ELSEVIER

Automation in Construction 12 (2003) 749–764

AUTOMATION IN CONSTRUCTION

www.elsevier.com/locate/autcon

A hybrid CAD-based construction site layout planning system using genetic algorithms

Hesham M. Osman, Maged E. Georgy*, Moheeb E. Ibrahim

Structural Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt

Accepted 26 June 2003

Abstract

The efficient layout planning of a construction site is a fundamental task to any project undertaking. In an attempt to enhance the general practice of layout planning of construction sites, the paper introduces a novel approach for producing the sought layouts. This approach integrates the highly sophisticated graphical capabilities of computer-aided design (CAD) platforms with the robust search and optimization capabilities of genetic algorithms (GAs). In this context, GAs are utilized from within the CAD environment to optimize the location of temporary facilities on site. The functional interaction between GAs and CAD and the details of the GA-based layout optimization procedure are presented. A fully automated computer system is further developed to demonstrate the practicality of the chosen approach. In order to evaluate the system's performance, a local construction project with a 24,000m^2 site is used. The automated system produced highly satisfactory results and showed notable flexibility through its CAD-based input/output media.

Keywords: Site layout planning; Computer-aided design (CAD); Genetic algorithms

1. Introduction

Efficient layout planning of a construction site is fundamental to any successful project undertaking. This task usually consists of identifying the temporary facilities needed to support construction operations, determining their size and shape, and positioning them in the unoccupied areas within the site boundaries. Examples of these temporary facilities include offices and tool trailers, parking lots, warehouses, batch plants, maintenance areas, fabrication yards or buildings, staging areas and lay-down areas [1].

The project manager or planner usually performs the task of preparing the site layout based on his/her own knowledge and expertise. Apparently, this could result in layouts that differ significantly from one person to another. To put this task into more perspective, researchers have introduced different approaches to systematically plan the layout of construction sites [1–9]. These approaches differ from one another in the level of detail they provide and the extent to which they yield a well round solution to the rather complicated problem of layout planning of construction sites.

Site layout planning can generally be classified according to two main aspects: (1) method of facility assignment and (2) layout planning technique. With

* Corresponding author. Tel.: +20-10-5848060.
E-mail address: mgeorgy@eng.cu.edu.eg (M.E. Georgy).

0926-5805/$ - see front matter
doi:10.1016/S0926-5805(03)00058-X

regard to the method of facility assignment, or in other words the manner in which temporary facilities are assigned on site, two distinct methods are commonly encountered. The two methods are called *facility to location assignment* and *facility to site assignment*. The method of *facility to location assignment* assigns a set of predefined facilities to a set of predefined locations on site such that (number of locations $\geq$ number of facilities). The method of *facility to site assignment*, on the other hand, assigns a set of predefined facilities to any unoccupied space available on site.

The method of facility to location assignment frequently neglects one important issue, that of facility size. All locations are assumed to be able to fit all facilities. This assumption is weakened by the fact that there are usually substantial differences in size among most construction site facilities. The method of facility to site assignment is considered more generic as it assumes that the planner has not yet settled on the feasible locations for facility assignment. Nonetheless, during this type of assignment, many spatial requirements must be satisfied simultaneously. This poses extra computational burden on any automated site layout planning system that adopts the later approach.

The second aspect, i.e., the layout planning technique, concerns the technique used in performing the assignment process of temporary facilities. Many techniques have generally been utilized in the past to perform the assignment process, ranging from purely mathematical models to knowledge-based systems. However, researchers have not reached a consensus on or acknowledged a certain technique to be more suitable than the others.

Mathematical techniques usually involve the identification of one or more goals that the sought layout should strive to achieve. A widely used goal is the minimization of transportation costs on site. These goals are commonly interpreted to what mathematicians term "objective functions". This objective function is then optimized under problem-specific constraints to produce the desired layout. Systems utilizing knowledge-based techniques, in contrast, provide rules that assist planners in layout planning rather than perform the process based purely on a specified optimization goal(s). Fig. 1 shows the classification of some recent studies in construction site layout planning based on the aforementioned aspects of method of facility assignment and layout planning technique.

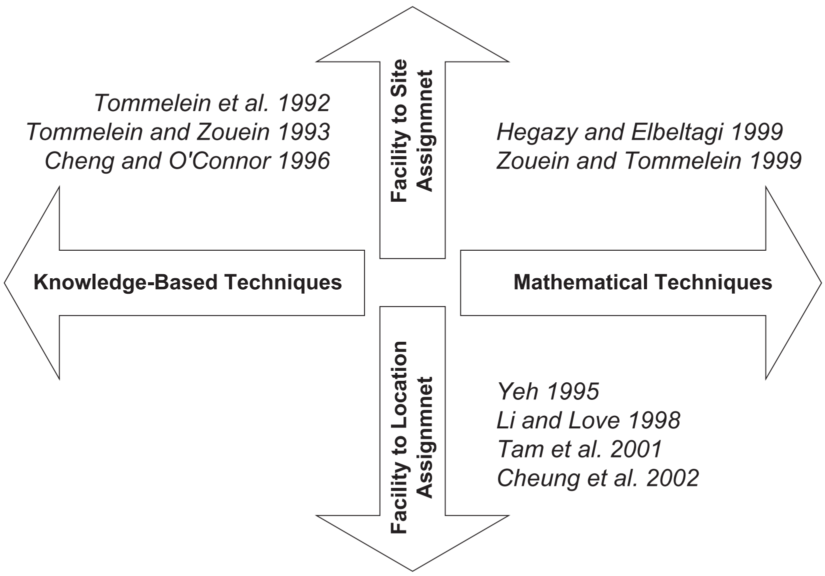


Fig. 1. Recent studies in construction site layout planning.

2. A computer-aided design (CAD)-based approach for site layout planning

CAD has been experiencing great advances since the late 1980s. Its use became inevitable in many engineering disciplines. However, the use of CAD applications in the construction stage of a project substantially lags behind the use of their counterparts in the design stage. Realizing their potential, Mahoney and Tatum [10] reported the broad benefits of using CAD in managing/planning many construction site operations. In particular, they suggested that CAD could be used to plan construction site layouts, as adoption of such systems allows easy and accurate visualization of the relationship between the permanent structures and temporary facilities on site.

Site layout planning is evidently graphical in nature. Site boundaries, existing buildings on site, obstacles and temporary site facilities all occupy space and have distinct shapes. Thus, the need to represent the relationship between all these entities in some sort of graphical format can be quite advantageous. For such reason, Cheng and O'Connor [4] utilized a geographical information system (GIS) to assist in the graphical representation of the site layout problem. However, full implementation of CAD-based site layout planning systems, particularly those utilizing mathematical techniques, has generally been limited till our time.

The current study introduces a novel approach for solving the site layout planning problem. It utilizes genetic algorithms (GAs), as function optimizers, in determining the temporary facility locations according to the graphical information depicted in a CAD environment. Based on the classification presented earlier, this approach performs a facility to site assignment using a mathematical layout planning technique.

