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Article

PSO - SA Hybrid Optimization: An Algorithm simulating the human Exploration-Convergence cognitive model

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Abstract: This paper introduces a novel hybrid optimization algorithm that integrates Particle Swarm Optimization (PSO) and Simulated Annealing (SA), thereby simulating the human "exploration - convergence" cognitive paradigm. The algorithm combines the collective exploration capacity of PSO with the stochastic convergence mechanism of SA. It models the cognitive process where humans broadly explore the problem space and then concentrate on solution optimization during problem - solving. In terms of convergence speed and global optimization ability, it outperforms conventional PSO and SA algorithms. Additionally, it demonstrates superior performance in escaping local optima. This provides a fresh perspective for designing intelligent optimization algorithms based on cognitive simulation. The algorithm's structure and mechanism are analyzed in detail. It first employs PSO for extensive exploration of the problem space. Subsequently, SA is utilized to fine - tune and optimize the solution. The algorithm's parameters are carefully calibrated to ensure optimal performance. Extensive experimental results validate its effectiveness and superiority over traditional algorithms.

Keywords: PSO; SA; hybrid algorithm; cognitive model; intelligent optimization

1. Introduction

In intelligent optimization, imitating natural phenomena and biological behaviors is a distinctive approach to algorithm optimization. Humans have a cognitive process of “initially exploring unknown spaces extensively, then converging toward valuable information,” which gives them advantages in solving complex problems.

The PSO algorithm, proposed by Kennedy and Eberhart in 1995, draws inspiration from bird flocks’ foraging behavior: individuals adjust flight direction by sensing companions’ positions and their own experiences, enabling efficient group food-finding. This “individual-group” collaboration forms the theoretical basis of PSO as its particle update rule (Bin and Xiang, 2011). PSO shows strong global exploration through particle swarm collaboration but tends to have slow convergence and susceptibility to local optima in later optimization stages. The SA algorithm, put forward by Kirkpatrick et al. in 1983, is based on metal annealing in statistical mechanics: when heated to molten state and slowly cooled, atoms shift from disorder to ordered, lowest-energy lattice structures, breaking through local energy barriers (analogous to local optima) to reach global minimum energy (analogous to global optimum) (Zhu and Zhu, 2025). SA maps physical “energy” to optimization’s “objective function value” for iterative search, escaping local optima well but with low global search efficiency.

This paper integrates the two to simulate the human “exploration-convergence” cognitive model in order to improve the PSO - SA hybrid optimization algorithm.

2. Related research

2.1. PSO Algorithm

PSO is inspired by the foraging behavior of bird flocks. Each particle in the group learns from its own historical optimal position (individual cognition) and updates the global optimal position of the group (social cognition). The iterative formula is:

$$v_{id}=w\cdot v_{id}+c_1r_1(p_{id}-x_{id})+c_2r_2(p_{gd}-x_{id}) \tag{1}$$

$$x_{id}=x_{id}+v_{id} \tag{2}$$

Among , v_{id} is the particle velocity, w is the inertia weight, c_1、c_2 is the learning factor, r_1、r_2 is a random number, introducing randomness to enhance search diversity, p_{id} and p_{gd} are respectively the individual optimal and global optimal positions . $c_1 r_1 (p_{id}-x_{id})$ is the cognitive term, which is the “individual cognitive” behavior of particles learning from their own historical optimum, reflecting the utilization of experience (Yao et al., 2024). $c_2 r_2 (p_{gd}-x_{id})$ represents the “social collaboration” behavior in which particles learn from the optimal group, reflecting the sharing of group information. However, PSO has the drawbacks of slow convergence in the later stage and being prone to fall into local optimum.

