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An Improved Red Panda Optimizer for Effective Construction Site Design

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Abstract

A properly planned design will minimize travel distance, handling of materials diligence, and operating costs, as well as saving time and ease site congestion. The majority of mathematical optimization approaches discovered thus far are effective for modest problems and frequently fall within global or local optimum solutions, which does not ensure continued convergence. As a result, the motive of this work is to propose an Improved Red Panda Optimizer (IRPO) algorithm inspired by the predatory habits of Red pandas, integrating with the Mutation and crossover strategy of Differential Evolution and Oppositional Based Learning and solving a shortcoming of earlier research. The analysis revealed that the proposed approach can lead to very positive results in connection with enhanced exploitation, convergence, avoiding local optima, and exploration. Additionally, the IRPO method yields better ideal solutions for the great majority of the design and shows that this strategy may be used for a variety of limited issues across different search domains. The results of the ideal site layout optimization method show how well the suggested approach works in real-world situations where search areas are ambiguous.

Keywords: Construction site design, Differential evolution, Improved red panda optimizer, Red panda optimization.

Introduction

The construction site plan has an important influence on the cost of the project, efficiency, security, and other factors (1). Yet the site design strategy can be created without consideration for the goals of the project, and in other circumstances, no particular site design strategy is implemented (2). As a consequence, the construction task takes longer to complete, costs more to build, and the project's quality suffers. The lack of available space on the building site in comparison to equipment and supplies (1) emphasizes the importance of good site design to conserve time as well as reduce site congestion. As a result, travel distance, handling of materials effort, and operating expenses are reduced (3). The planning process, also known as factors of production, is included in operational plans to generate a more efficient system (4). Furthermore, builders and workers on site devote the majority of their time to building zones. As a result, if they can move to the concerned location swiftly, and easily, and in turn productivity will increase (5).

Factors such as the workplace and the amount of communication between sites are taken into account when creating a building site design to avoid construction disputes and enhance the workspace (5, 6). Heuristic approaches and optimization methodologies are applied to solve the problem. Arithmetical optimization methodologies have been developed to obtain optimal solutions. They are, however, only applicable to modest problems, whereas artificial intelligence approaches have been devised for a larger challenge. To find the ideal configuration, optimization techniques are therefore applied (7). An updated model of the optimization techniques becomes faster over time than finding the information by hand (8). Furthermore, improving the flow of materials on the spot has been shown to cut 10- 30% of the cost of handling materials (9), demonstrating the model's efficacy. On the other hand, heuristic approaches typically yield a good answer in a reasonable amount of time and have produced an approximate estimate rather than a perfect solution for large problems.

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The paradigm of metaheuristic algorithms is frequently utilized to provide a solution for construction design challenges. Furthermore, hybrid methodologies were used, including the hybrid Whale Optimization Algorithm (WOA), Colliding Bodies Optimization (CBO), and a hybrid AI-based particle Bee Algorithm (BA) for building design optimization (10). Nonetheless, the Red Panda Optimizer has not been fully exploited in the site design. Furthermore, it is simple to develop high-quality solutions (11). An Improved Red Panda Optimizer (IRPO) algorithm, on the other hand, generates a faster, and better result in less time. The optimal solution to the site layout problem involves combining heuristic and optimization techniques to increase accuracy or precision within a specified time frame.

The goal of this work is to create an Improved Red Panda Optimizer (IRPO) algorithm to improve the accuracy and degree of convergence of the initial framework that was presented by Mirjalili in 2015 (12), notwithstanding the limitations of previous studies. To achieve the goal, Opposition-Based Learning (OBL) is adopted, followed by the Mutation and Crossover Strategy of Differential Evolution. The generated algorithm's performance is tested by comparing it to three genuine records (13), with the inclusion of an additional case study to guarantee its efficacy.

Building project management as well as engineering can be difficult. A construction site involves a large number of individuals and supplies, making it a complicated workspace. It is critical to optimize the building process or associated action to keep expenses, time frames, and total productivity as low as possible (14-16). Construction site layout must be planned with the dynamics and dangers of the site in mind. A carefully designed site layout adds greatly to time and cost savings, particularly when it comes to operating expenses. Furthermore, building a productive structure and a more secure environment through the use of pleasant equipment, supplies, and workflows (17-21). Reduced handling of materials conflicts, workplace congestion, and excursion distance, in particular, can reduce the cost of operations by 20% to 50% (22).

To achieve an efficient and effective optimization method, numerous decision-making tools were applied. Many studies on workplace design difficulties emphasize using artificial intelligence to discover ideal solutions. To find a solution, metaheuristic algorithms are frequently utilized. In 2018, a study was conducted to evaluate three systems' performance in three case studies. Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Symbiotic Organisms Search (SOS) are the three algorithms (13). The model was used to identify the best site layout by decreasing laborers' journey distance at every place given their frequency of travel. To find a more stable and ideal solution, a hybrid whale optimization technique (WOA) - colliding bodies optimization (CBO) method was also implemented in 2018 (10), as was a hybrid symbiotic organisms search algorithm in 2020 (22). The overall Distance to move (DT) (13, 22) is determined using the following equation [1-3].

$Minimize\ DT =$
$\sum_{a=1}^{m}\sum_{b=1}^{m}\sum_{c=1}^{m}\sum_{d=1}^{m} fr_{ac} dist_{bd} y_{ab} y_{cd}$ [1]

Subject to

$\sum_{a,b=1}^{m} y_{ab} = 1, a, b = 1,2,3, \ldots m$ [2]

$y_{ab} \in \{0,1\}$ where a,b=1,2,3,…m [3]

where m is the number of facilities, fr_{ab} represents the frequency and $dist_{ab}$ denotes the distance between site a and b.y_{ab} and y_{cd} are part of the location-facility allocation matrix.i.ey_{ab}= 1 ie facility a is allocated to location b; otherwise y_{ab}= 0. fr_{ab} represents the frequency of trips in building among the facilities a and b, $dist_{ab}$denotes the distance among the locations on a and b.

