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Genetic Algorithm for Solving Site Layout Problem with Unequal-Size and Constrained Facilities

P. P. Zouein, A.M.ASCE[1]; H. Harmanani[2]; and A. Hajar[3]

Abstract: This paper presents an investigation of the applicability of a genetic approach for solving the construction site layout problem. This problem involves coordinating the use of limited site space to accommodate temporary facilities so that transportation cost of materials is minimized. The layout problem considered in this paper is characterized by affinity weights used to model transportation costs between facilities and by geometric constraints that limit their relative positions on site. The proposed genetic algorithm generates an initial population of layouts through a sequence of mutation operations and evolves the layouts of this population through a sequence of genetic operations aiming at finding an optimal layout. The paper concludes with examples illustrating the strength and limitations of the proposed algorithm in the cases of (1) loosely versus tightly constrained layouts with equal levels of interaction between facilities; (2) loosely versus tightly packed layouts with variable levels of interactions between facilities; and (3) loosely versus tightly constrained layouts. In most problems considered where the total-objects-to-site-area ratio did not exceed 60%, the algorithm returned close to optimal solutions in a reasonable time.

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Introduction and Background

Construction site layout involves coordinating the use of limited site space to accommodate temporary facilities (such as fabrication shops, trailers, materials, or equipment) so that they can function efficiently on site. The layout problem is generally defined as the problem of (1) identifying the shape and size of the facilities to be laid out; (2) identifying constraints between facilities; and (3) determining the relative positions of these facilities that satisfy the constraints between them and allow them to function efficiently.

There are different classes of layout problems that have been studied in the literature. The variations stem from the assumptions made on the shape and size of facilities and on the constraints between them. Facilities may have a defined shape and size or a loose shape, in which case they will assume the shape of the site to which they have been assigned (for example, bulk construction material). The constraints can vary from simple nonoverlap constraints to other geometric constraints that describe orientation or distance constraints between facilities. In the layout problem addressed here, the shape and size of facilities are fixed. Facilities can have 2D geometric constraints on their relative positions along with proximity weights describing the level of interaction or flow between them.

The layout problem is an NP-complete combinatorial optimization problem, that is, optimal solutions can be computed only for small or greatly restricted problems (Kusiak and Heragu 1987). Hence, layout planners often resort to using heuristics to reduce their search for acceptable solutions. These heuristics comprise strategic knowledge prescribing the order in which to select objects and to meet constraints, and have been modeled with various degrees of truthfulness, detail, and success in operations research and artificial intelligence applications for space planning (Tommelein et al. 1991; Cheng 1992; Thabet 1992; Tommelein and Zouein 1993; Yeh 1995; Zouein 1995; Lin and Haas 1996; Feng et al. 1999; Zouein and Tommelein 1999).

The application of genetic algorithms (GAs) to solving layout problems is relatively recent. GAs work with a family of solutions, known as the ‘‘current population,’’ from which we obtain the ‘‘next generation’’ of solutions. When the algorithm is designed properly, we obtain progressively better solutions from one generation to the next. The main advantage of using GAs is in the fact that it only needs an objective function with no specific knowledge about the problem space. The challenge, however, remains in finding an appropriate problem representation that results in an efficient and successful implementation of the algorithm.

GAs (Goldberg 1989) have been applied to solving the facility layout problem (FLP) in the area of production facilities (Tanaka and Yoshimoto 1993; Tate and Smith 1993, 1995; Hamamoto et al. 1999) and to solving the ‘‘construction site-level facility layout’’ (Li and Love 1998). In both applications, the layout problem was modeled as a location-allocation problem, which consists of allocating a set of predetermined facilities into a set of predetermined sites where the smallest site can accommodate the largest facility. GAs have not been used, however, to solve the site layout problem as defined in this paper.

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This paper presents an evolutionary algorithm for optimally solving the site layout problem as characterized by affinity weights and 2D geometric constraints between facilities. The algorithm is tested on a variety of layout problems to illustrate its performance in the cases of (1) loosely versus tightly constrained layouts with equal levels of interaction between facilities; (2) loosely versus tightly packed layouts with variable levels of interaction between facilities; and (3) loosely versus tightly constrained layouts. The paper concludes with a discussion of the capabilities and limitations of the proposed approach.

Geometrically Constrained Site Layout Problem

The layout problem as modeled in this paper is characterized by rectangular layout objects with fixed dimensions representing the facilities to be positioned on site. Facilities can be positioned in one of two orientations only: a 0 or 90° orientation. In addition, facilities can have 2D constraints on their relative positions: namely, minimum and maximum distance, orientation, and nonoverlap constraints. Minimum and maximum distance constraints limit the distance between the facing sides of two facilities in the *x*- or *y*-direction to be greater than or less than a predefined value, respectively. Distance constraints can be used to model equipment reach or general clearance requirements. Orientation constraints limit a facility's position to be to the north, south, east, or west of another reference facility. These constraints can be used to locate access roads or gates with respect to the main facility. Nonoverlap constraints are default constraints that restrict the positions of any two facilities from overlapping. The geometric constraints are considered hard constraints that should be satisfied for the layout to be feasible.

