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OPTIMIZATION OF CONSTRUCTION SITE LAYOUT USING DYNAMIC HYBRID BACTERIAL AND ANT COLONY ALGORITHM

Pham Vu Hong Son[a,b,*]

[a] *Department of Construction Engineering & Management, Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet street, District 10, Ho Chi Minh City, Vietnam*
[b] *Vietnam National University Ho Chi Minh City, Linh Trung ward, Thu Duc district, Ho Chi Minh City, Vietnam*

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Abstract

The efficient plan of site arrangement during the construction phase has been considered a vital duty to successful project performance due to the productivity enhancement as well as safety in executions. The optimization of the Construction Site Layout Problem (CSLP) is a combinatorial complexity that regards numerous objectives and considerable growth of scale as increasing of constraints and facilities. The rearrangement on site may thus need to be had dynamic plannings at several interval schedules as construction evolves to accommodate site needs. To resolve the complexity of this problem, many studies based on the Meta-heuristic approach have been done, there are however always drawbacks and should be improved to be more optimal. This research proposes a new Hybrid Meta-heuristic model which is a combination of Ant Colony Optimization algorithm (ACO), Bacterial foraging algorithm (BFA), and Pair-Wise Exchange Heuristic algorithm (PWEH). The proposed algorithm is named Dynamic Hybrid Ant Colony Algorithm (DHACA) model that can enhance local and global searches simultaneously. In addition, parameter values are optimized to create a better solution. This research also demonstrates the effectiveness of DHACA compared with the previous studies such as Multi-objectives Genetic Algorithm (MOGA), Simulated Annealing Algorithm based Multi-objectives Genetic Algorithm (SA-based MOGA) on the CSLP. DHACA supports the construction site dynamic planning with constraints on facilities to improve work efficiency.

Keywords: meta-heuristic; hybrid model; ant colony optimization; bacterial foraging algorithm; pair-wise exchange heuristic; multiple objective.

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1. Introduction

On construction sites, the layout of auxiliary facilities in the execution stage has been regarded as an essential planning task, both in terms of geography and the right time, to achieve expected quality construction works at minimal costs as well as improved safety and working environment [1–3]. That layout plan, in particular large-scale construction projects, may impact considerably on time and cost issues [4–8]. For example, the facilities location planning management in large-scale hydropower construction is difficult in the metropolis and often suffers from a significant waste of resources due

*Corresponding author. *E-mail address:* pvhson@hcmut.edu.vn (Son, P. V. H.)

to the complexity of the real environmental condition, the uncertainties, and lengthy construction duration, and high construction cost. The provided transportation conditions and the available land for temporary facilities are limited and isolated. Furthermore, since the project schedule dividing into several constructed stages, the location of temporary facilities needs to be flexibly changed to adapt to each different stage. A reasonable site arrangement, which includes the layout of working areas, construction equipment, steering committee office, construction material storage, temporary transportation system, worker camps, utility areas, etc., will facilitate the works to be done quickly, as well as reduce travel distances, decrease material handling, avoid material clogging, optimize the expense and ensure labor safety [9, 10]. Nowadays, the scale of construction projects has become larger leading to the high complexity of technical requirements, thus, the layout design for the construction site needs to be satisfied with the efficiency in terms of safety and environmental friendly [11, 12].

Mostly, the construction site layout includes various items such as constructed areas, auxiliary buildings serving entire project, existing buildings or obstacles as trees, temporary road, benchmark milestone, even no boundary land or barriers [13]. Although there have been several proposed techniques to obtain site layout solutions, hand calculation has been one of the barriers to optimal finding [14]. Thus, it is necessary to apply optimization approaches to seek proper solutions for the layout on site. Elbeltagi et al. [15] optimized a model of site space allocation according to the schedule variation based on artificial intelligent technique application, hence, optimal alternatives for different phases in construction could be offered. Papadaki and Chassiakos [16] used the genetic algorithms to aim at optimizing a generalized cost according to location alternatives, in which cost problem is a combination involving the costs for constructing a facility, transportation, and any safety concerns in the shape of favored closeness or remoteness of specific facilities to others or working zones.

Recently, the concept of algorithms has been widely applied to the process of optimization. Zouein et al. [17] performed the optimization algorithm to minimized delivery and relocation expenditure of resources, rely on dealing with the dynamic layout of constraint; the material and human resources on site were represented the 2D geometric of rectangle shapes whose shift dimensions over time whether or not. Said and El-Rayes [18] targeted the minimum overall risk guarantee and general costs which were presented through four primary periods of developed frameworks: (i) identifying risks and simulating system, (ii) optimizing security lightning, (iii) optimizing security-expense, (iv) assessing efficiency. Atmaca [19] built a mechanism of automated arrangement to aim at recognizing proper zones to layout temporary facilities for the sake of maximizing construction productivity; the algorithm of branch and bound was integrated to solve the problem of dynamic layout for project managers directly constructed on site.