2.2. SA Algorithm

SA originates from the physical process of metal annealing and accepts the inferior solution with a certain probability, which decreases with iteration:

$$p=\begin{cases} 1, & \Delta E<0 \\ e^{-\frac{\Delta E}{T}}, & \Delta E\geq 0 \end{cases} \tag{3}$$

When $p=1(\Delta E<0)$, the new solution is better and must be accepted; Accept the inferior solution with probability when $p=e^{-\frac{\Delta E}{T}}(\Delta E\geq 0)$. Then $\Delta E=E_{new}-E_{current}$ represents the energy difference between the old and new solutions (corresponding to the difference in the objective function values); T (current temperature) determines inferior solution acceptance probability: higher T means greater probability and stronger exploration (Han et al., 2024); lower T reduces it, focusing on local development. SA resists local optima well but has low global search convergence efficiency. As shown in **Table 1**.

Table 1

A Comparative Analysis of PSO Algorithm and SA Algorithm

Characteristics	POS Algorithm	SA Algorithm
Core inspiration	The group collaboration mechanism of the foraging behavior of bird flocks	The physical cooling phenomenon during the metal annealing process

Search method	Particles update their positions through individual optimal and global optimal information and conduct group collaborative search	Iterative search based on the probabilistic acceptance criterion allows the acceptance of inferior solutions
Advantage	Strong global exploration ability and fast initial convergence speed	It has a strong ability to resist local optima and can theoretically converge to the global optimum
Defect	In the later stage, it is prone to fall into local optimum and the convergence speed slows down	The global search efficiency is low and the initial convergence speed is slow
Key formula	$v_{id}=w\cdot v_{id}+c_1r_1(p_{id}-x_{id})+c_2r_2(p_{gd}-x_{id})$ $x_{id}=x_{id}+v_{id}$	$p=\begin{cases}1, & \Delta E<0\\ e^{-\Delta E/T}, & \Delta E\geq 0\end{cases}$

3. Design of PSO - SA Hybrid Optimization Algorithm

3.1. Algorithm framework

The algorithm simulates human cognitive logic in two stages:

The first stage: The PSO exploration simulates human exploration. Like initial extensive human information collection, it adjusts direction by integrating one's knowledge and experience (PSO individual optimum) and others' successes (PSO global optimum) (Cheng 2024). PSO improves particle velocity update with adaptive weight $w_{adaptive}$, adjusting dynamically by particle-global optimum distance and iterations: increasing W for far particles to enhance global search; reducing it for near ones to focus on local search and accuracy.

$$w_{adaptive}=w_{max}-(w_{max}-w_{min})\cdot\frac{d(x_i,gBest)}{d_{max}}\times\frac{t}{T_{max}} \tag{4}$$

Among them, w_{max} and w_{min} are the maximum and minimum values of the inertia weight respectively; $d(x_i,gBest)$ represents the distance between the current position of particle i and the global optimal position; d_{max} is the maximum distance of all particles from the global optimal position; t is the current number of iterations; T_{max} is the maximum number of iterations (Li et al., *2025*).

The second stage: The SA convergence integrates the convergent cognitive model, analogous to fine optimization in human focused analysis. The solution

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generated by PSO is accepted through the probability acceptance mechanism of SA to break through local constraints. The SA probability acceptance criterion $P = min\{1, exp(-\Delta f/T_k)\}$ can enable the algorithm to escape the local optimum (Anirban and Om, 2020). During operation, even if particles fall into local optima, inferior new solutions have a probability P of being accepted to alter the system state and escape the “trap”. From Markov chain theory, SA converges to the global optimal state under conditions like Metropolis-compliant cooling and appropriate temperature decrease.

3.2. The process of the POS - SA hybrid optimization algorithm

Step One: Initialization: Initialize PSO (particle positions, velocities, and parameters like learning factors c_1, c_2, inertia weight w) and SA parameters (Saffaran et al., 2020); Calculate each particle’s fitness to determine initial individual optimal solutions *pBest* and global optimal solution *gBest*.