The objective is to find a feasible arrangement for all layout objects within the site space that minimizes the sum of the weighted distances separating the layout objects (Z):

$$Z=\Sigma\Sigma_{j<i}(w_{ij}\times d_{ij}) \qquad (1)$$

where w_{ij} is the affinity weight between objects *i* and *j* that could be used to represent the flow or the unit transportation cost between *i* and *j*, and d_{ij} is the rectilinear distance separating objects *i* and *j*. A feasible arrangement is obtained by finding positions for all layout objects that satisfy the 2D constraints between them.

Genetic Approach

The basic notion of evolutionary computation is to mimic some principles of natural evolution in order to solve optimization problems of high complexity. A group of randomly initialized points of the search space (*individuals*) is used to search the problem space. Each individual encodes all necessary problem parameters (*genes*) as bit strings, vectors, or graphs. The population evolves following a parody of Darwinian principle of the survival of the fittest. Individuals are selected according to their quality, as measured by a fitness function, to produce offspring and to propagate their genetic material (parts of the partial solution found so far) into the next generation. Each offspring undergoes a sequence of operators (for example, mutation, inversion, and crossover) with a certain probability to provide diversity of the population, avoiding premature convergence to a single local optimum. The iterative process of selection and combination of ''good'' individuals should yield even better ones, until a solution is found or a certain stop criterion is met.

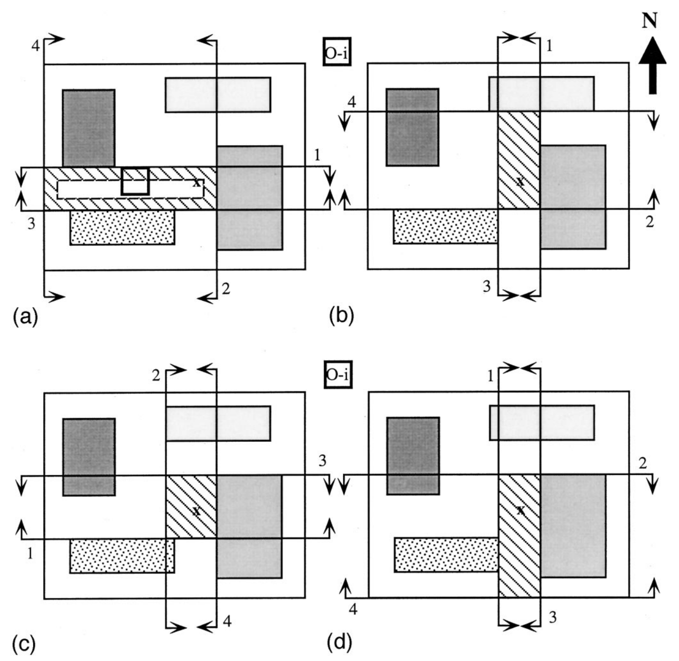


Fig. 1. (a) N-E-S-W cut; (b) E-S-W-N cut; (c) S-W-N-E cut; (d) W-N-E-S cut

Coding of Parameters

A population is a collection of chromosomes where each chromosome represents a layout solution. Every chromosome is coded as a vector whose length is equal to the number of facilities that exist on site *n*. Each facility *i* is represented by the coordinates of its position on site: X_i, Y_i, by its dimensions: L_i, W_i; and by a series of pointers pointing at the facilities that surround it in the four directions: north, south, east, and west. These pointers will be used to facilitate the check for overlap. The fitness function used is *Z*.

Genetic Operators

A number of genetic operators is used to evolve an initial population to the optimal solution. These operators are slight variations of the traditional mutation, reproduction, and cross-over operators. The genetic operators used call for the Find-a-Set-of-Possible-Positions function (simply termed here as Find-ASPP) that generates a set of feasible positions for an object in the neighborhood of a randomly selected location on site. This function takes as input a given location (say, P) and returns a set of four rectangles or less that together describe feasible positions of the centerpoint of the object to be positioned by making vertical and horizontal cuts through the site, as shown in Fig. 1. Fig. 1 illustrates how Find-ASPP generates the four rectangles given some previously positioned facilities on the site (represented by the gray-shaded rectangles) and a selected location P (marked as x) for the object to be positioned (shown outside the site space and labeled O-i).

The first rectangle [Fig. 1(a)] is generated by making, first, a horizontal cut (cut 1) through the edge of the closest object north of P, then a vertical cut (cut 2) through the edge of the closest object east of P in the half space containing P and generated by the first cut. Cut 2 divides the half-space in two: the one containing P is retained to make the next cuts. A third horizontal cut (cut 3) is made through the edge of the closest object to the south of P in the space defined by the two previous cuts. Finally, a vertical cut (cut 4) is made through the edge of the closest object to the west of P in the space containing P and defined by the previous three cuts. This last cut defines the fourth edge of the first rectangle generated by Find-ASPP [see the cross-hatched rectangle in Fig. 1(a)].

