World Academy of Science, Engineering and Technology
International Journal of Civil and Environmental Engineering
Vol:9, No:5, 2015

Dynamic Construction Site Layout Using Ant Colony Optimization

Y. Abdelrazig

Abstract**—**Evolutionary optimization methods such as genetic algorithms have been used extensively for the construction site layout problem. More recently, ant colony optimization algorithms, which are evolutionary methods based on the foraging behavior of ants, have been successfully applied to benchmark combinatorial optimization problems. This paper proposes a formulation of the site layout problem in terms of a sequencing problem that is suitable for solution using an ant colony optimization algorithm.

In the construction industry, site layout is a very important planning problem. The objective of site layout is to position temporary facilities both geographically and at the correct time such that the construction work can be performed satisfactorily with minimal costs and improved safety and working environment. During the last decade, evolutionary methods such as genetic algorithms have been used extensively for the construction site layout problem. This paper proposes an ant colony optimization model for construction site layout. A simple case study for a highway project is utilized to illustrate the application of the model.

Keywords**—**Construction site layout, optimization, ant colony.

I. Introduction

In the construction industry, site layout is a very important planning problem. The objective of site layout is to position temporary facilities both geographically and at the correct time such that the construction work can be performed satisfactorily with minimal costs and improved safety and working environment. During the last decade, evolutionary methods such as genetic algorithms have been used extensively for the construction site layout problem [1]-[5]. This paper proposes an ant colony optimization model for construction site layout. First, a brief introduction to the problem and ant colony optimization algorithms is presented. Next, a formulation of the site layout problem is proposed in terms of a sequencing problem that is suitable for solution using ant colony optimization algorithm. Finally, a simple case study for a highway construction project is utilized to illustrate the application of the model.

II. The Construction Site Layout problem

A construction site represents conflicting concerns, constantly calling for a broad and multi-criteria approach to solving problems related to site planning and design. As an important part of site planning and design, the objective of construction site layout is to allocate appropriate locations and areas for temporary site-level facilities such as warehouses, job offices, workshops and batch plants. Unless the site is part of large development, it is often confined by boundaries.

The construction site layout can have an important impact on the production time and cost, especially in the case of large projects [6]. In addition, such a problem becomes far from trivial if a construction site is confined due to the lack of available space, or if the site is very large, then traveling between facilities can be considerably time consuming. Layout problems have however been solved using operations research [7] and artificial intelligence [8], [9]. Unfortunately, they all have two main drawbacks; 1) they rely on the generation of a knowledge base which will allow choice between various geographical layouts. This is very difficult to produce for real projects. 2) The integration of the scheduling procedures with the geographical aspects to generate the site layout, and this also has proved difficult [10]-[17].

Positioning of major pieces of equipment might be considered to be a sub-set of the general site layout problem. Several authors report research into this topic by various methods. Tong and Tam [1] developed genetic algorithm model for site facility layout and an artificial neural network model for predicting tower-crane operations using a practical example. Their scope confines to a defined area of construction: the structural concrete-frame construction stage of public housing projects. Tam et al. [7] present a site layout genetic algorithm model for optimization of the tower crane and supply locations as the major site facilities for high-rise building construction. Hanna [18] presents a knowledge base expert system to aid in the selection of the most adequate crane type for any project. Fattah and Yandow [19] present the expert system CRANE to aid in the decision making process of selecting and placing stationary mast tower cranes on urban, general construction projects. These methods employ knowledge-based systems. They do not look at all aspects of the positioning although it might be possible to extend them to do so.

Yeh [20] and Zouein and Tommelein [21] identified a construction site layout problem. In Yeh's problem, there are *n* resources to be positioned and n available positions and all the information about operation and set-up cost is known. An assignment of resources to positions is searched to minimize the whole cost. An annealed neural network was used to solve the assignment type of construction site layout problem in which the problem is formulated as a discrete combinatorial optimization problem. This is a static and special case of more general construction site layout problems.