Step Two: PSO iteration: Update particle velocities and positions using the improved formula. Recalculate fitness, then update individual optimal solutions *pBest* and global optimal solution *gBest*.

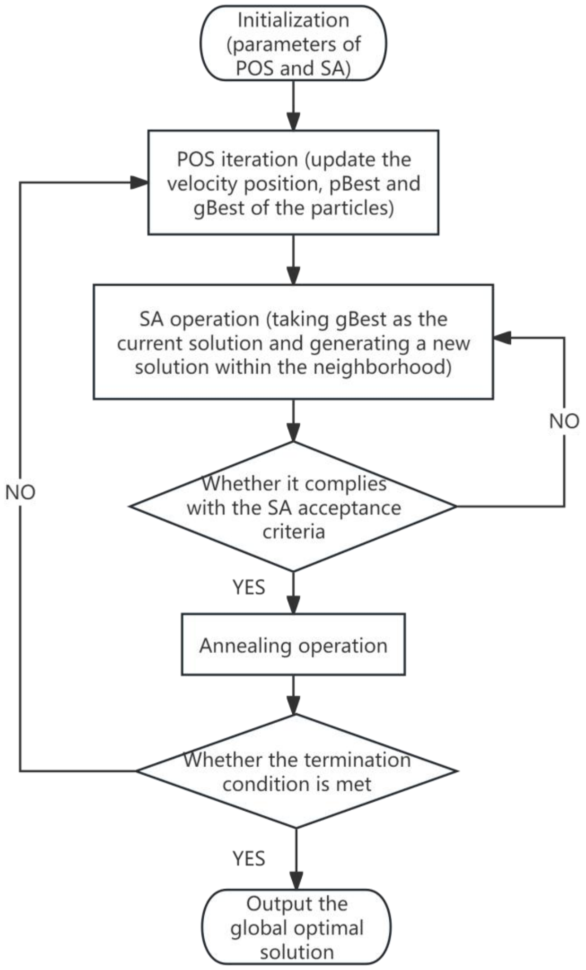
Step Three: SA operation: Take global optimal solution *gBest* as current solution, generate a neighboring new solution, calculate their fitness difference Δf, and decide acceptance per SA criteria. Perform annealing and lower temperature.

Step Four: Determine the termination condition: If the termination condition is met (such as reaching the maximum number of iterations or convergence of fitness values), output the global optimal solution; Otherwise, continue the iteration (return to Step two).

As shown in **Figure 1** of the process diagram, the above four steps are detailed.

Figure 1

Flowchart of the POS - SA hybrid optimization algorithm



4. Visual graphics of the POS - SA hybrid optimization algorithm

4.1. Problems and parameter Settings

Step One: the Rastrigin function is selected as the test function. This is a typical multimodal function and can verify the algorithm’s ability to escape the local optimum.

Step Two: Set the basic parameters such as the dimension, range and maximum number of iterations of the search space.

Step Three: Configure the key parameters such as the inertia weight of PSO, the learning factor, and the initial temperature and cooling rate of SA.

4.2. Core logic of the algorithm

Logic One: PSO exploration stage: Implement the particle update formula with adaptive inertia weight and dynamically adjust the search range based on the distance between the particle and the global optimum.

Logic Two: SA convergence stage: Based on the global optimum found by PSO, neighborhood search is conducted through the Metropolis criterion, allowing the acceptance of inferior solutions to escape the local optimum.

