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GA-ANN model for optimizing the locations of tower crane and supply points for high-rise public housing construction

C. M. TAM* and THOMAS K. L. TONG

Department of Building & Construction, City University of Hong Kong, 83 Tat Chee Avenue, Kowloon, Hong Kong

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Site layout planning is a complicated issue due to the existence of a vast number of trades and inter-related planning constraints. In this paper, artificial neural networks are used to model the non-linear operations of a key site facility: a tower crane — for high-rise public housing construction. Then genetic algorithms are used to determine the locations of the tower crane, supply points and demand points by optimizing the transportation time and costs. The scope of this study confines to a defined area of construction: the structural concrete-frame construction stage of public housing projects. The developed genetic algorithm model for site facility layout and the artificial neural network model for predicting tower-crane operations are evaluated using a practical example. The optimization results of the example are very promising and it demonstrates the application value of the models.

Keywords: Site layout, genetic algorithms, tower crane, public housing construction

Introduction

Facilities layout is believed to be the heart of efficient production. Construction site facilities layout planning (FLP), which defines the types, quantities and positioning of the mechanical plant, storage areas and fabrication yards has significant impacts on productivity, costs and duration of construction (Tam *et al.*, 2001). Although FLP is such a critical process in construction planning, the analysis of FLP is always difficult due to the existence of a vast number of trades and inter-related planning constraints, which create hurdles in optimizing the locations of key facilities on construction sites.

For the construction of high-rise public housing in Hong Kong, tower crane is the key facility for vertical transportation, especially for the heavy prefabrication units and large panel formwork. In this regard, the positions of tower crane and its surrounding supply points are crucial in the FLP process. There is strong need for a scientific approach that helps reduce human errors due to the different training background and emotional conditions of planners. Tam *et al.* (2001) presented an approach combining an analytical hoisting time calculation algorithm and a GA model in optimizing the tower crane transportation time. This paper presents an alternative approach by adopting artificial neural networks (ANN) and genetic algorithms (GA) techniques to optimize the positions of tower crane, supply and demand points by minimizing the transportation times.

The objectives of this paper are to investigate and analyse the relationship between the key storage areas and the tower crane by ANN and to develop a genetic algorithm model to optimize them, taking into account the complexity of the relationship between these facilities.

Previous studies

Site conditions – such as the topographical layout, the building blocks layout and the adjacent environment – are

*Author for correspondence. E-mail: bctam@cityu.edu.hk

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unique for each site. Consequently, they result in a great variation in site layout strategies and approaches. For high-rise building construction, the allocation of temporary facilities keeps changing and is inter-related with the progress of construction work, which further complicates the planning process. Optimization of FLP (a non-linear and discrete system) using a scientific approach is difficult, if not impossible, to achieve. Hence, FLP of construction sites in Hong Kong has been carried out mainly through human judgments. Because of human involvement, there are no conditions that lead consistently to the same result. Therefore, FLP is usually an art rather than a science.

Some researchers have used mathematical and computation techniques to search for optimal solutions. However, these scientific techniques normally require a certain degree of simplification from the reality, resulting in the loss of information at the modelling stage. Previous research works can be classified into three approaches: mathematical modelling (expert knowledge with minimal use of computer), computer modelling (expert plus the use of computer) and artificial intelligence (use of computers).

For Approach 1, mathematical models are established to map the relationship of different site facilities with site factors. For instance, Choi and Harris (1991) proposed a mathematical model for determining the most suitable single tower-crane location. The model aims to optimize the position of a tower crane that yields the least transportation time. Rodriguez-Ramos and Francis (1983) proposed a model in locating the parking position of crane's hook between movements.

For Approach 2, the expert knowledge is assisted with computers to determine site layout planning. For example, Gray and Little (1985) developed a computer package using decision flowcharts to optimize crane locations for irregular-shaped buildings. Wijesundera and Harris (1989) and Zhang *et al.* (1999) used the Monte Carlo simulation approach to optimize crane locations.

For Approach 3, researchers adopt artificial intelligence to minimize the dependence of computers on human judgments. Li and Love (1998) and Philip *et al.* (1997) applied genetic algorithms to optimize a set of predetermined facilities. However, the model has been much simplified with the shapes of facilities considered to be rectangular and without due consideration to the size constraint and space competition between facilities. Yeh (1995) applied annealed neural networks to solve construction site facility layout problems. Oversimplification makes the model and the solution out of the score of applications.

In addition to the above, there are two common ways in modelling site facility layout planning: analytical (Tam *et al.*, 2001) and statistical models (Leung and Tam, 1999). For the analytical, the modeller must first decide the factors of the system to be included in the model. The objectives of the model should be established, reference to which, the significance of each factor is then evaluated. For example, in modelling the hook travelling time of tower crane, the objective is to determine the time for a hook travelling from one position to another and the factors to be considered should include the physical parameters of tower crane operations and the geometrical properties of the layout. The success of the model depends on how well the significant factors and the relationships between them are defined.

