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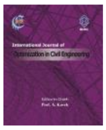

OPTIMIZATION OF TOWER CRANES AND SUPPLY POINTS LOCATION USING MBF ALGORITHM

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ABSTRACT

Tower cranes are essential for both vertical and horizontal movement of materials in construction and port operations. Optimizing their placement is crucial for reducing costs and enhancing overall efficiency. This study addresses the optimization of tower crane placement using the recently developed Mouth Brooding Fish (MBF) algorithm. The MBF algorithm is inspired by the life cycle of mouth-brooding fish, employing their behavioral patterns and the survival challenges of their offspring to find optimal solutions. The performance of the MBF algorithm is compared with the Genetic Algorithm (GA), Colliding Bodies Optimization (CBO), and Enhanced Colliding Bodies Optimization (ECBO). The results demonstrate that the MBF algorithm is effective and has potential advantages in tackling complex optimization problems.

Keywords: Tower cranes, Optimization, Mouth Brooding Fish, Enhanced Colliding Bodies Optimization (ECBO), Colliding Bodies Optimization (CBO), Supply points location, Construction.

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1. INTRODUCTION

In the last few decades, a significant amount of research has been dedicated to finding the most efficient solution for construction engineering optimization problems (CEOPs). CSLPs are fascinating CEOPs as they incorporate layout esthetics and usability qualities in facility

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design. Tower cranes are used in building construction to move heavy materials. Transporting materials is a key task in construction, involving precise planning for lifting heavy loads of cranes [1]. Adequate space for temporary facilities is necessary for safe and efficient construction projects.

CSLP is recognized as an 'NP-hard' problem due to its complexity [2]. Recent advancements in meta-heuristic algorithms based on swarm intelligence have proven effective in solving such optimization challenges [3-5], prompting researchers to apply these modern techniques to CSLP models.

Creating a layout for on-site facilities is a crucial part of construction site planning. Designing construction site spaces for safe and efficient work is a complex task that requires considering various scenarios. Combinatorial optimization problems are referred to as CSLPs. Two approaches exist for solving large problems: meta-heuristics and exact methods with global search [6]. Using meta-heuristic algorithms to solve real-life problems has become a fascinating subject in recent years. Many meta-heuristics, each with unique philosophy and characteristics, are developed and used in various domains. These optimization methods aim to explore the search space and discover global or near-global solutions. Because of their problem-independent nature and lack of derivative requirement, these algorithms have gained attention from both academia and industry [7]. Meta-heuristic methods imitate natural, human, or physical phenomena for global optimization. such as CBO and MBF) [8-11]. Meta-heuristic optimization methods rely on both exploitation and exploration. Exploitation serves to search around the current best solutions and select the best possible points, and exploration allows the optimizer to explore the search space more efficiently, often by randomization [7].

Previously, Li and Love [7] addressed a construction site-level facility layout problem by allocating facilities to a set of predefined locations. They approached the problem using a genetic algorithm, based on the assumption that these predefined locations are rectangular and sufficiently large to accommodate the largest facilities. Gharaie et al. [6] tackled their model with Ant Colony Optimization, while Kaveh et al. [12] employed Colliding Bodies Optimization along with its improved version. In a similar vein, Cheung et al. [13] proposed another model for construction site layout planning and resolved it using a Genetic Algorithm. Furthermore, Liang and Chao, Wong et al., and Kaveh et al. [14] applied Multi-search Tabu Search, Mixed Integer Programming, and CBO, ECBO, and PSO methods, respectively.

Jahani and Chizari (2018) proposed the Mouth Brooding Fish (MBF) algorithm as a novel meta-heuristic. The answer is found by studying the life cycle of mouthbrooding fish and their struggle for survival.

