DYNAMIC SITE LAYOUT OPTIMIZATION

;ANT COLONY OPTIMIZATION APPROACH

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ABSTRACT

Efficient allocation of sit space to accommodate resources throughout the duration of a construction project is a critical problem. layout may be approached as static or dynamic layout. Solving a dynamic layout problem may be approached by creating a sequence of layouts that span the entire project duration, given resources, the timing of their presence on site, their changing demand for space over time, constraints on their locations, as well as their relocation costs.

This paper attempts to solve a dynamic site layout problem for a construction project benefiting from ant colony optimization (ACO) algorithm. ACO is a heuristic algorithm that works with artificial ants which can introduce solutions some very desirable for many optimization problems. Previous experiments with ACO indicate that this method works very well for solving the combinatorial and discrete optimization problems. While solving the problem, an endeavor has been made to make modification on algorithm in order to make it consistent with the model required.

To examine the efficiency of the algorithm a semi-benchmark dynamic layout problem was considered and the results were compared with those available from the researches.

KEY WORDS

Site layout, Dynamic, Construction, ACO, Optimization

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INTRODUCTION

Construction site layout entails: (1) Identifying facilities that are temporarily needed to support construction operations on a project, but that do not form a part of the finished structure: (2) determining the size and shape of these facilities; and (3) positioning them within the boundaries of available on-site or remote areas. These temporary facilities usually remain on-site for a period of a few days to several months or years, a time period spanning the duration of a construction activity, the duration of a major phase, or the duration of the entire project construction. In some instances, temporary facilities are not dismantled after project completion, but are used instead for operations and maintenance when the constructed facility is in use. In other instances, some permanent facilities may be temporarily designated as construction support facilities.

A site-level facility layout has an important impact on the production time and cost savings, especially for large projects (Hamiani and Popcscu 1988). In addition, a site-level facility layout problem becomes far from trivial if a construction site is confined with available space or the site is very large in size where traveling between facilities can be considerably time consuming. To arrange a set of predetermined facilities into appropriate locations, while satisfying a set of layout constraints, is a difficult problem as there are many possible alternatives. For example, Yen (1995) stated that for 10 facilities, the number of possible alternatives is well above 3628000.

In recent years, researchers have experimented with non-traditional techniques based on artificial intelligence. The use of artificial neural networks was investigated by Yeh (1995) to improve a predetermined site layout. The model minimizes a total cost function that includes the cost of constructing a facility at the assigned location on site and the cost of interacting with other facilities. Li and Love (1998) used the genetic algorithms (GAs) technique to solve the layout-improvement problem.

The dynamics of construction layout planning has a recent origin (RossenBlat 1998; Smith 1987; Tommelein 1991). Alternative means exist to solve dynamic layout problems. In the area of production facilities, Rossenblatt (1986) and Montreuil and Venkatadri (1991) solved different formulations of dynamic facility layout problem subject to nonoverlap constraints between facilities and bounds on facilities' shape and area. Optimal algorithms for solving this problem are NP-complete, and exact solutions can be computed only for small or greatly restricted problems. In construction, Tommelein (1989), Cheng (1992), Thabet (1992, Tommelein and Zouein (1993), Riley (1994), and Lin and Haas (1996) explored alternative means to solve the dynamic layout problem, by using either interactive selection or computer-based positioning of resources.

This paper presents an ant colony optimization model for a dynamic layout problem. Resource positions are restricted by geometrical constraints and are positioned one at a time so as to minimize their transportation costs - costs associated with travel distance from storage location of a resource to point of use relocation costs and costs associated with travel distance from one storage area to another.

This algorithm allows for relocation of resources and reuse of space over time and may easily account for changes in space needs of resources over time

DYNAMIC SITE LAYOUT, GENERAL CONCEPT

Creating layouts that change over time as construction progresses is termed dynamic layout planning. Dynamic layout planning enhances the efficiency of construction operations. If not addressed properly, inefficient layouts will result in increased materials handling and other resource (re)location costs.

Depending on the type and extent of the construction problem, a period can be given in terms of months, quarters, years, etc. The major question involved in the Dynamic Site Layout Problem (DSLP) is what should be the layout in each period, or to what extent, if any, should changes in the layout be made.