Moreover, the Red Panda Optimizer (RPO) method has demonstrated its effectiveness as an instrument for optimization by outperforming seven prominent algorithmic methods: PSO, GA, SMS, BA, FPA, CS, and FA (12). Still, it demands substantial time of execution to provide a solution and a superior selecting approach to boost operational effectiveness (23, 24). Further investigation is necessary to enhance the efficacy of alternative random walks and enhance the performance of the RPO algorithm (12). Using Laplace distribution and opposition-based learning for a wider exploration region (25) and integrating Differential Evolution (DE) to gain higher accuracy, convergence, and run time (26, 27) are just a couple of the research projects that have successfully increased efficiency.

An extensive examination of multi-objective algorithmic strategies was also taken into consideration to showcase the article's analytical prowess. For TCQS trade-off optimization in building construction across India (AOSMA) an integrated model, the adaptive opposition slime mold technique is employed (28). In (29) the authors adopt the Hybrid Sine Cosine Optimization Technique for routing problems in Cement Transport Vehicle. Using a hybrid multi-verse optimizer to model a large discrete time-cost trade-off problem (30). An inventive time-varying Wolf-Inspired Optimized Support Vector Regression (WIO-SVR) model was created to estimate the 48-step-ahead power usage in projects (31). Building project time, cost, and quality can all be improved by using the slime mold algorithm (32). A water distribution system's design was enhanced by the application of artificial intelligence (AI) techniques (33). lowering the cost of supply construction by utilizing the Particle Swarm Optimization feature of the Dragonfly Algorithm (34). Slime Mold Algorithm (SMA) was adopted to handle the duration, price, and quality trade-off issues in a construction venture (35). The authors (36) use a Genetic algorithm for efficient utilization of construction resources.

Despite the prospect, there has been little investigation carried out using the RPO technique or its modified version for construction layout challenges. Taking into account the foregoing, the current research proposed an Improved Red Panda Optimizer algorithm that uses Opposition-based Learning to boost the junction point of every iteration. Furthermore, using OBL with the Differential Evolution strategy increases the likelihood of discovering the ideal solution. The suggested model is expected to become a more dependable and efficient instrument for decision-making than the other approach since it offers an ideal site layout with an ideal overall traveling distance between facilities.

Methodology

Red panda optimization

The eastern Himalayas and southern China are home to the little red panda. Its entire body and legs are covered in reddish-brown fur; its stomach and legs are black; its ears are lined with white, its nose is mostly white, and its tail is ringed. Its twisted semi-retractile fingers and flexible joints make it an excellent climbing-suited species (32). The red panda prefers places with coniferous and mild herbaceous and hybrid forests with uphill slopes and abundant bamboo cover close to water sources. Despite the red panda's native habits, its hunting approach that relies on its excellent senses of vision, hearing, and odor, as well as this animal's high competence in tree-climbing, is far more astounding. These organic red panda behaviors are mathematically modeled to create the suggested Red Panda Optimization (RPO) technique. The following phases make up the RPO approach:

Initialization

Red pandas make up the population-based metaheuristic algorithm that underpins the recommended RPO approach. Concerning the problem variables, each red panda in the RPO design represents a potential solution based on its location inside the search region. Consequently, a vector represents each red panda, or potential solution, in mathematics. Equation [4] can be used as a matrix to provide a mathematical description of the red pandas in the algorithm population. This data matrix has a red panda (i.e., a potential solution) in each row and recommended values for the parameter associated with the problem in each column. Red pandas are initially placed randomly in the search space at the start of RPO execution using equations [5] and [6].

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} n \times m \quad [4]$$

$$= \begin{bmatrix} y_{1,1} & \cdots & y_{1,j} & \cdots & y_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{i,1} & \cdots & y_{i,j} & \cdots & y_{j,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{n,1} & \cdots & y_{n,j} & \cdots & y_{n,m} \end{bmatrix} n \times m \quad [5]$$

$$y_{i,j} = lob_j + ro_{i,j}.\left(upb_j - lob_j\right), i = 1,2,3,\ldots..n, j = 1,2,\ldots\ldots m \quad [6]$$

where Y is the population matrix of the locations of the red pandas, yi is the ith red panda (i.e., candidate solution), yi,j is its jth dimension (i.e., problem variable), N is the number of red pandas, m denotes the number of problem variables, roi,j is a random number in the range (0, 1), and lobj and upbj are the lower bound and upper bound of the problem.

Recognizing that every red panda's location represents a possible solution allows one to find the objective function of the problem that corresponds to each panda's position. Equation [7] states that the set of values that have been assessed for the objective function can be represented as a matrix in which FU is the vector of objective function values and Fui is the value of the objective function as decided by the ith red panda.

$$FU = \begin{bmatrix} FU_1 \\ FU_2 \\ \vdots \\ FU_n \end{bmatrix} n \times m = \begin{bmatrix} F(Y_1) \\ F(Y_2) \\ .. \\ F(Y_n) \end{bmatrix} n \times m \qquad [7]$$

The updation of the candidate solution can be done in two steps exploration and exploitation as follows:

Exploration

By comparing the values of the goal function, one may use [8] to model the set of recommended food resource sites for each red panda. The matching red panda will select at random one of these suggested locations as its meal spot.

$$FP_i = \{y_k | \; k \in \{1,2, \ldots N\} \; and \; M_k < M_i\} \cup \{y_{best}\} \qquad [8]$$

where FPi is the set of recommended food sources for ith red panda, and ybest is the position of the red panda with the best value for the objective function (best candidate solution). Then, using equations [9] and [10], a new position is determined.

$$y_i^{l1}: y_{i,j}^{l1} = y_{i,j} + ran.(fs_{i,j} - I.y_{i,j}) \qquad [9]$$

$$y_i = \begin{cases} y_i^{l1}, fu_i^{l1} < fu_i \\ y_i, else \end{cases} \qquad [10]$$

Where y_i^{l1} is the updated position of the red panda, $y_{i,j}^{l1}$ is the dimension in the jth position, fu_i^{l1} is the value of the objective function, $fs_{i,j}$ is the source of food and I is a random value in the range of {1,2}.