2. MOUTH BROODING FISH ALGORITHM

Optimization algorithms are employed to optimize objective functions within specific constraints. The algorithms can be categorized into the penalty function approach that has been used for handling the constraints. Problems can be considered multi-objective and single-objective types. Multi-objective is typically involved in the majority of optimization problems. but for simplification, we have considered this problem as single-objective. The problem of single-objective optimization can be expressed in the following manner:

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find

$$X = [x_1, \quad x_2, \quad \dots, x_n]$$

to minimize

$$Mer(X) \tag{1}$$

subjected to

$$g_j(X) < 0, \quad j = 1,2,\dots,m$$
$$x_{i_{min}} < xi < x_{i_{max}}$$

where *X* represents the vector of all design variables with n unknowns.

The objective function is represented by *Mer(X)*. x_{imin} represents the lower bound of the design variable vector, while x_{imax} represents the upper bound. The objective function that needs to be minimized is defined as the merit (or pseudo-objective) function in Eq. 2.

$$Mer(X) = F(X) \times fpenalty\,(X) = F(X) \times (1 + K)$$
$$K = \max(0, g_X) \tag{2}$$

where *Mer(X)* is the merit function, *F(X)* is the objective function, *K* is the penalty parameter, and $f_{penalty}(X)$ is the penalty function.

The life cycle processes of the mouthbrooding fish (MBF) have served as inspiration for the MBF algorithm. The user determines the five controlling parameters of this algorithm. The variables include the mother's source point (SP), mother's source point damping (Spdamp), dispersion amount (Dis), dispersion probability (Pdis), and cichlid population (nFish). How cichlids encircle their mother forms the crucial foundation of an MBF algorithm. Figure 1 illustrates the flowchart of this algorithm, with the steps listed below.

- Main movements
- Additional movements
- Crossover
- Shark attack

2.1. The main movements.

The primary motions are determined in the following manner:

$$Asp = SP \times Cichlids \cdot Movements \tag{3}$$

SP is the origin point of the mother, while *Cichlids* . *Movements* represent their final movements.

$$SP = SP \times Spdamp \tag{4}$$

Spdamp represents the mother's source point damp, which ranges from 0.85 to 0.95, while *SP* denotes the mother's changing source point for the next iteration.

$$A_{lb} = Dis \times (Cichlids \cdot Best - Cichlids \cdot Position) \quad (5)$$

The current position of Cichlids is at Position and their best position is at the best. The user selects *dis* to either amplify or diminish the impact of this motion.

$$A_{gb} = Dis \times (Global \cdot Best - Cichlids \cdot Position) \quad (6)$$

The best position found for all cichlids in previous iterations is at *Global* . *Best*.

$$NewN.F.P = 10 \times SP \times Natureforce \cdot Position \quad (7)$$

Nature Force. *Position* is the cell that is chosen from 60% of the cells with the greatest difference in position between the last and current generation.

$$A_{nf} = Dis \times (New\ N \cdot F \cdot P - Nature\ Force \cdot Position) \quad (8)$$

The best position for cichlids in the last iteration is *Nature Force*. *Position*.

Each child can only move within the range of surrounding dispersion, either positive or negative.

The two parameters described earlier are designated as:

$$\begin{gathered} ASDP = 0.1 \times (Var_{Max} - Var_{Min}) \\ ASDN = -ASDP \end{gathered} \quad (9)$$

The variables Var_{Min} and Var_{Max} represent the minimum and maximum limits of the problem's variation.

Following that, we determine a fresh location for cichlids, taking into account their calculated movements. If their current position is outside the search space area, a new movement is generated through the mirror effect (i.e., by reversing the movement direction), and it follows this definition:

$$Cichlids \cdot Movements = -Cichlids \cdot Movements \quad (10)$$

Cichlids . *Movements* explore the before and after effects of mirror reflections on cichlids.

2.2 The additional movements

The mother can house numerous cichlids, while the rest are known as left-out cichlids and the calculation for the number of neglected cichlids (nm) is as follows:

$$nm = 0.04 \times nFish \times SP^{-0.431} \quad (11)$$

In order to survive, these cichlids must move away from the main group using a controlling parameter (*Pdis*) between 0 and 1. The calculation for the number of remaining cichlids is determined by Eq. (12).