The costs associated with the DSLP are those pertaining to the flow of the personnel and material and those involved with rearrangements of the layouts. The material flow costs are a product of flow and distance. For simplicity it will be assumed that the initial cost of assigning facility i to any location j is independent of the location. However, rearranging the layout will result in some shifting costs depending on the facilities involved in this shift. The rearrangement (shifting) costs may be viewed as fixed costs, or costs depending on the facilities involved in the change, or costs depending on the facilities involved and the distance between the various locations, or any combination of the above.

Defining x_{ij} as the location number allocated for facility *j* in period *i* (a decision variable) $d_{x_{ij}.x_{ik}}$ represents the distance between facility *j* and *k* in period *i*.

Upon this definition the objective function may consist of:

1) The total flow cost of the personnel and material defined as:

$$f_1 = \sum_{i=1}^{m}\left(\sum_{j=1}^{n}\sum_{k=1}^{n} f_{ijk}.d_{x_{ij}.x_{ik}}\right) \tag{1}$$

Where *i* is the index of periods and *m* is the total number of periods considered. In which f_{ijk} is the cost per unit length for material flow from facility *j* to facility *k* during period *i*.

2) The cost of rearrangement of the facilities defined as:

$$f_2 = \sum_{i=0}^{m+1}\left(\sum_{j=1}^{n}\left(\frac{\left|x_{i+1} - x_{i,j}\right|}{\left|x_{i+1,j} - x_{i,j}\right| + e}\right).(b_{j,x_{i+1,j}} + c_{j,x_{i,j}})\right) \tag{2}$$

Where $b_{j,x_{i+1,j}}$ $c_{j,x_{i,j}}$ are the cost of installation and remove of facilities, respectively. In this equation *i=0 and i=m+1* are for calculating the installation cost in the first period and remove cost in the last period. The term $\frac{\left|x_{i+1,j} - x_{i,j}\right|}{\left|x_{i+1,j} - x_{i,j}\right| + e}$ will be either 0 or 1 depending on the location of facility *j* in periods *i* and *i+1*. For $x_{i+1,j} = x_{i,j}$ (i.e., position of facility *j* remains unchanged for periods *i* and *i+1*),it ends up to zero, and one otherwise.

Consequently, the objective function will be:

$$F=Min(f_1+f_2) \tag{3}$$

$$F = \min\left[\sum_{i=1}^{m}\left(\sum_{j=1}^{n}\sum_{k=1}^{n} f_{ijk}.d_{xij.xik}\right)+\sum_{i=0}^{m+1}\left(\sum_{j=1}^{n}\left(\frac{\left|X_{i+1}-X_{i,j}\right|}{\left|X_{i+1,j}-X_{i,j}\right|+e}\right).(b_{j,xi+1,j}+c_{j,xi,j})\right)\right] \quad (4)$$

Inputs to the model consist of 4 matrices named as **F**, **D**, **B** and **C**.

F is a n*n matrix which indicates the flow cost between facilities in *m* periods.

D is a n*n matrix which defines the distances between locations

B is a n*n matrix representing the installation cost

C is also a n*n matrix which defines the remove cost

ANT COLONY BEHAVIOR

Ant colony algorithms have been founded on the observation of real ant colonies. By living in colonies, ants' social behavior is directed more to the survival of the colony entity than to that of a single individual member of the colony. An interesting and significantly important behavior of ant colonies is their foraging behavior, and in particular, their ability to find the shortest route between their nest and a food source, realizing that they are almost blind. The path taken by individual ants from the nest, in search for a food source, is essentially random (Dorigo et al. 1996). However, when they are traveling, ants deposit on the ground a substance called pheromone, forming a pheromone trail as an indirect communication means. By smelling the pheromone, there is a higher probability that the trail with a higher pheromone concentration will be chosen. The pheromone trail allows ants to find their way back to the food source and vice versa. The trail is used by other ants to find the location of the food source located by their nest mates. It follows that when a number of paths are available from the nest to a food source, a colony of ants may be able to exploit the pheromone trail left by the individual members of the colony to discover the shortest path from the nest to the food source and back (Dorigo and Di Caro 1999). As more ants choose a path to follow, the pheromone on the path builds up, making it more attractive to other ants seeking food and hence more likely to be followed by other ants.