Simply, GAs are algorithms that encode a potential solution to a specific problem on a simple chromosome like data structure and apply recombination operators to these structures so as to improve the solution while preserving all critical information [11]. Because of their characteristic of not utilizing gradient information, GAs are highly applicable to problems having non-differentiable functions, as well as functions with multiple local optima [12]. Al-Tabtabi and Alex [13] suggest that the use of GAs in optimization is appropriate in the following circumstances:

1. Conventional statistical and mathematical methods are inadequate.
2. The problem is very complex, because the possible solution space is too large to analyze in finite time.
3. The additional information available to guide the search is absent or not sufficient, so conventional methods are not practical.
4. The solution to the problem can be encoded in the form of strings and characters.
5. The problem is large and poorly understood.
6. There is an urgent need for near-optimal solutions to use as starting points for conventional optimization methods.

Several of the aforementioned circumstances promote the use of GAs in solving the site layout planning problem. Firstly, when modeling a large construction site, the available solution space is immense. The size of the solution space increases exponentially with the number of temporary facilities to be assigned and the available areas for facility placement. For illustrative purposes, consider a certain sector of a construction site with dimensions of 100×100 m. Consider also that no obstacles or permanent structures are present in this sector of the construction site and that four temporary facilities (1×1 m) need to be assigned in the given space.

Let $\mu =$ Number of locations available for temporary facility assignment (based on a 1 m pitch/increment)

$r =$ Number of temporary facilities needed to be assigned

Excluding all geometrical constraints among the temporary facilities

$$\mu \cong 100 \times 100 = 10,000 \tag{1}$$

$$\text{Solution Space} = {}^{\mu}P_{\mathrm{r}} = {}^{10,000}P_4 = 1 \times 10^{16}. \tag{2}$$

Another fundamental reason that makes GAs suitable for solving the problem at hand is the fact that the solution can be easily encoded in the form of strings. This will be explained in detail in Section 4. Finally, finding a comprehensive solution to the site layout problem is not always as simple as minimizing an objective function. Conditions on construction sites involve far more constraints, variables and uncertainties than those taken into consideration in most mathematical approaches. Practically, the difference between optimum and near optimum solution is not that significant, as even the optimum solution may require slight enhancements dictated by unforeseen site conditions.

3. The objective function

Researchers using mathematical techniques in site layout planning have developed many forms to represent their optimization goal(s) or *objective function(s)*. The pseudo models of these objective function(s) are given in Table 1.

The objective function of several models given in Table 1 takes the general form:

$$\text{Min:}\quad \left(\sum_{i=1}^{P-1}\sum_{j=i+1}^{P} W_{i,j}d_{i,j}\right) \tag{3}$$

Where P is the total number of permanent and temporary facilities on site; i,j is a certain pair of permanent and/or temporary facilities on site; $d_{i,j}$ is the distance between facilities i and j; $W_{i,j}$ is a term representing either the actual transportation cost per unit distance between facilities i and j (taking into consideration the number of trips made) or a relative proximity weight that reflects the required closeness between facilities i and j.

Table 1
Objective functions used in the literature

No.	Pseudo model of the objective function	Study (year)
1	To minimize the frequency of trips made by construction personnel	[5]
2	To minimize the total transportation costs of resources between facilities	[8,9]
3	To minimize the cost of facility construction and the interactive cost between facilities	[1]
4	To minimize the total transportation costs of resources between facilities (*presented through a system of proximity weights associated with an exponential scale*)	[6]
5	To minimize the total transportation costs of resources between facilities and the total relocation costs (*presented through a system of proximity weights and relocation weights*)	[7]

Table 2
The six-value scale commonly used in industrial facility layout planning

Desired relationship between facilities	Proximity weight
Absolutely necessary (A)	81
Especially important (E)	37
Important (I)	9
Ordinary closeness (O)	3
Unimportant (U)	1
Undesirable (X)	0

Using actual transportation costs to represent the term $W_{i,j}$ has the clear objective of minimizing the total transportation costs between site facilities. The objective is not as apparent when using the relative proximity weight representation. However, obtaining accurate values for the actual inter-facility transportation costs can become quite difficult, especially during project planning stages. This limitation promotes the use of proximity weights instead as they are generally much easier for the site planner to provide.

Several scales have been adopted in engineering applications to represent the proximity weights and facilitate their verbal representation. One common scale used in industrial facility layout planning is shown in Table 2 [14].

Many scales can be used to represent the proximity weights; the scale shown in Table 2 being an example. The site planner can use any other preferred scale appropriate to the case in hand. However, This study will particularly adopt the scale presented in Table 2. It is to be noted that whether accurate inter-facility transportation costs are provided or relative proximity weights are provided makes no difference whatsoever with the functionality of the automated system presented in Section 4.

4. Automated CAD-based site layout planning system

The automated CAD-based site layout planning system integrates the highly sophisticated graphical capabilities of CAD platforms with the robust search and optimization capabilities of genetic algorithms for producing the desired site layout(s). A schematic diagram of the system is illustrated in Fig. 2. The system is composed of three main components, i.e., input media, optimization engine and output media. In order to perform its presumed function, the system utilizes three main groups of data, namely, site geometrical data, temporary facility data and facility cost data.

Part of the system's novelty lies in its utilization of CAD capabilities as input/output media. The fact that most construction companies have their project plans and drawings in a CAD format greatly facilitates the use of the system. This way the plans and drawings can be input directly to the system. Genetic algorithms are then employed to perform the optimization process using the objective function described in Eq. (3). Following the optimization process, the system produces the desired layout(s) in the form of a series of CAD

