Augmented Gray Wolf-Cuckoo Algorithm-Based Research on Flexible Job-Shop Scheduling

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Abstract. The paper proposes an Augmented Gray Wolf-Cuckoo algorithm (AGWO-CS) to improve the Gray Wolf (GWO) algorithm's performance in flexible job-shop scheduling. AGWO-CS achieves this by incorporating a reverse learning strategy during initial population generation, optimizing exploration and exploitation of the search space. It further refines search parameters using the Cuckoo algorithm, leveraging Gray Wolf's enhancements for increased flexibility. Comparative analysis with Particle Swarm Optimization (PSO) algorithm and (Genetic Algorithm) GA reveals AGWO-CS's superior optimization, convergence, global search, and local search capabilities.

Keywords: Flexible job shop scheduling; Augmented Gray Wolf-Cuckoo algorithm; Cuckoo algorithm; Reverse learning strategy

1 Introduction

The Flexible Job Shop Scheduling Problem (FJSP) is a complex production scheduling challenge involving the synchronization of multiple jobs across various products, each with a multitude of processes on different machines [1]. It necessitates strategic planning of production orders, resource utilization, work schedules, and personnel allocation to enhance production efficiency, reduce costs, and accelerate delivery, presenting a substantial planning challenge. The complex, uncertain, and dynamic nature of job shop scheduling, coupled with multiple constraints, limits the effectiveness of traditional optimization methods and precise algorithms, prompting the adoption of intelligent optimization algorithms to address these challenges.

Various optimization algorithms have been proposed for FJSP: Zhang Liang et al. [2] improved search efficiency with a multi-target jellyfish algorithm; Wang Yanjie's team [3] enhanced machine utilization through a cross-mutation genetic algorithm and an improved Antlion optimization; Zhao Xiaohui et al. [4] focused on minimizing the maximum completion time with an ant colony algorithm; Wang Qiulian et al. [5] utilized a Pareto-based multi-target migratory bird optimization for high-dimensional scheduling; Ding Kai et al. [6] introduced an improved Tianniu algorithm with Longox

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whisker features; and Zhang Haonan et al. [7] optimized single-objective FJSP scheduling to minimize costs with a refined artificial bee colony.

Intelligent algorithms effectively address the complexities of FJSP for practical implementation. However, the NP-hard (non-deterministic polynomial) nature of FJSP presents challenges with slow convergence and suboptimal solution efficiency. Addressing these, the novel AGWO-CS integrates the strengths of its parent algorithms, improving search efficiency and precision while overcoming their limitations. Rigorous simulations have demonstrated the hybrid algorithm's superior performance, outperforming traditional optimization methods. This research validates the AGWO-CS's efficacy in resolving job-shop scheduling challenges, confirming its superiority and practicality compared to traditional optimization approaches.

2 Problem Description and Modeling

2.1 Problem Description

In a flexible job shop setting, where n workpieces are handled by m machines, the scheduling challenge lies in optimizing resource allocation to process diverse workpieces on various machines with varying steps and non-uniform processing times, aiming to minimize costs or maximize efficiency within constraints.

In the FJSP, the following assumptions are considered: (1) Machines attend to one workpiece at a time, (2) Job execution is uninterruptible, (3) Jobs are autonomous and can start at time zero, (4) Preemption and machine failures are not allowed, (5) Processing of different workpieces is of equal priority, and (6) Machine setup time before processing is disregarded.

2.2 Description of Related Symbols

The parameters of the FJSP model in this paper are shown in Table 1.

Table 1. Model parameter notation and definitions

Symbol	Definition
i	Job number
m	Machine population
k	Machine number
C_i	Completion time of workpiece
J_i	The ith workpiece
O_{ij}	The jth process of the ith workpiece
S_{ijk}	The processing start time of the jth process of workpiece J_i on machine k
t_{ijk}	The time required for the jth process of machining workpiece J_i on machine k
E_{ijk}	The end time of the jth process of machining workpiece J_i on machine k
X_{ijk}	If the jth process of workpiece J_i is processed on machine k, $X_{ijk} = 1$, Otherwise X_{ijk} =0

2.3 Model Establishment

This paper prioritizes minimizing the maximum completion time to effectively allocate processing machines to tasks and organize them rationally, translating this objective into a mathematical function Eq. (1).

$$minC_{max} = min[maxC_i] \tag{1}$$

$$\sum_{k=1}^{m} X_{ijk} = 1 \tag{2}$$

$$S_{ijk} + t_{ijk} = E_{ijk} \tag{3}$$

$$S_{ijk} \geq 0 \tag{4}$$

$$S_{ijk} + t_{ijk} \leq S_{i(j+1)k} \tag{5}$$

The system is subject to the constraints outlined below: Eq. (1) dictates that each process can only handle one workpiece at a time; Eq. (2) guarantees uninterrupted process duration; Eq. (3) specifies that all workpieces start processing at time zero; and Eq. (4) captures the sequential process dependencies within the same workpiece, requiring strict adherence to the predetermined processing order.