Generally speaking, evolutionary algorithms search for a global optimum by generating a population of trial solutions. Ant colony optimization, as an evolutionary algorithm, has many features which are similar to genetic algorithms (GAs). The most important difference between GAs and ACO algorithms is the way the trial solutions are generated. In ACO algorithms, trial solutions are constructed incrementally based on the information contained in the environment and the solutions are improved by modifying the environment via a form of indirect communication called stigmergy (Dorigo et al. 2000). On the other hand, in GAs the trial solutions are in the form of strings of genetic materials and new solutions are obtained through the modification of previous solutions (Maier et al. 2003). Thus, in GAs the memory of the system is embedded in the trial solutions, whereas in ACO algorithms the system memory is contained in the environment itself.

Let $t_{ij}(t)$ be the total pheromone deposited on path ij at time t and $h_{ij}(t)$ be the heuristic value of path ij at time t according to the measure of the objective function. We define the transition probability from node i to node j at time period t as:

$$P_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum\limits_{l \in allowed}[\tau_{il}(t)]^{\alpha}[\eta_{il}(t)]^{\beta}} & \text{if } j \in \text{allowed} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Where a and b = parameters that control the relative importance of the pheromone trail versus a heuristic value. Let q be a random variable uniformly distributed over $[0,1]$, and $q_0 \in [0,1]$ be a tunable parameter. Upon completion of a tour by all ants in the colony, the global trail updating is done as follows:

$$t_{ij}(t+1) \xleftarrow{iteration} r \cdot t_{ij}(t) + (1 - r) \cdot \Delta t_{ij} \tag{6}$$

Where $0 \le r \le 1$; $(1 - r)$ = evaporation (i.e., loss) rate; and the symbol $\xleftarrow{iteration}$ is used to show the next iteration. There are several definitions for $\Delta t_{ij}(t)$ (Dorigo et al. 1996; Dorigo and Gambardella 1997).

There are several definitions for $\Delta t_{ij}(t)$ but in this paper we use Ant Colony System-Global Best:

$$\Delta t_{ij}(t) = \begin{cases} Q / G^{k_{gb}}(m) & \text{if} \quad (i,j) \in T^{k_{gb}}(m) \\ 0 & \text{if} \quad (i,j) \notin T^{k_{gb}}(m) \end{cases} \tag{7}$$

Where Q is a constant and $G^{k_{gb}}$ =value of the objective function for the ant with the best performance within the past total iteration.

IMPLEMENTATION OF ACO

Consider a plant with eight facilities where, for simplicity (and without loss of generality), the facilities are assumed to be of equal size. The planning horizon consists of four periods. The flow data between the different facilities for the various periods are given by the following set of "From-To" matrices, F_i, where F_i is the material handling flow for period i.(Table 1) Obviously, upon the time scheduling of project some facilities are present in a period and probably are absent in other periods. In Fig 1 a schedule of presence of facilities is shown. For example in this graph the facility 3 is present in 1st and 4th periods and in periods 2 and 3 is not needed.

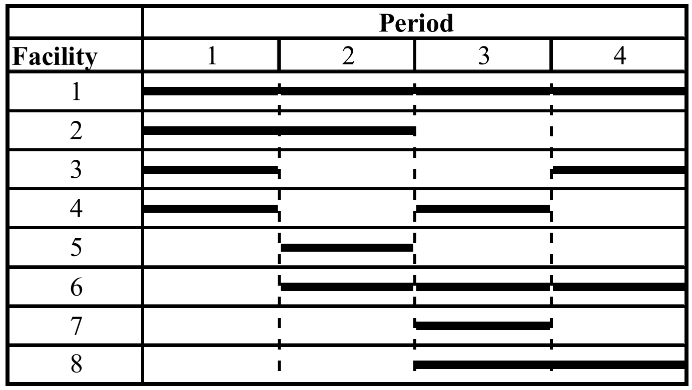

Fig 1-Time scheduling of the presence of facilities in the construction site

Table 1 contains the data for four 8*8 matrices providing flow cost for the numerical example. Remaining model input data including distance between locations, cost of installation and remove of the facilities at different locations are presented as three 8*8 matrices in Tables 2, 3 and 4, respectively. In matrices B and C large costs reflects the nonfeasible (or nondesirable) locations for given facilities.