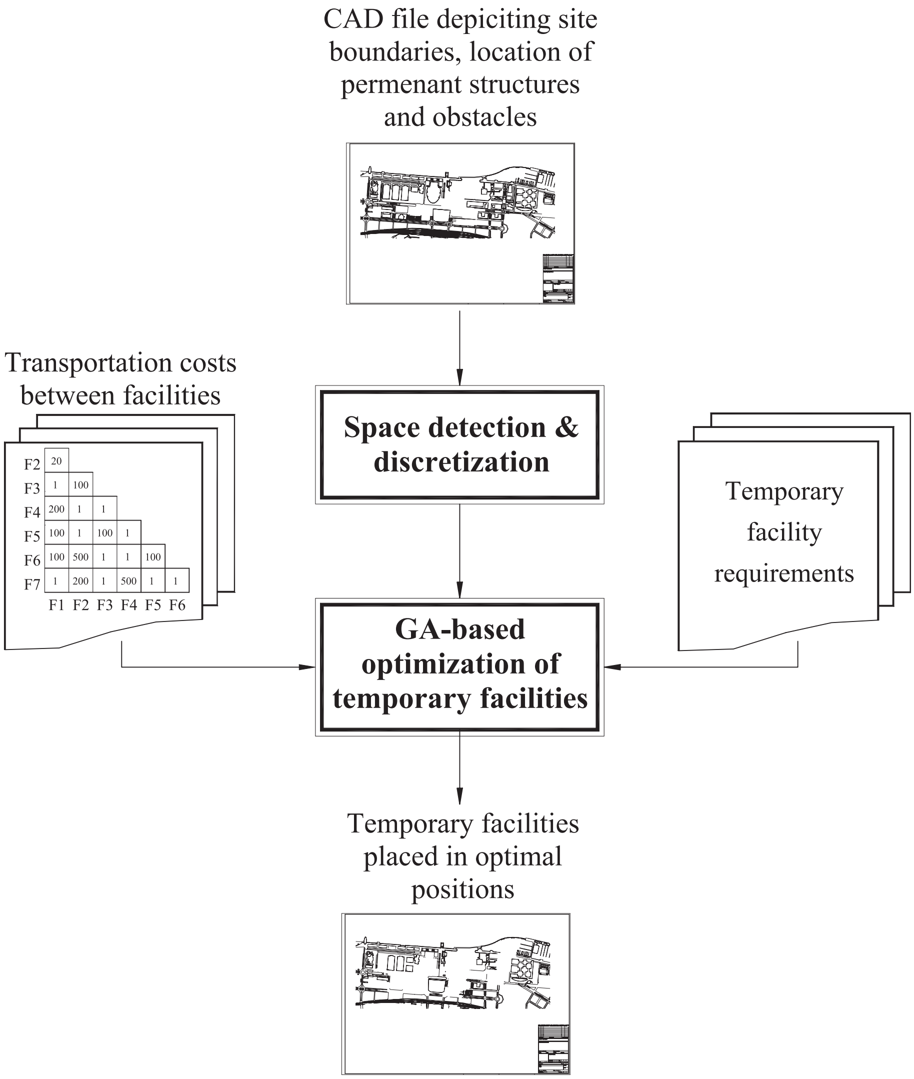


Fig. 2. Structure of the automated CAD-based site layout planning system.

drawings with all temporary facilities placed in their proper (optimal) locations. Limited efforts can further be made to integrate the automated site layout planning system with other commonly known planning functions for a comprehensive project management system.

The automated system was fully implemented using AutoCAD™ and greatly benefited from its programmable features and integrated capabilities with MS Visual Basic™, with which the optimization engine was developed.

4.1. Use of CAD capabilities

Performing the optimization process largely depends on identifying the specifics of the input CAD drawing, such as, site boundaries, permanent facilities and obstacles. Accurately identifying the available space on site for assigning the temporary facilities is essential to yield a feasible solution. In this context, CAD is utilized in performing two main tasks: (1) space detection and (2) constraint satisfaction. The first task is performed only once prior to the execution of the optimization process while the second task is continuously performed throughout the optimization process.

4.1.1. Space detection

Space detection concerns the identification of unoccupied space available for assignment of temporary facilities on site. It depends on the concept of "space discretization," shown in Fig. 3. In space discretization, the 2-D space encompassed by the boundaries of the construction site is divided into an orthogonal X–Y grid. This grid is then coded, each grid cell having a unique (X,Y) coordinate. The required level of accuracy in facility assignment determines the increments or pitch of the orthogonal grid. For example, if facilities are required to be assigned within an accuracy of 2 m, space discretization should be performed as illustrated on the left part of Fig. 3. After the grid coding is complete, grid cells with unoccupied space are identified after those with occupied space are excluded from the entire set. It is worth mentioning that the grid coding using the (X,Y) coordinates forms the building block of the GA string coding, as will be described in Section 4.2.

During space detection, CAD performs two main steps: (1) identification of space encompassed by site boundaries and (2) identification of fixed facilities and obstacles.

4.1.1.1. Identification of space encompassed by site boundaries.

(I) Using the rectilinear coordinates of the site boundary's vertices, CAD identifies a set of equations to represent the edges of the site boundary:

$$a_1y = b_1x + c_1 \quad a_2y = b_2x + c_2$$
$$a_3y = b_3x + c_3 \ldots \quad a_ny = b_nx + c_n$$

(II) Using a point inside the boundary, CAD identifies the space encompassed by the edges

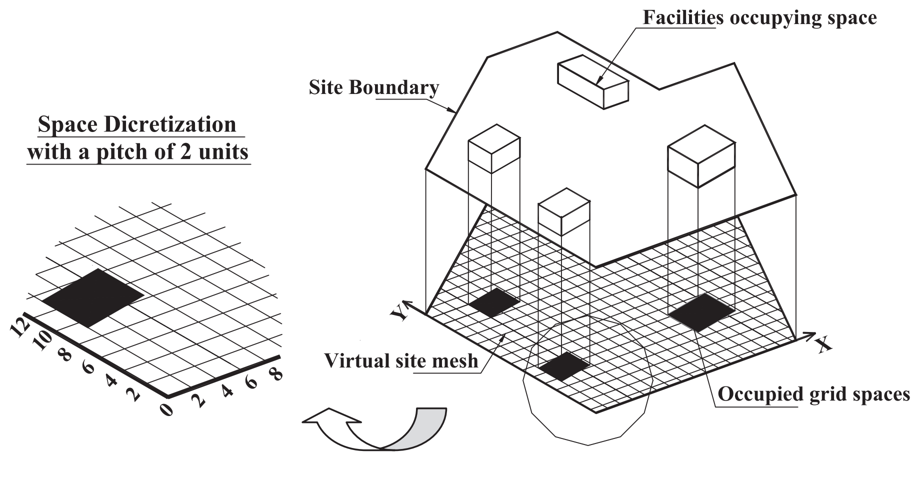


Fig. 3. Space discretization.

of the site boundary based on a set of inequalities:

$$a_1 y \geq b_1 x + c_1 \quad a_2 y \geq b_2 x + c_2$$
$$a_3 y \geq b_3 x + c_3 \ldots \quad a_n y \geq b_n x + c_n$$

(III) By toggling through coordinates of all grid points inside the "Bounding Box" of the site boundary, CAD selects those grid points that simultaneously satisfy all linear inequalities to represent the grid spaces encompassed by the site boundary. Any grid point that does not satisfy any linear inequality is determined to lie outside the site boundary.

4.1.1.2. Identification of fixed facilities and obstacles. Grid spaces inside the site boundary that are occupied by permanent facilities and obstacles are removed from those detected in "1". The remaining grid spaces represent the solution space for assignment of temporary facilities.