However, the definition of the objectives and their function is subjective, depending on individuals who define the system. The objectives need to describe a stated problem or project goals, based on which, the boundaries of the system and the level of modelling detail are established. This subjective approach results in smoothing out some significant parameters of the actual system. Assessments of design alternatives in terms of the specified performance measures are considered as model outputs. The entire model building approach is performed iteratively. When recommendations can be made based on the assessment of alternatives, an implementation phase is initiated. Implementation should be carried out in a well-defined environment with an explicit set of recommendations.

The hook travelling time of a tower crane developed by Tam *et al.* (2001) is a typical analytical model. The modeller analysed the physical system for tower crane operations. The factors of the operations were defined and the operational principles of the hoisting procedures were determined.

Another modelling approach is the statistical study. Leung and Tam (1999) established a regression model of tower crane hoisting time. This model is a polynomial function in which the input parameters are the independent variables and the output values are the dependent variables. The major procedure of such models is to select a set of related factors. The modeller first identifies the main factors from his own expert knowledge of the system domain, then the relationship between factors is identified by employing work-study techniques or questionnaire surveys. Statistical tests on the data set are used to screen out the most significant factors. These statistics include the t-test, the least square test and the principle components test, etc. The level of reliability is measured by the value of the coefficient of determination – R^2.

ANN model for predicting tower crane hoisting time

In this study, a new approach by combining artificial neural networks (ANN) and genetic algorithms is proposed. ANNs are used to model the non-linear nature of operations of the key site facility: a tower crane, for high-rise public housing construction. Using the predicted values from the ANN models, genetic algorithms are used to produce the optimization model in site facility layout.

The use of neural networks for construction engineering was explored by Moselhi *et al.* (1991). The back-propagation algorithm was used for estimating construction productivity (Chao and Skibniewski, 1994), and evaluation of acceptability of new construction technology (Chao and Skibniewski, 1995). Kartam (1996) used neural networks to determine optimal equipment combinations for earth-moving operations. Adeli and Wu (1998) formulated a regularization neural network and presented the architecture of the network for construction cost estimation. Hegazy and Ayed (1998) used a neural network approach to manage construction cost data and developed a parametric cost-estimating model for highway projects. Sonmez and Rowings (1998) presented a methodology based on regression and neural network modelling techniques for quantitative evaluation of the impact of multiple factors on productivity. Portas and AbouRizk (1997) developed a neural network model to estimate construction productivity for the concrete formwork task.

Shi (1999) stated that four steps are required in the development of a neural-network-based system: (l) analyse the real world problem and select a proper network architecture; (2) collect and pre-process data for training and testing; (3) design, train and test the network model; and (4) deploy the network. Extending the response concept defined by Smith *et al.* (1995), a tower crane hoisting system can be defined mathematically as:

$$T = f(k_1, k_2, \ldots, k_m)$$

where T is a response such as hoisting time (T, in practice, is a set of expected parameters, $T = \{t_1, t_2, \ldots, t_p\}$. $k_1, k_2, \ldots, k_m$ are the affecting factors such as weight of the load, and can be defined by another set $K = \{k_1, k_2, \ldots, k_m\}$.

This is a typical prediction problem in which the response is fully determined by a set of affecting factors. Back propagation (BP) networks have been proven to be very effective for this purpose. The first step in constructing a BP network is to determine the expected output parameters and the corresponding affecting factors.

Affecting factors

Leung and Tam (1999) described a detailed data collection process using work study techniques, through which they have identified a list of factor affecting both the supply and return time of a tower crane. Subsequently, Tame *et al.* (2001) then used the Group Method of Data Handling (GMDH) algorithm to further shortlist the major affecting factors. These factors were found significant in contributing to the supply time model (factors 1, 2, 4, 5 and 6) and the return time model (factors 1–5) and they are described as follows:

(1) Loading point (LP) – the position of loading points where loads are stored and await hoisting. The load locations have direct effects on the magnitude of angular movements and radial movements.
(2) Angular movement (AM) – the angle between the loading point and the unloading point.
(3) Simultaneous movement (SM) – this describes the portion of hoisting operations in which the radial movement and angular movement are activated at the same time. In this study, it is the ratio of the simultaneous movement time and the total hoisting movement time. (For the return time model only.)
(4) Hoisting height (HH) – the vertical hoisting distance between the loading point and the unloading point measured in metres (m).
(5) Unloading point (UP) – this is usually within the area of a floor layout and is the radial distance measured in metres between the unloading point and the centre of a crane.
(6) Weight (W) – the weight of a load measured in kilograms (kg). (For the supply time model only.)

The proposed ANN model has taken the geometrical plan and height of a high-rise building into account by considering the factors on the horizontal and vertical travelling distance, the angle of swing, the loading and unloading positions. The input and output variables are of the continuous type. The data has been automatically normalized by the software used (NeuroShell 2™) and the range of data is bounded by the maximum and minimum values of each input variable.

