DE GRUYTER OPEN Organization, Technology and Management in Construction 2018; 10: 1655–1664

Research Article Open Access

Panagiotis M. Farmakis and Athanasios P. Chassiakos*

Genetic algorithm optimization for dynamic construction site layout planning

DOI 10.1515/otmcj-2016-0026
Received September 14, 2017; accepted November 24, 2017

Abstract: The dynamic construction site layout planning (DCSLP) problem refers to the efficient placement and relocation of temporary construction facilities within a dynamically changing construction site environment considering the characteristics of facilities and work interrelationships, the shape and topography of the construction site, and the time-varying project needs. A multi-objective dynamic optimization model is developed for this problem that considers construction and relocation costs of facilities, transportation costs of resources moving from one facility to another or to workplaces, as well as safety and environmental considerations resulting from facilities' operations and interconnections. The latter considerations are taken into account in the form of preferences or constraints regarding the proximity or remoteness of particular facilities to other facilities or work areas. The analysis of multiple project phases and the dynamic facility relocation from phase to phase highly increases the problem size, which, even in its static form, falls within the NP (for Nondeterministic Polynomial time)-hard class of combinatorial optimization problems. For this reason, a genetic algorithm has been implemented for the solution due to its capability to robustly search within a large solution space. Several case studies and operational scenarios have been implemented through the Palisade's Evolver software for model testing and evaluation. The results indicate satisfactory model response to time-varying input data in terms of solution quality and computation time. The model can provide decision support to site managers, allowing them to examine alternative scenarios and fine-tune optimal solutions according to their experience by introducing desirable preferences or constraints in the decision process.

Keywords: construction site, layout planning, genetic algorithms, optimization, safety

***Corresponding author: Athanasios P. Chassiakos,** Department of Civil Engineering, University of Patras, Patras 26500, Greece, E-mail: a.chassiakos@upatras.gr
Panagiotis M. Farmakis, School of Science and Technology, Hellenic Open University, Patras 26335, Greece, Email: std102925@ac.eap.gr

1 Introduction

The dynamic construction site layout planning (DCSLP) problem refers to the efficient placement and relocation of temporary facilities within a construction site in time following the changing needs as the project progresses. The formulation of the DCSLP problem includes the identification of the required facilities at each project phase, the determination of their geometry and operational characteristics (size, shape, movements, etc.), the available space and topography characteristics of the construction site, and any constraints resulting from physical and operational limitations in facility placement. The optimization aims at minimizing construction, relocation, and project manufacturing costs and (ideally) enhancing safety and environmental protection in the construction site.

The general construction site layout planning (CSLP) problem can be classified as either *facility to location* problem where a set of *n* facilities can be placed in *n* (or more) predetermined locations of the construction site or *facility to site* problem where existing facilities can be arranged freely to any unoccupied space within the site boundaries satisfying though all spatial constraints. The latter problem provides a wider solution space than the former and thus the opportunity for more efficient layout exploitation. However, the number of feasible solutions in this case may be enormous, especially if the number of facilities and the construction site area increase. To reduce the computational effort, most studies on this problem typically start with a preliminary "reasonable" determination of locations around which optimization is performed. In actual construction sites, the available space for facility deployment is usually limited, and therefore, one can beforehand define approximate places where the facilities can be allocated, reducing thus practically the problem to the facility to location one. Another distinction within the CSLP problem refers to the equal or unequal area assignment depending on whether all locations can sufficiently host (in terms of size, shape, terrain, operation, safety, or other constraint) every single facility or not.

The site layout planning problem is a complex combinatorial optimization problem involving multiple objectives and has been researched by a variety of methods and techniques from mathematical models to knowledge-based systems. The problem grows significantly in size and complexity as the numbers of facilities and constraints increase and become even larger in the case of dynamic layout planning where time is involved as an additional parameter. For this reason, meta-heuristic techniques have been dominantly used in recent years because of their capability to produce acceptable (near-optimal) solutions in reasonable time for typical problem cases. Algorithms that have been applied to solve the CSLP problem fall within artificial intelligence techniques, evolutionary algorithms (EAs), and swarm intelligence (SI) algorithms. The decision for algorithm selection depends on the problem size and complexity, the solution quality sought, and the computational time requirement, especially for large-scale problems.

The consideration of m project phases and corresponding layouts (DCSLP problem) increases the magnitude of the problem to the power of m compared to the single-phase one. Existing studies typically generate the optimal layout for each phase separately and accept the most efficient of the individual layouts for the whole project duration in order to avoid the burden of any relocation cost. In the present study, all project phases are jointly integrated in the optimization model to search for a globally optimal solution considering both transportation costs in each phase as well as construction and relocation costs of facilities from phase to phase. In addition, the proposed model can take into account safety and environmental considerations in the form of preferences or constraints in placing certain facilities relative to others. The paper constitutes an extended and updated version of the one by Farmakis and Chassiakos (2017).

