728	78	18	3888	78	13	13	3	3	228	18	13	13	8028	23328	15768	8	8
F2		0	78	48	1548	468	78	43	3	3	13	13	8	8	23328	23328	15768	13	13
F3			0	0	1728	438	288	13	8	8	43	43	8	8	468	108	108	48	48
F4				0	78	43	3888	2598	1548	1548	1548	1368	1308	1308	43	1368	1368	258	258
F5					0	2628	1338	228	8	8	18	18	3	3	15768	23328	10368	43	43
F6						0	1308	48	3	3	18	18	8	8	18	648	648	18	18
F7							0	1338	16848	16848	16848	9108	3	3	18	48	48	23328	2808
F8								0	23328	23328	1368	1368	3	3	18	48	48	15768	10368
F9									0	0	18	18	7813	7813	0	3	3	15588	23328
F10										0	18	18	7813	7813	0	3	3	108	23328
F11											0	0	0	0	0	0	0	0	0
F12												0	0	0	0	0	0	0	0
F13													0	0	0	0	0	0	0
F14														0	0	0	0	0	0
F15															0	0	0	0	0
F16																0	0	0	0
F17																	0	0	0
B1																		0	0
B2																			0

Fig. 5 Total closeness relationship matrix

Table 3 List of facilities used in this study

ID	X	Y	Facility	Type	Dim(b, l)
F1	x1	y1	Car parking	TF	6,10
F2	x2	y2	Guardhouse	TF	3,3
F3	x3	y3	Labour resting area	TF	4,4
F4	x4	y4	Machine room	TF	4,4
F5	x5	y5	Site office	TF	8,10
F6	x6	y6	Washroom	TF	4,3
F7	x7	y7	Material storage	TF	15,8
F8	x8	y8	Rebar fabrication and bending yard	TF	20,12
F9	x9	y9	Tower crane#1 (R=35m)	TF	2,2
F10	x10	y10	Tower crane#2 (R=32m)	TF	2, 2
F11	37	13	Material hoist#1	Fixed	2,2
F12	90	29	Material hoist#2	Fixed	2,2
F13	52	33	Refuse chute#1	Fixed	4,2
F14	110	29	Refuse chute#2	Fixed	4,2
F15	33	0	Site entrance	Fixed	6,2
F16	33	20	Haul road#1	Fixed	6,40
F17	78	37	Haul road#2	Fixed	84,6
B#1	47	17	Building#1	Fixed	18,30
B#2	101	15	Building#2	Fixed	24,26

The algorithm was set to run for 1000 generations with the population size of 100 and was repeated 5 times. Average improvement from the initial solution was achieved by 20% as show in **Table 4**. The individual that has the best (lowest) fitness value after 1000 generation is also illustrated in **Table 4.**

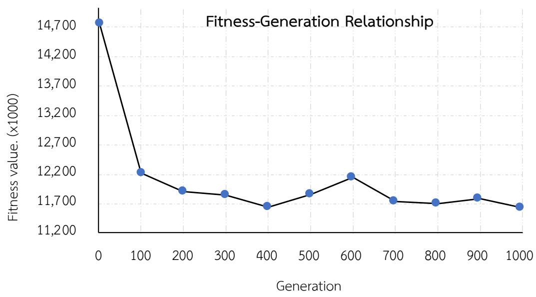

Fig. 6 Fitness-generation relationship

Table 4 Variations of fitness values

No. testing	Fitness value	Avg. improvement
Initial	14,771,781	20%
1	11,646,415	
2	12,623,190	
3	11,651,597	
4	11,473,525	
5	11,889,623	
Average	11,856,870	

x1	y1	x2	y2	x3	y3	x4	y4	x5	y5	x6	y6	x7	y7	x8	y8	x9	y9	x10	y10
24	21	25	14	17	9	48	52	23	7	21	14	71	15	70	25	62	17	97	29