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$$NCC = [nVar \times Pdis] \tag{12}$$

The second part of a movement is performed by neglected cichlids.

$$UASDP = 4 \times ASDP \cdot UASDN = -UASDP \tag{13}$$

UASDN and *UASDP* represent the extreme boundaries for the dispersion of cichlid movements.

To calculate the second part of the movement, follow these steps:

$$LeftCichlids \cdot Position = UASDP \pm Cichlids \cdot P \tag{14}$$

Left Cichlids . *Position* represents the new position of cichlids left out after the second part of movements, while *Cichlids* . *Prefers* to randomly selected cells of cichlids based on the number of *NCC*.

2.3 Crossover

The mouth-brooding fish permits its top cichlids to mate. The single point crossover generates the new fish using a 65 percent probability from the better parent and 35 percent from another parent. The newly hatched cichlids, in their new role, replace their parents and remain stationary.

2.4 Shark attack

The calculation of the number of cichlids affected by shark attacks is as follows:

$$nshark = 0.04 \times nFish \tag{15}$$

In this equation, *nshark* represents the number of cichlids involved in the shark attack effect. Shark attack affects 4 percent of the cichlids population on position and movements as follows:

$$Cichlids \cdot NewPosition = SharkAttack \times Cichlids \tag{16}$$

Cichlids . *Position* randomly selects cichlids from a 4 percent population, while *SharkAttack* tracks the number of cichlids and their frequency of change. [15]

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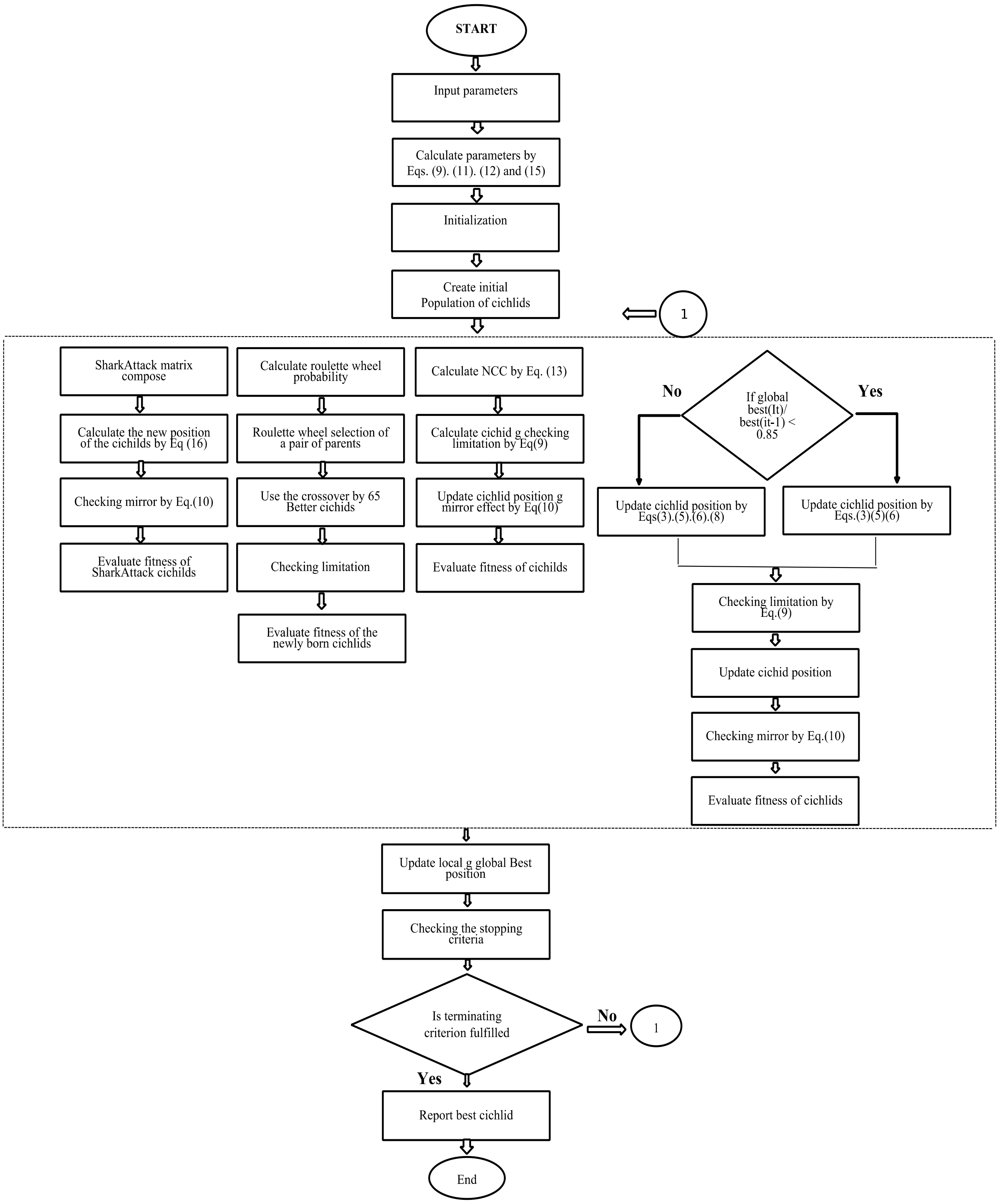