2 Background

A variety of methods have been proposed for the CSLP problem varying from mathematical models to meta-heuristic optimization techniques. The latter techniques have prevailed in the last two decades mostly due to their computational efficiency to tackle large combinatorial problems. Among them, Yeh (1995) applied simulated annealing combined with Hopfield neural networks for site layout planning. Li and Love (1998, 2000) utilized genetic algorithms (GAs) for the equal- and unequal-area CSLP problems, respectively, integrating instant constraints and requirements. Tam et al. (2002) proposed a nonstructural fuzzy decision support system integrating expert judgment into computer decision modeling. Cheung et al. (2002) applied the Evolver software that uses GA to manage a site precast yard layout planning problem. Mawdesley et al. (2002) developed a sequence-based genetic methodology and validated the results comparing them to those of Yeh (1995). El-Rayes and Khalafallah (2005) implemented GAs and developed a trade-off approach between safety and cost in layout planning. Lam et al. (2009) introduced a modified GA model conjoining a max–min ant system for identifying a more qualitative initial population of chromosomes. Wong et al. (2010) proposed a hybrid formulation merging GA and mixed integer programming (MIP) to provide efficient solutions, while Gholizadeh et al. (2010) presented a harmony search methodology as an alternative for solving CSLP problems.

Within SI methods, ant colony optimization (ACO) and particle swarm optimization (PSO) algorithms have been extensively used. Gharaie et al. (2006) presented an ACO algorithm for solving the CSLP problem and compared results with those of Li and Love (2000). Lam et al. (2007) investigated the effectiveness of an ACO algorithm comprising entropy technique and fuzzy logic to remove uncertainty from collected data. Calis and Yuksel (2010) applied local analysis in conjunction with the ACO algorithm (ACO-LA) attempting to improve the quality of the obtained results. Zhang and Wang (2008) implemented a PSO-based and quadratic assignment-formulated methodology for the facility to location unequal-area problem, while Lien and Cheng (2012) proposed a hybrid SI-based particle-bee algorithm combining the advantages of the behavior of honey bee and bird swarm. Finally, Ning and Lam (2013) presented a multi-objective optimization model combining random grid recognition strategy for generating feasible solutions and a Pareto-based ACO algorithm for the facility to site unequal-area CSLP problem.

Existing research efforts have mostly focused on the static (single project phase) CSLP problem, while fewer studies have investigated the dynamic case. Research efforts in the latter case have been directed to both problems, i.e., facility to location and facility to site one, including both equal- and unequal-area assignment cases. Zouein and Tommelein (1999) developed a hybrid incremental solution method in which a number of alternative feasible layout solutions are initially generated using a heuristic algorithm. Linear programming is subsequently used to evaluate the optimal position, minimizing transportation and relocation costs. The same researchers introduced later a heuristic improvement that is able to modify the activity schedule when site space is restricted (Zouein and Tommelein 2001). Elbeltagi et al. (2004) developed a model that incorporated productivity values (via closeness relationship weights) and safety concerns (through the introduction of safety zones around facilities) representing facilities and sites of any irregular shape and utilized GAs for the optimization process. Sanad et al. (2008) also proposed a model that integrated environmental and safety considerations by introducing minimum distances between facility pairs, safety zones, and prohibited areas around the construction areas, providing more realistic results by taking into calculation actual traveling routes between facilities. Andayesh and Sadeghpour (2013) presented a dynamic formulation based on the minimum total potential energy parameter. The model depicts facilities as circular particles, defines the total potential energy resulting from the internal forces and distances between facilities, and derives the optimum solution minimizing the energy value. Said and El-Rayes (2013) compared the performance of two global dynamic models employing GA and approximate dynamic programming (ADP), respectively, and found that ADP outperformed GA in terms of effectiveness (i.e., reaching an optimum solution) and efficiency (computational time). However, they concluded that GA is easy to apply and preferable for large-sized problems, especially in multi-objective optimization. A multi-objective artificial bee colony (MOABC) algorithm was developed by Yahya and Saka (2014). In this proposed formulation, the shape of the facilities is assumed to be orthogonal, while a modified rectangular distance measurement approach is embedded to calculate the additional travel distance for avoiding obstacles. Kumar and Cheng (2015) presented a BIM (Building Information Modeling)-based automated site layout planning framework for congested construction sites. The developed dynamic methodology initially utilizes information from a BIM model to estimate the required size and dimensions for each facility. Subsequently, an algorithm is used to compute the actual travel paths in conjunction with GAs for generating optimal solutions (layouts).

A hybrid two-stage model was put forward by Chau (2004) for DCSLP problem employing linear programming to attain the optimal solution for each discrete phase (static CSLP) and GAs to minimize the total cost of the entire project. An ACO algorithm MMAS (Max Min Ant System) was proposed by Ning et al. (2010) for solving the dynamic multi-objective equal-area facility to location problem. Two congruent objective functions were set to reduce the total cost resulting from interaction flows among facilities and maximize the level of safety by preventing accidents. Chandratre and Nandurkar (2011) attempted to apply a GA including rearrangement cost for a facility in the DCSLP problem but without much success as the model provides near-optimal layouts but not fully optimal ones. Xu and Li (2012) developed a multi-objective model under fuzzy random environment and proposed a PSO algorithm with permutation-based representation for solving the problem and providing a Pareto diagram for optimal solutions. Finally, a mathematical formulation was proposed by Huang and Wong (2015) to allocate facilities in predetermined locations applying binary mixed integer linear programming, which can be solved by a standard branch and bound algorithm using the LINGO software. The proposed model includes safety considerations and can manage rectangular-shaped facilities and locations with their dimensions being able to differentiate over time.