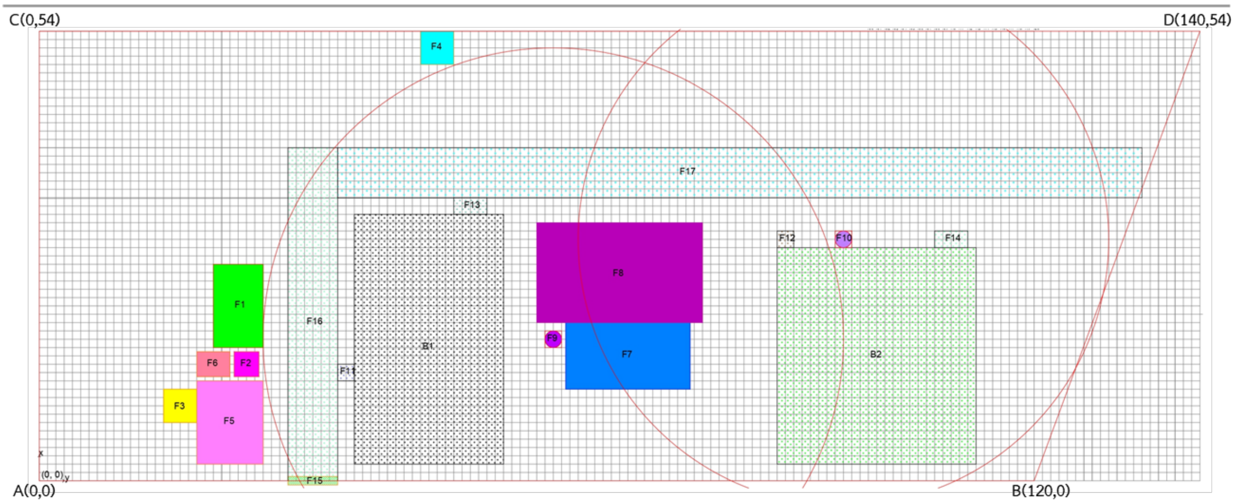

Fig. 7 Nearly optimal site layout generated by GA

The result in Fig. 7. shows that the model can find not only locations for facilities, but also for the tower cranes with a set of predefined constraints optimally. From Fig. 5, it is observed that the relationship between F7 and B1 obtained highest score among others. As a result, these facilities were positioned close to each other. The relationship F4 and F1, F4 and F2, F4 and F3, F4 and F5, F4 and F6 obtained low scores for closeness relationship. As a result, F4 should be located far away from F1, F2, F3, F5, and F6. However, the result is not significant for the location of guardhouse (F2) although it is desired to locate it close to the site entrance (F15). This is because GA considers not only the relationship score between site entrance (F15) and guardhouse (F2), but also the relationship scores between site entrance to other remaining facilities, the score between guardhouse (F2) and other remaining facilities with long distances.

6. Conclusions

Effective site layout is crucial for ensuring safety and enhancing work efficiency on a construction site. Various CSLP models have been developed in previous studies. This study proposed a model to improve the facility assignment, the tower crane location, and the effectiveness of closeness relationship using genetic algorithm. The facility assignment is facilitated using 1mx1m grid system, similar to the approach used in the studies by Benjaoran and Peansupap [1], and Lee [18]. The facilities are assigned to any available site area represented in trapezoid shape. This study included the optimization of tower crane and TF location simultaneously.

The prototype was developed to test the model using the GA optimization toolbox that is available in MATLAB. The results from testing indicated that the proposed model was able to optimize the facility location efficiently, and more flexible compared to previous studies by Lee [18] and Papadaki and Chassiakos [5] that used GA.

The proposed model can assist project managers to arrange facility and tower crane more efficiently. However, It should be noticed that input data such as initial location, facility size and proximity weight relationship are predefined by the user. The quality of solution relies on the diversity of initial populations that are provided during the genetic search. The model was developed on the assumption that TFs cannot be rotated to another angle. This assumption may limit the algorithm to find better arrangement of TFs. The future research could be developing a model that allows the TF to rotate during the optimization.

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