However, there have two main limitations of the aforementioned researches including (i) relying on creating a platform to allow the selection among geographical diversity of layouts is needed to be more effort in industry reality application; and (ii) consolidation of planning processes with geographic aspects to create a site layout has also been shown as challenging [20–22]. This paper's objective is to fill this gap of previous studies in optimizing the entire project costs by minimizing the delivery expenditure of construction equipment depending on the construction site movement. In addition, multi-objective constrained optimization is really a difficult problem for project managers. Thus, it requires several approaches permitting to find in a short time satisfactory solutions with low investment in a solution processing system. This research also focuses on finding an algorithm to apply to the resource arrangement on construction sites that supports project managers to come up with efficient solutions.

The remaining of this study is arranged as listed: section 2 performs the research methodology;

section 3 expresses the detailed notation, model assumption, and set-up; section 4 outlines the mathematical calculation, discussion, and verification; and section 5 concludes this study.

2. Model development and assessment

This work proposes a solution to develop a dynamic hybrid ant colony algorithm (DHACA) model to optimize the site layout that changes flexibly according to the project schedule and apply to the problem of the previous research to evaluate the effective level of the proposed DHACA. The ant colony algorithm (ACO) has been proved to be effective and appropriate in resolution to the layout of the construction site, moreover, the study is contributed to enrich the research results in comparing with previous studies through solving the problem again.

By comparing the effectiveness of Ant Colony Optimization algorithm (ACO), Genetic Algorithm (GA), and Simulated Annealing (SA) in seeking near-optimal solutions in the traveling salesman problem (TSP), it is concluded that ACO provided a better performance regarding speed and solution quality [23]. Also, ACO has been compared with GA, Particle Swarm Optimization (PSO) in dealing with site layout problems. In fact, the research results indicate that such three algorithms achieve the same favorable performance to find optimal solutions, however, the ACO has the outstanding speed for attaining results, followed by GA and then PSO. Therefore, in spite of all the above-mentioned approaches having been shown to be suitable solutions for the problem of construction site arrangement, ACO is eventually referred to as the best algorithm for the optimization problem [24, 25].

Nevertheless, the initialization of non-independent input parameters randomly in ACO has a huge impact on the optimal outcomes as well as the convergence speed of the algorithm. In 2015, this issue was investigated by Gulben Calis and Orhan Yuksel [26] by applying Parametric Analysis (PA) to decide the parameters for ACO. In 2016, Leng Ling and Hua Zhu [27] brought the Bacterial Foraging Algorithm (BFA) in setting the input parameters for ACO to solve the optimization problem of the path for the robot arm. Also in 2016, Jiuping Xu, Qiurui Liu, and Xiao Lei [28] used Simulated Annealing (SA) based on a Genetic Algorithm (GA) to deal with the optimization problem with multiple objectives in the arrangement of the auxiliary facilities of dynamic construction site with discrete simulation.

In 2002, the algorithm of a bionic optimization or BFA algorithm was introduced by Kevin M. Passino [29], rely on the process of hunting food in the human intestine of Escherichia coli. The algorithm simulates two processes of moving forward and flipping in the chemotaxis process. The inspiration from the E. coli bacterium foraging tactics produced the algorithm of the bacterial foraging. The E. coli is formed from plasma cells and contains “cytoplasm” and “nucleoid” [30]. In the advantage conditions of a specified temperature and a food source, the longevity of bacterium becomes longer and it has well reproduction [31]. In the foraging procedure, the patterns of bacteria motion (taxes) are called the chemotaxis process which governs by chemical attractants (nutrient region) and repellants (noxious region) (see Fig. 1).

Varying the movement direction through the control system assists the E. coli bacterium to find advantageously food sources and avoid the toxic areas. The searching strategy of food of the bacteria is stimulated to the model of mathematic in the BFA [32]. Five primary phases of the BFA are Chemotaxis, Swarming, Reproduction, Elimination, and Dispersion. A goal function $J(i, j, k, l)$ is determined to symbolize the fitness (cost) of the i^{th} bacterium at the position $\theta(j, k, l)$ in j^{th} chemotaxis, k^{th} reproduction, and the elimination-dispersion step. The bacteria positions may be randomly initialized or analyzed by existing information [33].