The literature review for the DCSLP problem indicates that most existing studies divide the entire project into a sequence of time intervals and separately generate the optimal layouts, ignoring the interaction between successive phases and accepting only the most efficient individual layout for the whole project length to avoid any relocation cost. In addition, most studies focus mainly on the computational performance rather than on adequate representation of the actual problem. Typically, the problem formulation aims to minimize the total traveling distance of project resources considering trip frequencies and distances between facilities but ignoring other critical parameters, such as the transportation cost and construction and relocation costs of facilities. In an effort to develop a more robust and realistic representation of the actual problem, the present study incorporates cost components, safety and environment considerations in the form of preferences or constraints in placing certain facilities relative to others, as well as characteristics of the construction site that may impede the site development and operation (e.g., inclined terrain).

3 Proposed model

The problem is modeled as a quadratic assignment problem (QAP) in which a set of n facilities are to be allocated to m predetermined locations ($n \leq m$). If the number of available locations exceeds the number of facilities or the number of facilities varies from one project phase to another, then fictitious facilities (with zero frequencies and effect to the objective function) are added to the model. The proposed multi-objective optimization model is designed to minimize the weighted sum of a generalized cost function associated with the following parameters (Papadaki and Chassiakos 2016):

- Transportation cost representing the cost for resource movement between facilities or between facilities and work fields.
- Construction and relocation costs associated with the required expenditure for initial placement of the facility and possible relocation between construction phases, if this is in favor of reduction in the transportation cost.

The transportation cost is a function of flow (frequency of trips), distance traveled, and unit cost that mostly relates to trip type (personnel, machinery, material, etc). The construction site topography (e.g., inclined terrain, roughness of site roads) is further considered to account for increased transportation cost, where necessary. Similarly, initial construction and relocation costs of facilities may be increased depending on location characteristics, which may impose extra construction work (e.g., surface preparation, excavation, or embankments).

In addition to purely economic parameters, operational, safety, and environmental considerations are taken into account in practice by the site manager in making decisions for allocation of facilities. For instance, site offices and labor residence units may be located farther away from noisy production facilities and fuel storage may be remotely placed from the main construction activity and away from environmentally sensitive assets (e.g., rivers). To account for such concerns, the user can introduce specific preferences or constraints to the model regarding the desirable (or required) proximity (or remoteness) of particular facilities to (from) other facilities or work areas. This is obtained by the introduction of user-specific bonuses (penalties), the magnitude of which represents the level of preference (or hardness of constraint).

The generalized objective function of the model consists of a weighted sum of economic and noneconomic components as follows:

$$MinF = w_1 f_1 + w_2 f_2 \tag{1}$$

$$f_1 = TC = \sum_{y=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n}\delta_{iky}\delta_{jly}f_{ijy}u_{ijy}d_{kl}\Delta t_y + \sum_{i=1}^{n}\sum_{k=1}^{n}\delta_{ik}c_{ik} + \sum_{y=2}^{m}\sum_{i=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n}\delta_{ikly}r_{ikl} \tag{2}$$

$$f_2 = SP = \sum_{y=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n}\delta_{iky}\delta_{jly}x_{kl}e_{ijy} + \sum_{y=1}^{m}\sum_{i=1}^{n}\sum_{k=1}^{n}\delta_{iky}x_{kl}b_{iy} \tag{3}$$

subject to

$$\sum_{i=1}^{n}\delta_{ijy} = 1, \quad j = 1, 2, \ldots, n, \quad y = 1, 2, \ldots, m \tag{4}$$

$$\sum_{j=1}^{n}\delta_{ijy} = 1, \quad i = 1, 2, \ldots, n, \quad y = 1, 2, \ldots, m \tag{5}$$

where TC is the total cost; SP is the equivalent safety and environment decision component (bonuses/penalties); w_1 and w_2 are weight coefficients related to the sub-objective functions f_1 and f_2, respectively; i and j represent facilities, k and l represent locations, and y represents project phases; n is the number of facilities (and locations); m is the number of construction phases; δ_{iky} and δ_{jly} are the permutation matrix parameters (zero-one variables indicating whether facilities i and j are assigned to locations k and l, respectively, in phase y); f_{ijy} is the trip frequency between facilities i and j, and u_{ijy} is the corresponding transportation cost; d_{kl} is the Euclidian distance between locations k and l; δ_{ik} is a zero-one variable indicating whether facility i is initially placed in location k, and c_{ik} is the corresponding construction cost; δ_{ikly} is a zero-one variable indicating whether the facility i is moved from location k to location l in phase y, and r_{ikl} is the corresponding relocation cost; Δt_y is the duration of project phase y; x_{kl} is a zero-one variable indicating whether the desired distance range between two facilities or between a facility and a location is attained or not with e_{ijy} and b_{iy} the corresponding penalties if the desired distance ranges are not achieved.

The DCSLP belongs to the NP-hard class of multi-objective optimization problems, and the domain of solutions grows exponentially as the number of facilities, constraints, or project phases increases. For this reason, GAs have been employed for the optimization process. In particular, the Palisade's Evolver software (which runs as an add-in of MS Excel) has been used for the problem analysis. BigPicture (another Palisade's software) is used to sketch a scaled facility allocation layout for enhanced solution overview and evaluation.

4 Case study

The proposed model has been tested with several case studies and project types, which include existing benchmark cases from literature (primarily building projects) and new ones developed in the framework of this study. The necessity for relocation of temporary project facilities (in order to accrue savings in the transportation cost) may be more indispensable in projects with wide spatial and temporal dispersion, such as road construction projects. Such a project, with highly dynamic development characteristics and wide dispersion in space, is analyzed in the present case study.