A dynamic construction site layout problem is considered with assigning a number of predetermined facilities into a

Y. Abdelrazig is with Florida A&M University – Florida State University, Tallahassee, FL 32310 USA (phone: 850-410-6453; fax: 850-410-6142; e-mail: yabdelrazig@fsu.edu).

number of predetermined places. This problem can be modeled as a Quadratic Assignment Problem (QAP). This formulation requires an equal number of facilities and locations. In this paper, it is assumed that the number of predetermined places should be equal or greater than the number of predetermined facilities. If the number of predetermined places is greater than the number of predetermined facilities, then a number of dummy facilities will be added to make both numbers equal.

This paper introduces a method to solve the site unequal-area facility layout problems, in which some of the predetermined facilities are only able to accommodate some of the facilities. This can adequately represent the real construction site case where predetermined places have different areas. The dynamic construction site layout problem can be formulated as given below and is adapted from [22] and [20]:

$$MinimizeCost = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N}\sum_{t=2}^{T} Ai_{jlt} Yi_{jlt} + \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N}\sum_{t=1}^{T} C_{ijklt} X_{ijt} X_{klt} \quad (1)$$

Subject to:

$$\sum_{j=1}^{N} X_{ijt} = 1$$

$$i = 1,\ldots.., N; t = 1,\ldots, T$$

$$\sum_{i=1}^{N} X_{ijt} = 1$$

$$j = 1,\ldots.., N; t = 1,\ldots, T$$

$$Y_{ijlt} = X_{ij(t-1)} * X_{ilt},$$

$$i, j, l = 1,\ldots.., N; t = 2,\ldots, T$$

$$X_{ijt} = \{0,1\} \quad i, j = 1,\ldots., N \text{ and } t = 1,\ldots., T$$

$$Y_{ijlt} = \{0,1\} \quad i, j, l = 1,\ldots., N \text{ and } t = 1,\ldots., T$$

where: N = number of locations; T = Number of time periods; A_{ijlt}= the cost of shifting facility I from location j to l in a period t; C_{ijklt} = Construction cost between Facility I located at location J and K located in l in period t; X_{ijt} =1 (if facility *i* is assigned to location j at period t); 0 (otherwise); Y_{ijlt} =1 (if facility *i* is shifted from location j to l at the beginning of period t); 0 (otherwise).

III. The Ant Colony Optimization Heuristic

Dorigo et al. [23] presented heuristics, which use artificial ants, to solve traveling salesperson problems, the QAP, and the job-shop scheduling problem. They are called Ant Colony Optimization (ACO) heuristics. These heuristics simulate how ants search for food, in order to find solutions. The authors discuss how ants are capable of finding the shortest path from a food source to the nest without using visual cues. In searching for food, the ants do not communicate directly but indirectly by adding a chemical trail (called pheromone trail) to the environment. Initially, ants explore the areas surrounding their nest in a random manner. The shortest path between a food source and the nest is determined based on the pheromone trail an ant leaves while returning back to the nest from the food source so that other ants can find the food source. The amount of the pheromone trail left by an ant is based on the amount of food found. If the paths between the food source and the nest are far apart, fewer ants will travel these paths, and the trail will eventually evaporate. However, when the path between the food source and the nest are close, more ants will travel this path, which will be indicated by a strong pheromone trail.

In ACO heuristics, the ant is defined as a simple computational agent, which iteratively improves or constructs a solution for a combinational optimization problem. The main traits of artificial ants are taken from real ants and their natural behavior. The main traits area as follows: 1) Artificial ants exist in colonies of cooperating individuals, 2) they communicate indirectly by depositing (artificial) pheromone, 3) they use a sequence of local moves to find the shortest path from a starting point to a destination (i.e. the optimal solution), and 4) they apply a stochastic decision policy using local information only (i.e. they do not look ahead) to find good solutions.

Gambardella et al. [24] presented an ACO heuristic called the hybrid ant colony system to solve the QAP (HAS-QAP). HAS-QAP is different from the traditional ACO heuristic, since it is an improvement heuristic instead of a construction one. First, a set of solutions is generated randomly such that each solution (i.e., layout plan) is represented by an ant. The set of solutions is improved by using a local search technique, and the best solution is obtained and used to initialize the pheromone trail matrix.