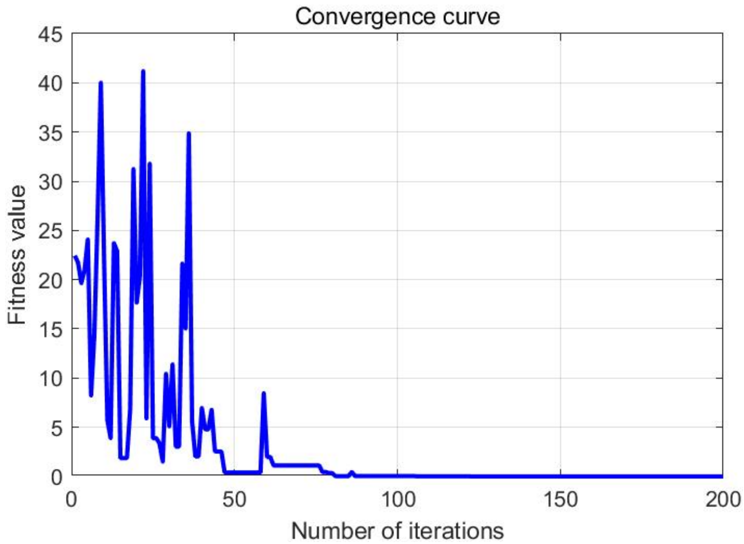
Logic Three: Two-stage collaboration: PSO quickly locates the potential optimal area, while SA conducts in-depth searches within this area, forming a hierarchical optimization mechanism.

4.3. Visual implementation

The convergence curve (horizontal axis: iterations; vertical axis: fitness value) shows optimization convergence. Early oscillations reflect extensive exploration (Pattanaik et al., 2019); later stability indicates development, with particles converging to a near-global optimum, demonstrating efficiency. The curve is shown in **Figure 2**.

Figure 2

Convergence curve



In the 2D solution space, particles are discrete points (Color Bar shows attributes). The central green mark is the global optimal, with red particles clustering around, reflecting late-stage "optimization" in high-quality regions. Background grid/symbols (such as “×”) show sampling, density, range, demonstrating coverage and local search focus (Pan et al.,2019).

In the 2D velocity plot, blue vectors indicate velocity/direction (length = speed). Central green is global optimal; radially converging vectors reflect movement guided by it—retaining random exploration while focusing on high-quality regions via speed updates.

The search space distribution and velocity vector plots are shown in **Figures 3** and **4**, respectively.

Figure 3

Search space and particle distribution map

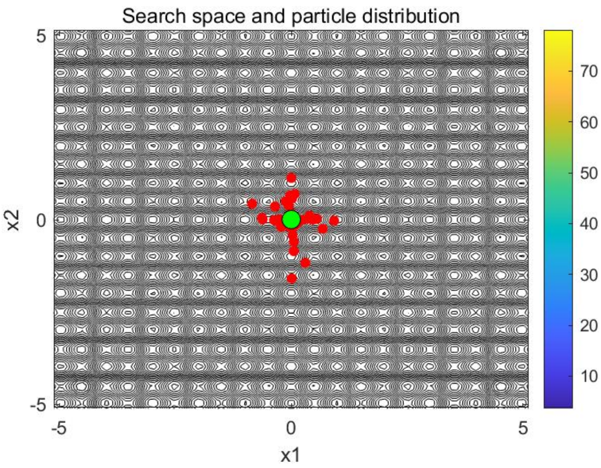
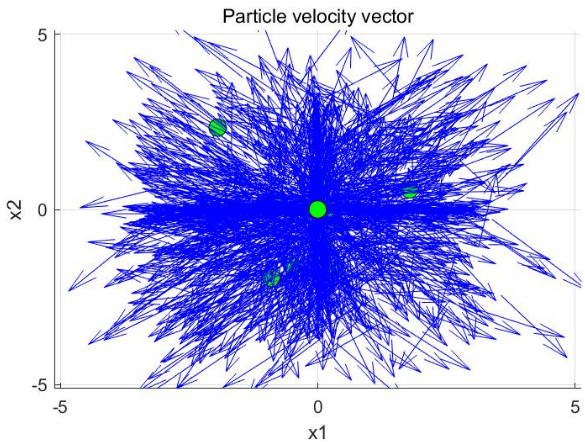


Figure 4

Particle velocity vector diagram



The SA temperature graph (horizontal: iterations; vertical: temperature) is exponentially decaying. Initial high temperature aids escaping local optima (Li et al., 2019); as iterations proceed, temperature drops, weakening inferior solution acceptance and enhancing local exploration. This is shown in **Figure 5**.