Table 1-Flow cost for the numerical example

	From \ To	1	2	3	4	5	6	7	8
F1	1	0	70	70	10	0	0	0	0
	2	70	0	60	80	0	0	0	0
	3	70	60	0	80	0	0	0	0
	4	80	70	60	0	0	0	0	0
	5	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0

	From \ To	1	2	3	4	5	6	7	8
F2	1	0	70	0	0	80	60	0	0
	2	60	0	0	0	60	70	0	0
	3	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0
	5	70	80	0	0	0	60	0	0
	6	60	60	0	0	80	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0

	From \ To	1	2	3	4	5	6	7	8
F3	1	0	0	0	70	0	60	80	60
	2	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	4	60	0	0	0	0	80	60	70
	5	0	0	0	0	0	0	0	0
	6	60	0	0	70	0	0	70	80
	7	70	0	0	80	0	60	0	60
	8	60	0	0	70	0	60	70	0

	From \ To	1	2	3	4	5	6	7	8
F4	1	0	0	60	0	0	70	0	60
	2	0	0	0	0	0	0	0	0
	3	60	0	0	0	0	80	0	60
	4	0	0	0	0	0	0	0	0
	5	0	0	0	0	0	0	0	0
	6	80	0	70	0	0	0	0	60
	7	0	0	0	0	0	0	0	0
	8	60	0	60	0	0	80	0	0

Table 2-Distances between locations

Location	1	2	3	4	5	6	7	8
1	0	2	4	3	7	3	4	4
2	2	0	5	7	7	2	5	6
3	4	5	0	6	3	2	3	3
4	3	7	6	0	4	5	3	4
5	7	7	3	4	0	2	4	3
6	3	2	2	5	2	0	3	5
7	4	5	3	3	4	3	0	6
8	4	6	3	4	3	5	6	0

Table 3-Costs of installation of facilities in different locations (*10^4)

Facility	Location							
	1	2	3	4	5	6	7	8
1	8	1000	1000	1000	5	4	9	5
2	1000	1000	1000	4	3	1000	7	1000
3	2	8	1000	9	1000	4	3	7
4	8	2	5	1000	7	4	4	1000
5	3	7	9	1000	1	2	1000	5
6	7	1000	6	7	3	1000	1000	4
7	1	5	1000	1000	4	5	1000	1000
8	1000	4	1000	11	9	1000	6	5

Table 4-Costs of remove of facilities in different locations (*10^4)

Facility	Location							
	1	2	3	4	5	6	7	8
1	4	1000	1000	1000	2	2	4	2
2	1000	1000	1000	2	1	1000	3	1000
3	1	4	1000	4	1000	2	1	3
4	4	1	2	1000	3	2	2	1000
5	1	3	4	1000	1	1	1000	2
6	3	1000	3	3	1	1000	1000	2
7	1	2	1000	1000	2	2	1000	1000
8	1000	2	1000	5	4	1000	3	2

To apply ACO algorithm to a specific problem, the following steps have to be taken: (1) problem representation as a graph or a similar structure easily covered by ants; (2) assigning a heuristic preference to generate solutions at each time step (i.e., selected path by ants); (3) defining a fitness function to be optimized

This problem has been represented as a graph in Fig 2 . In this graph the horizontal and vertical axes represent the facility and the location numbers, respectively. As an example in the first period, facility number 3 is positioned in location 6, whereas, the same facility in the forth period is positioned in location number 4. Note that facility number 4 will not be present during the 2nd and 3rd periods. (Fig 2 and Table 5)