After performing trail swaps for each ant, a local search technique is used to improve the solutions. If the best solution obtained so far has improved (or at the start of the heuristic), an intensification scheme is activated. When intensification is active, the better solution between the solution at the start of the iteration and the one obtained after the local search technique is used to start the next iteration. Also, a diversification mechanism is activated if a certain number of iterations are performed without improving the best solution found. When this strategy is invoked, all of the information is erased. The numerical results show that the HAS-QAP heuristic obtained very good results for the QAP.

For this research the following steps were applied to implement the model.

A. Step 1: Generate Initial Solution for Each Ant

In this step, the initial solutions are generated. First, for each ant, a permutation (or layout) for the first time period is generated. Then this layout is used for all the remaining layouts for time periods 2, 3, …, *T*. Thus, the layouts for all time periods are the same for each ant. Therefore, the rearrangement cost is zero.

B. Step 2: Use Pair-Wise Exchange Heuristic

In this step a pair-wise exchange heuristic is used to improve the solution or layout plan for each ant and let π^* represent the best solution.

The purpose of this step is to improve the initial solutions and use the best solution π* to initialize the pheromone trail matrix in step 3. This step is repeated for *N*N*T* iterations.

C. Step 3: Pheromone Trail Matrix Initialization

The pheromone trail is the most important component in the ACO heuristics. The pheromone trail matrix, *P*, allows the heuristic to accept uphill moves (i.e., non-improving solutions) so that the heuristic does not converge to a poor local optimum. Entries of matrix *P*, $P_{\pi_{it}jt}$ measures the desirability of assigning department π_{it} to location *j* at time period *t*. Initially, all the entries of *P* are set to *1/Qf (π*)* where *Q* is a heuristic parameter.

D. Step 4: Start main loop

Initialize and define additional heuristic parameters. Define *Imax*, which represents the total number of iterations performed and initialize all other parameters. Therefore, the stopping criterion is to terminate the heuristic after *Imax* iterations have been performed.

E. Step 5: Perform R pheromone trail swaps

In this step, a new solution is generated for each ant by considering *R* pheromone trail swaps. First, a time period is selected randomly. In this time period, two department locations are selected for exchange. First, department π^k_{ut} is selected randomly between 1 and *N*. Then, a location $v \neq u$ is selected using one of the two policies presented below. The first policy is selected with a probability *q*.

1. *v* is chosen such that $P_{r,\pi_s} + P_{s,\pi_r}$ is maximized. This policy consists of exploiting the pheromone trail.
2. *v* is chosen with probability $\frac{P_{r,\pi_s} + P_{s,\pi_r}}{\sum\left(P_{r,\pi_j} + P_{j,\pi_r}\right)}$. This policy consists of exploring the solution space. However, at the first iteration (also after implementing the diversification strategy), facilities *u* and *v* are randomly selected, since all the entries in the pheromone trail matrix are the same.

F. Step 6: Use The Pair-Wise Exchange Heuristic to Improve the Solutions

The solutions, from the previous step, are improved using the pair-wise exchange heuristic. This step is repeated for *N*N*T* iterations.

G. Step 7: Perform Intensification Strategy

This step is used to explore the neighborhood of good solutions more thoroughly. At the start of the heuristic once the best solution has improved, the intensification process will be activated. Each ant *k* starts its next iteration with the best set of permutations between the solutions from step 5 and the solutions from step 6. In contrast, if the best solution has not improved, the intensification strategy will not be activated and each ant starts its next iteration with the solutions from step 6. The intensification strategy remains active as long as one ant improves its solution during iteration.

H. Step 8: Update Pheromone Trail Matrix

To speed-up the convergence of the heuristic, the pheromone trail matrix is updated using only the best solution obtained thus far, as in [25]. First, all the pheromone trails are weakened (evaporated) by setting:

$$P_{\pi_{it}jt} = \left(1-\alpha_1\right) * P_{\pi_{it}jt} \tag{2}$$

where $0 < \alpha_1 < 1$ is a parameter that controls the evaporation of pheromone trails. A value of α_1 close to 0 implies that the pheromone trails remain active a long time, while a value close to 1 implies a high degree of evaporation and a shorter memory of the system. Then, the pheromone trails contained in the best solution *π** are reinforced by setting:

$$P_{\pi^*_{it}it} = P_{\pi^*_{it}it} + \frac{\alpha_2}{f(\pi^*)} \tag{3}$$

where α_2 is a parameter that controls the reinforcement of the pheromone trails.