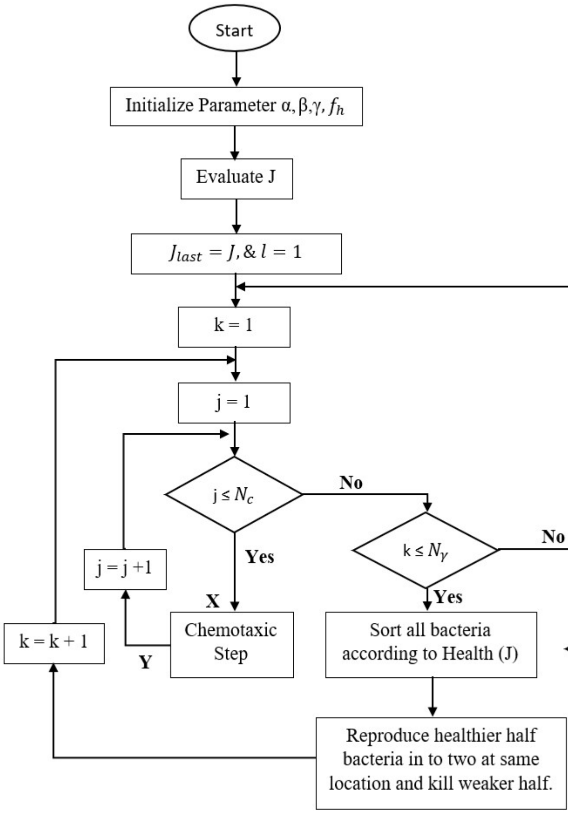

Figure 1. Bacterial Foraging Algorithm (BFA)

The nutrient concentration is the main factor that governs the process of food searching, i.e. nutrient-rich region and movement of bacteria in the seeking space. In the seeking region, the nutritious concentration is symbolized as a cost function $J(\theta)$ at any position θ. The movement of bacterium is to search a high concentration of nutritious space, i.e. to decrease cast value $J(\theta)$. Let the step distance of movement in the accidental direction is $\lambda(i)$ for the i^{th} bacterium. If the motion of the bacterium moves into the better nutritious space, the direction is maintained and continuous movement whereas cost function decreases or the number of steps N_s maximizes. If the direction of bacterium moves according to disadvantage tendency, i.e constant nutrition or toxic areas, the direction is varied randomly in the next step, termed as tumble. That movement direction is represented by the random vector $\Delta(i)$.

The following section presents a detailed description of the DHACA model to optimize the site layout. The original ACO is supported by BFA that helps to set the value-initializing strategy for inputting parameters in the search process. In addition, PWEH aims to enhance the original solutions and initialize the matrix of pheromone concentration by utilizing the best remedy as well as finding the superior solutions at the following search stages. DHACA works as an optimal searching tool to determine the site layout of construction in the project phases, with multiple goals: minimizing costs and ensuring safety. The frame diagram is depicted in Fig. 2.

Main steps of DHACA:

- Step 1: Use BFA to initialize parameters for ACO;
- Step 2: Use a set of parameters from BFA to run ACO;

- Step 3: Find a solution by BFA.

ACO uses the parameter set initialized by BFA to evaluate the target function, evaluate the solution. BFA uses the target function value from ACO to assess the optimal bacterial selection. These two processes are carried out in parallel. ACO is the original algorithm in DHACA. However, with the above method, ACO can be considered as a sub-algorithm in BFA.

