EFFECTIVENESS COMPARISON OF INTELLIGENT ALGORITHMS IN OPTIMIZING DYNAMIC NEIGHBORHOOD FOREST STAND MINGLING DEGREE

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Abstract. Optimizing the stand mingling degree is similar to a non-deterministic polynomial (NP) problem, and improving this degree can enhance biodiversity, productivity, and ecosystem stability. To evaluate 10 mainstream intelligent algorithms in optimizing the mingling degree of dynamic neighborhood forest stands, this study examined stands in Hunan's Wuyunjie Nature Reserve, categorized as small (25–40), medium (80–200), and large (300–600). Algorithm performance was analyzed based on improvement amplitude, convergence, and stability. Results showed that for small stands, the Artificial Bee Colony Algorithm achieved a 29.68% average improvement, matching the theoretical optimum of Mixed Integer Programming, with 100% convergence and optimal stability. For medium and large stands, the Tabu Search Algorithm performed best, with improvements of 27.42% and 19.12%, and stability coefficients of 0.73 and 1.05, respectively. Additionally, Mixed Integer Programming applies only to small stands; the Grey Wolf Optimization Algorithm yielded a mere 5.38% improvement in large stands; the Whale Optimization Algorithm had variation coefficients of 11.04 and 14.53 in improvement amplitude for medium and large stands. The study concluded that the Tabu Search Algorithm is suitable for mingling degree optimization across all scales; the Artificial Immune Algorithm suits stability-prioritized management; the Whale and Grey Wolf Optimization Algorithms, with insufficient optimization capability and stability, require cautious use.
Keywords: *artificial bee colony, mixed integer programming, Voronoi, biodiversity, convergence stability, tabu search*

Introduction

Forests, as the core components of terrestrial ecosystems, play an irreplaceable role in maintaining the stability of productivity, enhancing carbon sequestration capacity, and protecting biodiversity (Gao et al., 2021; Feng et al., 2025; Sanaei et al., 2021). As a key indicator describing the spatial configuration of tree species, the stand mingling degree directly reflects the intensity of species interactions among trees, and its optimization level is significantly positively correlated with forest multifunctionality (e.g., 15%-20% increase in productivity and 12.7% increase in carbon density) (Li et al., 2023). For instance, if the mingling degree of temperate mixed forests is maintained within the range of 0.6-0.8, the coordinated improvements of productivity and carbon storage can be achieved (Sheng et al., 2024); in addition, mixed tree species can reduce the risk of pests and diseases and enhance the stress resistance of ecosystems through the resource complementary effect (Giberti et al., 2023; Sun et al., 2020). Therefore, the precise

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regulation of stand mingling degree has become a core objective of sustainable forest management.

The essence of optimizing stand mingling degree lies in adjusting the neighborhood relationships of trees through measures such as selective cutting and tree species configuration to improve the overall mixing level (Zhang et al., 2022). However, in actual management, the neighborhood relationships of trees are dynamic, and it is necessary to reconstruct neighborhood units based on Voronoi topology after selective cutting (Li et al., 2014). This upgrades the optimization problem from “static spatial configuration” to “dynamic neighborhood adaptation”, posing significant challenges to traditional optimization methods. As a classical method, mixed integer programming (MIP) can obtain the theoretical optimal solution in small-scale stands (25-40 trees). Nevertheless, when the stand scale expands to medium (80-200 trees) or larger, its enumeration search mechanism fails due to the exponential growth of computational complexity and cannot converge within a reasonable time (Qiu et al., 2023).

Intelligent algorithms, with the characteristics of “group search and adaptive optimization”, provide a new path for solving dynamic neighborhood problems. Genetic algorithm (GA) and particle swarm optimization (PSO) have been applied to the optimization of forest spatial structure. Among them, PSO simulates the search for tree selective cutting schemes through particle position updates, showing certain potential in small-scale stands (Qiu et al., 2023). However, existing studies have two limitations: first, there is a lack of systematic evaluation of stands of different scales, and most studies focus on a single scale, failing to reveal the scale dependence of algorithm efficiency; second, the analysis of dynamic neighborhood adaptability is insufficient, and the response mechanism of the algorithm to “neighborhood reconstruction after selective cutting” has not been clarified. For example, the impact of changes in Voronoi units on search accuracy has not been explained. In addition, there are significant differences in the core mechanisms of different intelligent algorithms. For example, the “tabu list weight avoidance” mechanism of tabu search and the “group-level guidance” mechanism of gray wolf optimization may lead to order-of-magnitude differences in their performance in terms of optimization accuracy, convergence efficiency, and stability (Liu et al., 2023).

To this end, this study takes “small-scale-medium-scale-large-scale” stands with 25-600 trees as the research objects, selects 10 mainstream intelligent algorithms (including GA, PSO, tabu search, etc.), and systematically evaluates the optimization efficiency of the algorithms in dynamic neighborhoods by combining three core indicators: improvement range, convergence time, and stability. The purposes of this study are to answer: (1) Which intelligent algorithms can balance optimization accuracy and efficiency in stands of different scales? (2) How does the adaptability between the algorithm mechanism and dynamic neighborhood requirements affect its performance? (3) Can an algorithm selection strategy for full-scale stand optimization be proposed based on the evaluation results?