The operational plan includes ten major facilities that are to be allocated in 11 available locations within the site boundaries. Additionally, three workplaces have been assumed to adequately represent the actual work fields along the road. These workplaces attract considerable material transportation from other facilities and are considered thus as key facilities of the construction site. The list of facilities with their estimated costs for first placement and possible repositioning are shown in Table 1. Among them, the three work fields and the quarry area are considered to be at fixed locations. In terms of available locations, these have been represented with their coordinates and size (depending on the case solved, equal- or unequal-area problem) as given in Table 2. Two of the available locations (11 and 13) are assumed to lie at inclined terrain. Table 3 presents data regarding the type of movements in a range from 1 (mainly human resources) to 5 (mainly heavy vehicles), while Table 4 indicates the number of trips between facilities in a comparative range from 1 to 5.

Six scenarios are examined to evaluate the model capability to effectively and realistically respond to data input, preference, and constraint variations. These scenarios are:

- C1: single-phase project (static solution);
- C2: multi-phase project (dynamic solution) with unaltered work data from phase to phase;
- C3: multi-phase project (dynamic solution) with varying work data from phase to phase;
- C4: multi-phase project with varying work data from phase to phase and unequal location sizes;
- C5: multi-phase project with varying data from phase to phase and introduction of relocation costs; and
- C6: multi-phase project with varying data from phase to phase and partially inoperative facilities in certain phases.

In all scenarios, it is greatly preferred that the site office and labor rest area are placed as far away from the construction activity as possible.

The aim of the first two scenarios is to examine whether the dynamic model (three-phase process) can replicate the

Tab. 1: Construction and relocation costs of facilities.

Facility	Construction cost (€)	Relocation cost (€)
1. Quarry area (fixed)	90,000	0
2. Stone crusher	100,000	25,000
3. Concrete batch plant	150,000	25,000
4. Asphalt mixing plant	120,000	25,000
5. Concrete and aggregates depot	10,000	5,000
6. Asphalt and aggregates depot	10,000	5,000
7. Sub-base and aggregates depot	10,000	5,000
8. Work field 1 (fixed)	0	0
9. Work field 2 (fixed)	0	0
10. Work field 3 (fixed)	0	0
11. Asphalt storage	15,000	0
12. Site office	10,000	0
13. Labor rest area	10,000	0
14. Concrete (cement) storage	15,000	0
15. -	0	0

Tab. 2: Location and terrain characteristics.

Location	X	Y	Inclined terrain
1	300	200	
2	100	750	
3	200	1000	
4	100	1500	
5	650	1450	
6	550	950	
7	300	1300	
8	1000	600	
9[a]	900	1300	
10	1300	1300	
11	1300	300	✓
12	900	1050	
13	1450	600	✓
14	600	1200	
15[a]	350	700	

Note: [a]Location of limited area in certain scenarios.

Tab. 3: Type of movements between facilities (Phase 1).

Facility	Facility 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	5	1	1	1	1	1	1	1	1	1	1	1	1	0
2	5	0	1	1	5	5	5	1	1	1	1	1	1	1	0
3	1	1	0	1	4	1	1	4	1	1	1	1	1	3	0
4	1	1	1	0	1	4	1	1	1	4	3	1	1	1	0
5	1	5	4	1	0	1	1	1	1	1	1	1	1	2	0
6	1	5	1	4	1	0	1	1	1	1	2	1	1	1	0
7	1	5	1	1	1	1	0	1	4	1	1	1	1	1	0
8	1	1	4	1	1	1	1	0	1	1	1	2	1	1	0
9	1	1	1	1	1	1	4	1	0	1	1	2	1	1	0
10	1	1	1	4	1	1	1	1	1	0	1	2	1	1	0
11	1	1	1	3	1	2	1	1	1	1	0	1	1	1	0
12	1	1	1	1	1	1	1	2	2	2	1	0	3	1	0
13	1	1	1	1	1	1	1	1	1	1	1	3	0	1	0
14	1	1	3	1	2	1	1	1	1	1	1	1	1	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

results of the static one (single-phase process) at the same input data in both cases. In particular, a single 600-day phase project is initially modeled (case C1) with the input data of Tables 3 and 4 and the allocation of the facility is obtained optimizing the problem as a single-phase (static) one. Following, the same project is divided into three phases (200 days each) with exactly the same input data as in C1 in terms of facility usage and resource transportation (scenario C2). The experiment indicates that the facility allocation plan fully coincides in both cases (Figure 1). In Figure 1, each rectangle represents an available location, which is indicated by its number. The other three entries represent the facilities that are allocated to the particular location during the three project phases, respectively. The arrows between facilities indicate the movement of main materials from facility to facility (or work filed) following the input data of Tables 3 and 4.

Tab. 4: Number of trips between facilities (Phase 1).