The second rectangle [shown as the cross-hatched rectangle in Fig 1(b)] is generated similarly to the first, except that the cuts are done starting with the cut to the east and proceeding clockwise to finish with a cut to the north. The third and fourth rectangles [Figs. 1(c-d), respectively] are generated similarly, starting with the south and west cuts, respectively, and moving clockwise to perform the remaining cuts.

Finally, Find-ASPP reduces the length and width of each rectangle found by half the length and width of O-i, respectively, and returns the set of reduced rectangles that represent a feasible set of positions for O-i. Fig. 1(a) shows one such reduced rectangle in white with dotted edges inside the cross-hatched rectangle. Note that if the length and/or width of the object exceeds those of any of the rectangles found by Find-ASPP, then that rectangle is discarded from the set of rectangles returned by Find-ASPP.

Note that Find-ASPP does not find the complete set of feasible positions of an object on site; rather, it finds a subset of those in the neighborhood of a suggested location. Also note that if the cuts were performed in an anticlockwise direction, the resulting rectangles returned by the function would be different from those shown in Fig. 1. If the order of the cuts is altered, the rectangles would be different as well. Enhancement of the Find-ASPP function can look at broadening the range of feasible positions that it returns by varying the order of the cuts and the direction followed.

The genetic operators used are the following:

1. Mutation selects a random location (X, Y) and calls the Find-ASPP function to determine the range of feasible positions in the neighborhood of that location where the block can be inserted and not overlap with other blocks positioned on site, as shown in Fig. 1. If the block cannot be inserted—that is, Find-ASPP returns the null set—then the operation is aborted.
2. Inversion flips a block's position across a horizontal or vertical axis passing through the centroid of the site. This operator also uses the Find-ASPP function to determine if a range of feasible positions exists at the new position. If none exists, then the operation is aborted.
3. Flip2Edge is an operator similar to inversion, with one difference: the axes pass through the centroid of a randomly selected reference block and not the site.
4. Swap exchanges the positions of two randomly selected blocks in a chromosome. It is possible that either block may not fit in the place of the other block. If at least one block fits, then the other block is mutated, or else the operation is aborted.
5. Rotation rotates a block 90° anticlockwise about its upper-left corner.
6. Move moves a randomly selected block in a chromosome d units in the X- or Y-direction. The value of d is either Gaussian or unity, depending on the number of iterations in which the best solution did not change.
7. Add-missing-blocks act on chromosomes that contain missing blocks—that is, blocks for which no feasible position was found in the initialization phase (see next section for details). This may happen as a result of an inefficient use of the site space. This operator attempts to find feasible positions for the missing blocks in a chromosome by applying a sequence of mutations.
8. Fix blocks fixes the positions of two blocks that have distance or orientation constraints between them.
9. Aging destroys chromosomes whose fitness value did not change after x iterations where x is set to 50 and could be changed to influence the rate of convergence. This operator is intended to age solutions that will not lead to the optimal one and allow young chromosomes to evolve into better solutions.

Note that operators 1 through 7 call Find-ASPP to determine a Set of Possible Positions (ASPP) for the centroid of the block operated on in the neighborhood of the new suggested location. If Find-ASPP returns the null set, then the operation calling it is aborted. If the new suggested location belongs to the set returned by Find-ASPP, and if all geometric constraints between the object under consideration and the previously positioned objects on site are satisfied at the new suggested location, then the object is inserted at that location. Otherwise, another location is selected at random from the set of positions returned by Find-ASPP. That new location is checked to see if it satisfies all geometric constraints on the object under consideration; if not, then another location is sampled at random from the ASPP. This process of sampling locations from the set of feasible positions returned by Find-ASPP is repeated up to n times where n is set arbitrarily to 20. If still no location is found to satisfy the geometric constraints, then the operation calling Find-ASPP is aborted.