4.1.1.3. Illustration. To illustrate the process of space detection, consider the illustrative example shown in Fig. 4. Following the identification of the site boundaries as a set of linear equations, the space encompassed by the five edges of the site boundary can be identified as the space that satisfies the following inequalities simultaneously:

(1) $x \geq 5$
(2) $y \leq x + 55$
(3) $y \leq -2x + 180$
(4) $x \leq 75$
(5) $y \geq 10$
(6) $y \geq -x + 35$

4.1.2. Constraint satisfaction

Geometrical constraints are vital in the layout process. It is of utmost importance that temporary facilities be placed: (1) inside the site boundaries and (2) in such a manner that no overlap occurs between any two temporary facilities or between temporary facilities and permanent facilities. To satisfy the geometrical constraints, two main modules are utilized, namely, *CheckSite module* and *CheckOverlap module*. Both modules have been designed to deal with temporary facilities having rectangular shapes.

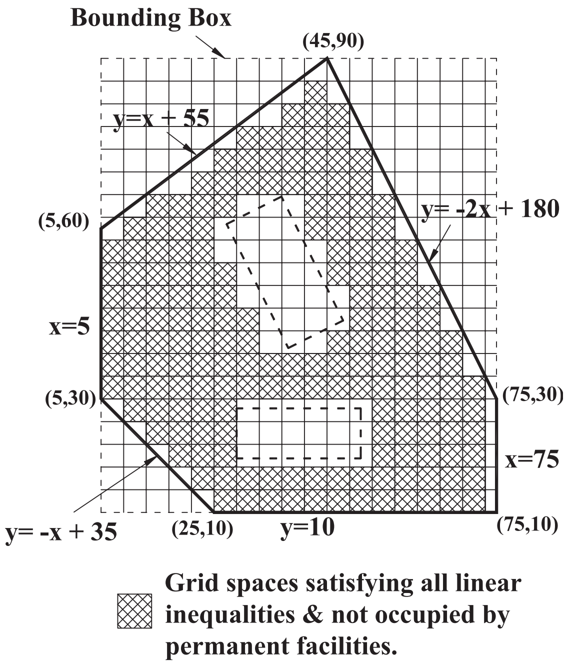


Fig. 4. Illustrated example for space detection.

4.1.2.1. CheckSite module. This module ensures that any temporary facility: (1) lies inside the site boundaries and (2) does not overlap with any permanent facility or site obstacle. This requires as input four variables; the *X*-coordinate and *Y*-coordinate of the bottom left corner of the temporary facility and its dimensions in the *X* and *Y* directions. It provides a Boolean true/false output. In its operation it toggles through all grid coordinates occupied by the facility and compares them with all available *X* and *Y* coordinates (Fig. 5).

If any (X,Y) of facility $\not\subset$ Available(X,Y)
Then CheckSite = False
Else CheckSite = True.

4.1.2.2. CheckOverlap module. This module ensures that any two temporary facilities do not overlap with each other. Two sequential tasks are performed in this module (Fig. 6):

(a) To make sure that the temporary facility being checked does not occupy a space already being

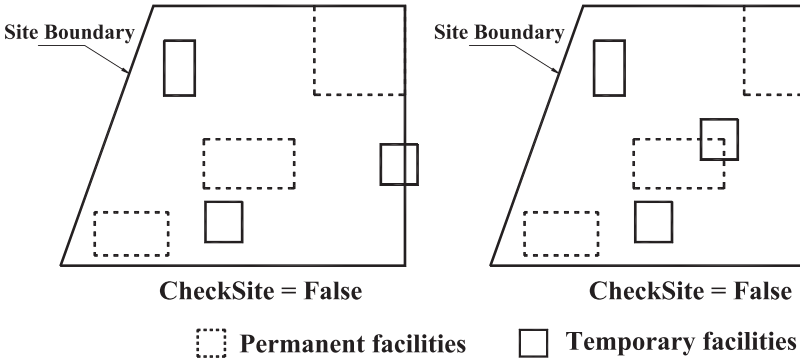


Fig. 5. Functionality of the *CheckSite module*.

reserved for another temporary facility assigned earlier on site.

If any (X,Y) of facility $\not\subset$ Occupied(X,Y)
Then CheckOverlap = False
Else CheckOverlap = True.

(b) If no overlap occurs, i.e., CheckOverlap = True, then the space is reserved for the temporary facility.

For $\forall$ (X,Y) of facility, Occupied(X,Y) = Facility(X,Y).

4.2. Use of genetic algorithms in site layout optimization

Usually there are two main components of genetic algorithms that are problem dependant, i.e., the string coding and the objective function evaluation [12]. String coding refers to the process of translating any solution into a unique string (similar to the biological chromosome) prior to commencing the genetic algorithm. The objective function evaluation is the process of deciphering the string back to its problem-equivalent value and then checking on the extent to which the problem objective is achieved.

4.2.1. GA string coding

Most CAD platforms use rectilinear coordinate systems in referencing entities, as depicted in Section 4.1. The string encoding primarily depends on this rectilinear referencing of entities to achieve the transformation from the graphical

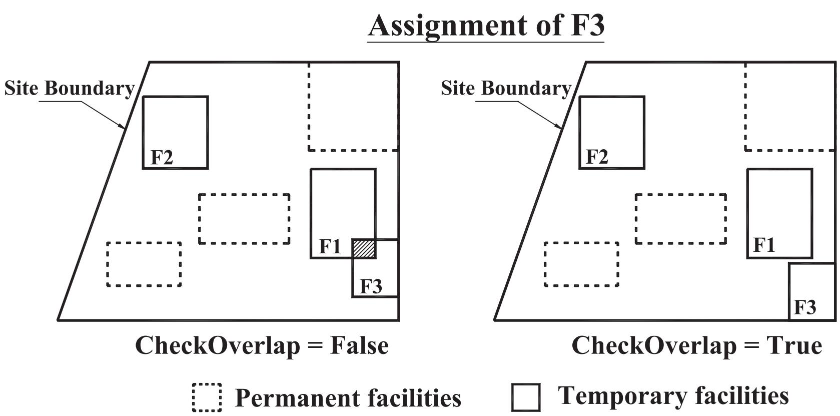
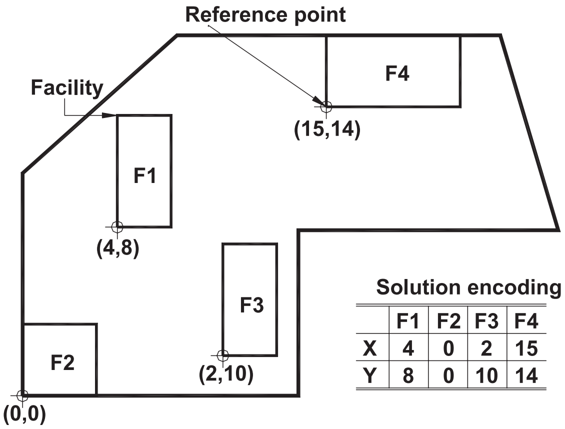


Fig. 6. Functionality of the *CheckOverlap module*.