Facility	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	5	1	1	1	1	1	1	1	1	1	1	1	0	0
2	5	0	1	1	3	3	3	1	1	1	1	1	1	1	0
3	1	1	0	1	3	1	1	3	1	1	1	1	1	2	0
4	1	1	1	0	1	3	1	1	1	3	2	1	1	1	0
5	1	3	3	1	0	1	1	1	1	1	1	1	1	2	0
6	1	3	1	3	1	0	1	1	1	1	2	1	1	1	0
7	1	3	1	1	1	1	0	1	3	1	1	1	1	1	0
8	1	1	3	1	1	1	1	0	1	1	1	1	1	1	0
9	1	1	1	1	1	1	3	1	0	1	1	1	1	1	0
10	1	1	1	3	1	1	1	1	1	0	1	1	1	1	0
11	1	1	1	2	1	2	1	1	1	1	0	1	1	1	0
12	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0
13	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
14	1	1	2	1	2	1	1	1	1	1	1	1	1	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The allocation plan also reveals that, despite the availability of location 5, which provides immediate accessibility to most of other facilities, the site office and labor rest area were placed far away from the construction activity and even at an inclined terrain (which incurs increased construction cost) due to the preference setting that these facilities are placed as far away from asphalt and concrete batch plants as possible.

The third scenario (C3) extends the previous one in considering varying transportation needs from phase to phase. In particular, it is assumed that the project execution requires high quantities of concrete to be launched

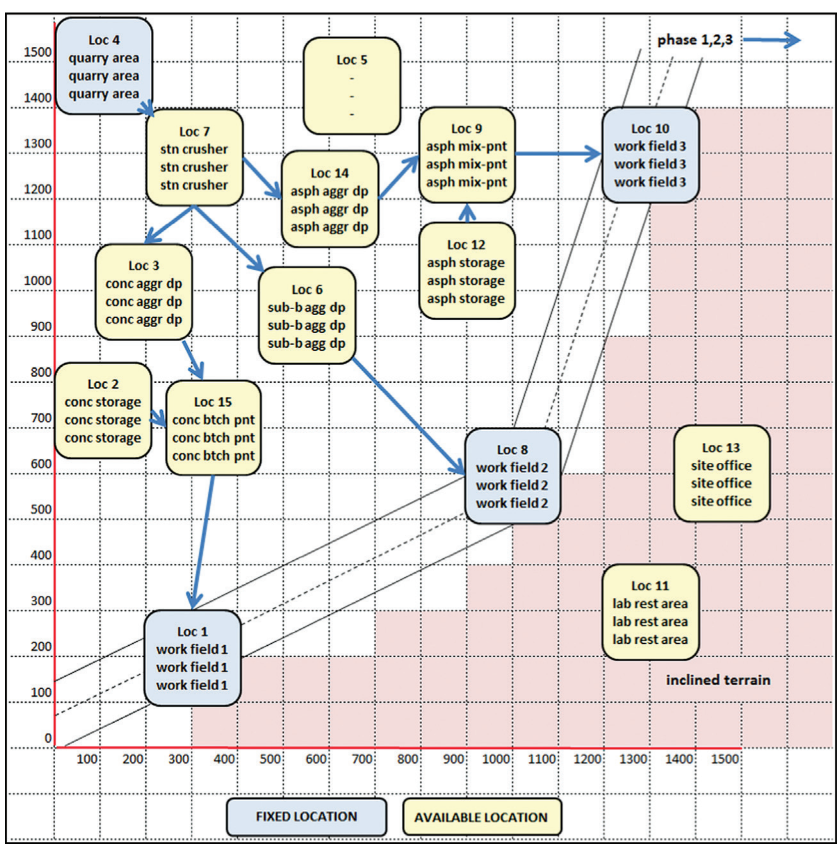

Fig. 1: Construction site layout for cases C1, C2, and C5.

in work field 1 in phases 1 and 2 and asphalt concrete in phase 3. Conversely, work field 3 requires mostly asphalt concrete in phases 1 and 2 and concrete in phase 3. The model advices for the mutual relocation of concrete batch plant and asphalt mix facilities at the end of phase 2, bringing the concrete and asphalt storage facilities closer to their corresponding mix plants in order to reduce the operational (transportation) costs (Figure 2).

In the next scenario (C4), the assumptions of scenario C3 still hold with the exception that locations 9 and 15 are not adequate to accommodate the concrete and asphalt batch plants. As expected, since the best placement of these facilities developed in C3 is not attainable, the model provides a solution in which the two facilities are placed at immediately neighboring locations to cut down the upsurge in the transportation cost. Furthermore, relocations of facilities (mostly location switching) are done to assure the vicinity of plants and material storage locations.

While C3 considers only construction and transportation costs, scenario C5 introduces in addition relocation costs of facilities. Depending on the magnitude of these expenses, the best solution may involve relocation of the facility or not following the trade-off between relocation and transportation costs. If the relocation costs are comparatively low (a special case is C3 in which such costs get zero value), the relocation is generally in favor of cost savings (Figure 3). Contrariwise, if the relocation costs are quite high, the best solution is to keep the facility allocation unchanged over the entire project length (as in Figure 1).

The last case study (C6) considers a more relaxed project structure in which certain facilities are not required in all project phases. In particular, the material type and major quantity needed in every work field and project phase are listed in Table 5. The optimal facility placement in this case is depicted in Figure 4. Observing the generated layout, it is noted that, since several locations remain unoccupied in phases 1 and 2, the model tends to allocate facilities toward the center of the construction site. In the third phase, however, in which heavy construction activity takes place (especially in workplace 3), facilities have moved toward workplace 3 covering all available locations around it in order to minimize the transportation cost.