I. Step 9: Perform Diversification Strategy

The diversification mechanism is activated after *S* consecutive iterations without improvement to the best solution obtained. Once this mechanism is activated, all of the information (e.g., solutions, trail matrix) is erased and the heuristic starts from the beginning where only the best solution obtained from an ant is used in the next iteration. The other *M – 1* initial solutions are generated randomly. The only other information that is used is the iteration number. Therefore, the heuristic is repeated for *Imax* – iteration number.

IV. Case Study

The following example is a simplified case study to illustrate the construction site layout problem for a highway project. In some projects on-site space can be a crucial resource. In highly congested sites, space becomes a very scarce resource that needs to be carefully planned and efficiently utilized. On the other hand, in large sites having abundant space availability, the proper positioning of site facilities with respect to each other will greatly influence material handling and travel costs. This example illustrates the optimal arrangement for placing a set of predetermined facilities into a set of locations on the site.

Construction site layout is concerned with the positioning, and timing of the temporary facilities that are used to carry out a construction project. It is important to virtually plan any construction project, and be able to see one step ahead, since it can significantly affect the cost of the project.

The objective of this optimization model is to minimize the total cost of movements of construction equipment from facilities i to j. This cost of movements will be represented as the product of the traveling distances between the facilities and the frequency of traveling.

The optimization objective is presented as:

$$MinZ = \sum_{i,j=1}^{n} f * d_{ij} \tag{4}$$

where f is the frequency of movements and d is the distance between facilities.

This case study example layout indicates that 6 facilities are located in 6 starting locations as shown in Fig. 1. The facilities are: (1) site office, (2) labor trailer (3) loader equipment, (4) storage, (5) trucks storage area, and (6) backhoes storage area.

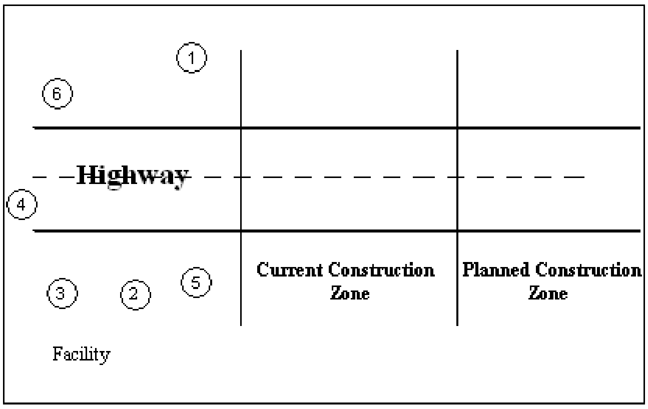

Fig. 1 Case study site layout

The frequencies of trips (in 1 day) made between facilities are assumed as: (Example column 1 row 3: the frequency of trips between site office and loader equipment is 2)

$$F = \begin{bmatrix} 0 & 2 & 2 & 1 & 4 & 9 \\ 2 & 0 & 7 & 4 & 9 & 6 \\ 2 & 7 & 0 & 7 & 8 & 5 \\ 1 & 4 & 7 & 0 & 5 & 7 \\ 4 & 9 & 8 & 5 & 0 & 3 \\ 9 & 6 & 5 & 7 & 3 & 0 \end{bmatrix}$$

The distances of the 6 locations, measured in meters, are shown in Fig. 2 and represented in matrix D. (Example column 1 row 3: the distance between site office and loader equipment location is 33 meters)

$$D = \begin{bmatrix} 0 & 25 & 33 & 42 & 47 & 30 \\ 25 & 0 & 8 & 17 & 22 & 55 \\ 33 & 8 & 0 & 9 & 14 & 49 \\ 42 & 17 & 9 & 0 & 5 & 40 \\ 47 & 22 & 14 & 5 & 0 & 35 \\ 30 & 55 & 49 & 40 & 35 & 0 \end{bmatrix}$$

Object oriented programming language (C++) was used to write a program for the implementation of the Ant colony optimization algorithm. The resulting optimum layout representation (solution) is presented in Fig. 3.