	F1	F2	F3	F4
X	4	0	2	15
Y	8	0	10	14

Fig. 7. CAD-based GA string encoding.

representation, i.e., (X,Y) coordinates, to the chromosome structure. The location of each facility is referenced via its bottom left corner as shown in Fig. 7.

Due to the specific nature of the optimization problem at hand, a special-purpose GA optimization engine has been particularly developed for this study and integrated in the automated system. Therefore, the automated system acts in a stand-alone fashion, as it does not require the use of any commercial GA software. A flowchart of the used GA optimization process is detailed in Fig. 8.

4.2.2. Initialization of population

Any GA starts with an initial population of solutions. The number of initial solutions generated influences the success of a GA in reaching its goal. It is known that increasing the population size has the following effects on the GA:

(1) Tremendously increases the time required for generating a new population.
(2) Causes a very slow convergence rate.
(3) Causes the GA to reach more optimum solutions.

In order to assist the GA in its blind search, a slight enhancement has been incorporated in the optimization process. Instead of working with a very large population throughout the GA, the initial population is selected as the best n solutions from an initial pool of N solutions, where n is a subset of N. The following procedure outlines this enhancement:

```
1. Generate random initial pool of solutions
   N.
2. Select best n solutions from initial pool
   as first population.
3. Start GA.
```

Thus, the GA benefits from the presence of a large initial population that assists its random search without paying the large computational penalty posed by dealing with a large population at each generation.

4.2.3. GA generations

The generation process adopted in this study is a steady-state generation. Traditional GAs move from generation (i) to generation $(i+1)$ via the generation of a new population. Steady-state generation moves from one generation to the other via the introduction of new offspring to replace the worst solutions in the population. In case the new offspring are not better than the worst solutions, they are disregarded and other offspring are chosen instead. Previous studies [6] have successfully utilized steady-state generation in the site layout optimization problem.

Elimination of the worst offspring means that as new solutions are introduced, the population as a whole would improve. It also means a chance for randomly bred offspring to even outperform the best solution in the population. Generation of new offspring involves the three traditional genetic operators:

i. *Replication:* Traditional roulette wheel selection is performed based on the fitness value for individual solutions. Utilizing a steady-state population replication, two offspring are chosen to replace the worst two solutions in the population.

ii. *Crossover:* The same roulette wheel selection procedure is applied to select the parents that will be crossed. Simple single-point crossover is used so as to minimize the disruption of the schemata. After the crossing, two checks are performed on the offspring:

1. Constraint satisfaction: To verify the feasibility of the new solutions.

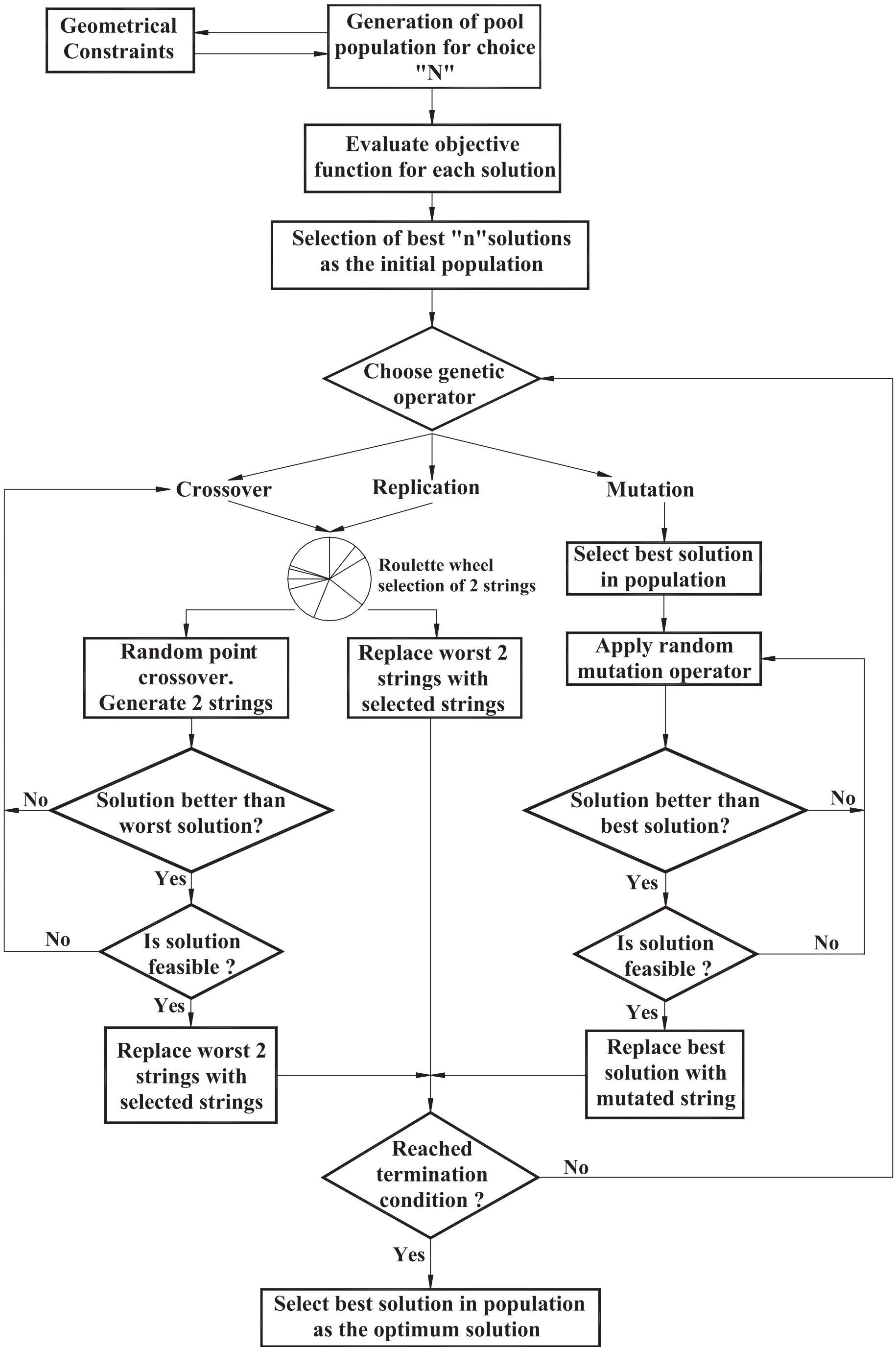


Fig. 8. GA optimization process flowchart.

