Journal of Network Intelligence
Taiwan Ubiquitous Information

Volume **10**, Number **3**, August **2025**

Construction Schedule Optimization on Meta-Heuristic Algorithm Under Resource Constraints

Hui Xu[1], Ding-Jie Yuan[1,*], Ze-Wei Kang[2]

[1]Construction Institute, Guangdong Technology College, Zhaoqing 526000, P. R. China
xuhui891023@gmail.com, gdlgxyydjxh@163.com

[2]School of Electrical Electronics and Computer Engineering, Mapúa University, Manila 1002, Philippines
zkang@mymail.mapua.edu.ph

*Corresponding author: Ding-Jie Yuan
Received January 26, 2024, revised June 13, 2024, accepted September 3, 2024.

Abstract. *The main problem addressed by the construction schedule optimisation model under resource constraints is how to effectively utilise limited resources, minimise the construction cycle and improve the efficiency and quality of the project. Existing studies have shown that through artificial intelligence technology, the demand and utilisation of resources can be predicted and simulated more accurately, the construction sequence and resource allocation can be optimised, and the construction efficiency and quality can be improved. Therefore, in order to effectively improve the accuracy and efficiency under resource constraints, a construction schedule optimisation model based on meta-heuristic algorithm is proposed. Firstly, the components of the construction schedule optimisation problem under resource constraints are analysed, and the corresponding mathematical model is established with the objective of the shortest duration according to the characteristics of the components. Secondly, to address the problems of slow convergence speed and easy to fall into local optimal solutions in the standard krill herd (KH) algorithm, an improved krill herd algorithm (PSOAKH) integrating the particle swarm algorithm and adaptive inertia weights is proposed. By introducing the particle swarm algorithm with strong local development ability into the KH algorithm, in order to improve the local search ability. Finally, the PSOAKH algorithm is used to solve the above mathematical model. The experimental results show that under the same constraints, the PSOAKH algorithm can obtain better duration and cost by setting the scaling factor reasonably.*
Keywords: Construction schedule; metaheuristic algorithm; resource constraints; krill swarm algorithm; adaptive inertia weights; particle swarms

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1. Introduction.

The research value of construction schedule optimisation model lies in the accurate planning of construction schedule through scientific tools, so as to improve construction efficiency, reduce costs, improve construction quality, and can provide scientific basis for project management decision-making [1, 2, 3]. In addition, the research and application of optimisation model can also promote the continuous innovation of construction management technology, promote the development of the whole construction industry, which has important practical application and theoretical significance.

In standard construction schedule optimisation models, only the time and resource constraints of construction tasks are usually considered [3, 4], while in construction schedule optimisation models under constraints, other additional constraints need to be considered, such as environmental, safety, and cost constraints [5, 6]. The main problem solved by the construction schedule optimisation model under resource constraints is how to effectively use the limited resources, minimise the construction period [7], and improve the efficiency and quality of the project. By optimising the construction schedule, the sequence and time of using resources can be arranged reasonably [8], avoiding the conflict and waste between resources, so as to achieve the rapid completion of the project and minimise the cost.

Artificial intelligence can simultaneously consider multiple constraints, such as time, resources, cost, safety and environmental limitations [9], and make comprehensive considerations based on the weights of different conditions to achieve comprehensive optimisation decisions based on multiple conditions [10]. Artificial intelligence can apply optimisation algorithms, such as various advanced meta-heuristic algorithms, to optimise the construction schedule, taking into account multiple constraints to make the schedule more reasonable and effective. Meta-heuristic algorithms are a general algorithmic framework for solving complex optimisation problems [11, 12], which usually rely on iterative processes and stochasticity to find better solutions in large search spaces. Construction schedules usually involve multiple constraints, such as resource limitations, time constraints, and technical requirements [13], and the stochasticity and diverse search strategies of meta-heuristic algorithms make it able to deal with these multi-constraint problems efficiently and find more optimal solutions. In addition, construction schedule planning usually involves large-scale data and complex computations, and metaheuristic algorithms are naturally suitable for parallelised processing, and are able to speed up computation by utilising multi-core processors or distributed computing resources [14, 15]. Therefore, the aim of this study is to use metaheuristic algorithms to quickly find the optimal solution of the construction schedule optimisation model under complex constraints, which improves the efficiency and accuracy of the schedule.