Materials and methods

Study area and data sources

This study was conducted in the typical forest ecosystems of Wuyunjie Nature Reserve, Changde City, Hunan Province. Geographically situated in the eastern segment of the Wuling Mountains, the region falls under the mid-subtropical monsoon humid

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climate zone, with an annual mean temperature ranging from 16.5 to 17.5°C and annual precipitation of 1300–1500 mm. The forest vegetation is dominated by evergreen broad-leaved forests and coniferous-broadleaved mixed forests, characterized by intact community structures and diverse tree species composition. Representative native species include *Cunninghamia lanceolata (Lamb.) Hook., Pinus massoniana Lamb., Cinnamomum camphora (L.) Presl, and Cyclobalanopsis glauca (Thunb.) Oerst.,* rendering it an ideal site for researching the optimization of subtropical stand spatial structures.

To systematically assess the optimization performance of algorithms across stands of varying scales, the study subjects were categorized into three groups based on tree count: small-scale (25–40 trees), medium-scale (80–200 trees), and large-scale (300–600 trees). Four typical sample plots were established for each scale. The plot layout adhered to the principle of "homogeneous habitat with heterogeneous structure," ensuring that site conditions such as altitude, slope aspect, and soil type were consistent across plots to eliminate the confounding effects of habitat variability on mingling degree optimization results. Additionally, gradient configurations of tree species composition (with dominant species accounting for 13.33%–75.83%) and initial mingling degree (0.42–0.83) were implemented to guarantee the representativeness of samples with respect to regional stand structures (*Tables 1–3*). The dataset, comprising 12 plots, includes per-tree measurements of species, coordinates (measured with a total station, ± 2 mm), DBH (±0.1 cm), and height (±0.1 m), with initial mingling degrees serving as the optimization baseline.

Table 1. *Basic information of small-scale stands (25–40 trees)*

Plot name	Tree count	Dominant tree species	Avg. DBH (cm)	Avg. tree ht (m)	Initial mingling degree
L1	25	*Cunninghamia lanceolata (8.00%), Liquidambar formosana (52.00%*), Cyclobalanopsis glauca (28.00%), Ilex chinensis (4.00%), Tilia tuan (8.00%)*	21.11	8.70	0.71
L2	30	*Cyclobalanopsis multinervis (13.33%), Pinus massoniana (66.67%*), Cyclobalanopsis myrsinifolia (3.33%), Liquidambar formosana (3.33%), Castanopsis eyrei (10.00%), Dalbergia hupeana (3.33%)*	19.61	17.53	0.54
L3	35	*Cunninghamia lanceolata (20.00%), Liquidambar formosana (48.57%*), Liriodendron chinense (22.86%), Ilex chinensis (5.71%), Cyclobalanopsis glauca (2.86%)*	17.37	14.69	0.74
L4	40	*Liquidambar formosana (70.00%*), Pinus massoniana (7.50%), Quercus chenii (20.00%), Litsea pungens (2.50%)*	15.70	11.25	0.47

Table 2. *Basic information of medium-sized stands (80–200 plants)*

Plot name	Tree count	Dominant tree species	Avg. DBH (cm)	Avg. tree ht (m)	Initial mingling degree
M1	80	*Castanopsis fargesii (12.50%), Castanopsis sclerophylla (7.50%), Cunninghamia lanceolata (51.25%*), Liquidambar formosana (3.75%), Schima superba (21.25%), Liriodendron chinense (1.25%), Cyclobalanopsis glauca (1.25%), Quercus fabri (1.25%)*	20.77	15.96	0.65
M2	120	*Cunninghamia lanceolata (13.33%), Cyclobalanopsis glauca (5.00%), Cinnamomum camphora (1.67%), Pinus massoniana (75.83%*), Liquidambar formosana (0.83%), Albizia julibrissin (3.33%)*	13.22	14.92	0.42
M3	160	*Pinus massoniana (75.62%*), Cinnamomum camphora (2.50%), Albizia julibrissin (7.50%), Liquidambar formosana (6.25%), Cyclobalanopsis glauca (5.00%), Cunninghamia lanceolata (3.12%)*	12.01	14.55	0.42
M4	200	*Pinus massoniana (69.50%*), Liquidambar formosana (1.50%), Cinnamomum camphora (25.50%), Albizia julibrissin (1.50%), Cunninghamia lanceolata (2.00%)*	12.41	14.87	0.46

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Table 3. *Basic information of large-sized stands (300–600 plants)*