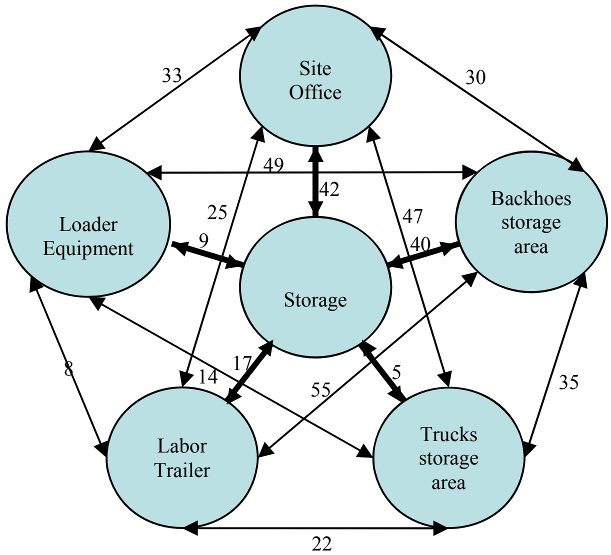

Fig. 2 Case study: Distances between facilities

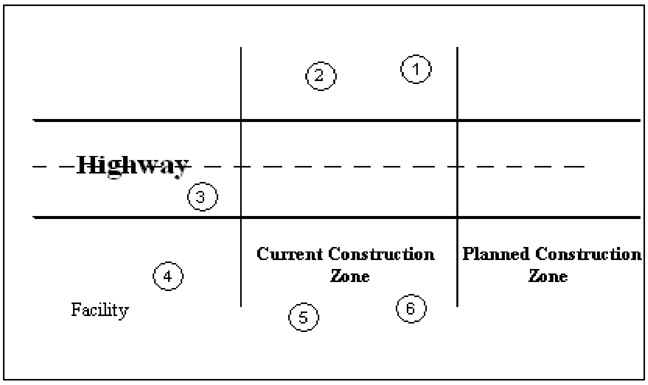

Fig. 3 Case study optimum site layout

V. Conclusions

This paper proposed a general formulation for the dynamic construction site layout problem using ant colony optimization algorithm. The problem formulation provided in this paper can be extended to include many other costs without significant increase in computation requirement. The ant colony optimization algorithm is very efficient and is able to solve difficult problems such as the proposed site layout problem. Dynamic Construction site layout problems are always encountered in the site planning and design and the ant colony approach can be included in the list of reliable and useful optimization tools for solving such problems.

Future research will focus on extending the problem formulation to include many other costs without significant increase in computer computation requirement. It may be possible to include more complex, less tangible but equally important aspects into the fitness function. Thus, work is ongoing to extend these ideas to include safety and environmental aspects and balance these with the finances of a project. Another research direction will investigate the viability of combining other optimization techniques such as Simulated Annealing (SA) and Tabu Search (TS) with the Ant

Colony Optimization algorithm. This hybrid approach will reduce computational time dramatically, especially for large size site layout problems.

REFERENCES

[1] T. Tong; C. Tam, GA-ANN model for optimizing the locations of tower crane and supply points for high-rise public housing Construction; journal of Construction Management and Economics, 21(3), 2003, 257-266

[2] H. Osman, M. Georgy, and M. Ibrahim, A hybrid CAD-based construction site layout planning system using genetic algorithms, Automation in Construction, 12(6), 2003, 749-764.

[3] M. Mawdesley, and S. Al-Jibouri, Proposed genetic algorithms for construction site layout; Engineering Applications of Artificial Intelligence, 16(5-6), 2003, 501-509.

[4] S. Cheung, T. Tong, and C. Tam, Site pre-cast yard layout arrangement through genetic algorithms", Automation in Construction, 11(1), 2002, 35-46.