1.1. **Related work.** At this stage, the research on construction schedule optimisation model mainly focuses on intelligent optimisation algorithm, multi-objective optimisation, constrained optimisation and so on, in order to achieve a more scientific, precise and efficient construction schedule.

Senouci and Al-Derham [16] proposed a construction project schedule planning model based on multi-objective optimisation aimed at managing and reducing construction project delays. By considering multiple objectives and using an evolutionary algorithm for optimisation, the model is able to effectively deal with conflicts between multiple objectives and improve the reliability and efficiency of construction schedule planning. Rahimi et al. [17] proposed a simulation-optimisation hybrid approach based resource-constrained scheduling model for construction projects. By combining discrete event simulation and meta-heuristic algorithm, this method can effectively solve the construction schedule optimisation problem under resource constraints, and improve the accuracy and robustness of the scheduling plan. Yuan et al. [18] proposed a construction project scheduling model based on artificial intelligence, which is designed to cope with the scheduling problem under resource-constrained situations in construction projects. By combining fuzzy logic and genetic algorithm, the model can effectively deal with the resource constraints and uncertainties in real projects, and improve the reliability and adaptability of construction scheduling.

The meta-heuristic algorithm [19, 20] has a clear advantage in this field as it has better global search capability, adaptability, parallelisation processing capability and can deal with complex nonlinear and non-convex optimisation problems [21] more effectively than traditional optimisation algorithms for construction schedule optimisation models under constraints. As an advanced meta-inspired algorithm, Krill Herd (KH) algorithm [22] adopts the idea of group intelligence, which achieves fast search and convergence of optimization problems by simulating the behaviour of krill populations, and therefore has a fast convergence speed. The parallelization processing of KH algorithm is simpler and more effective, and it is able to utilize multi-core processors or distributed computational resources, which can accelerate the computation speed. Abualigah et al. [23] proposed a novel hybrid KH algorithm to improve the global search performance and convergence speed of the algorithm by effectively integrating the KH algorithm with other optimization algorithms, and the experimental results show that the hybrid algorithm has a better search effect than the traditional KH algorithm in solving the global optimization problems. Aloui et al. [24] introduced an elite retention algorithm into the KH algorithm. KH algorithm, the elite retention strategy and adaptive hybrid mechanism are introduced to enhance the global search performance and exploration ability of the algorithm, and the experimental results show that the improved KH algorithm has better convergence speed and stability when solving numerical optimisation problems.

1.2. **Motivation and contribution.** The construction schedule optimisation model needs to be dynamically adjusted and optimised to take into account changing environmental factors, demand changes, etc., which puts forward higher requirements for the KH algorithm in practical applications. The construction schedule optimisation model under resource constraints usually involves a large number of tasks, resources and related constraints, resulting in a very large search space. Therefore, the traditional HK algorithm still has some deficiencies in local search capability and parameter setting, which makes it difficult to find the optimal solution within an acceptable time.

In order to solve the above problems, a construction schedule optimisation method based on the improved KH algorithm is proposed in order to effectively improve the optimisation accuracy and efficiency under resource constraints. The main innovations and contributions of this work include:

(1) The components of the construction schedule optimisation problem under resource constraints, including resources and project team, are given, and a mathematical description model for construction schedule optimisation with multiple constraints is designed.

(2) Aiming at the problem of poor local search ability of KH algorithm, Particle Swarm Optimisation (PSO) algorithm with strong local development ability was introduced [25]. The PSO algorithm was used to pre-update the positions of krill individuals, thus improving the ability of the KH algorithm to jump out of the local optimal solution. Adaptive inertia weights were introduced to address the shortcomings of the KH algorithm in parameter setting. A linear descent method is used to pick a suitable step scaling factor to regulate the inertia weights during the iteration process, so as to balance the global and local search ability of the KH algorithm, i.e., stability and accuracy.