Exploitation

Red pandas are placed in the second stage of the RPO due to their capacity to climb trees and take breaks there. The majority of the time, red pandas rest on trees. This animal first forages on the ground before climbing the neighboring trees. Red pandas move slightly as they approach and ascend the tree, which improves the potential of the suggested RPO method to exploit and localize search in promising locations. First, a new position is computed for every red panda by mathematically representing their usual climbing behavior using equations [11] and [12]. If the value of the goal function is raised, the new position then takes the place of the old one.

$$y_{i,j}^{l2} = y_{i,j} + \frac{lob_j + ra.(upb_j - lob_j)}{st}, i = 1,2, \ldots N, j = 1,2, ..m \; and \; st = 1,2, \ldots ST \qquad [11]$$

$$y_i = \begin{cases} y_i^{l2}, fu_i^{l2} < fu_i \\ y_i, else \end{cases} \qquad [12]$$

Where $y_{i,j}^{l2}$ is the new position based on the second phase, ST is the maximum iteration

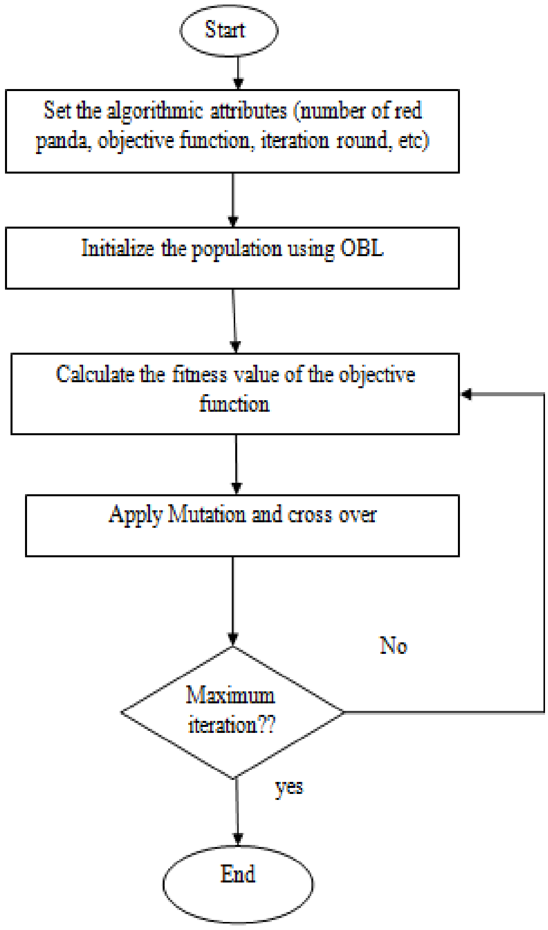

Figure 1: Workflow of the proposed system

Opposition-based learning

When employing OBL, over half of the instances for anticipated solutions depart from the globally most effective approach based on probability theory. The idea of opposition-based learning is to come up with a solution that is opposed to the original. Furthermore, this strategy applies to the algorithm's initial and updated solutions until it generates the optimum result. As a result, the opposite forecast is initiated to speed convergence (37).

Differential evolution

Differential evolution (DE) is an intuitive and strong population-based metaheuristic search algorithm that operates by utilizing the evolutionary process to continuously improve the candidate solution. Differential evolution employs four processes: initialization, mutation, crossover, and selection. The random individuals within the limits are initialized during the initialization step. DE's primary functions are selection, mutation, and crossover.

Mutation

The mutant vector is created via this operation. Equation (13) shows how to generate the mutant vector MVi for an individual Yi.

$$MVi = Yr1 + MF* (Yr2 - Yr3) \quad [13]$$

Where MF represents the mutation factor that regulate the difference Yr2 − Yr3 and Yr1,Yr2 and Yr3 are randomly chosen individuals

Crossover

To sustain population variety, the DE employs single-point binary crossover. Based on the individual Yi and the vector MVi specified in Equation (14), it generates the trial vector Zi.

$$Yi,j = \begin{cases} MV_{i,j} \\ \text{Yi, j elsewhere} \end{cases} , if\ ra \leq CR || j == r \quad [14]$$

Improved red panda optimizer

The proposed method adopted Improved Red Panda Optimizer i.e. integration of Red Panda Optimizer, Opposition based Learning, and Differential Evolution. The workflow is represented in Figure 1.

Initially, the populations are initialized using oppositional-based Learning. Then the red panda optimization is applied to the objective function mentioned in equations 1 to 3. The populations are initialized using Equations 4 to 6. The positions of the red panda are then updated using equations 7 to 12. Then the crossover and mutation strategy of Differential Evolution is adopted by applying equations 13 and 14. The steps will be repeated until the maximum iteration.

Results and Discussions

The proposed technique is used in three instances (1-3) from Prayogo's work (13). The results were subsequently analyzed with other metaheuristics algorithms such as Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Symbiotic Organisms Search (SOS) methods with a population size of 100 and executed for 50 cycles. The equations mentioned in [1-3] and the mechanism of Improved Red Panda Optimizer are applied to minimize the overall distance to be traveled by the site workers with the given facilities.

Case study 1

The first case study has eleven sites for 11 Provisions. In this scenario, the side Entrance (SE) and main entrance (ME) are fixed in positions 1 and 10, accordingly. Figure 1 depicts the preliminary site arrangement. The information about the original spot of the facilities is shown in Table 1. Furthermore, Table 2 illustrates the distance to travel, and Table 3 illustrates the frequency with which workers travel between sites.