Initialization Phase

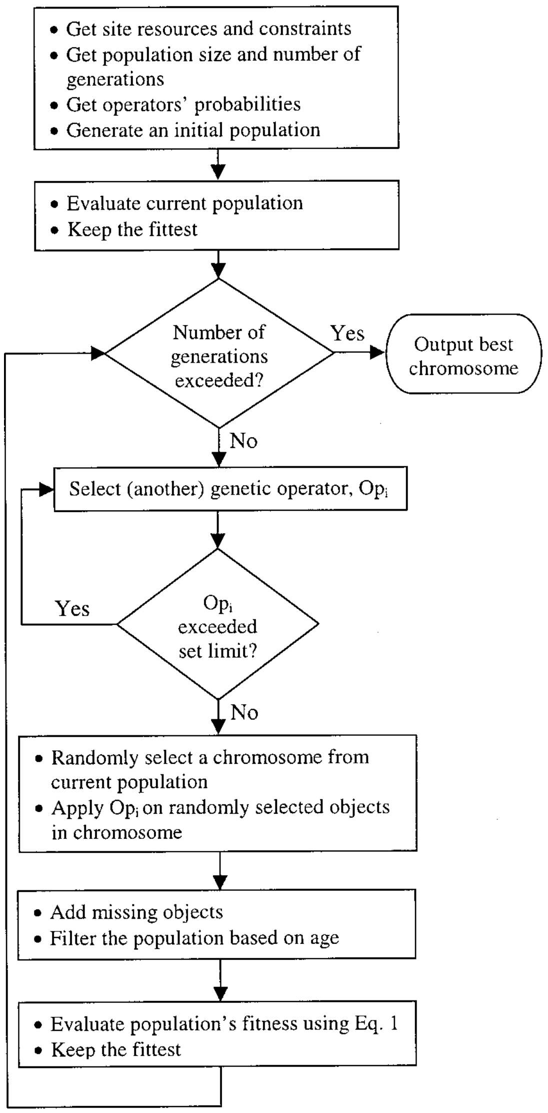
Chromosomes in the initial population are generated randomly by applying a sequence of mutation operations. First, blocks with user-defined fixed positions on site are added to a chromosome; these blocks cannot be moved by the above GA operations. Next, mutation is applied on the remaining blocks by selecting randomly a block at a time. If applying mutation on a given block results in an infeasible range for block insertion, then mutation is repeated on the same block up to 100 times to find a feasible position for that block. If after 100 trials no feasible position is found, this block is left out of the chromosome. Hence, this method may result in chromosomes representing partial layout solutions. The operator Add-Missing-Blocks will be responsible for completing such partial solutions in the evolutionary phase.

Evolutionary Phase

Following the generation of the initial population, the genetic operators are applied to evolve the initial population into better ones as depicted in the flow chart of Fig. 2.

Every operator has a probability associated with it. The product of the operator's probability and the population size determines the maximum number of times this operator can be fired in one generation. Operator's probabilities and values of other parameters were determined experimentally and are as shown in Table 1.

Also experimentally, it was found that the pure survival of the fittest does not always work for this type of layout problems. Hence some ''bad'' chromosomes (that is, chromosomes representing partial solutions or chromosome with high fitness value) were preserved in the next generation as this could in the long run help the algorithm converge to a global optimum. The following criteria were used in selecting chromosomes for reproduction:



Get site resources and constraints
Get population size and number of generations
Get operators' probabilities
Generate an initial population
Evaluate current population
Keep the fittest
Number of generations exceeded?
Yes
Output best chromosome
No
Select (another) genetic operator, Op$_i$
Yes
Op$_i$ exceeded set limit?
No
Randomly select a chromosome from current population
Apply Op$_i$ on randomly selected objects in chromosome
Add missing objects
Filter the population based on age
Evaluate population's fitness using Eq. 1
Keep the fittest

Fig. 2. Flow chart of proposed genetic algorithm

1. Choose 5% from the best chromosomes;
2. Randomly choose 10% from "bad" chromosomes with density fitness less than 60% or more that 150% of the best chromosome. The density fitness is the ratio between fitness value and number of blocks available in the chromosome. Note that a chromosome's fitness value can exceed 100% if the chromosome represents a partial solution;
3. Randomly choose 80% from those chromosomes with density fitness between 80 and 120% of the best chromosomes; and
4. Choose randomly the remaining chromosomes.

Table 1. Operators and Probabilities

Parameter	Value	Parameter	Value
Population size	100	Probability of rotation	0.2
Probability of mutation	0.1	probability of swap	0.1
Probability of move	1	Probability of Flip2Edge	0.2
Probability of inverse	0.1	Maximum age for aging	50

Table 2. Input for Case 1 Problems

Problem	Number of objects	Dimensions of object	W_{ij}, $\forall i$, and $\forall j$	Total object-to-site-area ratio (OSAR) (%)
1 [Fig. 3(a)]	10	2×1	1	10
2 [Fig. 3(b)]	25	2×1	1	23
3 [Fig. 3(c)]	45	2×1	1	40
4 [Fig. 3(d)]	60	2×1	1	54

Examples Application

The proposed GA was run on different sets of problems to test the algorithm's performance as the total object-to-site-area ratio (OSAR) is varied in the following cases: equal size with equal weight objects, unequal size with unequal weight objects, unequal size with unequal weight objects, and 2D constraints between objects. In all these cases, the population size is set to 100 and the number of generations is limited to 400.

Case 1: Layout of Equal-Size with Equal-Weight Objects

In this section, the GA is used to solve bin-packing-like problems where objects have the same dimensions and have equal weights between them. No geometric constraints were considered between objects for problems in this case. The four problems selected and shown here illustrate the GA's performance in solving problems with different numbers of objects to be laid out (10, 25, 45, and 60 objects) and thus different OSARs. Table 2 shows the input used with the four problems of Case 1.