Figure 1: The algorithm for mouth-brooding fish (MBF) is presented in a flowchart. [15]

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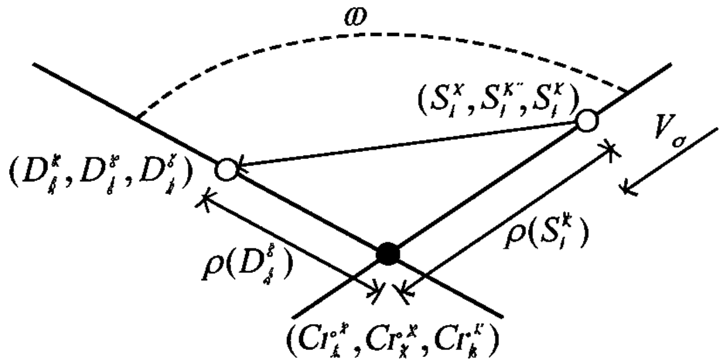
3. OPTIMIZATION OF TOWER CRANE LOCATION AND MATERIAL SUPPLY POINTS

MATERIAL SUPPLY POINTS

Numerous studies have investigated the time it takes to locate and transport a tower crane. For instance, Choi and Harris [12] enhanced a mathematical model to determine the optimal location for a tower crane. Huang et al. [13] created a mixed integer linear programming (MILP) to optimize crane and supply locations. Their model reduced hook travel time by 7% compared to previous genetic algorithm results. The equation can be used to calculate the travel distance between the supply and demand points. (8) through Eq. (9) referring to Figs. 5 and 6.



— The rib of the crane
---- Angular movement path of the rib of the crane (tangent movement)
○ Hook position
← Change of hook position (radial movement)
• Crane position

Figure 2: Radial and tangent movements of the

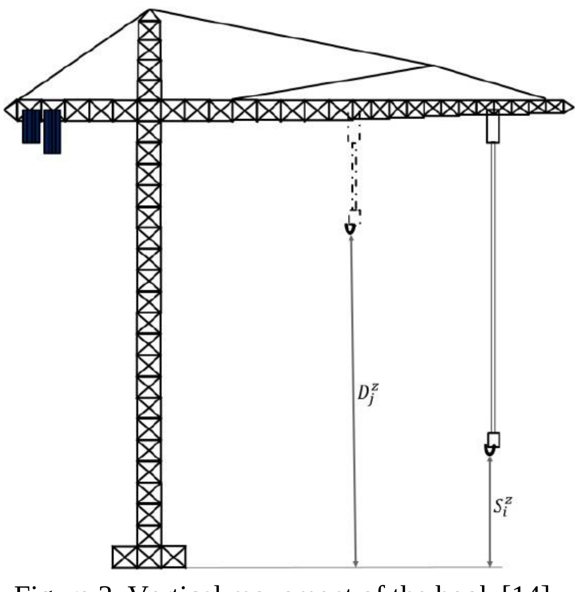


Figure 3. Vertical movement of the hook [14]