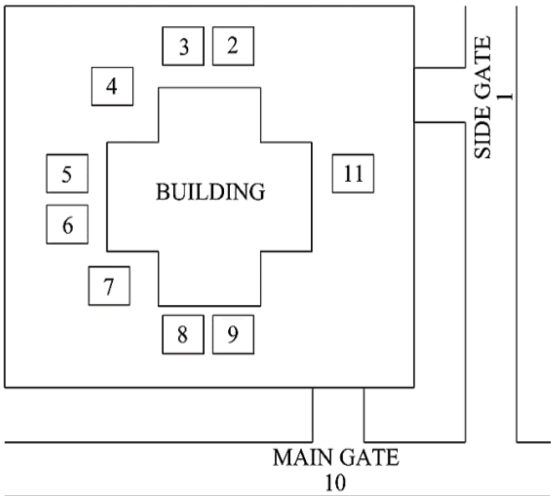

Figure 2: The original design of case 1 (13)

Table 1: Additional data for case study 1

Position	Provisions	Indication
1	Side Gate(SG)	Permanent
2	Site office (SO)	-
3	False workshop (FS)	-
4	Labor residence (LR)	-
5	Storeroom 1 (S1)	-
6	Storeroom 2 (S2)	-
7	Carpentry workshop (CW)	-
8	Reinforcement steel workshop (RW)	-
9	Electrical water, and utility control room (UR)	-
10	Main gate (MG)	Permanent
11	Concrete batch workshop (BW)	-

Table 2: Case study 1 distance among the positions (in meters)

Position	1	2	3	4	5	6	7	8	9	10	11
1	0	15	25	33	40	42	47	55	35	30	20
2	15	0	10	18	25	27	32	42	50	45	35
3	25	10	0	8	15	17	22	32	52	55	45
4	33	18	8	0	7	9	14	24	44	49	53
5	40	25	15	7	0	2	7	17	37	42	52
6	42	27	17	9	2	0	5	15	35	40	50
7	47	32	22	14	7	5	0	10	30	35	40
8	55	42	32	24	17	15	10	0	20	25	35
9	35	50	52	44	37	35	30	20	0	5	15
10	30	45	55	49	42	40	35	25	5	0	10
11	20	35	45	53	52	50	40	35	15	10	0

Table 3: Case study 1 frequency of movement among the positions

Provisions	SO	FS	LR	S1	S2	CW	RW	SG	UR	BW	MG
SO	0	5	2	2	1	1	4	1	2	9	1
FS	5	0	2	5	1	2	7	8	2	3	8
LR	2	2	0	7	4	4	9	4	5	6	5
S1	2	5	7	0	8	7	8	1	8	5	1
S2	1	1	4	8	0	3	4	1	3	3	6
CW	1	2	4	7	3	0	5	8	4	7	5
RW	4	7	9	8	4	5	0	7	6	3	2
SG	1	8	4	1	1	8	7	0	9	4	8
UR	2	2	5	8	3	4	6	9	0	5	3
BW	9	3	6	5	3	7	3	4	5	0	5
MG	1	8	5	1	6	5	2	8	3	5	0

Table 4: Case study 1 overall distance travelled for different techniques

Techniques	Minimum distance (m)	Maximum Distance(m)	Average Distance(m)	Standard Deviation (m)
PSO	12546	12840	12583	70.321
ABC	12546	13190	12812.07	169.552
SOS	12546	12714	12560.07	39.953
IRPO	12546	12516	12481.12	23.108

Table 5: Optimal distance travelled based on positions for case study 1

Techniques	SO	FS	LR	S1	S2	CW	RW	SG	UR	BW	MG	Distance Travelled
PSO	9	11	5	6	7	2	4	1	3	8	10	12546
ABC	9	11	4	5	7	6	3	1	2	8	10	12546
SOS	9	11	4	6	7	5	3	1	2	8	10	12546
IRPO	8	10	5	5	6	4	2	1	2	7	9	12546

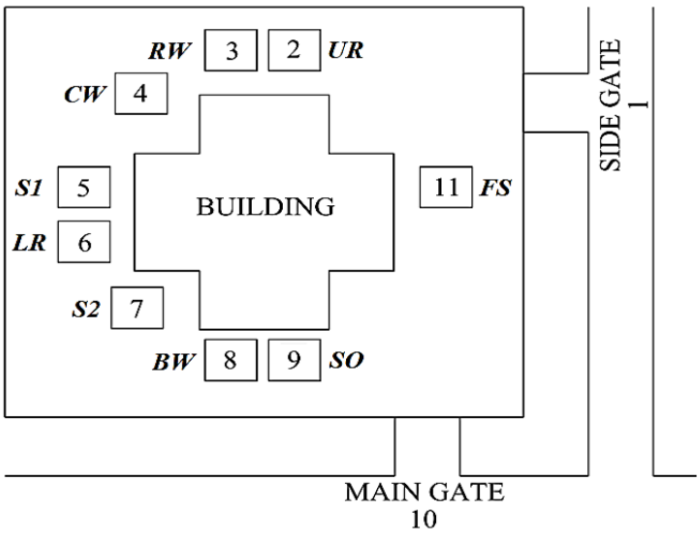

Figure 3: Optimal design layout using IRPO for case study 1

The algorithm iterates through 200 cycles with 100 populations to increase speed. The convergence curve of the proposed algorithm is compared with previous studies on the WOA-CBO algorithm (10). The objective function value indicates that the IRPO completed the optimal journey distance in less time and at a faster pace than the WOA-CBO (Figure 2 and 3; Table 4 and 5).

Case study 2

Ten locations for ten facilities from a residential building project in Surabaya, Indonesia, make up the second scenario. The placements of the entrance gate (EG) and guard post (GP) are determined in places 4 and 5 as shown in Figure 4, below Table 6 contains data regarding predetermined places, whereas Tables 7 and 8 indicate the distance traveled and periodicity across each of them consecutively. The following is the original layout for the given scenario (Figure 5 and Table 9 and 10).