2. Components of the construction schedule optimisation problem under resource constraints.

2.1. **Resources.** Construction projects typically consist of multiple tasks, each with specific work content, time, and resource requirements. There is a sequence and dependency between these tasks. The construction process requires a variety of resources, including manpower, materials, and equipment. These resources may have time constraints, such as available work time for specific personnel, available time for equipment, etc.

Resources play a vital role in the construction schedule optimisation problem and have a significant impact on the solution of the problem. Resources can be classified according to their nature and use, such as human resources, material resources, equipment resources and so on. Different types of resources play different roles in the construction process and have different impacts on the project schedule and cost. The resources required for a construction project will have an impact on its supply and demand. The relationship between the supply and demand of resources is an important factor to be considered in the construction process. Reasonable planning of the supply and demand of resources can effectively optimise the construction progress. In actual construction projects, resources are usually subject to limitations and constraints, such as the available working time of specific personnel, the available time of equipment, and so on. These resource limitations and constraints will have a significant impact on the scheduling of construction progress. For the analysis of resource elements, it is also necessary to consider how to rationalise the scheduling and allocation of resources between different tasks in order to meet the project schedule and cost requirements. For renewable resource constraints, the representation is shown below:

$$\sum_{j \in I_t} r_{jk} \leq R_k \qquad \forall k, t \tag{1}$$

where R_k is the supply capacity of the k-th type of construction personnel, I_t is the set of all sub-projects that are in the execution state at the moment t, and r_{jk} is the demand for the k-th type of construction personnel at the moment t for sub-project j.

2.2. **Project team.** Since all construction personnel belong to the same project team, the project team belongs to the same construction project. It is geographically close, so the transfer time of construction personnel between projects is short and negligible. Therefore the representation of the logical relationship between sub-projects [25] is shown below:

$$S_j \geq F_p + C_p \qquad p = 1, 2, \ldots, NP \tag{2}$$

where S_j is the planned start time of sub-project j, F_p is the completion time of sub-project j, C_p is the interval that the sub-project must wait before moving on to the next sub-project, and NP is the number of all sub-projects in sub-project j.

3. **Mathematical model for construction schedule optimisation under constraints.** In the process of schedule progress optimisation, the main objective is to achieve the desired value of the minimum cost within the allowed duration, assuming that in the process of improving this desired value, the schedule adjustment strategy used is $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]$, where λ_i is the name of the task to be performed at each point in time, and the duration and cost are set to be $T(\lambda)$ and $E(\lambda)$, respectively, then the schedule optimisation problem is transformed into:

$$\begin{cases} \min E[C(\lambda)] \\ E[T(\lambda)] \leq T^0 \\ T^0 \geq 0 \end{cases} \tag{3}$$

where T^0 denotes the contract duration and E denotes the desired solution.

The mathematical description of the construction schedule optimisation method under constraints continues below:

Suppose it is necessary to construct a duration model for n tasks with m resources. Let the number of resources k required by task i be $r_{i,k}$, and R_k be the total number of resources k.

Suppose PST_i is the start time of task i, PST_j is the start time of task j, PP_j is the duration of task j respectively, and $P(i)$ denotes the previous task of i. Then the entire project duration *Period* optimisation model is shown as follow:

$$\begin{cases} PST_j + PP_j \le PST_i, \quad \forall j \in P(i), i = 1, 2, \ldots, n \\ r_{i,k} \ge 0,\ i = 1, 2, \ldots, n,\ k = 1, 2, \ldots, m \\ \sum_{i \in Tc(t)} r_{i,k} \le R_k,\ k = 1, 2, \ldots, m,\ CT \le t \le CT + Period - 1 \\ PP_i > 0,\ i = 1, 2, \ldots, n \end{cases} \tag{4}$$

where $Tc(t)$ and CT are the set of tasks being executed at moment t and the current time, respectively.

The direct constraints listed in Equation (4) are mainly the start and stop times of the tasks in the project, the sequential relationships and the use of resources for the tasks. The formation of these direct constraints is influenced by a variety of factors during the operation of the project. These factors present some differences depending on the type of project [27], and some of them are shown in Table 1.