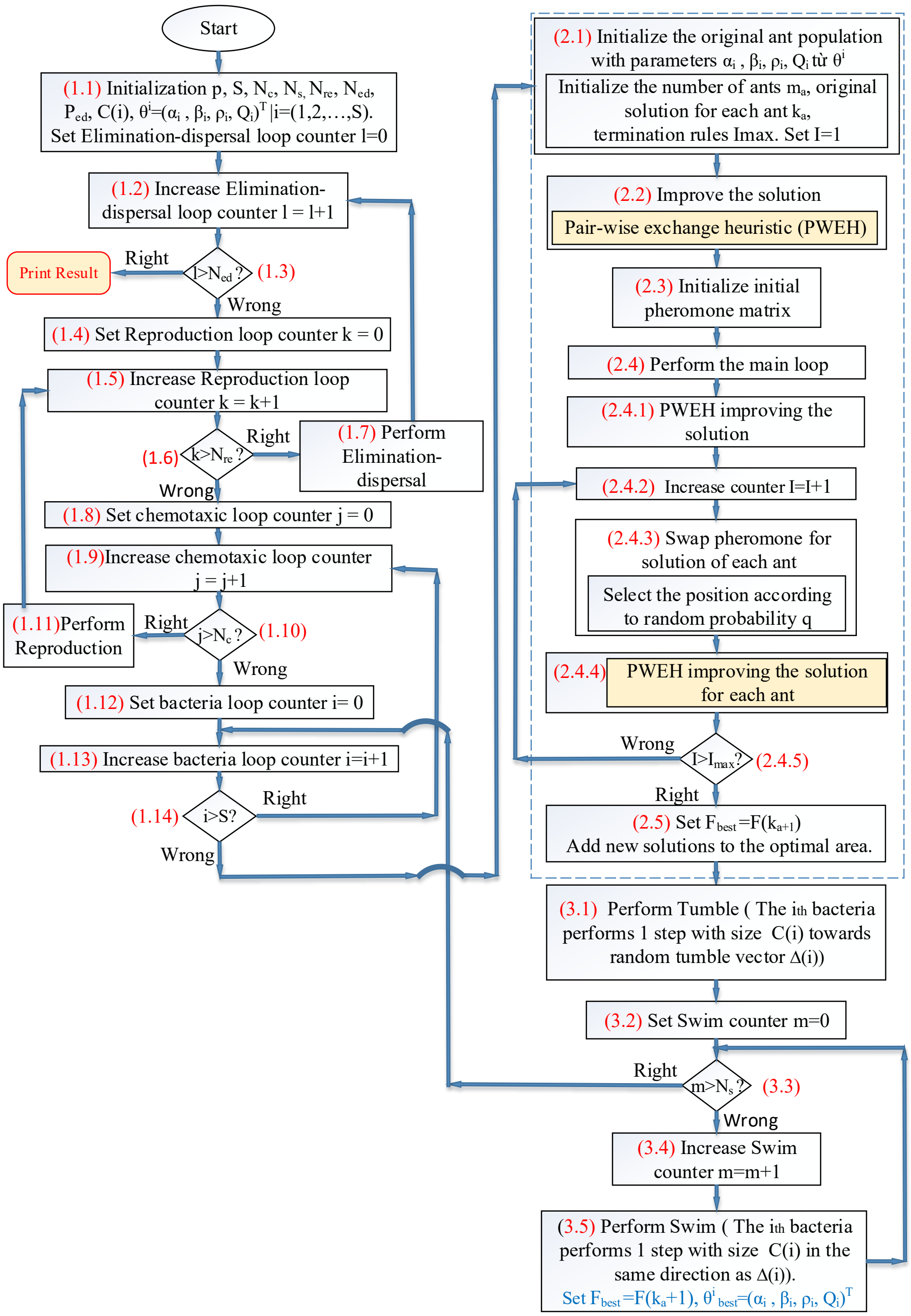

Figure 2. The overall procedure of DHACA

The objective function of the model:

$$\min f_1 = C^*(t) = \min\left\{C^*(t-1) + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{k=1}^{M}(a_{im}+c_i)\,x_{imk}(t)\right\} + F(t) \tag{1}$$

$$F(t) = \sum_{i=1}^{I}\sum_{j=1}^{I}\sum_{m=1}^{M}\sum_{k=1}^{M}\sum_{n=1}^{M}\sum_{l=1}^{M} v_{ij}(t)d_{ik,jl}x_{imk}(t)x_{jnl}(t) \tag{2}$$

$$\min f_2 = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{I}\sum_{m=1}^{M}\sum_{k=1}^{M}\sum_{n=1}^{M}\sum_{l=1}^{M} R_{ij}(t)d_{ik,jl}x_{imk}(t)x_{jnl}(t) \tag{3}$$

$$f = w_1 f_1 + w_2 f_2 \tag{4}$$

$$x_{imk}(1) = 0, \forall i \in \Phi, m \in \Omega, k \in Y \tag{5}$$

$$\sum_{m=1}^{M}\sum_{k=1}^{M} x_{imk}(t) = 1, \forall i \in \Phi, t \in \Psi \tag{6}$$

$$\sum_{n=1}^{M}\sum_{l=1}^{M} x_{jnl}(t) = 1, \forall j \in \Phi, t \in \Psi \tag{7}$$

$$\sum_{i=1}^{I} x_{imk}(t) \leq 1, \forall m \in \Omega, t \in \Psi, k \in Y \tag{8}$$

$$\sum_{j=1}^{I} x_{jnl}(t) \leq 1, \forall n \in \Omega, t \in \Psi, l \in Y \tag{9}$$