Case study 3

The building site design for a hotel project in Surabaya, Indonesia, is shown in Figure 6. The tower crane (TC), power supply (PS), site gate (SG), main gate (MG), and tower crane (TC) are all secured in their proper locations, with positions 1, 2, 7, and 9 in that sequence. Information for the third case such as 14 positions and 14 provisions are provided in Tables 11, 12, and 13 respectively.

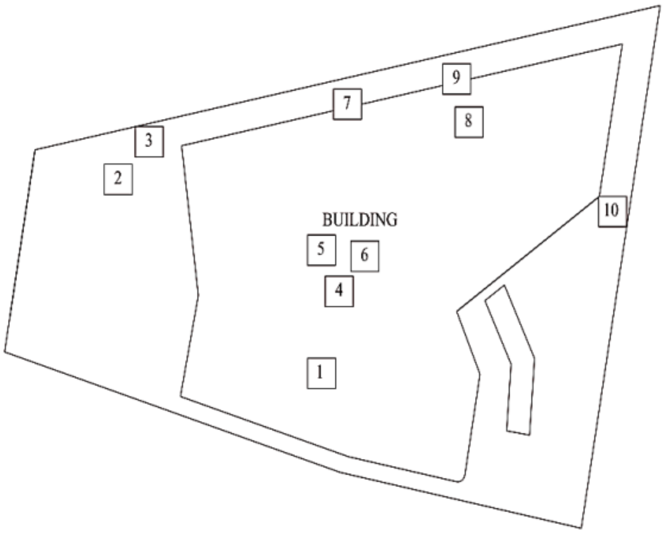

Figure 4: The original layout for case study 2 (13)

Table 6: Additional data for case study 2

Position	Provisions	Indication
1	Batching plant (BP)	-
2	Site office (SO)	-
3	Formwork workshop (FW)	-
4	Entrance gate (EG)	Permanent
5	Guard post (GP)	Permanent
6	GRC fabrication (GF)	-
7	Contractor office (CO)	-
8	Steel storage (SS)	-
9	Steel fabrication 1 (SF1)	-
10	Steel fabrication 2 (SF2)	-

Table 7: Case study 2 distance among the positions (in meters)

Position	1	2	3	4	5	6	7	8	9	10
1	0	139	156	33	39	49	139	170	174	150
2	139	0	19	106	100	112	128	160	165	188
3	156	19	0	125	119	131	112	144	148	207
4	33	106	125	0	12	23	111	143	147	123
5	39	100	119	12	0	12	99	131	135	111
6	49	112	131	23	12	0	89	121	125	101
7	139	128	112	111	99	89	0	32	36	104
8	170	160	144	143	131	121	32	0	9	42
9	174	165	148	147	135	125	36	9	0	102
10	150	188	207	123	111	101	104	42	102	0

Table 8: Case study 2 frequency of movement among the positions

Provisions	BP	SO	FW	EG	GP	GF	CO	SS	SF1	SF2
BP	0	10	8	9	3	9	0	0	0	0
SO	10	0	8	12	8	9	11	5	0	1
FW	8	8	0	4	3	8	0	0	0	0
EG	9	12	4	0	6	15	10	10	8	5
GP	3	8	3	6	0	9	5	3	2	1
GF	9	9	8	15	9	0	0	0	0	0
CO	0	11	0	10	5	0	0	7	7	10
SS	0	5	0	10	3	0	7	0	25	27
SF1	0	0	0	8	2	0	7	25	0	16
SF2	0	1	0	5	1	0	10	27	16	0

Table 9: Case study 2 overall distance travelled for different techniques

Techniques	Minimum distance (m)	Maximum Distance(m)	Average Distance(m)	Standard Deviation (m)
PSO	39184	40736	39327.07	303.011
ABC	39184	46698	41733.77	2013.849
SOS	39184	40666	39243.4	274.206
IRPO	39184	39820	39198.10.	177.62

Table 10: Optimal distance travelled based on positions for case study 2

Techniques	BP	SO	FW	EG	GP	GF	CO	SS	SF1	SF2	Distance Travelled
PSO	2	6	3	4	5	1	10	7	9	8	39184
ABC	2	6	3	4	5	1	10	7	9	8	39184
SOS	2	6	3	4	5	1	10	7	9	8	39184
IRPO	2	5	3	3	4	1	8	6	7	7	39184