Besides the case studies presented previously, extensive testing in similar size problems was implemented to evaluate the solution accuracy. The results indicate

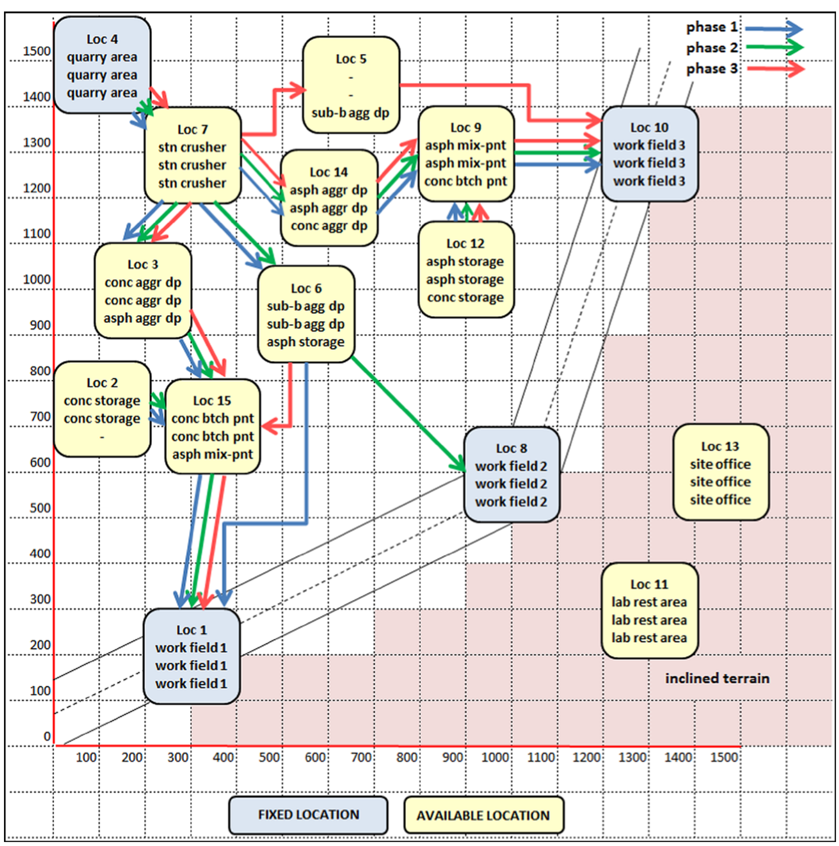

Fig. 2: Construction site layout for case C3.

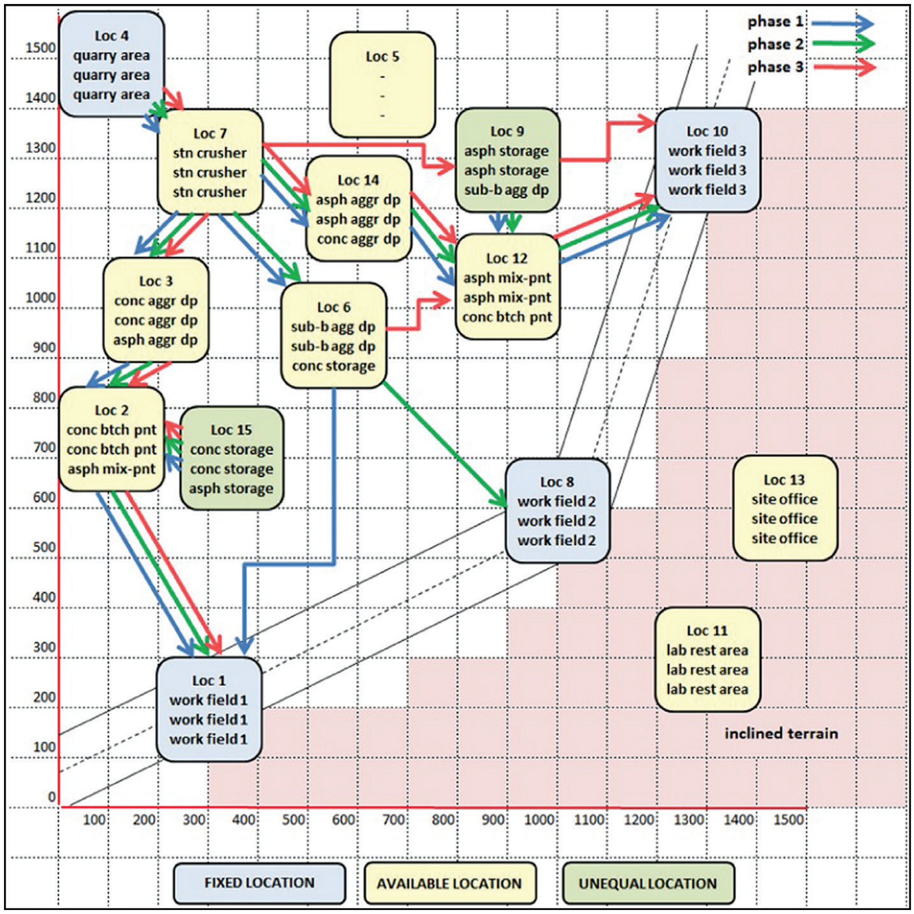

Fig. 3: Construction site layout for case C4.

Tab. 5: Operational needs for case C6.