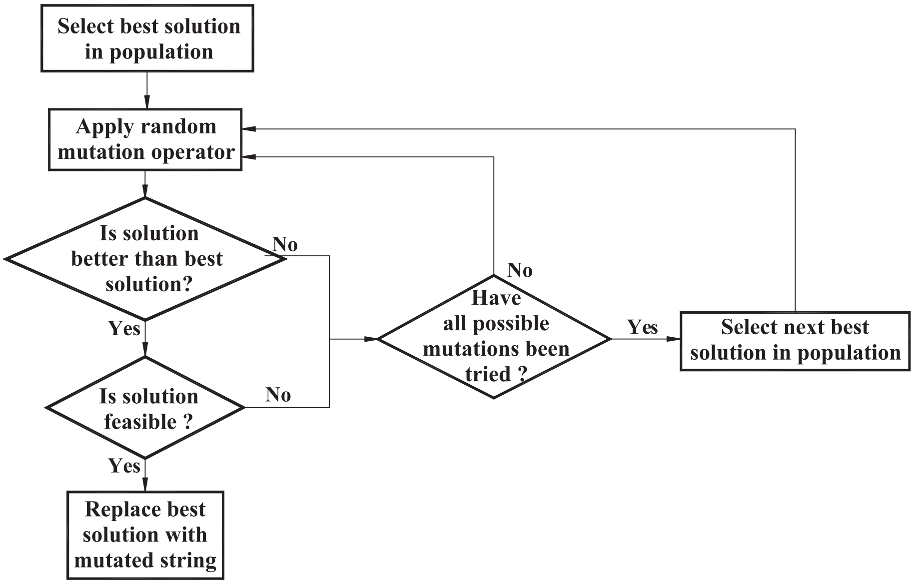


Fig. 9. Mutation operator flowchart.

2. Objective function improvement: To verify that the new solutions are not worse that those being replaced.

iii. *Mutation:* Mutation is used mainly to break the stagnation in improvement by introducing new genetic information into the population. It was noticed during the testing of the automated site layout planning system that performing the GA without mutation led to near optimum solutions. These near optimum solutions required slight

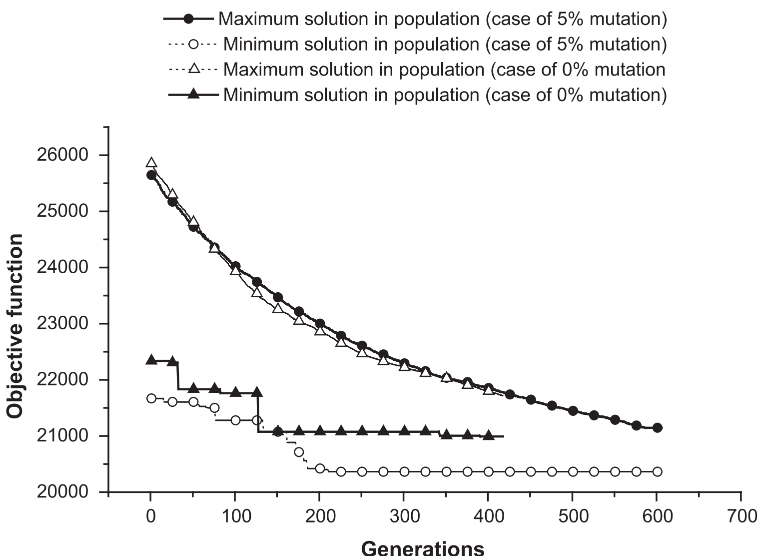


Fig. 10. Convergence of population parameters at different levels of mutation.

refinements to reach optima. These refinements involved very small movements of one or more temporary facilities in a specific direction. A modified mutation operator is developed to attain this function (Fig. 9). The mutation operator randomly performs the following steps:

1. Chooses the temporary facility to be moved.
2. Chooses the movement heading (towards *X*- or *Y*-axis).
3. Chooses the movement direction (+ve or −ve direction).
4. Applies a movement of one unit to the temporary facility chosen in step 1 and in the direction chosen in steps 2 and 3. Then, the new solution is checked for constraint satisfaction and objective function improvement. If violated, the mutation procedure is repeated.

4.2.4. Convergence condition

Generally, the GA generation process continues until a convergence condition is reached. In the GA of this study, convergence is reached when there is little variation (Δ) within the population itself or, in other words, there is a small difference between the maximum and minimum population values. Convergence occurs when the following condition is satisfied:

$$\Delta < \text{Convergence Value} \quad (4)$$

$$\Delta = \frac{\text{Max} - \text{Min}}{\text{Max}} \quad (5)$$

Where Min: minimum solution in current population, Max: maximum solution in current population, Convergence Value: user specified tolerance (usually 5–10%).

During experimentation with the GA, it was found that the modified mutation operator assisted the GA to reach more optimal solutions. In turn, its use caused slower convergence. Fig. 10 shows how the maximum and minimum population values—at different levels of mutation—vary till the convergence condition is reached. Although the modified mutation operator causes a slower convergence, the optimal solution

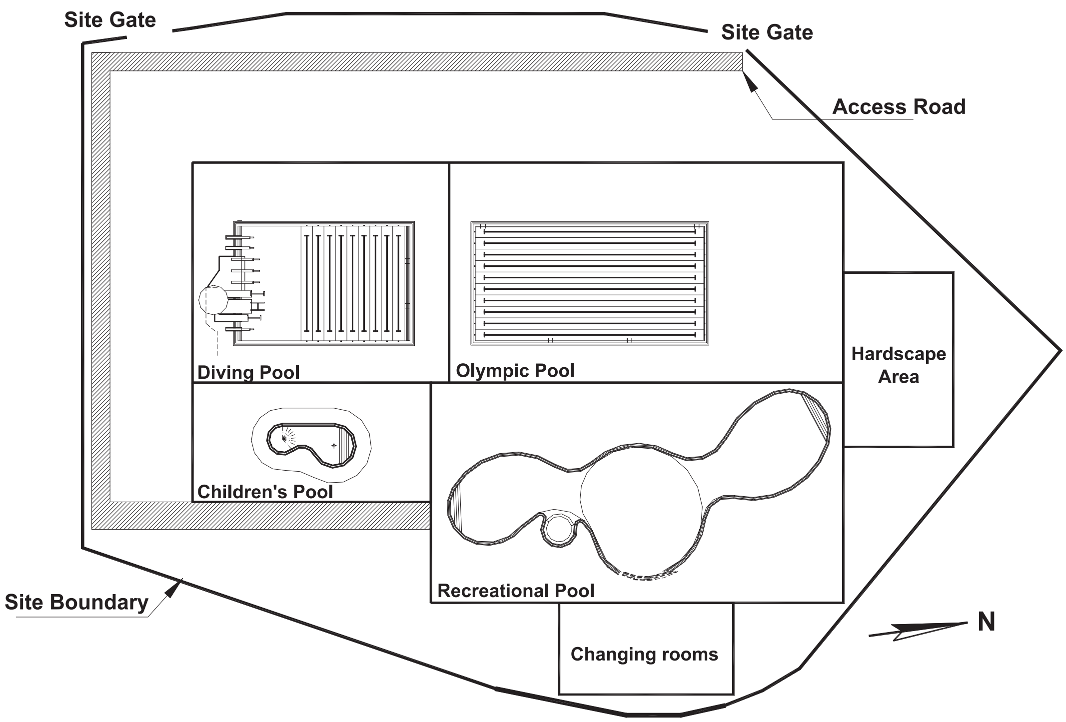


Fig. 11. Arrangement of permanent facilities and obstacles on site.