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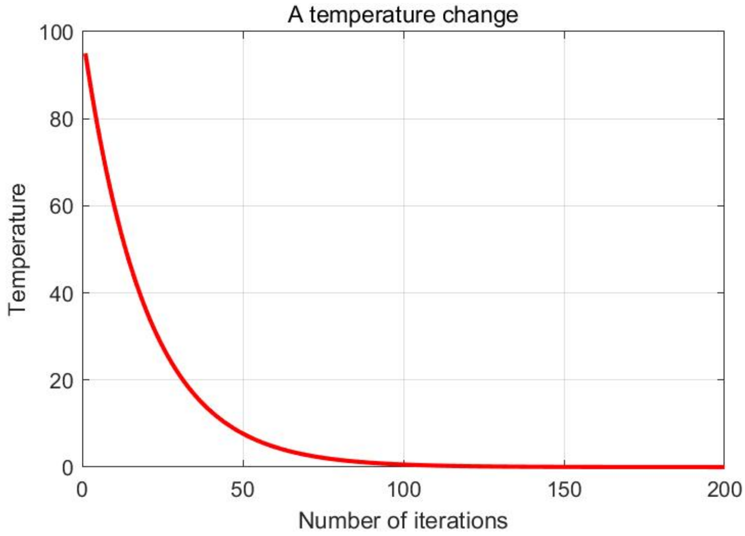
Figure 5

Particle velocity vector diagram

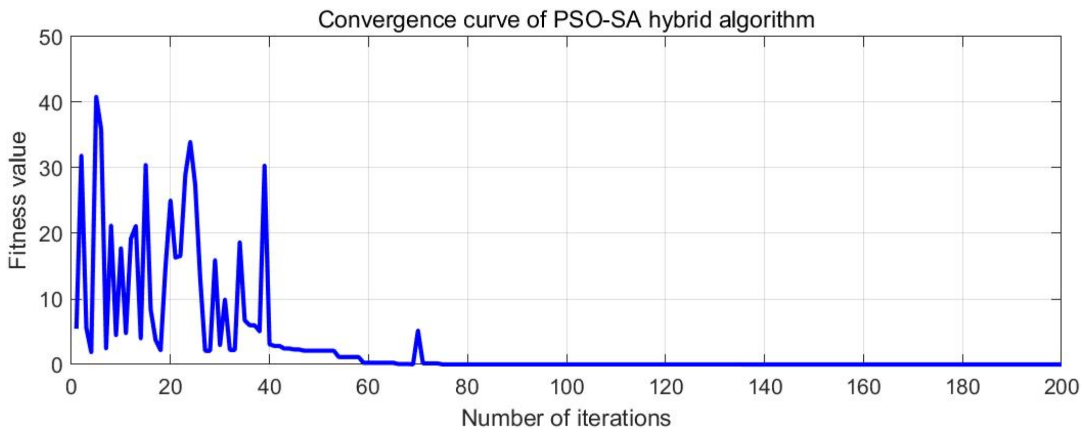


4.4. Result output

The PSO - SA convergence curve (horizontal axis: iterations; vertical axis: fitness value) shows its optimization process. Early fluctuations reflect exploration and SA escaping local optima (Sanchez et al., 2018). It stabilizes after about 60 iterations, demonstrating efficiency. Curve in **Figure 6**.

Figure 6

Convergence curve of the PSO - SA hybrid optimization algorithm



The 3D search space (A, B as inputs; fitness as height) and optimal solution form a surface with multi-peaks (complex multi-modality). Color gradients show nonlinear terrain (Deng et al., 2025). The red sphere in the fitness valley verifies the PSO - SA algorithm’s success in finding the global optimum via particle cooperation and annealing (Pavão et al., 2017). The 3D search space and optimal solution are viewed from three aspects, with the side view in **Figure 7**, and top views in **Figures 8** and **9**.