$$x_{imk}(t), x_{jnl}(t) \in \{0, 1\}$$

$$\Phi = \{1, 2, \ldots, I\}, Y = \{1, 2, \ldots, K\}$$

$$\Omega = \{1, 2, \ldots, M\}, \Psi = \{1, 2, \ldots, T\}$$

where f_1 is the first objective function for minimizing the total site location cost and handling cost between the facilities. The cost for a single facility is composed of two parts, namely the fixed cost and the variable cost; f_2 is the objective function related to safety for minimizing the closeness relationship effect; f is the general objective function; w_1 and w_2 are the weight of the corresponding objective functions, respectively; Φ is the temporary facilities, $i, j \in \Phi$; Y is a set of viable provisional positions, $l, k \in Y$; Ω is the set of temporary facility type, $m, n \in \Omega$; Ψ is the set of phases of the whole project, $t \in \Psi$; $d_{ik,jl}$ is the distance between position k of facility i and position l of the facility $j, i, j \in \Phi, l, k \in Y$; $v_{ij}(t)$ is the cost between facility i and $j, i, j \in \Phi, t \in \Psi$; a_{im} is the cost when facility i is built in position $m, i, m \in \Phi$; c_i is the cost when facility i is built, $i \in \Phi$; $F(t)$ is the total value of the interaction flow during the period $t, t \in \Psi$; $C^*(t)$ is the minimum cost of fineness up to stage $t, t \in \Psi$; $x_{imk}(t) = \begin{cases} 1, & \text{move base } i \text{ from position } m \text{ to position } k \\ 0, & \end{cases}$, is the decision variable to define the moving of the facility i from position m to position k.

3. Model Validation

The proposed model of this research is based on the site layout problem of Jinping II Hydropower Construction Plant project in China including 3 stages which were studied by Jiuping Xu, Qiurui Liu, and Xiao Lei [28] as shown in Fig. 3.

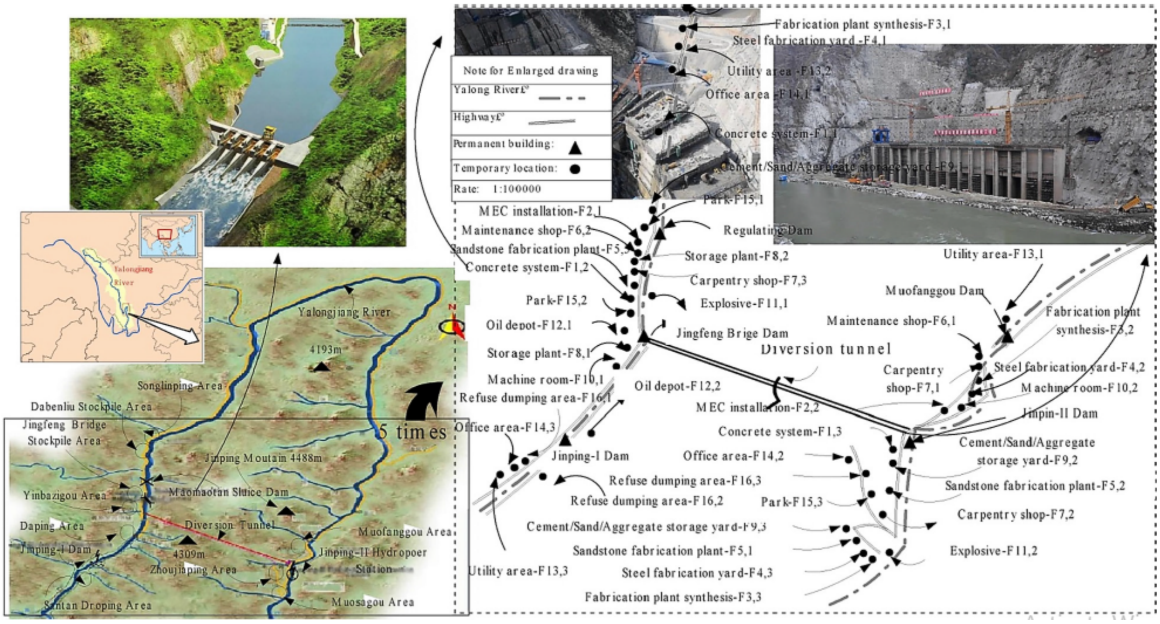

Figure 3. The plan of Jinping II hydropower construction site

Referring to the previous studies, the research proposes the input parameters for the model as follows: $P = 4; S = 20; N_c = 4; N_s = 4; N_{re} = 2; N_{ed} = 2; P_{ed} = 0.1; C(i) = 1; d_{attract} = 0.32; w_{attract} = 0.2; h_{repell} = 0.32; w_{reppell} = 0.1; k_a = 3; I_{\max} = 3; \alpha_i \in (0; 10); \beta_i \in (0; 20); \rho_i \in (0; 1); Q_i \in (\dfrac{1}{150}; \dfrac{1}{150})$.