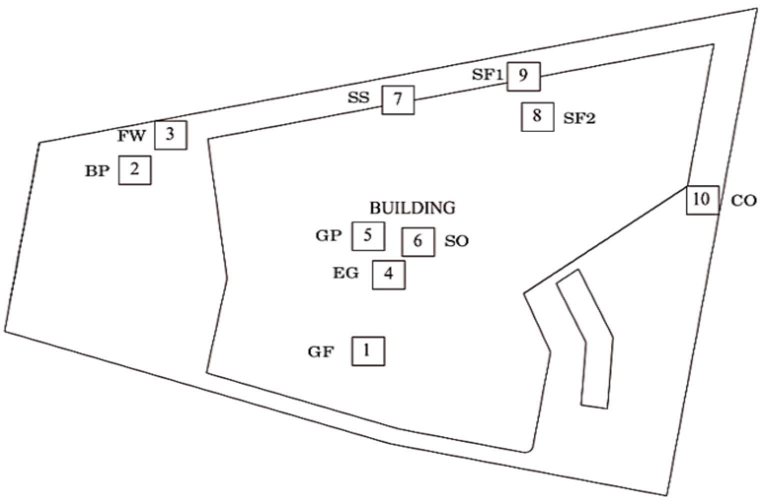

Figure 5: Optimal design layout using IRPO for case study 2

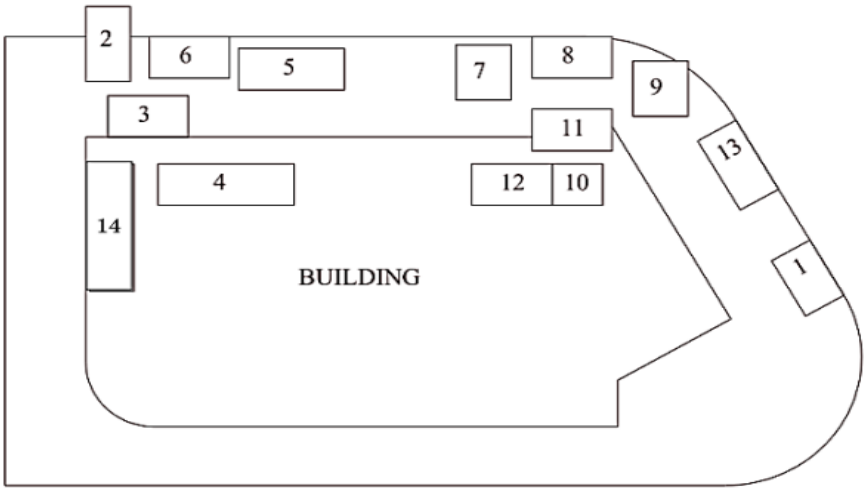

Figure 6: The original layout for case study 3 (13)

Table 11: Additional data for case study 3

Position	Provisions	Indication
1	Main gate (MG)	Permanent
2	Site gate (SG)	Permanent
3	Guard post (GP)	-
4	Office (O)	-
5	Workers toilet 1 (WT1)	-
6	Wiremesh storage (WS)	-
7	Tower crance (TC)	Permanent
8	Workers toilet 2 (WT2)	-
9	Power source (PS)	Permanent
10	Health post (HP)	-
11	Material storage (MS)	-
12	Workers barrack (WB)	-
13	Reinforcement fabrication (RF)	-
14	Formwork fabrication (FF)	-

Table 12: Case study 3 distance among the positions (in meters)

Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	65	60	43	38	37	25	17	10	8	11	17	0	51
2	65	0	7	14	15	7	23	33	51	45	40	36	47	15
3	60	7	0	7	12	4	20	30	43	37	31	28	45	8
4	43	14	7	0	9	9	12	23	26	20	15	11	32	6
5	38	15	12	9	0	2	4	14	22	23	15	14	34	18
6	37	7	4	9	2	0	8	18	26	25	19	15	35	12
7	25	23	20	12	4	8	0	2	10	10	6	10	12	28
8	17	33	30	23	14	18	2	0	8	9	5	13	10	38
9	10	51	43	26	22	26	10	8	0	12	5	15	1	42
10	8	45	37	20	23	25	10	9	12	0	1	9	6	36
11	11	42	34	15	15	19	6	5	5	1	0	6	4	36
12	17	36	28	11	14	18	10	13	15	9	6	0	15	27
13	0	47	45	32	34	35	12	10	1	6	4	15	0	51
14	51	15	8	6	18	12	28	38	42	36	36	27	51	0

Table 13: Case study 3 frequency of movement among the positions

Provisions	MG	SG	GP	O	WT1	WS	TC	WT2	PS	HP	MS	WB	RF	FF
MG	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SG	0	0	1	1	1	30	1	1	1	3	15	2	2	0
GP	0	1	0	1	0	0	1	1	1	1	1	1	1	0
O	0	1	1	0	3	1	1	1	1	2	2	3	2	2
WT1	0	1	0	3	0	0	1	0	0	2	0	4	0	0
WS	0	30	0	1	0	0	0	1	0	4	2	4	4	0
TC	0	1	1	1	1	0	0	1	1	1	0	1	0	0
WT2	0	1	1	1	0	1	1	0	1	2	2	2	2	2
PS	0	1	1	1	0	0	1	1	0	0	0	1	0	0
HP	0	3	1	2	2	4	1	2	0	0	3	3	2	2
MS	0	15	1	2	0	2	0	2	3	3	0	2	15	2
WB	0	2	1	3	4	4	1	2	3	3	2	0	2	2
2RF	0	2	1	2	0	4	0	2	2	2	15	2	0	0
FF	0	0	0	2	0	0	0	2	2	2	2	2	0	0

Table 14: Overall distances travelled for case study 3 for different technique

Techniques	Mininum distance (m)	Maximum Distance(m)	Average Distance(m)	Standard Deviation (m)
PSO	4276	4973	4553.93	159.39
ABC	4391	4932	4662.46	157.69
SOS	4281	4531	4398.4	67.02
IRPO	4008	4230	4121.1	59.18

Table 15: Optimal distance travelled based on positions for case study 3

Techniques	MG	SG	GP	O	WT1	WS	TC	WT2	PS	HP	MS	WB	RF	FF	Distance Travelled
PSO	1	2	8	5	10	3	7	12	9	4	6	11	14	13	4276
ABC	1	2	6	11	12	3	7	10	9	4	5	8	14	13	4391
SOS	1	2	5	8	13	6	7	12	9	4	3	11	14	10	4281
IRPO	1	2	4	9	10	2	5	7	8	3	6	10	11	11	4008