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$$\rho\ (D, C_r)\ =\ \sqrt{(X_D - X_C)^2 + (Y_D - Y_C)^2} \tag{17}$$

$$\rho\ (S, C_r)\ = \sqrt{(X_S - X_C)^2 + (Y_S - Y_C)^2} \tag{18}$$

$$L = \sqrt{(X_S - X_D)^2 + (Y_S - Y_D)^2} \tag{19}$$

$$T_a = \frac{|\rho_D - \rho_S|}{V_a} \tag{20}$$

$$T\omega\ = \frac{1}{V_\omega}\ arccos\left[\frac{L^2 + \rho_D^2 + \rho_S^2}{2\times\rho_D\times\rho_S}\right],\ [0\ < arccos\ (\Theta)\ \ < \text{л}\ ] \tag{21}$$

Evaluating the total time of material transportation with a tower crane relies on hook movement time. To reflect operating costs accurately, the hook movement time has been divided into horizontal and vertical paths with a suitable cost-time factor. Figures display movement paths in different directions. 2 and 3. A continuous type parameter α indicates the degree of coordination of the hook movement in radial and tangential directions which depends on the control skills of a tower crane operator, times for horizontal and vertical hook movements can be calculated in Eqs. The ages of (22) and (23) are in that order.

$$T_h =\ max\{T_a\ +\ T_\omega\}\ +\ \alpha\ \times\ min\ \{T_a\ +\ T_\omega\ \} \tag{22}$$

$$T_v \frac{|D_D -\ D_S|}{V_h} \tag{23}$$

The total travel time of the tower crane at location k between supply point i and demand point j, T_{ij}^K, can be determined using Eq. (24) by specifying the continuous type parameter *ß* for the degree of coordination of hook movement in horizontal and vertical planes. The movement of the tower crane and hook operation may be affected by various factors, such as site conditions, operator skills, and visibility level, resulting in reduced efficiency and longer operating time [12]. If the operator’s line of sight is blocked, then the travel time from the supply location to the demand point needs to be increased. To address these challenges in site operation, we introduce a new numerical parameter *ƛk* to enhance the original factor.

The travel times of the tower crane and hook are provided in Eq. (24). Various *ƛk* can be utilized for distinct tower crane positions *k* in order to assess location-specific impacts on a construction site. Installing an advanced vision system in tower cranes can speed up operations and allow for a smaller *ƛk* setting [13].

$$T_{ij}^K =\ ƛk\ X\ [max\{T_h\ +\ T_v\}\ +\ \beta.min\ \{T_h\ +\ T_v\}] \tag{24}$$

Three scenarios were presented by Huang et al. [6] to showcase the adaptability of their MILP model for tower crane placement. The formulation will be expanded to include homogeneous and non-homogeneous storage supply points, allowing for different materials to be stored using different strategies by adding additional linear governing constraints.

A single tower crane can be modeled and assigned to any available location. For a given location k, binary variables like ζk are defined. ζk equals 1 if the location k is chosen for a tower crane, or 0 if it is not selected. The optimization framework mandates selecting the best tower crane location due to the requirement of constraint as in Fig. (25).

$$\Sigma_{k=1}^{k} \ \zeta_k = 1, \quad \forall K \in \{1, k\} \tag{25}$$

The introduction of binary variables Δj signifies the presence of a potential demand point at each demand location. Depending on the input material demand profile $QI.j$ for material type l, constraint set (26) is required to ensure the binary variable Δj to be "1" if there is a demand at location j and "0" if the demand does not exist. M represents a large whole number without any specific value.

$$M\Delta_j \geq \Sigma_{I=1}^{L} \ Q_{I.j} > \Delta_j, \ \forall j \ \in \{1, J\} \tag{26}$$