Network architecture

The one expected parameter and the five affecting factors are treated as the output and input neurons of the BP network, respectively, as shown in Figure 1. The number of hidden layers and the numbers of neurons in each hidden layer are selected on the basis of the accuracy with which the networks respond to training and test patterns.

Multilayer feedforward network

Figure 1 shows the multilayer feedforward network (MLFF) architecture with three layers: input, output and intermediate or hidden layers. Different activation

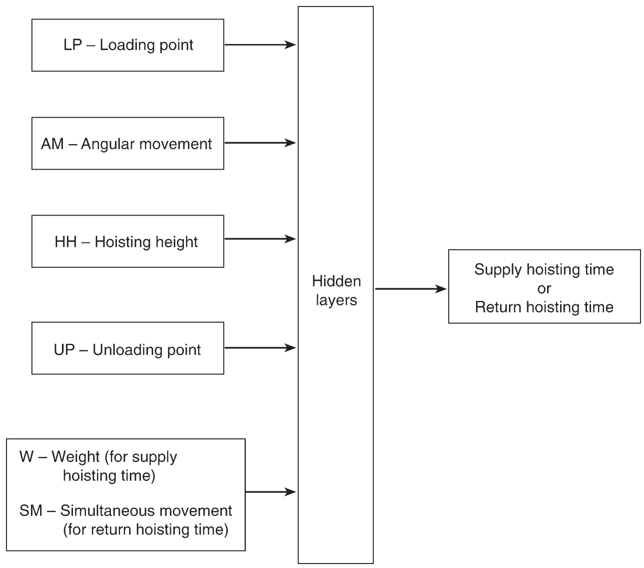

Figure 1 BP network architecture for supply and return hoisting time

functions applied to hidden layer slabs detect different features in a pattern processed through a network. For example, a network design may use a Gaussian function on one hidden slab to detect features in the mid-range of the data and may use a Gaussian complement in another hidden slab to detect features from the upper and lower extremes of the data. Thus, the output layer will get different 'views of the data'. Combining the two feature sets in the output layer may lead to a better prediction. As suggested by NeuroShell 2™, a 3-hidden-slab network with different activation functions is used to establish the model. This is a back-propagation network that adds a third slab to the hidden layer.

Training data acts as a coach while training a neural network. The data must be representative and consistent, and cover all situations to which the network will be applied. For instance, if the training data includes only weights between 1000 kg and 5000 kg, the trained network should not be expected to predict precisely situations with weights outside that range. Because of the random nature of construction operations, a small sample of observations may not always provide a global picture of an operation. While noisy data patterns will affect the convergence during training and result in large errors in neural predictions on one hand, a certain level of randomness in training data is essential on the other hand to avoid the situation in which an over-trained network 'memorizes' training patterns and responds incorrectly to testing or predicting patterns. Therefore, collected samples should be re-processed before they are treated as training and test patterns.

Neural network models of hoisting times

Based on the results of identifying factors affecting the hoisting time, five inputs for modelling supply time are used in the neural network models as shown in Figure 1. Since there is a slight difference in the input variables between the supply hoisting time and return time, the supply hoisting time and return hoisting time should be modelled separately. There have been 1301 and 1232 data sets with respect to the supply hoisting time and the return hoisting time respectively, collected from seven construction sites. For the supply hoisting time model, the training data set is composed of 1000 cases, which are obtained from six construction projects, and the verification data set is extracted from the remaining 301 cases of the seventh project. For the return hoisting time cases, there are also 1000 cases for training and 232 cases for testing.

Based on the inputs, outputs, the training data set and test results, the structure of the MLFF network is set to be 5-15-15-15-1 meaning 5, 3×15 and 1 neuron(s) in the input, hidden and output layers, respectively. The momentum coefficient and the 'learning rate' are the principal parameters in a BP learning algorithm, which roughly describe the relative importance given to the current and past error values in modifying connection strengths. In the analysis, the initial learning rate is chosen to be 0.1, with an associated momentum coefficient of 0.1.

For the supply hoisting time model, the mean square error (MSE), mean absolute error, and the minimum and maximum absolute errors were 129.625, 8.952, 0.001 and 39.259 respectively for the MLFF network with a BP algorithm. For the return hoisting time model, the mean square error (MSE), mean absolute error, and the minimum and maximum absolute errors were 51.002, 5.751, 0.005 and 27.015 respectively for the MLFF network with a BP algorithm.

Prediction of hoisting times

Supply time model

In order to test the modelling methods and the performance of the established models in predicting hoisting times, the established supply hoisting time models are used to predict the new data collected from the seventh project. The prediction curves are shown in Figure 2. The adjusted R^2 value is 0.84. The results demonstrate that the neural network models of hoisting times can predict the hoisting time satisfactorily.

Return time model

Similarly, the return time model is verified. The adjusted R^2 value is 0.7803. Figure 3 shows the prediction curves of the return time model. Again, the results are satisfactory.