Table 3
Temporary facilities and their dimensions

Temporary facility	Dimension (m × m)
Storage area	42 × 20
2 Administrative caravans	10 × 3
2 Engineer's caravans	10 × 3
Parking area	12 × 4
Toilets	10 × 3
Steel fabrication yard	10 × 18
Steel storage	10 × 12
Generators	2 × 2
Water tanks	Variable

reached in the case of $p_{\mathrm{mutation}} = 5\%$ was better than the case when no mutation was used.

5. Case study

The selected case study is a major swimming pool complex with all auxiliary buildings. The site, whose area totals 24,000 m^2, is part of the new Heliopolois Sports Club located 30 km east of Cairo, Egypt. The complex is comprised of six main permanent structures: (1) three main swimming pools (an Olympic, diving and recreational pools), (2) a children's pool, (3) changing rooms and (4) a hardscape area. An underground basement occupies a large portion of the Olympic and diving pools.

Before the start of the project, an access road was set by the contractor and considered as an obstacle for the temporary facility assignment. Arrangement of the permanent facilities and obstacles within the site boundary is shown in Fig. 11. These permanent facilities and obstacles occupy nearly 15,000 m^2 of the site area, leaving 9000 m^2 for assigning all needed temporary facilities.

The temporary facilities needed to sustain the construction operations and the dimensions of these facilities are shown in Table 3. Water tanks were neglected in the layout planning, as the contractor assigns a tank inside the premises of each permanent facility for water supply.

Based on input from the project manager, the inter-facility proximity weight matrix was developed (Fig. 12). The values for the proximity weights follow the

	Storage Area	Steel Fab. yard	Steel Storage	Car Parking	Adm. Caravan 1	Adm. Caravan 2	Eng. Caravan 1	Eng Caravan 2	Toilets	Generator	Diving Pool	Olympic Pool	Children's Pool	Recreational Pool	Changing rooms	HardScape Area
Steel Fab. Yard	U															
Steel Storage	U	A														
Car Parking	U	X	X													
Adm. Caravan 1	U	X	X	U												
Adm. Caravan 2	U	X	X	I	A											
Eng. Caravan 1	U	X	X	I	E	E										
Eng. Caravan 2	U	X	X	I	E	E	A									
Toilets	U	U	U	U	A	A	A	A								
Generator	U	U	U	U	E	E	E	E	O							
Diving Pool	A	I	E	E	X	X	I	I	U	I						
Olympic Pool	A	I	E	E	X	X	I	I	U	I	N/A					
Children's Pool	E	U	I	I	X	X	I	I	U	I	N/A	N/A				
Recreational Pool	E	U	I	I	X	X	I	I	U	I	N/A	N/A	N/A			
Changing Rooms	E	U	I	I	X	X	I	I	U	I	N/A	N/A	N/A	N/A		
HardScape Area	I	U	I	I	X	X	I	I	U	O	N/A	N/A	N/A	N/A	N/A	
Gate	I	I	X	A	A	A	E	E	U	U	N/A	N/A	N/A	N/A	N/A	N/A

Desired relationship between facilities
Absolutely necessary (A)
Especially important (E)
Important (I)
Ordinary closness (O)
Unimportant (U)
Undesirable (X)

Fig. 12. Proximity weight matrix for the case study.

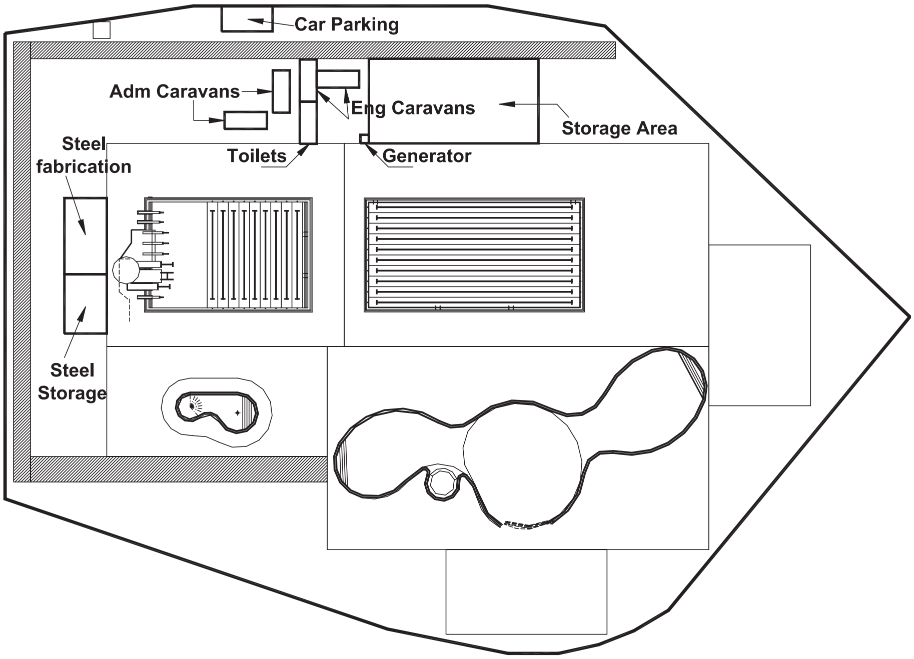


Fig. 13. Existing layout of temporary facilities.

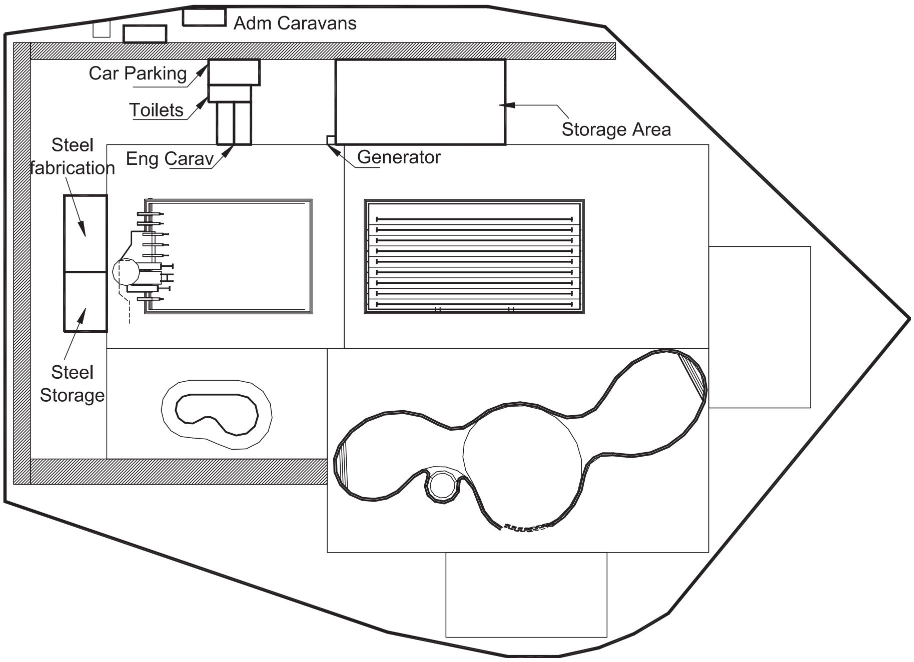


Fig. 14. Automated system assignment of temporary facilities.

six-value scale previously presented in Table 2. This matrix was then transformed into its quantitative equivalents before being input to the automated system.