[5] E. Elbeltagi, and T. Hegazy, A hybrid-based system for site layout planning in construction; journal of Computer-Aided Civil and Infrastructure Engineering, 6(2), 2001, 79-93.

[6] E. Elbeltagi, T. Hegazy, A. Hosny, and A. Eldosouky, Schedule-dependent evolution of site layout planning; journal of Construction Management and Economics, 19 (7), 2001, 689-697.

[7] C. Tam, T. Tong, and W. Chan, Genetic algorithm for optimizing supply locations around tower crane; Journal of Construction Engineering and Management, 127 (4), 2001, 315-320

[8] H. Li, and P. Love, Genetic search for solving construction site-level unequal-area facility layout problems; Automation in Construction, 9(2), 2000, 217-226.

[9] H. Harmanani, P. Zouein, and A. Hajar, An evolutionary algorithm for solving the geometrically constrained site layout problem; journal of Computing in Civil and Building Engineering, 2, 2000, 1442-1449.

[10] F. Karray, E. Zaneldin, T. Hegazy, A. Shabeeb, and E. Elbeltagi, Computational intelligence tools for solving the facilities layout planning problem; Proceedings of the American Control Conference, 6, 2000, 3954-3958.

[11] E. Elbeltagi, and T. Hegazy, Genetic optimization of site layout planning; Transactions of the Annual Meeting of AACE International, 1999, IT.05.1-IT.05.8.

[12] T. Hegazy, and E. Elbeltagi, EvoSite: Evolution-based model for site layout planning; Journal of Computing in Civil Engineering, 13(3), 1999, 198-206.

[13] M. Philip, N. Mahadevan, and K. Varghese, Optimization of construction site layout - a genetic algorithm approach; Proceedings of the Congress on Computing in Civil Engineering, 1997, 710-717.

[14] A. Hamiani, and G. Popescu, CONSITE: a Knowledge-based Expert System for Site Layout; Proceeding of 5th Conference of Computing in Civil Engineering, ASCE, New York, 1988, 248-256.

[15] J. Seehof, and U. Evans, Automated layout design program; Industrial Engineering, 18, 1967, 690–695.

[16] A. Hamiani, Knowledge representation for the site layout problem; Proceedings of Computing in Civil Engineering, ASCE, Reston, VA, 1989, 283–289.

[17] I. Tommelein, R. Levitt, B. Hayes-Roth, and T. Confrey, Sightplan experiments: alternate strategies for site layout design; ASCE Journal of Computing in Civil Engineering, 5(1), 1991, 42–63.

[18] A. Hanna, SELECTCRANE: An expert system for optimum crane selection; Proceedings of the 1st Congress on Computing in Civil Engineering, 1, ASCE, Washington, DC, USA 1994, 958-963.

[19] C. Fattah, and C. Yandow, CRANE, an expert system for optimal tower crane selection and placement, proceeding of the Sixth Conference on Computing in Civil Engineering, Atlanta, GA, 1989, 290-297.

[20] I. Yeh, Construction-site layout using annealed neural network; Journal of Computing in civil engineering, 9(3), 1995, pp. 201–208.

[21] P. Zouein, and I.D. Tommelein, Dynamic layout planning using a hybrid incremental solution method, Journal of Construction Engineering and Management, 125(6), 1999, 400–408.

[22] J. Balakrishnan, and F.R. Jacobs, and M.A. Venkataramanan, Solutions for the constrained dynamic facility layout problem, European Journal of Operational Research, 57, 1992, 280-286.

[23] M. Dorigo, V. Maniezzo, and A. Colorni, The Ant System: Optimization by a Colony of Cooperating Agents; IEEE Transactions on Systems, Man and Cybernetics-Part B, 26(1), 1996, 29-41.

[24] L.M. Gambardella, E.D. Taillard, and M. Dorigo, Ant Colonies for the Quadratic Assignment Problem, Journal of Operational Research Society, 50, 1999, 167-176.

[25] M. Dorigo, and L.M. Gambardella, Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem, IEEE Transactions on Evolutionary Computation, 1(1), 1997, 53-66.