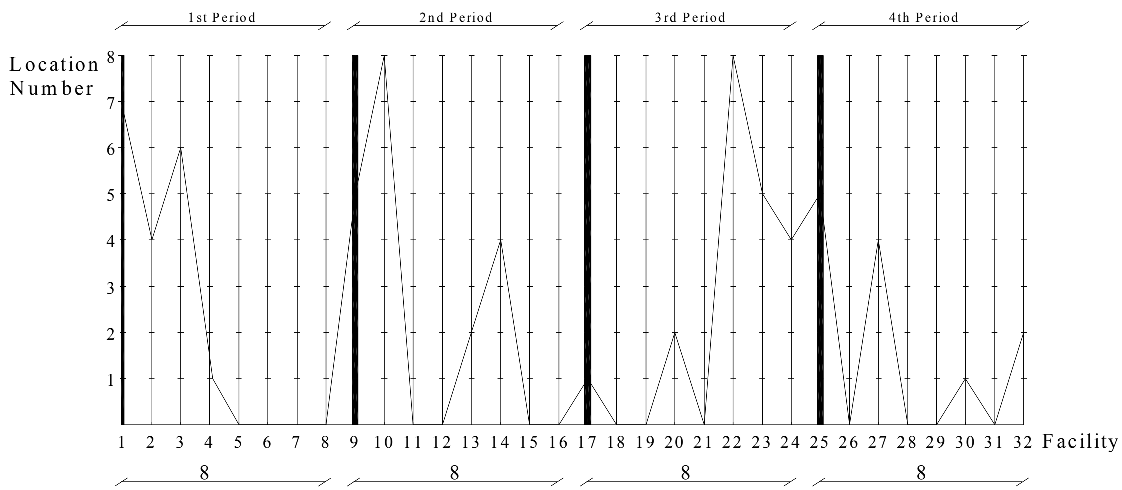

Fig 2- representation of the layout problem

Table 5- A sample position of facilities in the different periods

	Facility							
	1	2	3	4	5	6	7	8
Period 1	7	4	6	1				
Period 2	5	8			2	4		
Period 3	1			2		8	5	4
Period 4	5		4			1		2

The heuristic information on this problem is determined by considering the criterion as minimum flow cost between two decisions:

$$h_{l_1 l_2 f_1 f_2} = \frac{1}{d_{l_1 l_2} f_{f_1 f_2}} \qquad (5)$$

Where $d_{l_1 l_2}$ =distance between location l_1 and location l_2; $f_{f_1 f_2}$ =flow cost between facility f_1 and facility f_2 .

The fitness function is a measure of the goodness of the generated solutions according to the defined objective function. For this study, total cost is defined as Eq. (4)

MODEL APPLICATION

The developed site layout model was solved using number of ants ranging from 100 to 500. A 1-opt Local search with a minor modification has been implemented in the algorithm. Upon this modification the routs of selected ants are broken just in the points that the periods change and consequently the produced routs will be feasible.

The developed model was applied to a semi-benchmark site layout problem previously defined and solved by Khalilian(2003). Using GA, Khalilian came up with an objective function value of 12135000 with 500 population size and 250 generation. The results of GA and ACO are presented in table 6. In this comparison it is supposed that the population in GA is equivalent to the Number of ants.

Results of the proposed ACO model are presented in Figs 3 for different number of agents. The best result was obtained for $r = 0.9$, $a = 2$, $b = 0$ and $q_0 = 0$, which resulted from parameter-tuning. The best layout resulted from these parameters is presented in table 7.