Using a personal laptop with core configuration i7-4510U, ram 8GB, and running DHACA with 50 iterations, the results are shown in Fig. 4, Tables 1 and 2.

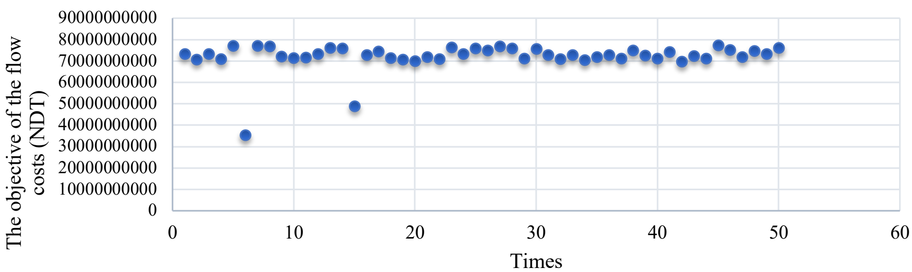

Figure 4. Diagram evaluating the convergence of DHACA

It has been demonstrated that DHACA has converged quite well since the 20th run. From there, the research assessed the results of the last 30 times. From the results of these 30 runs, it is evident that DHACA contributes beneficial and consistent results. The best option has a target value of 7694, and the execution time is 114 seconds.

Table 4 shows the effectiveness of DHACA compared to SA-based MOGA and MOGA. The optimal value ($f = 7697$) by DHACA is greater than the optimal value ($f = 7554$) by SA-based MOGA. The optimal cost values f_1, f_2 by DHACA is though greater than f_1, f_2 values optimized by

Table 1. The optimal result after 30 times running DHACA

No.	F1 (NDT)	F2	F	Time (s)	No.	F1 (NDT)	F2	F	Time (s)
1	71801960096	710020	7516	123	16	72663216312	719629	7623	115
2	70786902495	746660	7545	117	17	71007471626	743919	7661	116
3	76212251008	757927	7534	116	18	74756532115	757379	7598	116
4	73039435163	738412	7632	116	19	72555301789	777434	7547	114
5	75796407732	738808	7540	115	20	71031935752	709826	7613	116
6	74738308483	738537	7624	115	**21**	**74102790211**	**746410**	**7694**	**114**
7	76722966649	775396	7562	116	22	69602564497	718204	7600	115
8	75844621307	727518	7627	118	23	72096415581	780456	7639	130
9	71121820377	784563	7600	117	24	71107743302	795880	7548	129
10	75464547591	754413	7608	117	25	77086751858	979199	7509	117
11	72728230772	731021	7565	118	26	75048495344	773992	7618	118
12	70862702502	781239	7644	114	27	71642206476	700756	7590	114
13	72686812269	750513	7568	114	28	74643780549	773321	7645	117
14	70404149930	753813	7667	114	29	73187183003	769192	7597	115
15	71694508800	755021	7535	116	30	75935764546	759848	7674	115

Table 2. Statistical table describing the result of the problem

	F1 (NDT)	F2	F3	T
The average value	73212459271.1	758310.1	7597.3	116.9
Median	72707521520.2	754113.4	7599.6	116.0
Standard deviation	2144522930.4	48320.4	49.5	3.9
MAX	77086751857.6	979199.3	7694.3	130.0
MIN	69602564497.0	700755.8	7508.6	114.0

Table 3. Optimal solution by DHACA

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16
$t = 1$	F1-1	F2-2	F3-1	F4-1	F5-3	F6-2	F7-3	F8-2	F9-3	F10-2	F11-2	F12-2	F13-3	F14-1	F15-3	F16-2
$t = 2$	F1-1	F2-2	F3-2	F4-2	F5-3	F6-1	F7-2	F8-1	F9-2	F10-2	F11-1	F12-1	F13-1	F14-2	F15-1	F16-1
$t = 3$	F1-1	F2-1	F3-3	F4-3	F5-2	F6-2	F7-2	F8-1	F9-3	F10-1	F11-2	F12-1	F13-3	F14-2	F15-2	F16-1

SA-based MOGA, they are close to the data value of the project; besides, the deviation of the optimal target value by DHACA with the project data (12.5%) is lower than that by SA-based MOGA (22.06%) and MOGA (29.00%) that shows more reliable results. The optimal target values by DHACA are smaller than the project data, showing that DHACA solves the optimization problem with higher reliability than SA-based MOGA and MOGA.