Fig. 3 shows, to the left, the best layout solution found by the GA and, to the right, the optimal solution or the best incumbent found for each of the four problems. Note that, for some problems, there exist alternative optimal layouts, only one such layout is shown in Fig. 3.

Table 3 shows a comparison between the fitness value of the layouts generated by the GA along with the run-time of each problem and the optimal or "best" layouts found. The GA solutions found are on average within 5% of the optimal solution. This is considered a very good result, given the size of the problems solved. The GA was tested on a variety of other problems of the same class of problems shown here, that is, with equal size objects and equal weights between them. It returned solutions that are equally good for OSAR values up to 50%. The "goodness" of the GA solutions, however, deteriorates when the OSAR is raised above 60%.

Case 2: Layout of Unequal Size with Unequal Weight Objects

In this section, the GA is used to solve layout problems with layout objects of different dimensions and having different weights between them (that is, with different levels of interactions between them). No geometric constraints were considered for problems in this case as well. The four problems selected and shown here have the same OSAR as the four problems of Case 1. This choice is intentional to test how the GA's performance varies when layout objects are not all equal. The inputs associated with the four problems are as shown in Table 4.

Fig. 4 shows, on the left, the layout solutions returned by the GA, and on the right, the optimal or best incumbent solution for

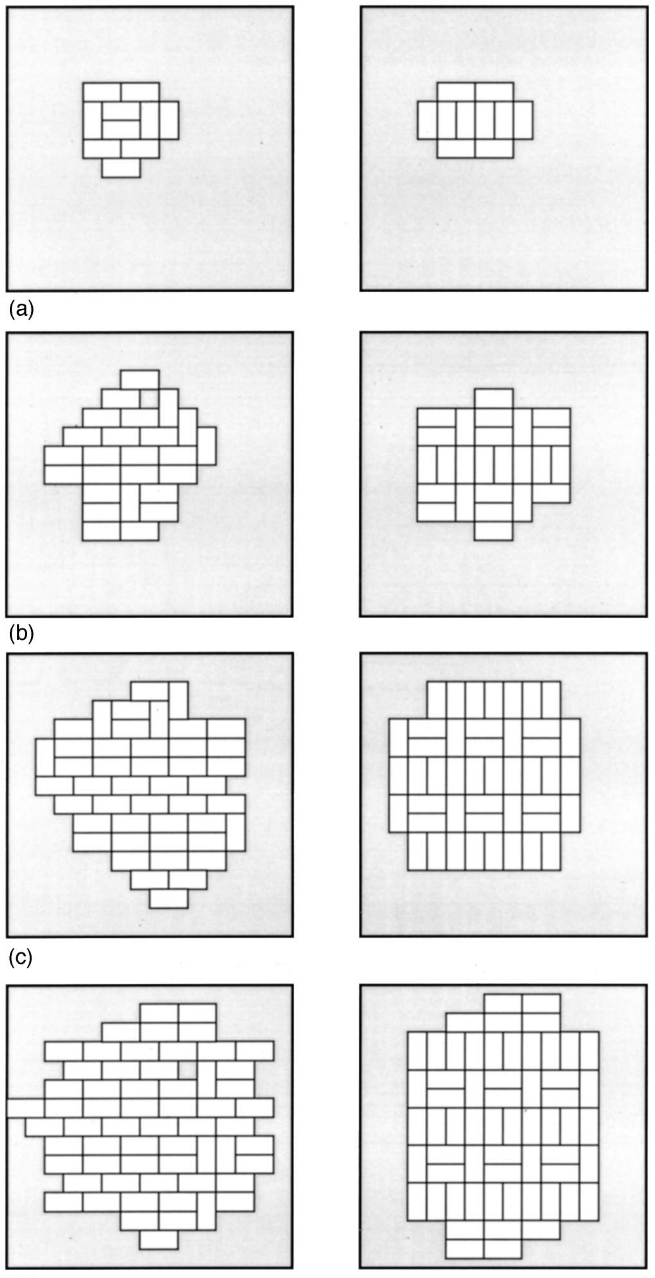

(a) (b) (c) (d)

Fig. 3. (Left) GA solution and (right) optimal or best solution of (a) Case 1 problem 1; (b) Case 1 problem 2; (c) Case 1 problem 3; (d) Case 1 problem 4

each of the four problems described in Table 3. Table 5 shows a comparison between the fitness value of the layouts generated by the GA along with the run-time of each problem and the optimal or ''best'' layouts found. The GA solutions for problems with OSAR less than 50% are on average within 6% from the optimal solution. The ''goodness'' of the solution drops suddenly for problems with OSAR greater than 50% as it is illustrated by the solution of problem 4 (Fig. 4(d); Table 5).