Figure 7

Three-dimensional search space and side view of the optimal solution

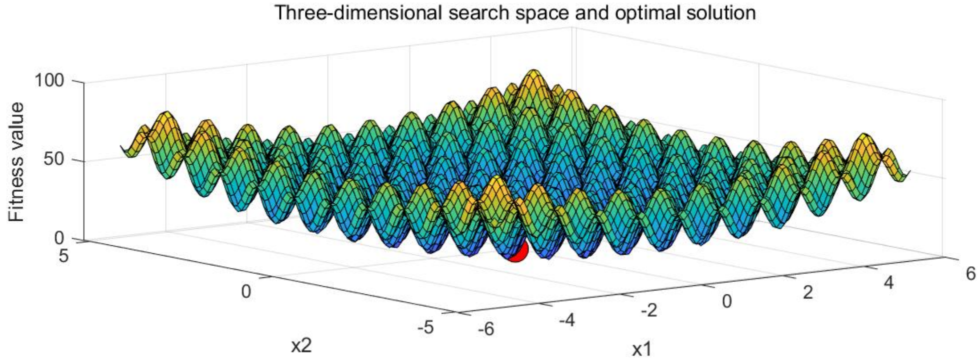


Figure 8

Three-dimensional search space and top view of the optimal solution

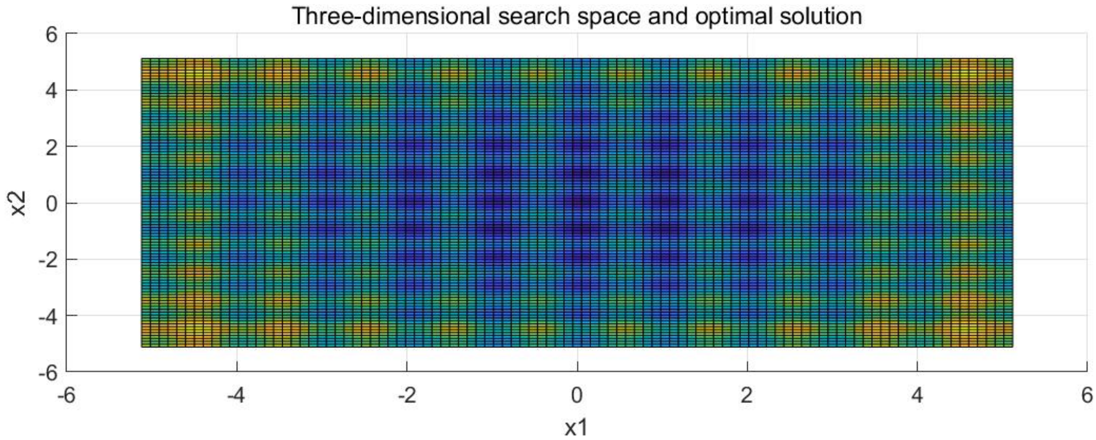
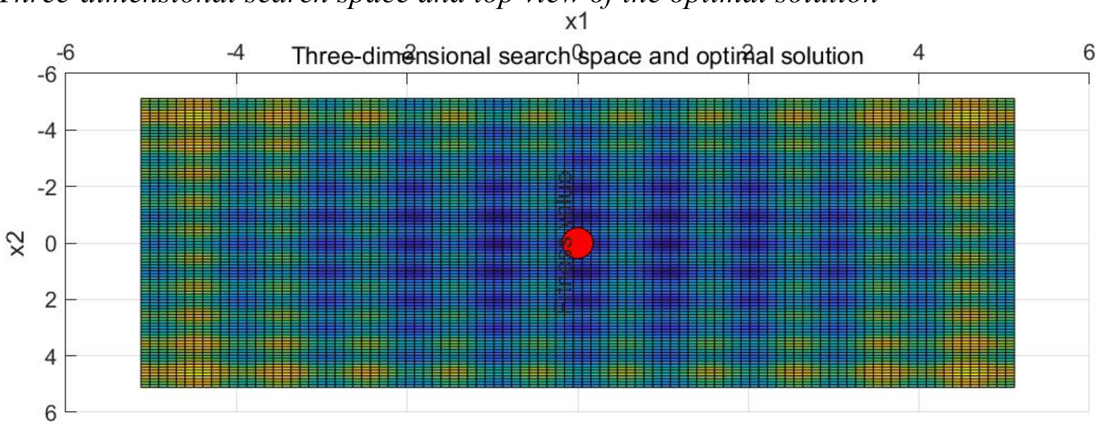