Using a convergence condition of ($\Delta < 5\%$) to terminate the GA optimization process, the automated system completed the temporary facility assignment in 53 min running on a Pentium-3 800 MHz processor. The genetic parameters of $P_{\text{mutation}} = 0.05$, $P_{\text{crossover}} = 0.7$ and population size = 250 were used in the process and the convergence condition was reached after 2660 generations. The optimal solution had a representative score of 36,669, in contrast to a representative score of 38,647 for the actual site layout planned by the project management team.

The layout generated by the automated system indicates that the system managed to properly recognize all spatial constraints imposed by the site geometrical characteristics and assigned all temporary facilities accordingly. No major discrepancies were found between the existing layout (Fig. 13) and that produced by the automated system (Fig. 14), though the automated system produced a more optimal solution. A close comparison of the two layouts shows that the storage area and the steel fabrication/storage yards were assigned in their exact positions. The fact that extensive efforts were made by the project management team in preparing the site layout indicates that the automated system could serve as a valuable tool in site layout planning.

Although the system-generated layout scored higher than the actual layout produced through accumulated planning experience, this does not necessarily mean that the system's layout is superior in all aspects. When the system-generated layout was shown to the project manager, he indicated that some temporary facilities, such as the administrative caravans, were placed in more favorable positions than those in the actual layout. On the other hand, he considered some other temporary facilities, such as the engineers' caravans and parking area, to be placed in unfavorable positions in comparison to the actual layout. This was due to some secondary objectives, such as minimizing local congestions, as the tightly packed assignment interferes with resource handling and material flow. This confirms that the automated system does not necessarily yield the best layout. Minor adjustments may be required to the system-generated layout in order to attain other secondary objectives not taken into consideration in the optimization process.

6. Summary and conclusions

The paper presents an automated hybrid system for layout planning of construction sites. The automated system benefits from the optimization capabilities of GAs in performing the task of temporary facility assignment. A special-purpose GA, that uses a steady-state generation with a modified mutation operator, was developed in order to suit the site layout planning problem. An important aspect worth of consideration in GA systems is the accuracy of solution reached through the optimization process. The GA itself does not assure optimum solutions, but may yield near optimum solutions. The solution reached is very sensitive to the GA parameters used such as population size, p_{mutation} and $p_{\text{crossover}}$.

Due to the evident graphical nature of the problem, the GA was integrated with a widely known CAD platform, i.e., AutoCAD™. The CAD environment is utilized in space detection of the site layout and in the satisfaction of geometrical constraints dictated by the facility assignment problem. The fact that geometrical constraints are modeled using CAD and not through traditional mathematical formulations adds to the flexibility of constraint representation.

The optimization goal taken into consideration in the current study is to minimize the total transportation costs (or its proximity weight equivalents) between facilities. This is not necessarily the only goal the site layout should strive to achieve. For example, the layout should decrease site congestions and provide for safe working environment. Unfortunately, some of these goals are very difficult to gauge and the formulation of a comprehensive mathematical model that takes into consideration all these goals would be a very complicated task. However, some of these goals can be dealt with in a different manner. Supplementary modules that utilize artificial intelligence (AI) techniques, particularly knowledge-based systems (KBS), could be developed in the future to account for the less tangible aspects of site congestion precautions and safety regulations.

In conclusion, the use of GA in site layout planning can provide the planner with a good initial layout to start with and modify according to the other secondary objectives. By minimizing the objective function the GA accomplishes the complex task of assigning temporary facilities in positions consistent with their respective proximity needs, and at the same time abiding to spatial constraints imposed by the site geometry. The fact that the presented GA optimization engine is incorporated with a CAD-based input/output media greatly increases its practicality for use. Possible future expansion of the automated system to account for aspects such as safety regulations would substantially improve its capabilities in solving the site layout planning problem.

References

[1] I.-C. Yeh, Construction-site layout using annealed neural network, J. Comput. Civ. Eng., ASCE 9 (1995) 201–208.

[2] I.D. Tommelien, R.E. Levit, B. Hayes-Roth, SitePlan model for site layout, J. Constr. Eng. Manag., ASCE 118 (1992) 749–766.

[3] I.D. Tommelien, P.P. Zouein, Interactive dynamic layout planning, J. Constr. Eng. Manag., ASCE 119 (1993) 266–287.

[4] M.Y. Cheng, J.T. O'Connor, ArcSite: enhanced GIS for construction site layout, J. Constr. Eng. Manag., ASCE 122 (1996) 329–336.

[5] H. Li, P.E. Love, Site level facilities using genetic algorithms, J. Comput. Civ. Eng., ASCE 12 (1998) 227–231.

[6] T. Hegazy, E. Elbeltagi, EvoSite: evolution based model for site layout planning, J. Comput. Civ. Eng., ASCE 13 (1999) 198–206.

[7] P.P. Zouein, I.D. Tommelien, Dynamic layout planning using a hybrid incremental solution method, J. Constr. Eng. Manag., ASCE 125 (1999) 400–408.

[8] C.M. Tam, T.K. Tong, W.K. Chan, Genetic algorithm for optimizing supply locations around tower crane, J. Constr. Eng. Manag., ASCE 127 (2001) 315–321.

[9] S.-O. Cheung, T.K.-L. Tong, C.-M. Tam, Site pre-cast yard layout arrangement through genetic algorithms, Autom. Constr. 11 (2002) 35–46.

[10] J.J. Mahoney, C.B. Tatum, Construction site applications of CAD, J. Constr. Eng. Manag., ASCE 120 (1994) 617–631.

[11] W.T. Chan, D.K. Chaua, G. Kannan, Construction resource scheduling with genetic algorithms, J. Constr. Eng. Manag., ASCE 122 (1996) 125–132.

[12] D. Whitley, A genetic algorithm tutorial, Tech. Rep. CS-93-103, Colorado State University, Fort Collins, CO, 1993.

[13] H. Al-Tabtabi, A. Alex, An evolutionary approach to the capital budgeting of construction projects, Cost Eng., AACE 40 (1998) 28–34.

[14] R.G. Askin, C.R. Standrige, Modeling and Analysis of Manufacturing Systems, Wiley, New York, 1993.