Case 3: Layout of Unequal Size with Unequal Weight and 2D Constraints between Objects

Finally, this section treats the class of layout problems where objects are of different size and have variable weights between them and have geometric constraints on their relative positions in addition to the default nonoverlap constraints. Only two problems are presented in this section. These problems are intended to test the GA's performance in solving problems with a relatively smaller number of layout objects, but with a larger variety of geometric constraints between them. The layout objects' dimensions and proximity weights between them for both problems are given in Tables 6 and 7, respectively. Both problems have an OSAR value of approximately 50%.

The first problem has in addition to the weights defined in Table 6, the following geometric constraints between objects: Object 6 is constrained to be to the north of object 7, and object 9 and object 10 should have a minimum distance of 5 units in the *Y*-direction between them. The GA solution to the above problem is shown in Fig. 5 (left) and has a fitness value of 1,325. Note that the gray-shaded rectangle represents object 4. The optimal solution for this problem has a fitness value of 1,262.5. There are alternative optimal layouts for this problem. Fig. 5 shows only one such optimal layout.

The second problem considered has the same objects and relationships between them as the previous one. It has, however, two additional geometric constraints, namely, a maximum distance constraint of 8 units in the *Y*-direction between object 5 and object 7 and a minimum distance constraint of 5 units in the *Y*-direction between object 1 and object 10. The GA solution to this problem is shown in Fig. 6 (left) and has a fitness value of 1,350. The optimal solution to this problem is the same as for the previous problem and is shown in Figs. 5 and 6 (right).

Table 8 summarizes the results of this last case. As can be seen, the proposed GA found solutions for problems with an OSAR value of 50% that are within 7% of the optimal solution. The GA's performance drops when used on problems with higher OSAR values and a larger number of geometric constraints between objects.

Analysis of Results

As can be seen from the results shown in Tables 3, 5, and 8 and summarized in Table 9, the GA found close to optimal solutions

Table 3. Comparison between GA Optimal or Best Incumbent Solution for Case 1 Problems

Problem	OSAR (%)	GA solution fitness value	Time (s)	Optimal or best incumbent fitness value	Error (%)
1 [Fig. 3(a)]	10	135	144	131	3
2 [Fig. 3(b)]	23	1,438	406	1,407	2
3 [Fig. 3(c)]	40	6,226	1,336	5,852	6
4 [Fig. 3(d)]	54	12,145	1,851	12,389	2

Table 4. Input for Case 2 Problems

Problem	Objects	$L \times W$	Number of objects	W_{ij}	OSAR (%)
1 [Fig. 4(a)]	1	4×2	1		10
	2, 3, 4, 5	2×2	4	5; $\forall i=2,...,5$ $\forall j=i+1=2,...,5$	
				20; $i=1$ and $j=2$	
2 [Fig. 4(b)]	1, 2, 3	4×2	3	10; $\forall i=1,...,3$ $\forall j=i+1=1,...,3$	23
	4, 5, 6, 7, 8, 9, 10	2×2	7	5; $\forall i=4,...,10$ $\forall j=i+1,...,10$	
				20; $i=1$ and $j=4$ $i=2$ and $j=5$	
3 [Fig. 4(c)]	1, 2, 3, 4, 5, 6, 7	4×2	7	10; $\forall i=1,...,7$ $\forall j=i+1,...,7$	40
	8, 9, 10, 11, 12, 13, 14, 15	2×2	8	5; $\forall i=8,...,15$ $\forall j=i+1,...,15$	
				20; $i=1$ and $j=8$ $i=2$ and $j=9$ $i=3$ and $i=10$	
4 [Fig. 4(d)]	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	4×2	10	10; $\forall i=1,...,10$ $\forall j=i+1,...,10$	54
	11, 12, 13, 14, 15, 16, 17, 18, 19, 20	2×2	10	5; $\forall i=11,...,20$ $\forall j=i+1,...,20$	
				10; $i=1$ and $j=11$ $i=2$ and $j=12$ $i=3$ and $j=13$	

(on average within 6% of optimal) for the three classes of layout problems considered. In the first class of problems, the geometric constraints were reduced to the default nonoverlap constraints, and the interactions among objects were equated across all pairs of layout objects. The intent was to test the GA's capability in solving bin-packing-like problems. The optimal solution for this class of problems results in tightly packed objects, as shown in Fig. 3. For the four problems considered, the proposed GA returned exceptionally good results, with less than 5% error on the largest problem (with 60 objects and 60% OSAR). The algorithm converged to a solution in less than 250 generations for all problems solved in this case.

In the second class of problems, the GA's performance was equally good except for problems where the total-objects-to-site-area ratio exceeded 50% (as in the case of problem 4). In this class of problems, the restrictions on the size and weights between objects were relaxed. The geometric constraints, however, remained restricted to nonoverlap constraints only between objects. The writers suspect that this sudden drop in performance could be due to the fact that the levels of interactions between objects were made different between different pairs of objects, thus shifting the problem from a single packing problem, as in the first case of problems, to many packing problems within a problem.