Using the proposed method, the processing time to obtain the optimum site layout is much faster than in previous research. The proposed model was set from the results of the preliminary experiments that were conducted to observe the behavior of the algorithm at different parameter settings. To reduce potential statistical errors, the convergence iteration number and computing time of the algorithm were also calculated. The proposed methodology provided a systematic approach to narrow down the number of alternatives, and to facilitate the decision-making process. These results are quite useful and could be used as a reference for the decision-makers to choose the appropriate set of parameters to optimize the decision-making process.

Table 4. The comparing results of DHACA, SA-based MOGA, and MOGA

Algorithm			DHACA			SA-based MOGA			MOGA		
Stage			1	2	3	1	2	3	1	2	3
Cost	$f_1(10^6)$	Result	41543	70015	74103	31568	62838	72422	26653	43392	58793
		Data	32574	66556	77208	32574	66556	77208	32574	66556	77208
		Increase	8969	3459	3105	1006	3718	4786	5921	23164	18415
		Rate	27.53%	5.20%	4.02%	3.09%	5.59%	6.20%	18.18%	34.80%	23.85%
	f_2 (Data = 795470)	Result	746410			706654			718261		
		Data	795470			795470			795470		
		Increase	49060			88816			77209		
		Rate	6.17%			11.17%			9.71%		
Target	f	Best	7694			7554			6092		
		Worst	7509			7532			5945		
		Average	7597			7500			6076		
Variance			12.50%			22.06%			29.00%		
Convergence			1			1			5		
Time			114.861			67.893			7.047		

4. Conclusions

This study proposes DHACA which is a hybrid algorithm based on the original algorithm ACO combined with other auxiliary algorithms such as BFA, PWEH, in which ACO has many advantages in local and global search, BFA is used to initialize inputting parameters, and PWEH is applied to create adjacent solutions, support local optimization, improve solutions in the problem of ACO. This new Meta-heuristic hybrid algorithm is designed to solve the dynamic site layout problem with many constraints that need to be satisfied, in line with the development reality of the construction industry, then giving project managers an additional plan to consider and evaluate the optimum in the site layout.

The current research can be extended in many directions in the future. One of them is the consideration of additional factors of environmental pollution and construction delay or research on smaller-scale problems such as the layout of building construction. Although the GWO has been used in previous studies, its combination with a fuzzy system to optimize the system is one of the new research directions. Therefore, problems with combinations of optimal searching algorithms and machine learning models such as CNN and any of GA, PSO, FA, and LFA need to be studied.

References

[1] 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):536–544.

[2] Taheri Amiri, M. J., Hematian, M., Haghighi, F., Javaheri Barforooshi, M. (2021). Site Layout Optimization and it's Impact on the Cost of Construction Projects by invasive weeds optimization algorithm. *Amirkabir Journal of Civil Engineering*, 53(2).

[3] Liu, B., Yang, B., Xiao, J., Zhu, D., Zhang, B., Wang, Z., Dong, M. (2021). Review of Optimization Dynamically Applied in the Construction and the Application Potential of ICT. *Sustainability*, 13(10): 5478.

[4] Elbeltagi, E., Hegazy, T., Hosny, A. H., Eldosouky, A. (2001). Schedule-dependent evolution of site layout planning. *Construction Management and Economics*, 19(7):689–697.

[5] Jaafar, K., Elbarkouky, R., Kennedy, J. (2020). Construction site layout optimization model considering cost and safety in a dynamic environment. *Asian Journal of Civil Engineering*, 22(2):297–312.

[6] Kim, M., Ryu, H.-G., Kim, T. W. (2021). A Typology Model of Temporary Facility Constraints for Automated Construction Site Layout Planning. *Applied Sciences*, 11(3):1027.

[7] Tuan, N. M. (2019). An analysis of the integration of Lean construction principles in the BIM coordination process. *Journal of Science and Technology in Civil Engineering (STCE) - NUCE*, 13(1):109–116.

[8] Tam, N. V., Huong, N. L., Ngoc, N. B. (2018). Factors affecting labour productivity of construction worker on construction site: A case of Hanoi. *Journal of Science and Technology in Civil Engineering (STCE) - NUCE*, 12(5):127–138.

[9] RazaviAlavi, S., AbouRizk, S. (2017). Genetic Algorithm–Simulation Framework for Decision Making in Construction Site Layout Planning. *Journal of Construction Engineering and Management*, 143(1): 04016084.

[10] Yang, Y. (2021). Genetic Algorithm Based optimization of Construction Site Layout of Prefabricated Buildings. In *2021 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)*, IEEE.

[11] Petroutsatou, K., Apostolidis, N., Zarkada, A., Ntokou, A. (2021). Dynamic Planning of Construction Site for Linear Projects. *Infrastructures*, 6(2):21.