Table 1. Some constraints of the project

Direct constraint	**Indirect constraints**
All task execution start and stop times X_1	Policies and industry standards x_1
	Coordination time x_2
	Construction period x_3
Sequential relationships between tasks X_2	Design time x_4
	Supervision time x_5
	Testing time x_6
Resource performance of the mandate X_3	Project funding x_7
	Project materials x_8
	Project equipment x_9
	Natural environment of the project x_{10}
	Project duration x_{11}

4. **Construction schedule optimisation model solution based on improved KH algorithm.**

4.1. **Standard KH algorithm.** The KH algorithm is a novel meta-inspired algorithm inspired by Antarctic krill during population survival and evolution [28]. The direction of motion of each individual krill in space is guided by three vectors, namely neighbour-induced motion, foraging motion and random diffusion motion. The final motion direction of an individual in a krill swarm can be abstracted as follows:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{5}$$

where X_i denotes the position information of the i-th krill individual, N_i denotes the neighbour-induced movement of the individual, F_i denotes the foraging movement of the individual, and D_i denotes the stochastic diffusion movement of the individual. For the induction of "neighbour" particles, it is necessary to generate an annular region with a radius according to the sensitive spacing, as shown in Figure 1, where krill individuals are the evolving particles at this time.

Each of these three component exercises is described in detail below.

(1) Neighbourhood induced movement.

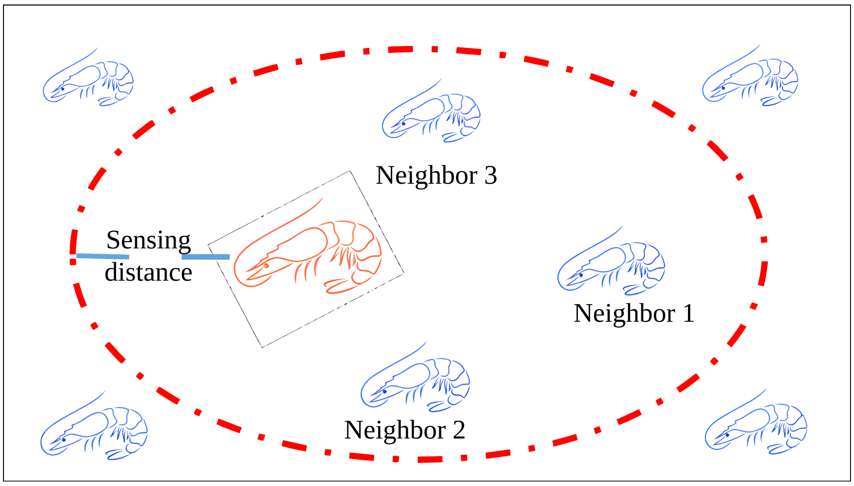

Figure 1. "Neighbor" of krill particles

Inspired by the fact that actual krill individuals will maintain a denser morphology during movement, induced motion refers to the component of motion of a krill individual that is induced by surrounding krill during movement. For each krill individual i, the neighbourhood induced motion is defined as follows:

$$N_i = N_i^{max} a_i + w_n N_i^{old} \tag{6}$$

where N_i^{max} is the maximum velocity of the induced motion, w_n is the inertia weight controlling the search step in the range $(0, 1]$, N_i^{old} is the previous induced motion of individual i, and a_i is the direction of the induced motion (the induced direction is affected by two factors).

$$a_i = a_i^{local} + a_i^{target} \tag{7}$$

where a_i^{local} denotes being affected by the local effect of neighbouring krill, and a_i^{target} denotes being affected by the target effect of globally optimal krill.

(2) Foraging campaigns.

The foraging movements of individual krill are mainly determined by food location and prior experience of being fed. For each individual krill i, the foraging movement F_i is calculated as follows.

$$F_i = V_f \beta_i + w_f F_i^{old} \tag{8}$$

where w_f is the inertia weight controlling the search step in the range $(0, 1]$, V_f is the foraging velocity with respect to the surrounding food, F_i^{old} is the velocity of the previous foraging movement, β_i^{food} denotes the attractiveness of the food received by the i-th krill individual, and β_i^{best} denotes the krill individual with optimal attractiveness of the krill individual with optimal fitness (optimal foraging experience obtained by the krill population during the foraging process).