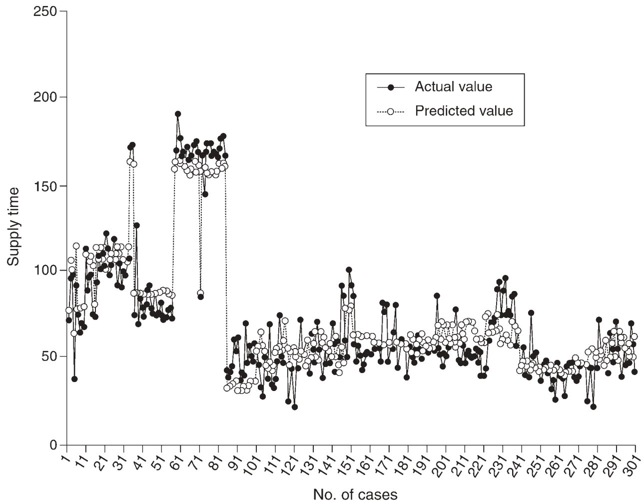

Figure 2 Prediction curves of supply time using an MLFF network with a BP algorithm

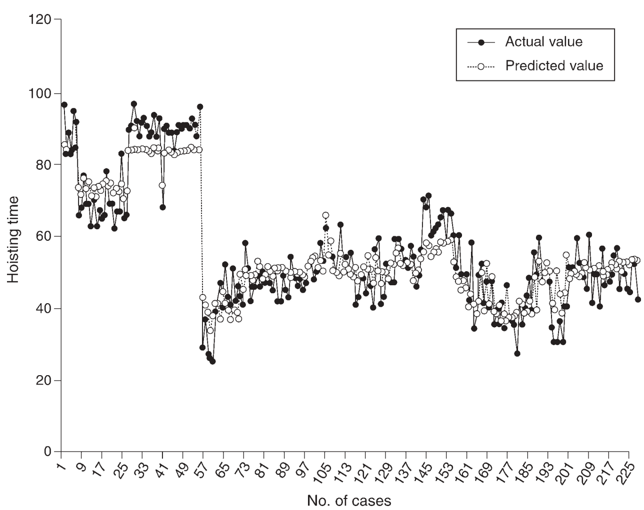

Figure 3 Prediction curve of return time using an MLFF network with a BP algorithm

GA model for site facility layout

The next is to apply the prediction models generated from the ANN to construct a GA model for optimizing site facility layout. Three steps are involved in optimizing the locations of a generic tower crane and supply points. First, the permissible locations of the supply points $\{S_i \mid \text{coordinates of all available supply point locations}, S_i\ (X_{Si}, Y_{Si}, Z_{Si}), \forall i \in [1, 2, \ldots, n]\}$ are determined from the site map, taking into consideration the jib length of tower crane and its radius-load capacity, the required areas of the supply points, and other site constraints. The demand points $\mathbf{D}_\mathbf{i}$ (X_{Di}, Y_{Di}, Z_{Di}) are determined by the geometric shape of the permanent building. The possible locations of tower crane C_{ri} $(X_{Cri}, Y_{Cri}, Z_{Cri})$ are then located, which are dependent on the structural design layout, space provisions for the permanent structure, convenience for other site activities, etc. Using the above information, a GA model is developed to optimize two outputs: the tower crane and the supply-points locations for various trades.

For the GA modelling purposes, the following assumptions are made:

- for each supply and demand pair, the demand nature and levels for transportation are known; e.g. the total number of lifts, nature of the object, maximum load and so on;
- materials transported between a supply-demand pair are handled by one crane only;
- the feasible locations for tower crane and supply points are limited by the site conditions and shape of the permanent building;
- the area of each supply point selected should be large enough to accommodate the storage requirements; and
- the reach of a crane tower is determined by its jib length and the lifting capacity is decided by the radius-load curve. Hence, the locations of both the supply and demand points must fall within the permissible weight-radius circle of the tower crane. Since the demand points are fixed, attention is focused on the permissible locations of supply points.

The following summarizes the essentials of a GA operation:

(1) Establishment of a representation of the problem.
(2) Setting values for the various parameters that the genetic algorithm uses. This process involves the setting of parameters to determine the 'optimal' solution through convergence. These parameters include population size, probabilities of applying genetic operators. The duration for and probability of convergence, therefore, is dependent on the values of the parameters set.
(3) Creation of an initial population of potential solutions. An initial population is randomly generated. The individuals of this population will be a set of chromosomes or strings of characters (letters and/or numbers) that represent all the possible solutions to the problem.
(4) Rating the population in terms of their fitness. A fitness function shall be applied to assess each chromosome in order to measure the quality of the solution encoded. Knowing each chromosome's fitness, a selection process takes place to choose the individuals (presumably, the fittest)

that will be the parents of the next generation. The most commonly used selection schemes include proportionate reproduction, ranking selection and tournament selection.