Work field	Phase		
	1	2	3
1	Aggregates	Concrete	Asphalt
2	Aggregates	Concrete	Asphalt
3		Aggregates	Concrete/asphalt

an accuracy range of 97%–100% of the expected global optimal solution. The highest deviations from the optimal solutions are observed in cases where the facility's relocation costs are large compared to transport cost earnings, and therefore, facility rearrangement is not preferable. In this case, the model needs to find the solution of the static problem through a dynamic formulation while any other solution than the static solution considerably deviates from the optimal one in terms of the objective function value. Contrariwise, if rearrangement of the facility is propelled by low relocation costs, there may be several solutions with small deviations from the optimal one, and therefore, the accuracy is increased. In terms of the variation in problem size, the model's capability in larger CSLP problems obviously decreases; the extent of decline remains an issue for further research.

5 Conclusions

Efficient layout planning of a construction site is fundamental for successful project undertaking as it enhances both productivity and safety of operations. The site layout planning problem is a complex combinatorial optimization problem involving multiple objectives, and it grows exponentially in size as the numbers of facilities and constraints increase. In addition, as construction evolves, the site layout may need to be dynamically reorganized at various schedule intervals to accommodate the operational needs. This is known as DCSLP, which refers to the efficient placement of temporary construction facilities within a dynamically changing construction site environment, considering the facilities' characteristics and work interrelationships; the size, shape, and topography of the construction sites; and the time-varying project needs.

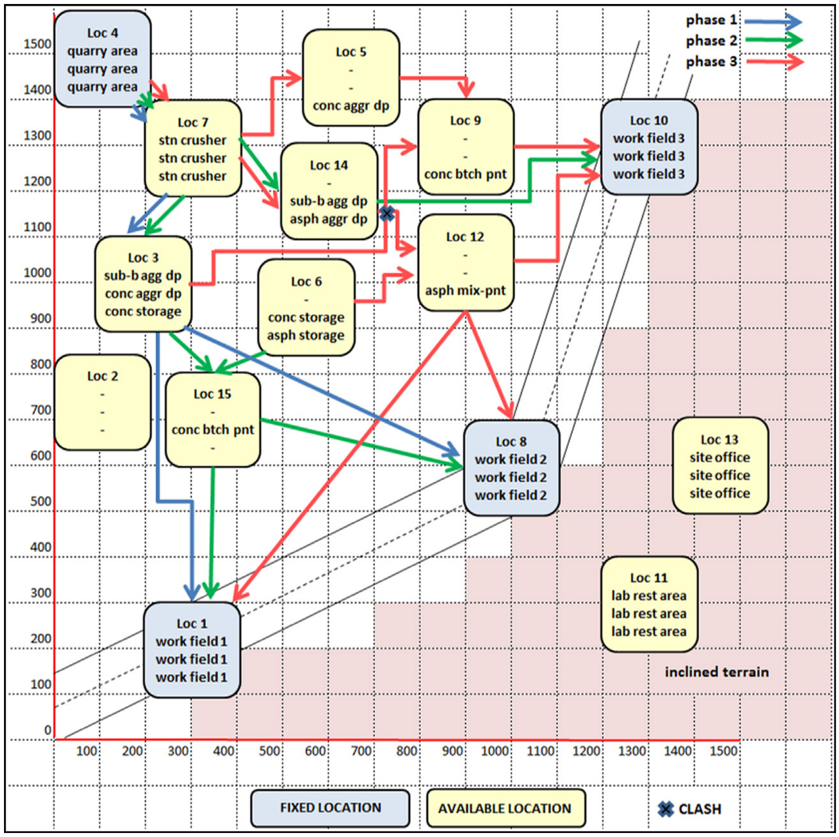

Fig. 4: Construction site layout for case C6.

Existing studies on the DCSLP problem typically generate the optimal layout for each phase separately (ignoring the interaction between successive phases) and accept only the most efficient of the individual layouts for the whole project duration to avoid the burden of any relocation cost. In the present study, all project phases are integrated in the optimization model to search for a globally optimal solution considering both transportation costs within each phase as well as construction and relocation costs of facilities from phase to phase. In addition, safety and environmental considerations, resulting from site operations, are taken into account in the form of preferences or constraints regarding the proximity or remoteness of particular facilities to other facilities, work areas, or nearby eco-sensitive assets (e.g., rivers).

The inclusion of several project phases and site reorganization requires solving a significantly larger problem than a static layout one. For this reason, the development integrates the representation of the realistic problem with the optimization capabilities of GAs. The model had been tested on several case studies considering both static and dynamic layout configurations. The results indicated that it provides rational solutions, in response to decision parameters and problem constraints, and that dynamic modeling develops more effective layout planning than a static one. The model can provide decision support to site managers allowing them to examine alternative scenarios and to fine-tune optimal solutions according to their experience, balancing economic and preference priorities.

References

Andayesh, M., & Sadeghpour, F. (2013). Dynamic site layout planning through minimization of total potential energy. *Automation in Construction, 31*, 92-102.

Calis, G., & Yuksel, O. (2010). A comparative study for layout planning of temporary construction facilities: Optimization by using ant colony algorithms. In: *Proceedings of the 13th International Conference on Computing in Civil and Building Engineering, Nottingham, UK*, p. 267.

Chandratre, K. V., & Nandurkar, K. N. (2011). Applying genetic algorithm to dynamic layout problem. *International Journal of Applied, 1*(3), pp. 1-9.