[12] Kang, H., Sung, S., Hong, J., Jung, S., Hong, T., Park, H. S., Lee, D.-E. (2021). Development of a real-time automated monitoring system for managing the hazardous environmental pollutants at the construction site. *Journal of Hazardous Materials*, 402:123483.

[13] Atmaca, M., Akcay, C. (2021). Construction site layout planning using GIS overlay analysis—A case study. *Arabian Journal of Geosciences*, 14(7).

[14] Dorrah, D. H., Marzouk, M. (2021). Integrated multi-objective optimization and agent-based building occupancy modeling for space layout planning. *Journal of Building Engineering*, 34:101902.

[15] Elbeltagi, E., Hegazy, T. (2001). A Hybrid AL-Based System for Site Layout Planning in Construction. *Computer-Aided Civil and Infrastructure Engineering*, 16(2):79–93.

[16] Papadaki, I. N., Chassiakos, A. P. (2016). Multi-objective Construction Site Layout Planning Using Genetic Algorithms. *Procedia Engineering*, 164:20–27.

[17] Zouein, P. P., Harmanani, H., Hajar, A. (2002). Genetic Algorithm for Solving Site Layout Problem with Unequal-Size and Constrained Facilities. *Journal of Computing in Civil Engineering*, 16(2):143–151.

[18] Said, H., El-Rayes, K. (2010). Optimizing the planning of construction site security for critical infrastructure projects. *Automation in Construction*, 19(2):221–234.

[19] Sing, M. C. P., Fung, I. W. H., Edwards, D. J., Liu, H. (2021). Dynamic construction site layout planning: an application of branch and bond algorithm. *International Journal of Building Pathology and Adaptation*, ahead-of-print(ahead-of-print).

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

[21] Tam, C. M., Tong, T. K. L., Chan, W. K. W. (2001). Genetic Algorithm for Optimizing Supply Locations around Tower Crane. *Journal of Construction Engineering and Management*, 127(4):315–321.

[22] Hegazy, T., Elbeltagi, E. (1999). EvoSite: Evolution-Based Model for Site Layout Planning. *Journal of Computing in Civil Engineering*, 13(3):198–206.

[23] Lazarova, M., Borovska, P. (2008). Comparison of parallel metaheuristics for solving the TSP. In *Proceedings of the 9th International Conference on Computer Systems and Technologies and Workshop for PhD Students in Computing - CompSysTech '08*, ACM Press.

[24] Adrian, A. M., Utamima, A., Wang, K.-J. (2014). A comparative study of GA, PSO and ACO for solving construction site layout optimization. *KSCE Journal of Civil Engineering*, 19(3):520–527.

[25] Le, N. (2020). Vietnam Construction Industry Performance Issues and Potential Solutions. *Journal for the Advancement of Performance Information and Value*, 9(2):7–20.

[26] Calis, G., Yuksel, O. (2015). An Improved Ant Colony Optimization Algorithm for Construction Site

Layout Problems. *Journal of Building Construction and Planning Research*, 03(04):221–232.

[27] Li, P., Zhu, H. (2016). Parameter Selection for Ant Colony Algorithm Based on Bacterial Foraging Algorithm. *Mathematical Problems in Engineering*, 2016:1–12.

[28] Xu, J., Liu, Q., Lei, X. (2016). A fuzzy multi-objective model and application for the discrete dynamic temporary facilities location planning problem. *Journal of Civil Engineering and Management*, 22(3): 357–372.

[29] Mai, X.-F., Li, L. (2012). Bacterial foraging algorithm based on gradient particle swarm optimization algorithm. In *2012 8th International Conference on Natural Computation*, IEEE.

[30] Xiong, X., Wu, W., Li, N., Yang, L., Zhang, J., Wei, Z. (2019). Risk-Based Multi-Objective Optimization of Distributed Generation Based on GPSO-BFA Algorithm. *IEEE Access*, 7:30563–30572.

[31] Rajasekar, N., Kumar, N. K., Venugopalan, R. (2013). Bacterial Foraging Algorithm based solar PV parameter estimation. *Solar Energy*, 97:255–265.

[32] Verma, O. P., Parihar, A. S. (2017). An Optimal Fuzzy System for Edge Detection in Color Images Using Bacterial Foraging Algorithm. *IEEE Transactions on Fuzzy Systems*, 25(1):114–127.

[33] Abedinia, O., Amjady, N., Ghasemi, A., Hejrati, Z. (2012). Solution of economic load dispatch problem via hybrid particle swarm optimization with time-varying acceleration coefficients and bacteria foraging algorithm techniques. *International Transactions on Electrical Energy Systems*, 23(8):1504–1522.