In the third class of problems, the GA was tested on a number of problems, two of which were presented in this section. In this class of problems, all restrictions were relaxed. Objects have different dimensions, and different levels of interactions and geometric constraints between them. Here too, the GA returned very good solutions (within 7% of optimal solutions) for problems with less than 55% OSAR. The GA's performance is noted to drop for tightly packed problems (that is, problems with OSAR higher than 60%) or problems with a large number of geometric constraints between objects.

Hence, the proposed GA could be used to solve different classes of layout problems and is expected to return ''good solutions'' (within 7% of optimal solutions). However, from the problems considered in this paper and others not shown here, one can conclude that the GA performed better in loosely constrained problems with a small total-objects-to-site-area ratio (55% or less) even when the number of blocks was high. This result is expected because of the very nature of GAs.

Conclusions

This paper presented the results of a pioneering investigation on the application of genetic algorithms for solving the site layout problem, as characterized by rectangular facilities with proximity requirements between them and with geometric constraints that further restrict their relative positions. Key features of the proposed algorithm are that it uses a large number of different GA operators to vary positions of objects around the site. The GA operators are programmed so that the chance of finding a feasible

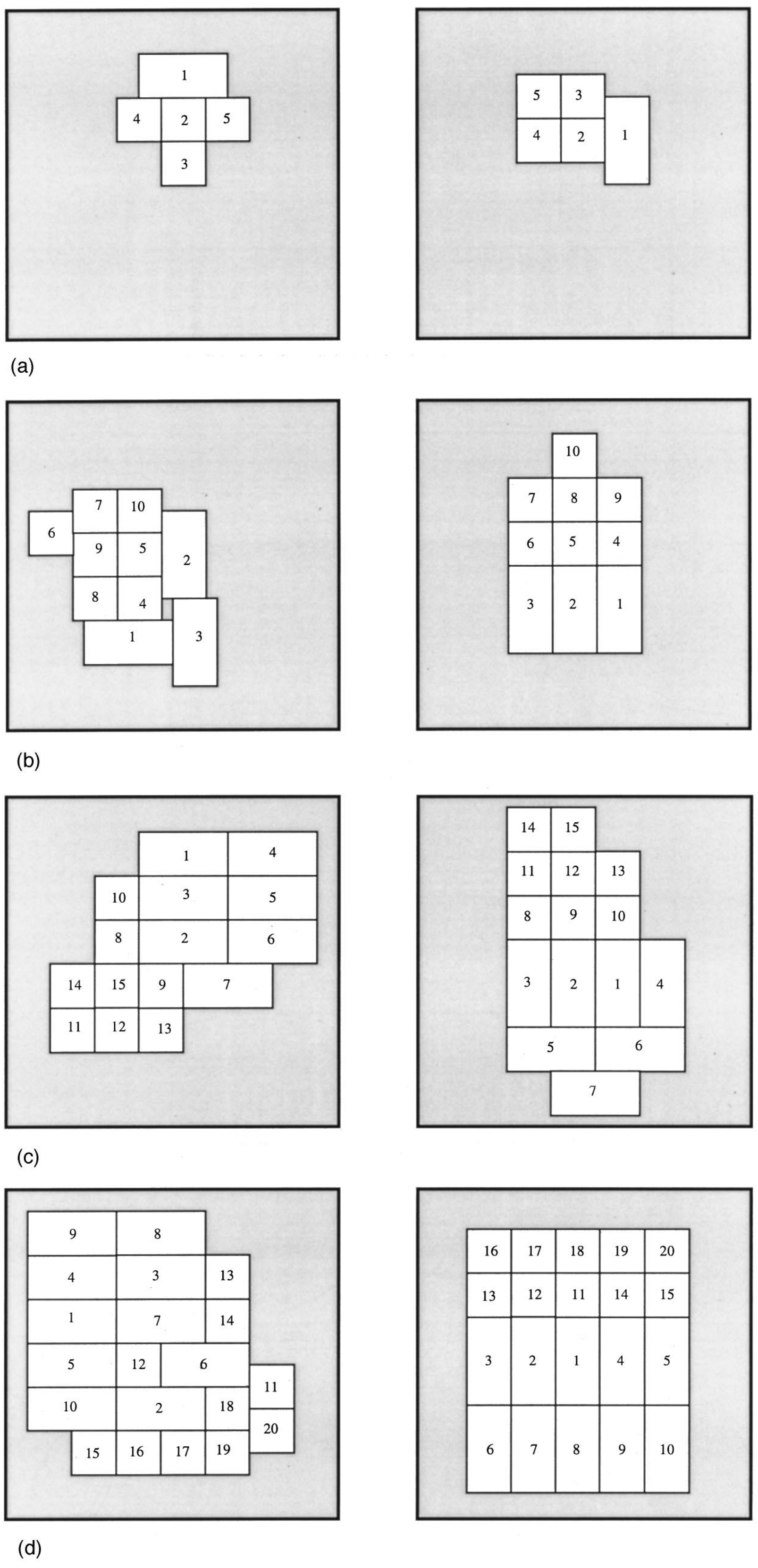


Fig. 4. (Left) GA solution and (right) optimal or best solution of (a) Case 2 problem 1; (b) Case 2 problem 2; (c) Case 2 problem 3; (d) Case 2 problem 4