(3) Stochastic diffusion movements.

Random diffusion movement is an important stochastic process in the KH swarm algorithm, which can enhance its global exploration capability. For each krill individual i, the stochastic diffusion D_i is calculated as follows.

$$D_i = D^{max} \left(1 - \frac{I}{I_{max}}\right) d_i \tag{9}$$

where D^{max} is the maximum velocity of the random diffusion motion, d_i is the vector of random diffusion directions in the range $[-1, 1]$, I is the current iteration number, and I_{max} is the maximum iteration number.

(4) Location update.

The positional update of krill individual i at t is defined as follows.

$$x_i(t + \Delta t) = x_i(t) + \Delta t \frac{dx_i}{dt} \tag{10}$$

where Δt can be considered as a scaling factor for the velocity vector, and its value is related to the actual search space.

$$\Delta t = C_t \sum_{j=1}^{NV} (UB_j - LB_j) \tag{11}$$

where NV is the dimension of the search variable; UB_j and LB_j are the upper and lower bounds of the j-th variable, respectively; $C_t \in (0, 2]$ is a constant representing the step scaling factor, and a reasonable setting of C_t is conducive to the improvement of the algorithm's search capability.

(5) Cross-operation.

Inspired by the genetic algorithm, the krill algorithm tries to introduce the crossover operation in the genetic algorithm to improve the performance of the algorithm. The krill algorithm will randomly select two krill individuals for crossover operation according to a certain crossover probability, and then randomly select the crossover bits to complete the crossover combination to form two new individuals.

$$x_{i,m}^r = \begin{cases} x_{r,m} & rand_{i,m} < C_r \\ x_{i,m} & \text{else} \end{cases} \tag{12}$$

where $r \in [1, 2, 3, \ldots, NK]$, NK is the number of krill individuals, $rand_{i,m}$ is the number of random numbers between $[0, 1]$, and C_r is the crossover probability.

4.2. **Improvement strategy of KH algorithm.** Aiming at the problems of slow convergence speed and easy to fall into local optimal solutions of the standard KH algorithm, an improved KH (PSOAKH) algorithm incorporating PSO and adaptive inertia weights is proposed.

4.2.1. *Introduction of particle swarm algorithm.* The balance between the global exploration capability and the local exploitation capability of a metaheuristic algorithm has a crucial impact on the search performance. The induced motion of the standard KH algorithm is a local search strategy, while the foraging motion and random diffusion motion are both global search strategies. Therefore, the standard KH algorithm can explore the global relatively quickly, but it does not have effective local search ability.

If the standard KH algorithm is used to solve the construction schedule optimisation model, it is easy to lead to the problem of hovering near the optimal solution and insufficient search efficiency. PSOAKH algorithm is introduced into the PSO algorithm, which has strong local development ability, to improve its local search ability.

In order to overcome the problem of poor local search ability of standard KH algorithm, this paper introduces PSO algorithm in standard KH algorithm. The main idea is to use the PSO algorithm to pre-update the position of krill individuals on the basis of the krill algorithm, and the specific steps are as follows:

Step 1: Initialise the hyperparameters of PSO and KH algorithms, including I_{max}, D_{max}, N_{max}, V_f, NK, NP, w_n, w, w_f, C_1, C_2.

Step 2: Set the fitness function, and randomly generate the initial krill individual position X. Calculate the fitness of the optimal position F_{best} and the fitness of the worst position F_{worst}. Calculate the current optimal position X_{ib} and the global optimal position X_{gb}.

Step 3: Update the position of individual krill using PSO algorithm. In KH algorithm PSO algorithm updates the speed and position as follows:

$$V = wV + C_1 rand(NK, NP)(X_{ib} - X) + C_2 rand(NK, NP)(X_{gb} - X) \quad (13)$$

$$X = X + V \quad (14)$$

Step 4: Calculate the direction of motion for neighbourhood-induced motion, foraging motion, and random diffusion motion for each individual krill according to Equation (6) $\sim$ Equation (9).