(5) Population evolution through genetic operators.

After the chromosomes being selected, crossover takes place. Crossover involves exchange of genes between the chromosomes. During this stage, the genetic material of a pair of chromosomes is exchanged in order to create the population of the next generation. Mutation is another genetic operator. During mutation, a portion of the new individuals will be flipped to generate a new bit. Mutation helps to maintain diversity within the population by allowing new members to enter the population and restrain any premature convergence or restore any characteristics that may have been removed from the population earlier (Al-Tabtabai *et al.*, 1999).

Setting values for the parameters

Setting of the population size, probability of crossover and mutation is a trial and error process, which relies heavily on the knowledge and experience of the researchers. The initial parameters are often set at figures that are perceived as sensible based on previous work (Al-Tabtabai *et al.*, 1999). In general, if the problem involves a large search space and many chromosomes, a large population size is warranted. The rate of convergence and avoidance of local maxima/minima traps are other aspects requiring consideration.

Initial population

The initial population is represented with continuous chromosomes, which ensure each chromosome being mapped to a special and predetermined position. It requires two sets of chromosomes: Chromosomes δ_i $\{\delta_i \mid \text{Random numbers}, \forall i \in [1, 2, \ldots, n]\}$ mapped to location number i for each element A_j where $S_{Aj} = \{S_i \mid S_i \in A_j\}$; and Chromosomes $\varepsilon i \in (1, i)$ mapped to locations numbered C_{ri} for tower crane positions. A mixed integer program (MIP) is used to denote the selected tower crane locations where n is the integer used to indicate the state of selection.

$$[N \mid Cr_i] = \begin{cases} 1 & \textit{selected to be tower crane position} \\ 0 & \textit{otherwise} \end{cases}$$
$$\forall i \in [1, 2, \ldots, n] \quad (1)$$

Rating the population in terms of their fitness

The fitness of the chromosome is assessed using the total transportation cost given by:

$$\min TC = \min \{N * [\sum_{j=1}^{n} \sum_{k=1}^{n} T_{jk} Q_{jk} C_{jk}]\} \quad (2)$$

where T is the hoisting time predicted by the ANN model:

$$= T_{SHT} + T_{RHT} \quad (3)$$

T_{SHT} is the supply hoisting time predicted and T_{RHT} is the return hoisting time predicted

$$\rho(D_i) = \sqrt{(XD_i - XCr_i)^2 + (YD_i - YCr_i)^2} \quad (4)$$

$$\rho(S_i) = \sqrt{(XS_i - XCr_i)^2 + (YS_i - YCr_i)^2} \quad (5)$$

Figure 4 shows all the parameters of the tower crane operations. Time for trolley tangent movement is as follows:

$$T_w = Arc\cos\left(\frac{l_i^2 - \rho(D_i)^2 - \rho(S_i)^2}{2 * \rho(D_i) * \rho(S_i)}\right) * \frac{180}{\pi} \quad (6)$$
$$(0 \le Arc\cos(\theta) \le \pi)$$

where w is all possible and available supply locations; j is the element number; i is the location number of each position; A_j is all supply locations available for element j; S_i is the supply point at location number i; S_i (XS_i, YS_i, ZS_i) is the co-ordinate of supply point i; D_i is the demand

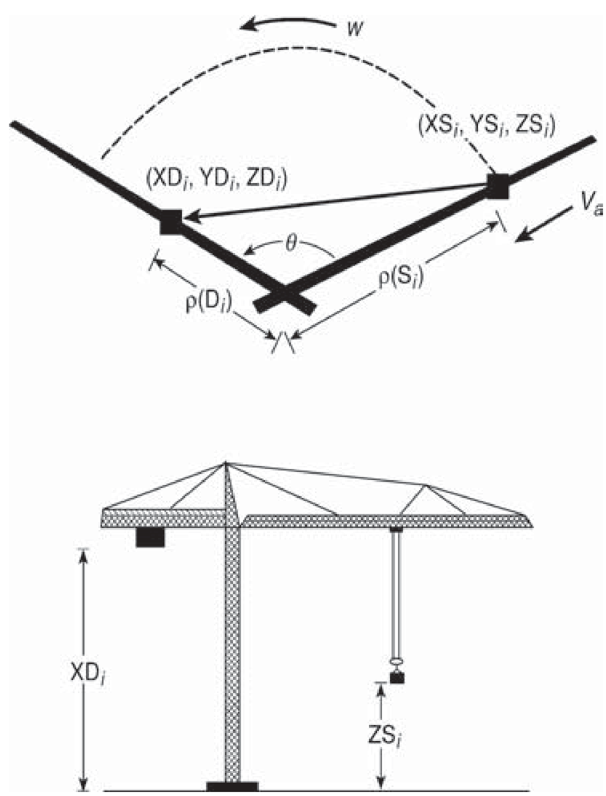

Figure 4 Hook travel time

point for element j; D_i (XD_i, YD_i, ZD_i) is the co-ordinate of demand point i; S_{Aj} is the selected supply location number of element j; k is the number of times that the transportation of element j needs to repeat; Q_{jk} is the quantity of material flow from S_i to D_j; C_{jk} is the cost of material flow from S_i to D_j per unit quantity and unit time; TC is the total cost; Cr_i (XCr_i, YCr_i, ZCr_i) is the co-ordinate of tower crane; l_{cr} is the jib length of tower crane; and T is the hoisting time.