3.1 Homogeneous material supply point

As a management problem, it is worth examining the total cost of transporting all the required materials to demand points through a tower crane if the materials can be stored and supplied in more than one location without setting a storage limit on various supply locations realizing that the supply locations have infinite material storage capacity, which is always the case in large-scale construction sites. In a homogeneous material supply system, each supply point has a temporary storage area limited to one material type. During optimization, it is crucial to allocate only one material type per supply location. Constraint sets (27) and (28) define and regulate a set of binary decision variables Xi,l mathematically. In the equation. (27), for each material type l = {1,L} , where L is the total number of material types to be ,considered, there must be one assigned supply location within a site. For each supply location i = {1,I}, where I is the total number of available supply points in a site capable of storing the construction material, only one material type can be assigned, as indicated in Eq. (28).

$$\Sigma_{i=1}^{I} X_{i,l} = 1, \qquad \forall l \ \in \{1, L\} \tag{27}$$

$$\Sigma_{l=1}^{L} X_{i,l} \leq 1, \qquad \forall i \ \in \{1, I\} \tag{28}$$

The objective function is the total cost of material transportation, which is influenced by the amount of material flowing between supply and demand locations. We define a set of auxiliary binary variables $\delta i,j,k,l$ to represent material flows. These variables are equal to "1" if material type l at supply point i is transported by a tower crane at location k to demand point j, and "0" otherwise [16].

The decision variables Xi,l represent the linkage between material l and supply location i, Δj represent demand location j, and ζk represents the selection of the tower crane k^{th} location, all with the constraint set (1). Numerically, when all Xi,l, Δj, and ζk are set to 1, the material flow linkage is confirmed by $\delta i,j,k,l$ = 1. For all other cases, $\delta i,j,k,l$ equals 1 to exclude transportation costs from the objective function.

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$$M\left(1-\delta_{i,j,k,l}\right) \geq \left(3-\ X_{i,l}-\Delta_j-\xi_k\right) \geq \left(1-\delta_{i,j,k,l}\right), \forall i\ \in \{1, I\}, \forall j\ \in \{1, J\}, \forall k\ \in \{1, K\}, \forall l\ \in \{1, L\} \quad (29)$$

With the use of the auxiliary variable $\delta_{i,j,k,l}$ to represent material flows, the equation can be used to calculate the overall cost of material transportation by a tower crane from different supply points to demand points. (30) that can be set as an objective function for optimization in the present formulation. The total cost TC^h is defined as the sum of transportation costs between supply and demand locations by a tower crane at location *k* using material flow variables $\delta_{i,j,k,l}$ for a homogenous material supply system. In the equation. (30), $Q_{l,j}$ is the required quantity of material *l* at demand point *j*, *C* is the cost per unit time in operating a tower crane, and $T_{i,j}^k$ is the actual transport time between supply location *i* and demand location *j* by a tower crane at location *k*. The current formulation can be optimized by evaluating and setting the total cost as an objective function.

$$TC^h = \Sigma_{i=1}^{I} \Sigma_{j=1}^{J} \Sigma_{l=1}^{L} \delta_{i,j,k,l} T_{i.j}^k\ Q_{1,j}\ C, \forall k \in \{1, K\} \quad (30)$$

The tower crane position in a homogeneous material supply system can be optimized by formulating the objective function in Eq. (28) subject to constraint sets in Eqs. (17) to (29).

4. NUMERICAL EXAMPLES

Previous studies used case studies to assess the effectiveness and performance of Huang et al. [6], addressed by Mbf. Within a site that has 12 potential tower crane locations, the material supply and demand system consists of 3 material types, 9 supply locations, and 9 demand locations. The hoisting velocity of the hook is 60 m/min, radial velocity is 53.3 m/min, and the sewing velocity of the tower crane branch is 7.57 rad/min. With the assumed operating cost per unit of time at \$1.92 per minute, the tower crane has material demand quantities of 10 units for material type 1, 20 units for material type 2, and 30 units for material type 3 at all demand points. Demonstrating the coordination of hook movement in vertical and horizontal planes during practical operation is the parameter β, which is set at 0.25. The coordination of hook movement in radial and tangential directions in the horizontal plane is specified by the parameter α, assumed to be 1.0 [17]. To show, all γk values are set to 1.0, assuming no significant differences among the locations for the tower crane operation. Table 1 provides the (x, y, z) coordinates for the demand points, material supply points, and tower crane locations.