Step 5: Update the position of individual krill according to Equation (10) to Equation (12).

Step 6: Apply the intersection operation of Equation (13) to increase the global search range.

Step 7: Update the individual's current optimal position X_{ib} and the global optimal position X_{gb}. Update the fitness of the optimal position F_{best} and the fitness of the worst position F_{worst}.

Execute Step 3 to Step 7 until the iteration condition is satisfied.

4.2.2. *Introduction of adaptive inertia weights.* The standard KH algorithm still has some deficiencies in parameter setting, which poses a challenge to its application in the task of solving construction schedule optimisation models under constraints. Therefore, adaptive inertia weights are introduced in this paper. A linear descent method is used to pick a suitable step scaling factor to regulate the inertia weights during the iteration process, so as to balance the global and local search capabilities of the KH algorithm, i.e., stability and accuracy.

The main parameters of the KH algorithm play an important role in the performance of the algorithm and it is important to select reasonable basic parameters to improve the performance of the algorithm when dealing with optimisation problems. A linear descent method is used to pick a suitable step scaling factor Ct. Larger Ct in the pre-iterative period allows the KH algorithm to explore more regions that work.

$$Ct = Ct_{max} - \left(1 - \frac{t}{t_{max}}\right) Ct_{max} \quad (15)$$

where Ct_{max} and Ct_{min} are the maximum and minimum step scaling factors, respectively.

If the fitness value of the i-th particle decreases after an iteration, then its inertia weight will be reset to zero at the next iteration, i.e., $w_n = 0$, $w_f = 0$. If the fitness value of the i-th particle gets better after an iteration, then its inertia weight will be unchanged at the next iteration.

$$w_{n,i}^{j} = \begin{cases} 0 & f(x_k^j) < f(x_k^{j-1}) \\ w_n & \text{else} \end{cases} \quad (16)$$

$$w_{f,j}^{j} = \begin{cases} 0 & f(x_k^j) < f(x_k^{j-1}) \\ w_f & \text{else} \end{cases} \quad (17)$$

where f is the value of the fitness function.

Equation (18) is used to solve for the linear decrease in the step scaling factor Ct. The discrete-system computation is able to mitigate the Ct downward trend, and subsequently pushes the convergence rate of the particles.

$$Ct = Ct_{max} - \left(1 - \frac{t}{t_{max}}\right)^3 Ct_{max} \tag{18}$$

5. Experimental results and analyses.

5.1. Algorithm performance testing.

In order to verify the superiority of the PSOAKH algorithm, the convergence accuracy and convergence speed of the three algorithms, PSOAKH algorithm, PSO algorithm, and KH algorithm, were tested on several complex Benchmark functions.

The value of the optimal solution for all eight Benchmark functions used in the test was 0. Since all metaheuristic algorithms contain some random process, all three algorithms were tested on the Benchmark function 20 times and averaged in order to get an accurate metric. The number of iterations of all three algorithms is set to 300 times, and the iteration is stopped when the optimal solution is found or the maximum number of iterations is reached. The test results of the three algorithms on Benchmark function are shown in Table 2.

Table 2. Benchmark function test results

No.	Benchmark	PSO	KH	PSOAKH
F1	Schwefel2.22	2.87E-06	11.69717	0.073653
F2	Schwefel1.2	1388.169	5.041088	0.33998
F3	Schwefel2.21	0.759653	0.356356	0.188145
F4	Step	0	0	0
F5	Quartic	0.023737	0.021317	1.676655
F6	Penalty	1.226196	3.22359	1.390366
F7	Ackley	15.30997	15.3215	15.31591
F8	Griewangk	102.7783	0.002345	0.000643

It can be seen that all three algorithms are able to search for the optimal value for function F4. The KH algorithm shows better global search ability and achieves better solutions for all the tested functions, but its convergence accuracy is not high enough. The PSOAKH algorithm has the highest convergence accuracy for functions F2, F3, and F8, and its fitness value is much better than the other two algorithms for the functions F2 and F8 with many local wave crests. Therefore, based on the above test results, the PSOAKH algorithm has better search ability and convergence accuracy than the other two algorithms.