Table 5. Comparison between GA Solution and Optimal or Best Incumbent Solution for Case 2 Problems

Problem	OSAR (%)	GA solution fitness value	Time (s)	Optimal or best incumbent fitness value	Error (%)
1 [Fig. 4(a)]	10	130	74	120	8.3
2 [Fig. 4(b)]	23	600	164	580	3.4
3 [Fig. 4(c)]	40	1,880	156	1,760	6.8
4 [Fig. 4(d)]	54	4,840	436	3,950	22

Table 6. Input Data for Two Problems of Case 3

Object	*(L, W)*	Area	Object	(L, W)	Area
Cons. Site	(30, 20)	600	Object 6	(9, 4)	36
Object 1	(7, 5)	35	Object 7	(9, 5)	45
Object 2	(4, 4)	16	Object 8	(10, 4)	40
Object 3	(8, 5)	40	Object 9	(2, 2)	4
Object 4	(2, 1)	2	object 10	(4, 4)	16
Object 5	(7, 7)	49			

Table 7. Proximity Weights for Two Problems of Case 3

Object *i*	Object *j*	W_{ij}	Object *i*	Object *j*	W_{ij}
Object 1	Object 2	25	Object 6	Object 7	100
Object 2	Object 3	50	Object 8	Object 9	25
Object 4	Object 5	50	Object 9	Object 10	25

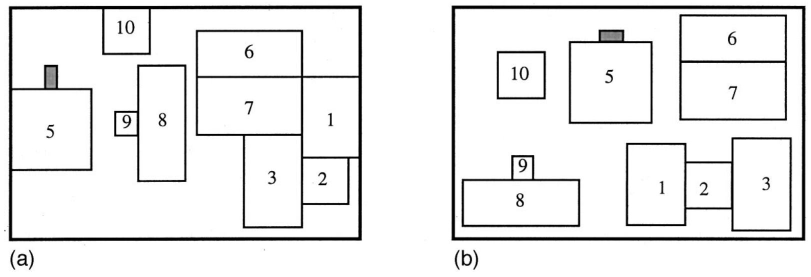


Fig. 5. (a) (Left) GA solution of problem 1; (b) (right) optimal solution of Case 3 problem 1

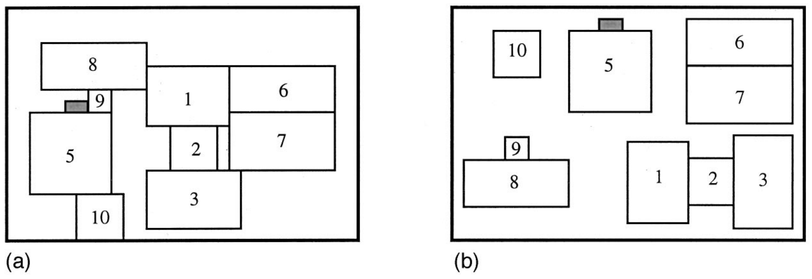


Fig. 6. (a) (Left) GA solution of problem 2; (b) (right) optimal solution of Case 3 problem 2

Table 8. Summary of Results for Problems of Case 3

Problem	OSAR (%)	GA solution fitness value	Time (s)	Optimal or best incumbent fitness value	Error (%)
1 (Fig. 5)	47	1,325	126	1,262.5	5
2 (Fig. 6)	47	1,350	314	1,262.5	7

Table 9. Comparison of Results and Attributes of Three Cases

Attributes	Case 1 problems	Case 2 problems	Case 3 problems
Dimensions of objects	Equal-size objects	2 categories of objects	Objects have variable dimensions
Maximum number of objects	60	20	10
Geometric constraints	No	No	Yes
Weights between objects	Equal between pairs of objects	Equal within same category and different between categories	Different between objects
Max OSAR considered	60%	55%	47%
GA solutions	⩽6% error on largest problem considered	⩽7% error for OSAR 40% >15% for larger OSAR	⩽7% on largest problem considered

position for a selected block is maximized through the use of a function that finds and stores sets of feasible positions for a selected object. Another key feature is that it maintains in each generation chromosomes representing partial layout solutions. These so-called ''bad'' chromosomes were kept to help the evolution process get out of local optima.

The algorithm was tested on different problems with a varying number of blocks, proximity requirements, and constraints on relative positions of facilities. In most cases where the total-objects-to-site-area ratio did not exceed 60%, the algorithm returned close to optimal solutions in a reasonable time (less than 2 min) after 250 generations. In problems with higher total-objects-to-site-area ratio the algorithm failed to find ''good'' and in some cases feasible solutions. Finally, the relationship between computational time and the number of layout objects was found to be approximately linear. Future research will focus on experimenting more with different population sizes and probabilities of GA operators to study their effect on the rate of convergence.

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