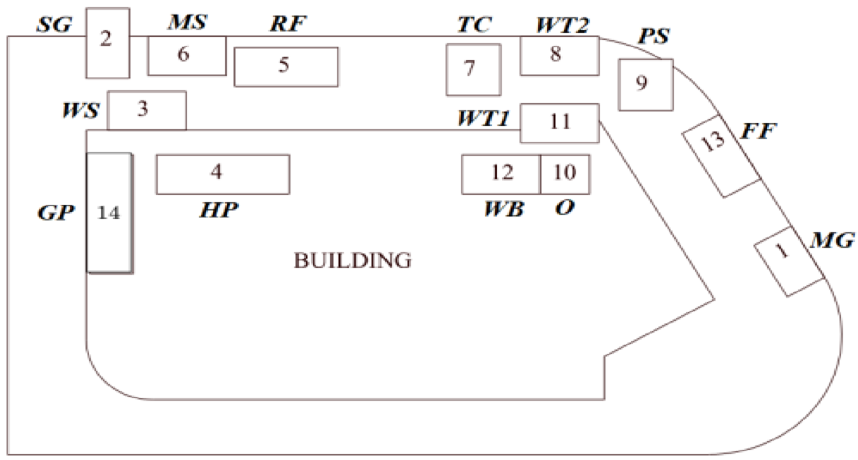

Figure 7: Optimal design layout using IRPO for case study 3

The IPRO results are compared with PSO, ABC, and SOS algorithms in the tables below. When compared to the other three methods, the suggested model yields the lowest mean and standard deviation, indicating accuracy and consistency. A structure design based on the recommended method is shown in Figure 7 and Table 14 and 15.

The purpose of this study is to increase the Red Panda Optimizer (RPO) algorithm applicability for construction design optimization through repeated evaluations based on given requirements rather than developing unnecessary hypotheses concerning the optimization issue. Combining the suggested Improved RPO with other techniques like the crossover and mutation approach of differential evolution and oppositional-based learning, it emphasizes how it enhances exploration and exploitation with global and local searches. Because of this, it is anticipated that the novel enhanced red panda optimizer (IRPO) algorithm will prove to be an effective tool for making decisions by producing the best possible plan for the construction site that has the shortest total commute time.

Conclusion

The planning of the building site layout has a significant impact on the project's efficiency, budget, and schedule. A carefully planned layout will help to save a period reduce site congestion, and reduce commute time, handling effort, and operational expenditures. Enhancing effectiveness, security, and improving workflow. For the building site scheduling problem, artificial intelligence-based approaches, like metaheuristic algorithms, have been thoroughly investigated. The solution was discovered using optimization techniques. Furthermore, developing effective solutions helps to reduce the cost of handling materials by 10-30% because of improved material flow.

An enhanced Red Panda Optimizer algorithm was created to offer an ideal solution for construction site layout problems. Developments were made by combining OBL and MCS to increase the likelihood of producing an ideal solution. The proposed approach is contrasted with a prior study that used PSO, ABC, and SOS algorithms for three case studies. Furthermore, determines the optimal overall journey distance and site architecture layout for a single real-world case study. With the lowest mean and standard deviation, the hybrid ALO algorithm outperformed the other approach in terms of consistency, precision, and convergence, according to the overall result. As a result, it is consistent in offering optimal solutions and is appropriate as an alternate choice tool for this specific situation. To have a more accurate picture of the problem, the proposed model can be updated for further study by taking into account the facility's dimension, cost aspect, and building stages.

Abbreviations

Nil

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Author contributions

All the authors are equally contributed.

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References

1. Sadeghpour F, Andayesh M. The constructs of site layout modeling: An overview. Can J Civ Eng 2015;42:199–212. https://doi.org/10.1139/cjce-2014-0303.
2. Mawdesley MJ, Al-jibouri SH, Yang H. Genetic Algorithms for Construction Site Layout inProject Planning. J Constr Eng Manag 2002;128:418–26. https://doi.org/10.1061/(asce)0733-9364(2002)128:5(418).
3. Kim M, Ryu H-G, Kim TW. A Typology Model of Temporary Facility Constraints for Automated Construction Site Layout Planning. Appl Sci 2021;11. https://doi.org/10.3390/app11031027.
4. Pérez-Gosende P, Mula J, Díaz-Madroñero M. Facility layout planning. An extended literature review. Int J Prod Res 2021;59:3777–816. https://doi.org/10.1080/00207543.2021.1897176.
5. Samaneh Z, Javier I. Current Trends in Construction Site Layout Planning. Constr Res Congr 2014 2023:1723–32. https://doi.org/doi:10.1061/9780784413517.176.
6. Cheng M-Y, Lien L-C. A hybrid AI-based particle bee algorithm for facility layout optimization.EngComput 2012;28:57–69. https://doi.org/10.1007/s00366-011-0216-z.
7. Sanad HM, Ammar MA, Ibrahim ME. Optimal Construction Site Layout Considering Safety andEnvironmental Aspects. J Constr Eng Manag