The Schwefel2.21 function is a typical complex high-latitude function, and the existence of multiple local traps makes the algorithms searching for the optimal solution need to be more difficult. The convergence speed of the above three algorithms is tested on this function and the test results are shown in Figure 2.

It can be seen that the PSO algorithm has a slower convergence rate and requires several iterations to converge to the vicinity of the optimal value of the function. The KH algorithm is able to search near the optimal value in a shorter time, but due to the lack of effective local exploration. The KH algorithm shows a significant slowdown in convergence during the search process, and takes more time to search for the global optimal solution. In contrast, the stagnation phenomenon of the PSOAKH algorithm with the introduction of PSO pre-updating is greatly improved, and it obviously has a faster convergence speed.

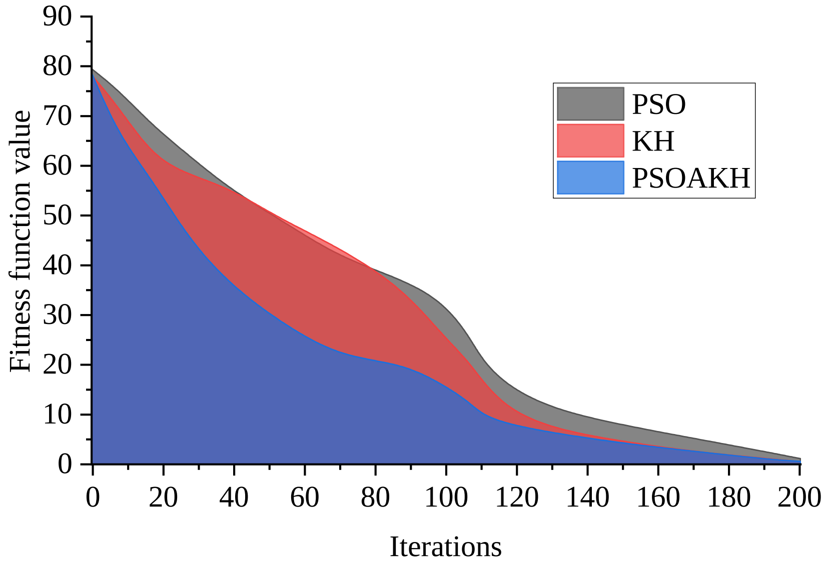

Figure 2. Convergence speed comparison

5.2. **Case validation.**

5.2.1. *Case solving.* In order to test the construction schedule optimisation performance of the PSOAKH algorithm, case solving is carried out for 5 different types of construction projects undertaken by a large construction group in the year 2022.

The relevant construction data of the case is shown in Table 3. Firstly, the construction schedule optimisation model is solved using the PSOAKH algorithm to determine the optimisation results obtained under different constraints. Secondly, the performance of the four schedule optimisation algorithms is compared for the five projects. The constraints regarding the sequence of each process, task start and finish times, equipment usage sequence and duration control of the tasks within the five projects are obtained from the samples.

Table 3. Simulation Sample

Project	Construction/day		Cost/ten thousand yuan	
	Prescribed value	Limit value	Regular value	Limit value
A	181	155	1688	181
B	228	193	2488	228
C	118	91	1288	118
D	78	61	988	78
E	198	170	2188	198

5.2.2. *PSOAKH based schedule optimisation.* The construction optimisation of PSOAKH algorithm is carried out to find the shortest construction value using construction limit values as constraints. Then construction optimisation of PSOAKH algorithm is carried out with cost limit values as constraints to find the minimum cost value. Finally construction optimisation is carried out with construction specified values and cost limit values and the optimisation results are calculated and the results are shown in Table 4.