3 Augmented Cuckoo-Gray Wolf Algorithm

3.1 Cuckoo Search Algorithm

The cuckoo search algorithm, introduced by Yang and Deb (2009) [8], mimics cuckoo nesting behavior and the strategy of laying eggs in foreign nests. Cuckoos place their eggs in other species' nests, camouflaging them to survive alongside host eggs, which enhances their chick's survival chances. Despite the risk of detection, cuckoos carefully select hosts with similar eggs and incubation periods to reduce the likelihood of being found out. They predominantly lay eggs when the host is not present and may expel the host's eggs to ensure their chicks receive full attention and resources. The cuckoo's nest-searching path update formula is as follows：

$$X_i^{t+1} = X_i^t + \alpha \times Levy(\lambda) \tag{6}$$

The formula presented includes X_i^t for the position of the ith nest at tth iteration and X_i^{t+1} for the same nest at the $(t+1)$th iteration. The parameter α, typically set to α=1, controls the step size. Levy flight, a random search path based on the Levy distribution, is used to efficiently explore the global optimal solution and avoid local optima traps. The Levy flight expression is as follows:

$$Levy(\lambda) = \sigma\mu/|v|^{1/\beta} \tag{7}$$

$$\begin{cases} \sigma = \left[\dfrac{\Gamma(1+\beta)\sin(\pi\beta/2)}{2^{(\frac{\beta-1}{2})}\Gamma\left[\frac{\beta+1}{2}\right]\beta}\right] \\ \sigma_v = 1 \end{cases} \tag{8}$$

Among $\mu \sim N(0,\sigma_\mu^2)$, $v \sim N(0,\sigma_v^2)$, μ, v and all follow a normal distribution; The value of β is 1.5, σ represents variance, Γ represents the standard gamma coefficient.

3.2 Grey Wolf Optimization

The Grey Wolf Optimization Algorithm (GWO), introduced in 2014, is a population-based optimization method that abstracts the grey wolf pack's hunting strategy into an optimization process, modeling the social dynamics of grey wolves [9]. Grey wolves, which live in packs of 5 to 12 and maintain a strict hierarchical structure with four dominant levels, exhibit distinct roles: alphas lead hunts and shelter searches, betas support and lead in absence of alphas, deltas follow alpha and beta commands for scouting, and omegas, the lowest in the hierarchy, receive location updates from alphas, betas, or deltas. The GWO hunt is staged into encircling and tracking, chasing and harrying, and attacking, with an initial encircling stage employing a specific position update equation.

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{9}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}\vec{D} \tag{10}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{11}$$

$$\vec{C} = 2\vec{r_2} \tag{12}$$

In the above equation, t is the current number of iterations, $\vec{A}$ and $\vec{C}$ represent coefficient vectors, the position vector of the prey is denoted as $\overrightarrow{X_p}$, while that of the gray wolf is represented as $\vec{X}$. The convergence factor, $\vec{a}$, diminishes linearly from 2 to 0 with increasing iterations. And $\vec{r_1}$ and $\vec{r_2}$ follow a uniform distribution between [0,1].

Upon locating prey, the gray wolf pack, led by the alpha (α), beta (β), and delta (δ), encircles it. The α leads, with the β and δ following, while convergence factors a_1 , a_2, a_3 and random vectors C_1, C_2 and C_3, D_α , D_β, D_δ and Move guide their movement towards the prey, as shown in Fig.1. As convergence factors decrease, their direction aligns with the prey's location, within the wolves' activity range.

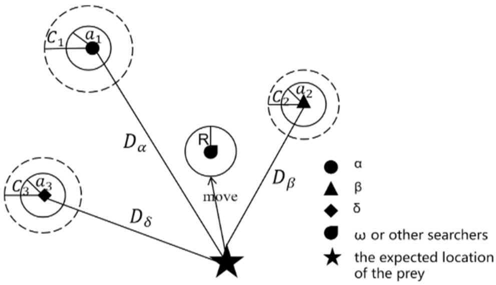

Fig. 1. Schematic diagram of individual tracking mechanism in GWO algorithm

During the hunting phase, pack members, X_i, refine their positions using the α, β, and δ coordinates, X_α, X_β andX_δ:

$$\begin{cases} \overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} * \overrightarrow{X_\alpha} - \vec{X}\right| \\ \overrightarrow{D_\beta} = \left|\overrightarrow{C_2} * \overrightarrow{X_\beta} - \vec{X}\right| \\ \overrightarrow{D_\delta} = \left|\overrightarrow{C_3} * \overrightarrow{X_\delta} - \vec{X}\right| \end{cases} \tag{13}$$

Where D_α, D_β and D_δ correspond to the respective distances of α, β, and δ from neighboring entities; X_α, X_β, and X_δ denote the current coordinates of α, β, and δ; C_1, C_2, and C_3 represent random direction vectors; and X indicates the present location of the gray wolf. The specific formula for positional updating among gray wolves is provided below:

$$\overrightarrow{X_1} = \left|\overrightarrow{X_\alpha} - A_1 * \overrightarrow{D_\alpha}\right| \tag{14}$$

$$\overrightarrow{X_2} = \left|\overrightarrow{X_\beta} - A_2 * \overrightarrow{D_\beta}\right| \tag{15}$$

$$\overrightarrow{X_3} = \left|\overrightarrow{X_\delta} - A_3 * \overrightarrow{D_\delta}\right| \tag{16}$$

$$\vec{X}(t+1) = (\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3})/3 \tag{17}$$

3.2.1 Augmented Gray Wolf algorithm.

Reverse learning, a heuristic search, employs the reverse of the current solution to direct the search process, facilitating rapid convergence to the optimal region and expanding the search space. This strategy is incorporated into the initial population of the GWO to enhance its search capabilities.