2008;134:536–44.https://doi.org/10.1061/(asce)0733-9364(2008)134:7(536).
8. Kumar SS, Cheng JCP. A BIM-based automated site layout planning framework for congested construction sites. Autom Constr2015;59:24–37. https://doi.org/10.1016/j.autcon.2015.07.008.
9. Besbes M, Zolghadri M, Costa Affonso R, Masmoudi F, Haddar M. 3D facility layout problem. JIntell Manuf 2021;32:1065–90. https://doi.org/10.1007/s10845-020-01603-z.
10. Kaveh A, Moghaddam MR. A hybrid WOA-CBO Algorithm for construction site layout planning problem. Sci Iran 2018;25:1094–104. https://doi.org/10.24200/sci.2017.4212.
11. H. Givi, M. Dehghani and Š. Hubálovský, "Red Panda Optimization Algorithm: An Effective Bio-Inspired Metaheuristic Algorithm for Solving Engineering Optimization Problems," in *IEEE Access*, vol. 11, pp. 57203-57227, 2023, doi: 10.1109/ACCESS.2023.3283422.
12. Mirjalili S. The Ant Lion Optimizer. Adv Eng Softw2015;83:80–98. https://doi.org/10.1016/j.advengsoft.2015.01.010.70
13. Prayogo D, Sutanto JC, Suryo HE, Eric S. A Comparative Study on Bio-Inspired Algorithms in Layout Optimization of Construction Site Facilities. Civ Eng Dimens2018;20:102–10. https://doi.org/10.9744/ced.20.2.102-110.
14. Liu B, Yang B, Xiao J, Zhu D, Zhang B, Wang Z, et al. Review of optimization dynamically applied in the construction and the application potential of ICT. Sustain 2021;13.https://doi.org/10.3390/su13105478.
15. Petroutsatou K, Apostolidis N, Zarkada A, Ntokou A. Dynamic planning of construction site for linear projects. Infrastructures 2021;6:1–22. https://doi.org/10.3390/infrastructures6020021.
16. Javad M, Amiri T, Hematian M, Haghighi F, Barforooshi MJ. Site Layout Optimization and itsImpact on the Cost of Construction Projects. Amirkabir J Civ Eng 2021;53:121–2.
17. Atmaca M, Akcay C. Construction site layout planning using GIS overlay analysis—A case study. Arab J Geosci2021;14:1–14. https://doi.org/10.1007/s12517-021-06793-1.
18. Yang Y. Genetic Algorithm Based optimization of Construction Site Layout of Prefabricated Buildings. 2021 IEEE Asia-Pacific Conf. Image Process. Electron. Comput., 2021, p. 1254–7. https://doi.org/10.1109/IPEC51340.2021.9421175.
19. Adrian AM, Utamima A, Wang K-J. A comparative study of GA, PSO and ACO for solvingconstruction site layout optimization. KSCE J Civ Eng 2015;19:520–7.https://doi.org/10.1007/s12205-013-1467-6.
20. Prayogo D. Using Biological Knowledge for Layout Optimization of Construction Site Temporary Facilities : A Case Study 2019;2001:0–4.
21. Papadaki IN, Chassiakos AP. Multi-objective Construction Site Layout Planning Using Genetic Algorithms. Procedia Eng 2016;164:20–7. https://doi.org/10.1016/j.proeng.2016.11.587.
22. Prayogo D, Cheng MY, Wu YW, Redi AANP, Yu VF, Persada SF, et al. A novel hybridmetaheuristic algorithm for optimization of construction management site layout planning.Algorithms 2020;13. https://doi.org/10.3390/A13050117.
23. Kilic H, Yuzgec U, Karakuzu C. Improved antlion optimizer algorithm and its performance on neuro fuzzy inference system. Neural Netw World 2019;29:235–54.https://doi.org/10.14311/NNW.2019.29.016.
24. Dong H, Xu Y, Li X, Yang Z, Zou C. An improved antlion optimizer with dynamic random walkand dynamic opposite learning. Knowledge-Based Syst 2021;216:106752.https://doi.org/10.1016/j.knosys.2021.106752.
25. Dinkar SK, Deep K. Opposition based Laplacian Ant Lion Optimizer. J Comput Sci 2017;23:71–90. https://doi.org/10.1016/j.jocs.2017.10.007.
26. Kılıç H, Yüzgeç U. Improved antlion optimization algorithm via tournament selection and its application to parallel machine scheduling. Comput Ind Eng 2019;132:166–86.https://doi.org/10.1016/j.cie.2019.04.029.
27. Kılıç H, Yüzgeç U. Tournament selection based antlion optimization algorithm for solvingquadratic assignment problem. Eng Sci Technol an Int J 2019;22:673–91.https://doi.org/10.1016/j.jestch.2018.11.013.
28. Son PVH, Khoi LNQ. Adaptive opposition slime mold algorithm for time–cost–quality–safetytrade-off for construction projects. Asian J Civ Eng 2023. https://doi.org/10.1007/s42107-023-00612-6.
29. Pham VHS, Nguyen VN. Cement Transport Vehicle Routing with a Hybrid Sine CosineOptimization Algorithm. Adv Civ Eng 2023;2023:2728039. https://doi.org/10.1155/2023/2728039.
30. Son PVH, Nguyen Dang NT. Solving large-scale discrete time–cost trade-off problem using hybridmulti-verse optimizer model. Sci Rep 2023;13:1987. https://doi.org/10.1038/s41598-023-29050-9.
31. Ngo N-T, Truong TTH, Truong N-S, Pham A-D, Huynh N-T, Pham TM, et al. Proposing a hybridmetaheuristic optimization algorithm and machine learning model for energy use forecast in nonresidentialbuildings. Sci Rep 2022;12:1065. https://doi.org/10.1038/s41598-022-04923-7.
32. Son PVH, Khoi LNQ. Application of slime mold algorithm to optimize time, cost and quality inconstruction projects. Int J Constr Manag 2023:1–12.https://doi.org/10.1080/15623599.2023.2174660.
33. Pham Vu Hong S, Nguyen Thanh V. Application of artificial intelligence algorithm to optimize thedesign of water distribution system. Int J Constr Manag 2022:1–11.https://doi.org/10.1080/15623599.2022.2101593.
34. Son PVH, Duy NHC, Dat PT. Optimization of Construction Material Cost through LogisticsPlanning Model of Dragonfly Algorithm — Particle Swarm Optimization. KSCE J Civ Eng2021;25:2350–9. https://doi.org/10.1007/s12205-021-1427-5.

35. Son PVH, Khoi LNQ. Utilizing artificial intelligence to solving time – cost – quality trade-offproblem. Sci Rep 2022;12:20112. https://doi.org/10.1038/s41598-022-24668-7.
36. Mani M, Bozorg-Haddad O, Chu X. Ant Lion Optimizer (ALO) Algorithm BT – AdvancedOptimization by Nature-Inspired Algorithms. In: Bozorg-Haddad O, editor., Singapore: SpringerSingapore; 2018, p. 105–16. https://doi.org/10.1007/978-981-10-5221-7_11.
37. Fang Y, Li J. A review of tournament selection in genetic programming. Lect Notes Comput Sci (Including SubserLect Notes ArtifIntellLect Notes Bioinformatics) 2010;6382 LNCS:181–92. https://doi.org/10.1007/978-3-642-16493-4_19.