5. RESULTS AND DISCUSSION

Each scenario was tested through 30 independent experimental runs over 300 iterations in this study. The MBF optimization method in PYCHARM 2023.1 resolved the problem. To optimize the algorithm's performance, multiple experiments were conducted to determine the control parameters for MBF.

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Table 1: Coordinates of the potential locations

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Demand point j	X	34	34	51	60	76	76	60	51	43			
	Y	41	51	65	65	51	41	26	25	44			
	Z	15	15	15	15	15	15	15	15	15			
Supply point i	X	73	83	87	73	55	35	22	36	55			
	Y	26	31	45	67	73	67	46	27	15			
	Z	2	2	1.5	1.5	1.5	0	0	1	1			
Tower crane position, k	X	45	65	65	45	51	60	70	70	60	51	42	42
	Y	36	36	57	57	33	33	41	52	58	58	52	41
	Z	30	30	30	30	30	30	30	30	30	30	30	30

5.1 Results and discussion for homogeneous material supply point scenario

Table 2 presents the previous research findings, which include optimized total costs, suitable supply point locations for demand points, and tower crane locations. Comparing these results, the method employed in this study achieves 4% higher than the results obtained by CBO, ECBO, VPS, and MILP approaches, and 3% lower than that obtained by the GA method.

Table 2 shows that tower crane number 5 is positioned in relation to supply and demand points. The supply points are allocated to the demand points as [2, 2, 3], meaning that demand points 1 and 2 are served by supply point 2, and demand point 3 is served by supply point 3., the best calculated cost for these allocations is 527.5537, with a standard deviation of zero, showing that the mean cost and best cost are identical.

Table 2: Comparison of the optimized design for the homogeneous material supply point

Method	Tower crane, k	Order of allocation of supply points to material type			Best cost	Mean cost	Standard deviation	Worst cost
		1	**2**	**3**				
GA (9)	2	3	2	9	540.7587	N/A	N/A	N/A
MILP (1)	8	2	5	1	504.7631	N/A	N/A	N/A
CBO	8	2	5	1	504.7631	505.9426	1.3319	508.2809
ECBO	8	2	5	1	504.7631	504.8804	0.6423	508.2809
VPS	8	2	5	1	504.7631	504.8383	0.4121	507.0204
MBF	5	2	2	3	527.5537	527.5537	0.0000	527.5537

Note: N/A: Not available

6. CONCLUSIONS

This study achieved significant success in optimizing material transportation costs using the MBF method, reporting a cost efficiency of 527.55. The results indicate that MBF has greater potential for improvement compared to methods like MILP (with a best cost of 504.7631) under specific conditions and additional constraints, such as real-world site conditions and various crane designs. While MBF shows promising capabilities, other algorithms like CBO and ECBO also delivered notable results, with ECBO providing more stable solutions than VPS and both outperforming CBO. However, in scenarios with non-homogeneous material supply, MBF did not reach the optimality level of MILP, indicating the need for further optimizations. Overall, MBF can be particularly effective in complex operational contexts and diverse design scenarios.