3.3 The AGWO-CS Optimization Algorithm

The AGWO-CS algorithm merges AGWO's fast convergence and low parameter sensitivity with CS's adaptive search, improving global search while avoiding premature convergence. By using CS's adoption behavior and Levy flight, it adjusts AGWO's search steps to balance randomness and directionality, enhancing global convergence and escaping local optima. This balance may, however, slightly reduce local exploration efficiency. AGWO-CS structures its approach by integrating AGWO and CS features for optimal control element selection, reducing AGWO's local minima vulnerability. The algorithm is organized as follows:

(1) Initial Population Generation

The AGWO-CS algorithm merges GWO and CS approaches, maintaining a diverse population through the reverse learning strategy. The population includes grey wolf positions, n_1, and cuckoo nests, n_2, with adjustable ranges for both to ensure $n_2 < n_1$ at each iteration.

(2) Selection of Control Parameters

The AGWO-CS algorithm utilizes grey wolves' encirclement strategy during the hunting phase, with control parameters optimized using the CS. To address CS's static nest reconstruction problem, AGWO-CS adopts an average-based reconstruction method in three stages: ranking, averaging, and replacing nests with fitness below the average threshold, leveraging CS's output for optimal control parameters.

(3) Establishment of Social Hierarchy

The grey wolf population's hunting process is based on a fitness-determined social hierarchy, with α as the lead, β as the secondary, and δ as the tertiary search subject. Their orientation and position are calculated via Eq. (14-16). The AGWO-CS algorithm flowchart is presented in Fig.2.

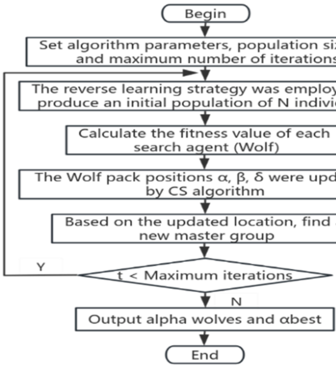

Fig. 2. Flow chart of AGWO-CS algorithm

4 Case Analysis

To validate the effectiveness of AGWO-CS in solving the FJSP, we chosen literature instances [10] for evaluation. In the examined case, five workpieces are assigned to five machines. AGWO-CS, GA and PSO are benchmarked. With a weight parameter $a_1 = 1$, the emphasis is on optimizing for the earliest possible completion time to minimize it.

Fig.3 displays the iteration curves for AGWO-CS, GA, and PSO algorithms in solving the example. AGWO-CS demonstrates superior optimization and convergence over GA and PSO. The scheduling Gantt chart is presented in Fig.3.

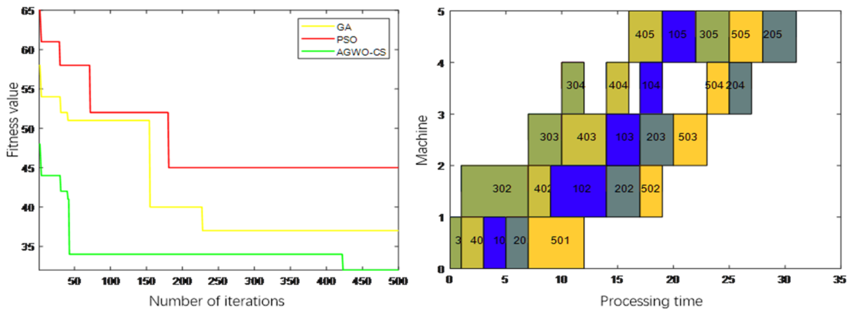

Fig. 3. Each algorithm iteration curve and schedule the Gantt chart

5 Conclusion

This paper introduces an augmented Grey Wolf-Cuckoo Search algorithm for FJSP aimed at minimizing the maximum completion time. The hybrid algorithm employs a reverse learning strategy to initialize the population, thereby guaranteeing diversity and enhancing the search efficiency. During population location updates, a more effective CS algorithm is selected, and the issue of premature convergence in the GWO is mitigated by integrating Levy flight and the cuckoo's earlier foraging strategy. This significantly enhances the overall algorithm's problem-solving effectiveness.

The AGWO-CS algorithm outperforms traditional GA and PSO in optimization capabilities and convergence. Experimental findings show that AGWO-CS is more efficient and faster converging for FJSP, offering an effective approach to industrial job shop scheduling and substantial potential for enhancing production efficiency and reducing costs.

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