It can be seen that for the same sample, with different constraints used, the optimisation results of PSOAKH vary significantly. For Project A, the minimum construction obtained by PSOAKH is 181 days when no cost is taken into account, but the cost exceeds

Table 4. Optimisation results of PSOAKH

Project	Optimal individual	Construction/day	Cost/ten thousand yuan
A	Construction of the shortest individual	181	1845
	Lowest Cost Individual	234	1710
	PSOAKH Best Individual	189	1755
B	Construction of the shortest individual	220	2824
	Lowest Cost Individual	286	2508
	PSOAKH Best Individual	234	2514
C	Construction of the shortest individual	119	1408
	Lowest Cost Individual	166	1317
	PSOAKH Best Individual	132	1332
D	Construction of the shortest individual	88	1072
	Lowest Cost Individual	105	1018
	PSOAKH Best Individual	93	1020
E	Construction of the shortest individual	198	2319
	Lowest Cost Individual	237	2225
	PSOAKH Best Individual	206	2236

the limit value. When looking at cost savings only, the minimum cost obtained was 17.1, but construction exceeded the specified value. When constraints such as construction stipulated values and limit costs are added at the same time, PSOAKH obtains construction and costs of 189 days and 17.55, respectively, both within construction stipulated values and cost limits. For the other four projects, when only one constraint was selected, even though the construction or cost obtained from their optimisation was advantageous, it could not be used in the actual schedule optimisation strategy because construction or cost exceeded the specified range.

5.2.3. *Schedule optimisation with different algorithms.* GA algorithm, PSO algorithm, KH algorithm and PSOAKH algorithm were used to optimise the construction schedule of five projects and the construction, cost and computing time of the algorithms obtained are shown in Table 5.

It can be seen that for the same kind of project, there is a large gap between the optimal solutions obtained by the four algorithms for optimisation under the dual constraints of construction specification values and cost limit values. For project A, the PSOAKH algorithm obtains better construction and cost solutions. As for the optimisation time, the GA and PSOAKH algorithms take less time and the time used by both is very close. Whereas PSO-SVR and Hybrid Legacy are more time-consuming, the PSOAKH algorithm still shows a great advantage in the optimisation of the other five projects.

Comparing horizontally, the optimisation efficiency of the four algorithms is not absolutely related to the construction length and cost, the optimisation efficiency of the four algorithms in Project C is generally higher, while the optimisation efficiency of the four algorithms in Project B is lower, which may be due to the differences in the process steps and the number of equipments of the construction of different projects, resulting in the optimisation of solving the model complexity to climb. Comprehensive comparison, although the PSOAKH algorithm is slightly lower than the GA algorithm in terms of optimisation efficiency, it has an absolute advantage over the other three algorithms in terms of schedule and cost optimal solution, and its adaptability to the construction schedule of different types of construction projects is stronger.

Table 5. Optimal solutions of four algorithms (Project A)

Project	Algorithm	Construction/day	Cost/ten thousand yuan	Solving time/s
A	GA	169	1294	6.172
	PSO	171	1213	8.891
	KH	164	1198	8.834
	PSOAKH	156	1172	6.353
B	GA	177	1300	8.642
	PSO	179	1219	10.749
	KH	172	1204	10.926
	PSOAKH	164	1178	8.791
C	GA	167	1280	5.377
	PSO	169	1199	7.695
	KH	162	1184	7.732
	PSOAKH	154	1158	5.408
D	GA	181	1285	6.035
	PSO	183	1204	7.634
	KH	176	1189	7.699
	PSOAKH	168	1163	6.191
E	GA	182	1298	8.379
	PSO	184	1217	10.191
	KH	177	1202	10.273
	PSOAKH	169	1176	8.502

6. **Conclusion.** In this work, a PSOAKH-based construction schedule optimisation model solution method is proposed in order to effectively improve the optimisation accuracy and efficiency under resource constraints. Firstly, the components of the construction schedule optimisation problem under resource constraints, including resources and project team, are given, and a mathematical description model for construction schedule optimisation with multiple constraints is designed. Secondly, the PSO algorithm is used to pre-update the position of krill individuals, which improves the ability of the KH algorithm to jump out of the local optimal solution. Meanwhile, a linear descent method is used to pick a suitable step scaling factor to regulate the inertia weights during the iteration process, so as to balance the global and local search ability of the KH algorithm. Subsequent attempts will be made to combine the KH algorithm with deep learning methods, which can improve the fitting ability and global search ability for complex problems.

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