Population evolution

Crossover and mutation are used as genetic operators for the evolution of the population. A single point continuous crossover is selected as the crossover operator because this is a resource allocation problem, as suggested by Evolver™ – the software used in this study. During the crossover stage, the best-fit chromosomes survive while the poor perish. In a single-point crossover, the position of a chromosome is chosen at random as the crossover point. Two parent strings are each sliced at the chosen position into two segments apiece. Appropriate segments from different parents are then concatenated to yield two offspring.

Mutation of enumerated chromosomes

After the crossover stage has finished, the mutation begins. Mutation is a very important operator as it injects new genetic information into the population to change a gene of a chromosome randomly. The population resulting from the mutation stage then overwrites the old population (the one prior to selection), completing one generation. Subsequent generations follow the same cycle of selection, crossover, and mutation. The near optimal solution emerges when the pre-determined termination condition is met. A flowchart on the procedures of the GA model is shown in Figure 5.

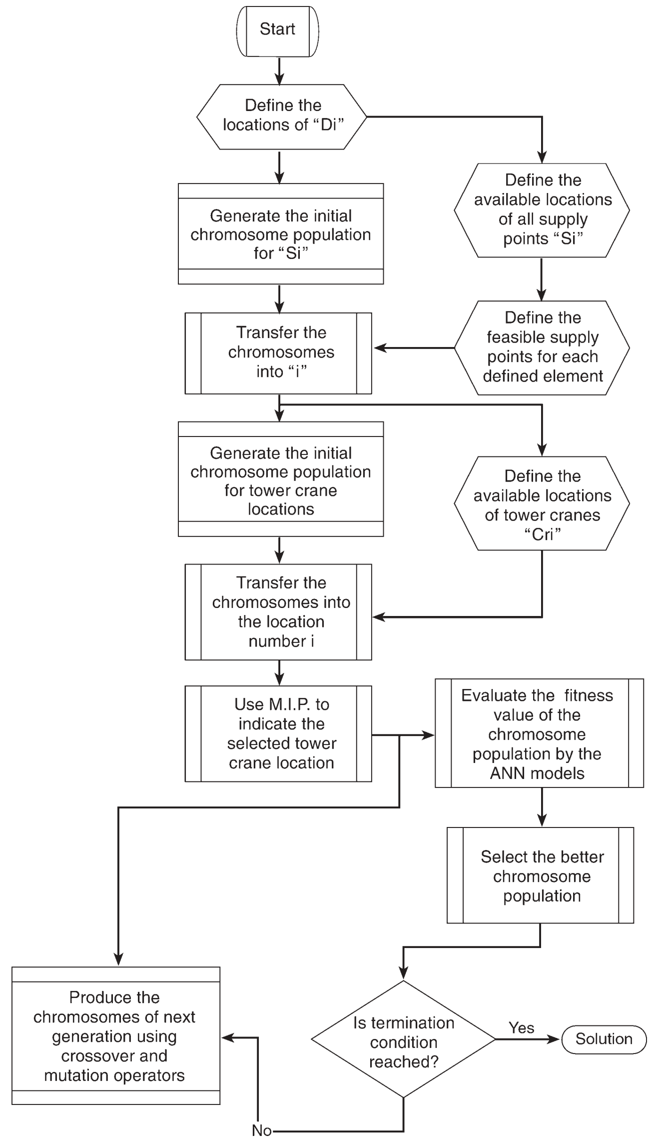

Figure 5 Flowchart of the GA model for tower crane and supply point location selection

Practical example

As the site layout for high-rise building construction keeps changing at different stages of construction, this study focuses on a particular construction stage: the use of a tower crane during concrete frame construction. The major materials transported by tower cranes are: (1) large-panel formwork, (2) precast concrete façades and (3) reinforcing bars. Concrete is normally transported by hoist and barrows or concrete pumps. Hence, our model considers the positioning of the bending yard, the façade storage yard and the assembly area for large-panel formwork.

Suppose the three storage areas, including the large-panel formwork, precast façades and the bending yard areas, are denoted as A_1, A_2 and A_3 respectively. For A_1, there are six possible locations (S_1, S_2, S_3, S_4, S_5 and S_6) after considering its size, shape and other constraints. For A_2, there are four possible locations (S_1, S_2, S_3, S_4) and for A_3, five possible locations (S_5, S_6, S_7, S_8, S_9). For tower crane positions, some site layout planners prefer to locate a climbing crane within the structure where the crane must not obstruct other site activities. Sometimes, a static tower crane may be located at the corner of two building wings, depending on the preference of site planners. Hence, there are 12 possible locations for the tower crane (Cr_1, Cr_2, ... Cr_{12}). Meanwhile, there are nine demand points. As a result, there are 9*12*6*4*5 = 12960 possible combinations, among which the optimal solution cannot be obtained easily by a polynomial equation as the problem is close to non-polynomial hard. Thus, the GA search technique is proposed. These site layout parameters are shown in Figure 6.