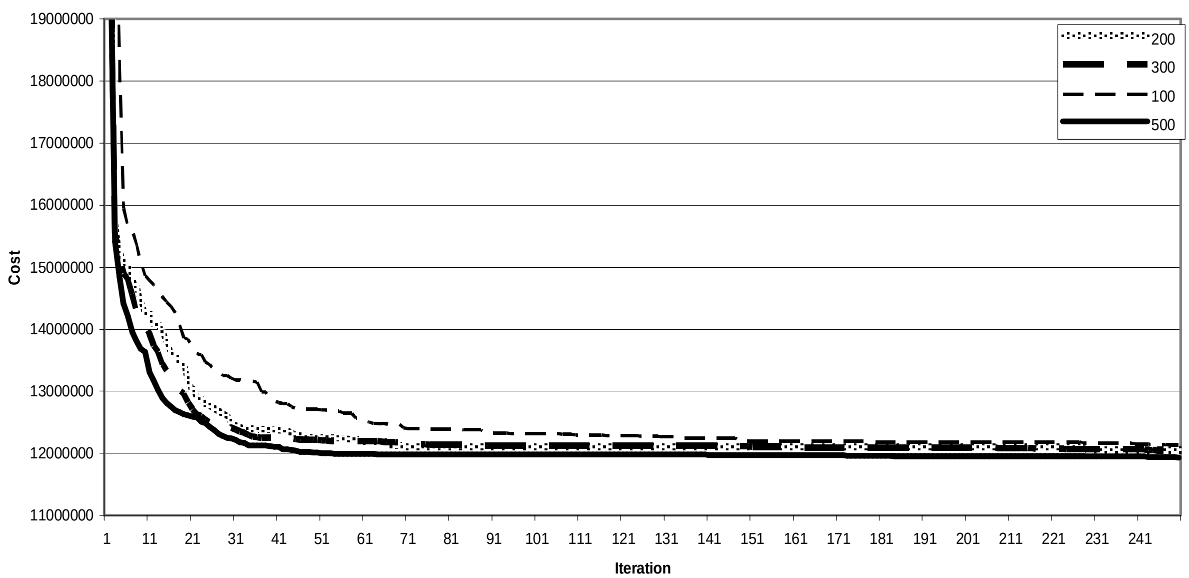

Fig 3- Convergence pattern of the best solutions for different number of ants.

Table 6-Comparison between the results if GA and ACO

Population/Number of Ants	Total Cost (GA)	Total Cost(ACO)
100	12882500	11750000
200	12350000	11770000
300	12550000	11750000
500	12135000	11770000

Table 7-The best layout

	Facility							
	1	2	3	4	5	6	7	8
Period 1	5	7	6	3				
Period 2	5	7			6	3		
Period 3	6			7		3	1	2
Period 4	6		7			3		5

CONCLUSION

This paper has introduced a representation scheme for representing construction site layout problems into a graph suitable for ACO algorithms. It then demonstrated the robustness of the ACO approach in solving layout problems as combinatorial optimization problems that are difficult to solve by conventional methods. Also the proposed method has been compared with a similar algorithm (GA).

For medium or large construction projects, it is not unusual to have up to 40 temporary facilities that need to be located on site. It is expected that the system developed in this study can easily handle the problem size. However, extensive tests will be conducted to ensure the usefulness of the system in dealing with facility allocation problems with larger sizes.

REFERENCES

Dorigo, M., Maniezzo, V., and Colorni, A. (1996). "The ant system: optimization by a colony of cooperating ants." *IEEE Trans. Syst. Man. Cybern.*, 26, 29-42.

Dorigo, M., and Di Caro, G. (1999). "The ant colony optimization metaheuristic. " *New ideas in optimization*, D. Corne, M. Dorigo, and F. Glover, eds., McGraw-Hill, London, 11-32.

Dorigo, M., Bonabeau, E., and Theraulaz, G. (2000). "Ant algorithms and stimergy." *Future Generation Comput. Systems*, 16, 851-871

Hegazy, T.,Elbeltagi, E.(1999)."EvoSite: Evolution –Based Model for Site Layout Planning." *J. Comp, in Civ. Eng.,ASCE*,13(3),198-206

Jalali, M.R. (2005). "Optimum design and operation of hydrosystems by ant colony optimization algorithms; A new metaheuristic approach." *PhD. Thesis*, Iran University of Science and Technology, Tehran, Iran.

Khalilian, S., Afshar, A., Kaveh, A. (2003)."Dynamic Site Layout by Genetic Algorithm." *MSc Thesis*, Iran University of Science and Technology, Tehran, Iran

Tommelein, I.D., Levit, R.E., and Confrey, T. (1991). "SitePlan experiments: Alternate strategies for site layout design." *J. Comp, in Civ. Eng.,ASCE*, 5(1), 42-63.

Yeh, I.C. (1995). "Construction- site layput using annealed neural network." *J. Comp, in Civ. Eng.,ASCE,* 9(3), 201-208.

Zouein, P.P., Tommelein. I.D. (1999)."Dynamic Layout Planning Using a Hybrid Incremental Solution Method." ASCE, *J. of Constr. Engrg. and Mgmt*.,125(6),400-408