Figure 9

Three-dimensional search space and top view of the optimal solution



5. Theoretical Analysis of the Performance of the POS - SA

5.1. Convergence analysis

In the PSO - SA hybrid algorithm, PSO quickly locates potential optimal regions, and SA conducts deep searches within them to overcome local optima. Their synergy enables the algorithm system to continuously approach the global optimal state during iteration. A Lyapunov function $V(X_t)$ can be constructed, where X_t represents the system state of the algorithm at the tTH iteration (including parameters such as the position and velocity information of the particle swarm and the current temperature of SA).By analyzing the variation of $V(X_t)$ in each iteration, it is proved that for any given $\epsilon>0$, there exists an iteration number N. When $t > N, |V(X_t) - V^* | < \epsilon$, where V^* is the Lyapunov function value corresponding to the global optimal solution.This indicates that as the number of iterations increases, the “distance” between the algorithm system state and the global optimal state (measured by the Lyapunov function) can be arbitrarily small, thereby strictly proving the convergence of the algorithm (Wang et al., 2014).

5.2. Analysis of Global Optimization Ability

In complex multi-modal optimization problems, PSO tends to fall into local optima due to rapid particle aggregation, while SA, though able to escape local optima via probabilistic acceptance criteria, has low search efficiency. The PSO - SA hybrid algorithm combines their strengths into a hierarchical search mechanism:

In the early stage, PSO uses inter-particle information sharing and adaptive inertia weight adjustment for efficient global search across the solution space, identifying potential superior regions to narrow down the search range later.

As the algorithm progresses, SA conducts in-depth searches within these regions via probabilistic jumps. Its probabilistic acceptance criteria allow accepting worse solutions to escape local optima (Song et al., 2015).

In terms of search space coverage, PSO provides directional guidance for SA, while SA compensates for PSO’s tendency to get trapped in local optima. This makes the hybrid algorithm's global optimization ability superior to using either alone, enabling more reliable solutions to complex multi-modal optimization problems.

6. Conclusion

In the early phase, PSO's adaptive inertia weight adjustment and particle information sharing enable efficient global solution space search, quickly identifying potential optimal regions. In the later stage, SA's probability jump mechanism explores local areas in depth, with its probability acceptance criterion overcoming local optima traps. Theoretical analysis shows this algorithm outperforms conventional single algorithms, with enhanced anti-local optimum capabilities, convergence speed, and global optimization, providing a reliable solution for complex multi-modal optimization problems.

The PSO - SA hybrid algorithm transcends the simplistic bio mimicry of conventional intelligent optimization algorithms. Starting from human problem-solving cognitive logic, it offers a new perspective for intelligent algorithm innovation. Its application in complex domains like machine learning parameter tuning and engineering optimization is worth exploring. Integrating with learning techniques can optimize hierarchical search strategies, boosting efficiency in solving high-dimensional and highly nonlinear problems, and facilitating cross-fertilization of cognitive simulation and intelligent optimization.

Conflict of interest: The authors declare no conflict of interest.

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