REFERENCES

1. Sawhney A., Mund A. Adaptive probabilistic neural network-based crane type selection system. *J Constr Eng Manage.* 2002; **128**(3):265-73.
2. Kaveh A. *Advances in Metaheuristic Algorithms for Optimal Design of Structures.* Switzerland: Springer International Publishing; 2017.
3. Huang C., Wong C. K., Tam C. M. Optimization of tower crane and material supply locations in a high-rise building site by mixed-integer linear programming. *Autom Constr.* 2011; **20**(5):571-80.
4. Shayegan D. S., Lork A., Hashemi S. A. H. A new hybrid algorithm for cost optimization of waffle slab. *Slovak J Civ Eng.* 2020; **28**(3):40-46.
5. Michalek J., Choudhary R., Papalambros P. Architectural layout design optimization. *Eng Optim.* 2002; **34**(5):461-84.
6. Jahani E., Chizari M. Tackling global optimization problems with a novel algorithm-Mouth Brooding Fish algorithm. *Appl Soft Comput.* 2018; **62**:987-1002.
7. Choi C. W., Harris F. C. A model for determining optimum crane position. *Proc Inst Civ Eng.* 1991; **90**:627-34.
8. Kaveh A., Bakhshpoori T. Water evaporation optimization: A novel physically inspired optimization algorithm. *Comput Struct.* 2016; **167**:69-85.
9. Erol O. K., Eksin I. A new optimization method: big bang–big crunch. *Adv Eng Softw.* 2006; **37**(2):106-11.
10. Kaveh A., Ilchi-Ghazaan M. A new meta-heuristic algorithm: vibrating particles system. *Sci Iran.* 2017; **24**(2):551-66.
11. Kaveh A., Vazirinia Y. Tower cranes and supply points locating problem using CBO, ECBO, and VPS. *arXiv preprint* arXiv:1811.05963, 2018.
12. Ghadiri A., Shayegan D. S., Amirkardoust A. Multi-objective firefly optimization algorithm for construction site layout planning. *Iran J Optim.* 2022; **14**(4):1-15.
13. Shahebrahimi S. S., Lork A., Shayegan D. S., Kardoust A. A. Solving the problem of multi-stakeholder construction site layout using metaheuristic algorithms. *Power Syst Technol.* 2023; **47**(4):1-15.
14. Shayegan D. S. Optimum cost design of reinforced concrete slabs using a metaheuristic algorithm. *Int J Optim Civ Eng.* 2022; **12**(4):545-55.
15. Saberi A. A., Shayegan D. S. Optimization of Haraz Dam reservoir operation using CBO metaheuristic algorithm. *Int J Optim Civ Eng.* 2021; **11**(4):599-610.
16. Saberi A. A., Ahmadi H., Shayegan D. S., Amirkardoust A. Prediction of electricity consumption using three meta-heuristic algorithms. *Int J Optim Civ Eng.* 2023; **13**(1):111-25.

[DOI: 10.22068/ijoce.2024.14.4.596]

17. Shayegan D. S., Lork A., Hashemi A. H. Optimum cost design of reinforced concrete slabs using Mouth Brooding Fish (MBF) algorithm. *J Appl Eng Sci.* 2020; **10**(23):95-100.
18. Shahebrahimi S. S., Lork A., Shayegan D. S., Kardoust A. A. Impact of construction site layout planning optimization on construction project management (case study of launcher/receiver stations in pipeline projects in Khorasan Province). *Int J Optim Civ Eng.* 2024; **4**(1):83-93.
19. Yahya M., Saka M. Construction site layout planning using multi-objective artificial bee colony algorithm with Levy flights. *Autom Constr.* 2014; **38**:14-29.
20. Kaveh A. *Applications of Metaheuristic Optimization Algorithms in Civil Engineering.* Switzerland: Springer; 2017.
21. Kaveh A., Bakhshpoori T. *Metaheuristics: Outlines, MATLAB Codes and Examples.* Switzerland: Springer; 2019.
22. Kaveh A., Mahdavi V. R. *Colliding Bodies Optimization: Extensions and Applications.* Switzerland: Springer; 2015.
23. Kaveh A., Eslamlou A. D. *Metaheuristic Optimization Algorithms in Civil Engineering: New Applications.* Switzerland: Springer; 2020.
24. Kaveh A. *Applications of Artificial Neural Networks and Machine Learning in Civil Engineering. Stud Comput Intell.* 2024; **1168**.
25. Kaveh A., Mahdavi V. R. Colliding Bodies Optimization: A novel meta-heuristic method. *Comput Struct.* 2014; **139**:18-27.
26. Kaveh A., Dadras Eslamlou A. Enhanced colliding bodies optimization for design problems with continuous and discrete variables. *Comput Struct.* 2016; **169**:1-13.

[DOI: 10.22068/ijoce.2024.14.4.596]