Chau, K. W. (2004). A two-stage dynamic model on allocation of construction facilities with genetic algorithm. *Automation in Construction, 13*(4), pp. 481-490.

Cheung, S. O., Tong, T. K. L., & Tam, C. M. (2002). Site pre-cast yard layout arrangement through genetic algorithms. *Automation in Construction, 11*(1), pp. 35-46.

Elbeltagi, E., Hegazy, T., & Eldosouky, A. (2004). Dynamic layout of construction temporary facilities considering safety. *Journal of Construction Engineering and Management, 130*(4), pp. 534-541.

El-Rayes, K., & Khalafallah, A. (2005). Trade-off between safety and cost in planning construction site layouts. *Journal of Construction Engineering and Management, 131*(11), pp. 1186-1195.

Farmakis, P. M., & Chassiakos, A. P. (2017). Dynamic multi-objective layout planning of construction sites. *Procedia Engineering, 196*, pp. 674-681.

Gharaie, E., Afshar, A., & Jalali, M. R. (2006, February). Site layout optimization with ACO algorithm. In: *Proceedings of the 5th WSEAS International Conference on Artificial Intelligence,* February 15 - 17, 2006, Madrid, Spain, pp. 90-94.

Gholizadeh, R., Amiri, G. G., & Mohebi, B. (2010). An alternative approach to a harmony search algorithm for a construction site layout problem. *Canadian Journal of Civil Engineering, 37*(12), pp. 1560-1571.

Huang, C., & Wong, C. K. (2015). Optimisation of site layout planning for multiple construction stages with safety considerations and requirements. *Automation in Construction, 53*, pp. 58-68.

Kumar, S. S., & Cheng, J. C. (2015). A BIM-based automated site layout planning framework for congested construction sites. *Automation in Construction, 59*, pp. 24-37.

Lam, K. C., Ning, X., & Lam, M. C. K. (2009). Conjoining MMAS to GA to solve construction site layout planning problem. *Journal of Construction Engineering and Management, 135*(10), pp. 1049-1057.

Lam, K. C., Ning, X., & Ng, T. (2007). The application of the ant colony optimization algorithm to the construction site layout planning problem. *Construction Management and Economics, 25*(4), pp. 359-374.

Li, H., & Love, P. E. (1998). Site-level facilities layout using genetic algorithms. *Journal of Computing in Civil Engineering, 12*(4), pp. 227-231.

Li, H., & Love, P. E. (2000). Genetic search for solving construction site-level unequal-area facility layout problems. *Automation in Construction, 9*(2), pp. 217-226.

Lien, L. C., & Cheng, M. Y. (2012). A hybrid swarm intelligence based particle-bee algorithm for construction site layout optimization. *Expert Systems with Applications, 39*(10), pp. 9642-9650.

Mawdesley, M. J., Al-Jibouri, S. H., & Yang, H. (2002). Genetic algorithms for construction site layout in project planning. *Journal of Construction Engineering and Management, 128*(5), pp. 418-426.

Ning, X., & Lam, K. C. (2013). Cost–safety trade-off in unequal-area construction site layout planning. *Automation in Construction, 32*, pp. 96-103.

Ning, X., Lam, K. C., & Lam, M. C. K. (2010). Dynamic construction site layout planning using max- min ant system. *Automation in Construction, 19*(1), pp. 55-65.

Papadaki, I. N., & Chassiakos, A. P. (2016). Multi-objective construction site layout planning using genetic algorithms. *Procedia Engineering, 164*, pp. 20-27.

Said, H., & El-Rayes, K. (2013). Performance of global optimization models for dynamic site layout planning of construction projects. *Automation in Construction, 36*, pp. 71-78.

Sanad, H. M., Ammar, M. A., & Ibrahim, M. E. (2008). Optimal construction site layout considering safety and environmental aspects. *Journal of Construction Engineering and Management, 134*(7), pp. 536-544.

Tam, C. M., Tong, T. K., Leung, A. W., & Chiu, G. W. (2002). Site layout planning using nonstructural fuzzy decision support system. *Journal of Construction Engineering and Management, 128*(3), pp. 220-231.

Wong, C. K., Fung, I. W. H., & Tam, C. M. (2010). Comparison of using mixed-integer programming and genetic algorithms for construction site facility layout planning. *Journal of Construction Engineering and Management, 136*(10), pp. 1116-1128.

Xu, J., & Li, Z. (2012). Multi-objective dynamic construction site layout planning in fuzzy random environment. *Automation in Construction, 27*, pp. 155-169.

Yahya, M., & Saka, M. P. (2014). Construction site layout planning using multi-objective artificial bee colony algorithm with Levy flights. *Automation in construction, 38*, pp. 14-29.

Yeh, I. C. (1995). Construction-site layout using annealed neural network. *Journal of Computing in Civil Engineering, 9*(3), pp. 201-208.

Zhang, H., & Wang, J. Y. (2008). Particle swarm optimization for construction site unequal-area layout. *Journal of Construction Engineering and Management, 134*(9), pp. 739-748.

Zouein, P. P., & Tommelein, I. D. (1999). Dynamic layout planning using a hybrid incremental solution method. *Journal of Construction Engineering and Management, 125*(6), pp. 400-408.

Zouein, P. P., & Tommelein, I. D. (2001). Improvement algorithm for limited space scheduling. *Journal of Construction Engineering and Management, 127*(2), pp. 116-124.