Generating a set of four chromosomes {ε1, ε2, ε3 and ε4} where $\varepsilon i \in (0, 1)$, the first three for the supply points and the last for tower crane positions, an initial population of random solutions is created. Each chromosome is mapped to a unique supply location S_i for supply points A_1, A_2 and A_3, avoiding the repetition of locations for more than one supply point (for example, if S_1 is selected for A_1, S_1 will not be available for A_2). Similarly, the last chromosome is mapped to the tower crane position (Cr_i). The type of chromosomes used is the real value integer chromosomes using a direct mapping technique.

- *Step (1)*: the co-ordinates of the supply points, demand points and tower crane positions need to be defined as given in Tables 1, 2 and 3. The cost of crane time (*Cjk*) is assumed to be US$1.92 (HK$15) per minute and the quantities of material flow for each element per concrete floor cycle (*Qjk*) is set at 10 for A1, 20 for A2, 30 for A3.
- *Step (2)*: in the GA model, the mutation type is a uniform one with the mutation rate set at 0.06 and the crossover rate at 0.5. The results of three rounds of modelling with different initial chromosome populations are shown in Figures 7, 8 and 9.
- *Step (3)*: run the Evolver™ and the results of the optimization by the genetic algorithms (GAs) are shown in Table 4.
- *Step (4)*: after optimization, three supply points in three-dimensional co-ordinates are selected by the genetic algorithm model. The points are S_2 (87, 45, 1.5), S_1 (73, 26, 2) and S₉ (55, 15, 1) as shown in Table 5.
- *Step (5)*: the location of tower crane in 3D co-ordinates (Cr_6) as shown in Table 3 is selected.

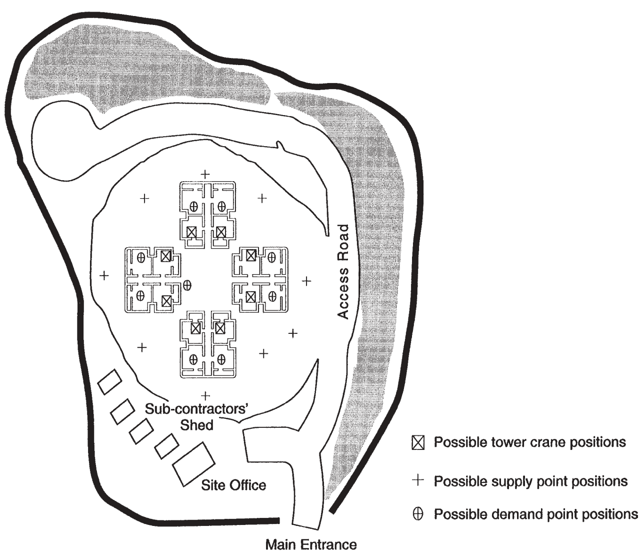

Figure 6 Permissible locations for tower crane, supply points and demand points

Table 1 Co-ordinates of demand points

Number	Co-ordinates of demand points		
	X	Y	Z
D_1	34	41	15
D_2	34	51	15
D_3	51	65	15
D_4	60	65	15
D_5	76	51	15
D_6	76	41	15
D_7	60	26	15
D_8	51	25	15
D_9	43	44	15

Table 2 Co-ordinates of supply points

Number	Co-ordinates of supply points		
	X	Y	Z
S_1	73	26	2
S_2	83	31	2
S_3	87	45	1.5
S_4	73	67	1.5
S_5	55	73	1.5
S_6	35	67	0
S_7	22	46	0
S_8	36	27	1
S_9	55	15	1

Table 3 Co-ordinates of tower crane positions

Number	Co-ordinates of tower crane positions		
	X	Y	Z
Cr_1	45	36	30
Cr_2	65	36	30
Cr_3	65	57	30
Cr_4	45	57	30
Cr_5	51	33	30
Cr_6	60	33	30
Cr_7	70	41	30
Cr_8	70	52	30
Cr_9	60	58	30
Cr_{10}	51	58	30
Cr_{11}	42	52	30
Cr_{12}	42	41	30

The above results demonstrate the effectiveness of the model in minimizing the cost of crane time. In order to verify the application value of the model, the results have been discussed with two experienced site planning engineers; one working as a senior planning engineer in a large construction firm and the other serving in a

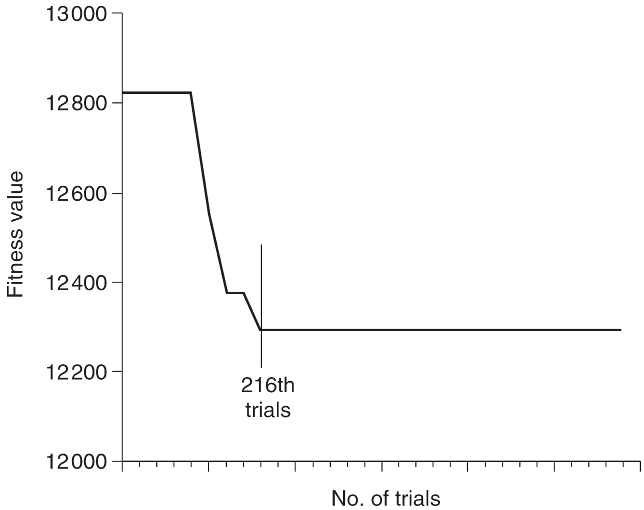

Figure 7 Graph showing optimization process for test 1 (216 trials)

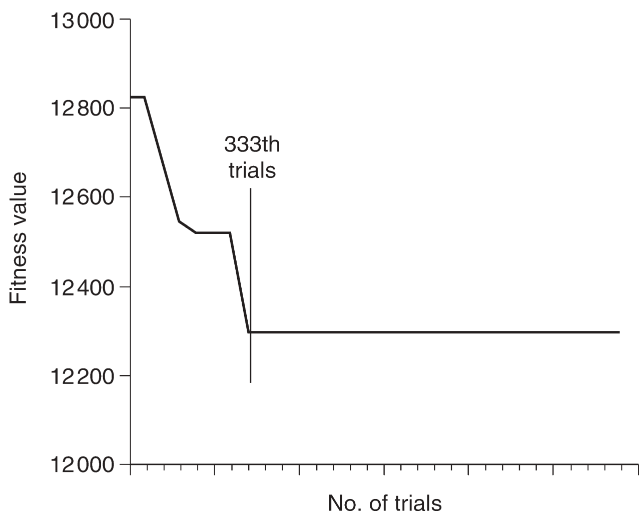

Figure 8 Graph showing optimization process for test 2 (333 trials)

medium sized contractor. Judging from their professional experience, both have confirmed the practicality of the proposed layout.

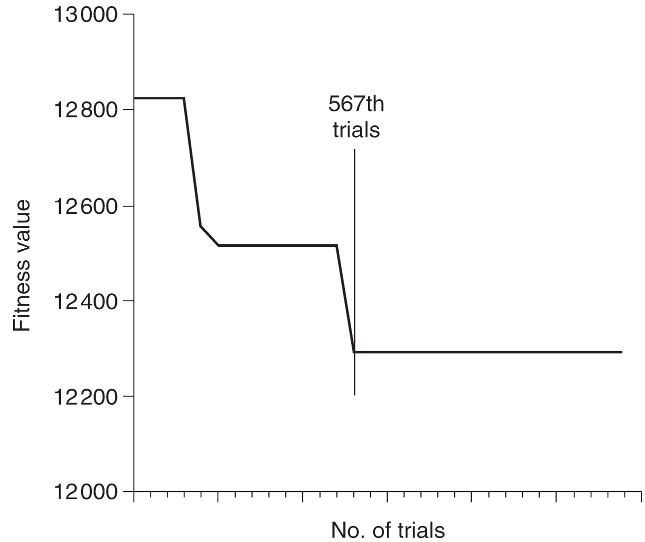

Figure 9 Graph showing optimization process for test 3 (567 trials)

Conclusions

The GA model described helps improve conventional site supply points and tower crane location methods. It gives an objective, quantitative and scientific way to evaluate the effectiveness of a site facility layout.

Experimental results indicate that the model performs satisfactorily. The practical example has demonstrated the application of the models in which the transportation cost was optimized. This infers that a systematic approach to site facility planning is important to improving site production efficiency. The methodology so described in this paper, through the use of an illustration example, is shown to be an efficient method to obtain a near 'optimal' solution. Efficiency is achieved in terms of the small population size and relatively short convergence process.

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Table 4 Results of optimization by genetic algorithms

Run results	No. 1	No. 2	No. 3
No. of trials	3966	4416	4317
Original value	15640.99904	15640.99904	15640.99904
Best value found	12293.16875	12293.16875	12293.16875
Occurred on trial no.	216	333	567
Time to reach the near-optimal value	00:00:43	00:01:14	00:01:35
Termination conditions	No change until 3750 trials	No change until 3750 trials	No change until 3750 trials
Evolution time	00:03:06	00:03:42	00:03:25

Table 5 The three selected supply points in 3D co-ordinates

Supply points				
No.	X	Y	Z	Choice
A_1	83	31	2	S_2
A_2	73	26	2	S_1
A_3	55	15	1	S_9

Hong Kong Special Administration Region, China (Project no. 9040492, CityU 1018/00E).

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