Plot name	Tree count	Dominant tree species	Avg. DBH (cm)	Avg. tree ht (m)	Initial mingling degree
H1	300	*Pinus massoniana (18.67%), Cunninghamia lanceolata (16.33%), Cinnamomum camphora (17.67%), Cyclobalanopsis glauca (15.33%), Albizia julibrissin (20.33%*), Liquidambar formosana (11.67%)*	12.57	14.51	0.83
H2	400	*Cyclobalanopsis glauca (11.00%), Liquidambar formosana (4.75%), Cinnamomum camphora (0.25%), Cunninghamia lanceolata (66.75%*), Pinus massoniana (17.25%)*	12.64	14.42	0.51
H3	500	*Cunninghamia lanceolata (22.80%), Liquidambar formosana (0.20%), Pinus massoniana (31.00%), Cyclobalanopsis glauca (0.20%), Albizia julibrissin (0.20%), Cinnamomum camphora (45.60%*)*	19.05	21.16	0.64
H4	600	*Pinus massoniana (63.83%*), Albizia julibrissin (5.00%), Cunninghamia lanceolata (27.50%), Liquidambar formosana (0.50%), Cinnamomum camphora (1.67%), Cyclobalanopsis glauca (1.50%)*	14.66	15.17	0.52

* indicates the dominant tree species of the sample plot, with the highest proportion of individuals, The coordinates (X, Y) of all trees in the sample plots were measured using a total station (with an accuracy of ±2 mm), and indicators such as tree species, DBH (at 1.3 m height, accuracy ±0.1 cm), and tree height (accuracy ±0.1 m) were recorded for each tree. The initial mingling degree was calculated based on the Voronoi neighborhood partitioning method (see the chapter "Calculation of Mingling degree" for details), providing a baseline value for subsequent algorithm optimization. During data preprocessing, boundary trees were identified via Delaunay triangulation (see the chapter "Scheme for Selecting Adjacent Trees" for details) to eliminate the interference of edge effects on mingling degree calculations

Quantification scheme of mingling degree

The stand mingling degree is an important index describing the spatial mingling degree of different tree species in a forest community, which is used to quantify the degree of tree species difference between individual trees in the stand and their surrounding adjacent individuals (Zhang et al., 2020; Li et al., 2020), as shown in *Equation 1*.

$$M_i = \frac{1}{n}\sum_{j=1}^{n} \vartheta_{ij} \qquad \text{(Eq.1)}$$

M_i is the Mingling degree value of the target tree i, n is the number of neighboring trees of the target tree i, and ϑ_{ij} is the variable value. When the j_{th}neighboring tree is of the same species as the target tree i, $\vartheta_{ij} = 0$; otherwise $\vartheta_{ij} = 1$. For example, the spatial distribution of the target tree with Mingling degree of 0.83 and 0.40 is shown in *Figure 1*.

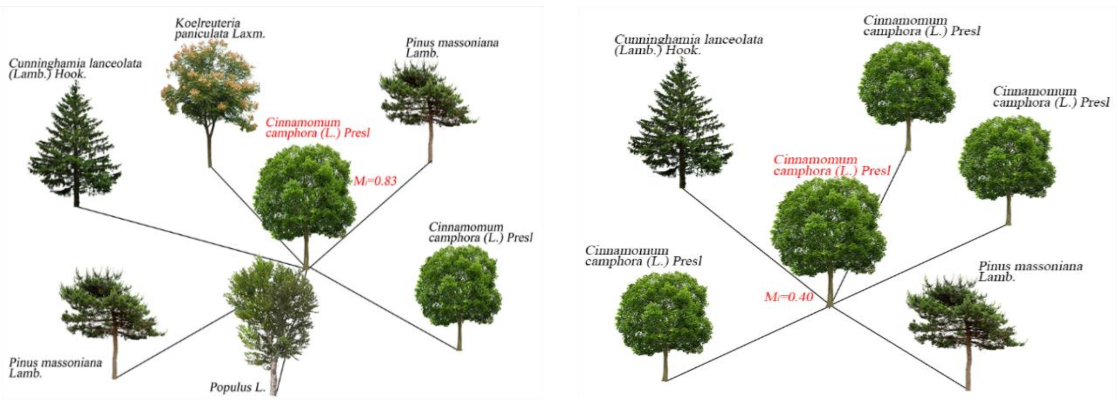

Figure 1. *Examples of spatial distribution of species mingling degree*

The Stand Mingling degree value is the average of the mingling degrees of all trees, as shown in *Equation 2*.

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$$\overline{M} = \frac{1}{N}\sum_{i=1}^{N} M_i \quad \text{(Eq.2)}$$

$\overline{M}$ is the Stand Mingling degree value, and N is the total number of trees in the forest stand (Excluding boundary trees).

Dynamic neighborhood problem

This study addresses neighborhood identification and edge effect mitigation through Voronoi diagrams and Delaunay triangulation, respectively, as detailed in the following subsections.

Scheme for selecting adjacent trees

Selecting neighboring trees for a target tree is fundamental to quantification of Stand Mingling degree. This study employs the Voronoi diagram theory to determine neighboring trees for the target tree. The neighboring trees of tree number 17 are {8, 16, 9, 6, 30}, and those of tree number 18 are {19, 13, 28, 31}. The spatial distribution of trees based on Voronoi diagram theory is shown in *Figure 2*.

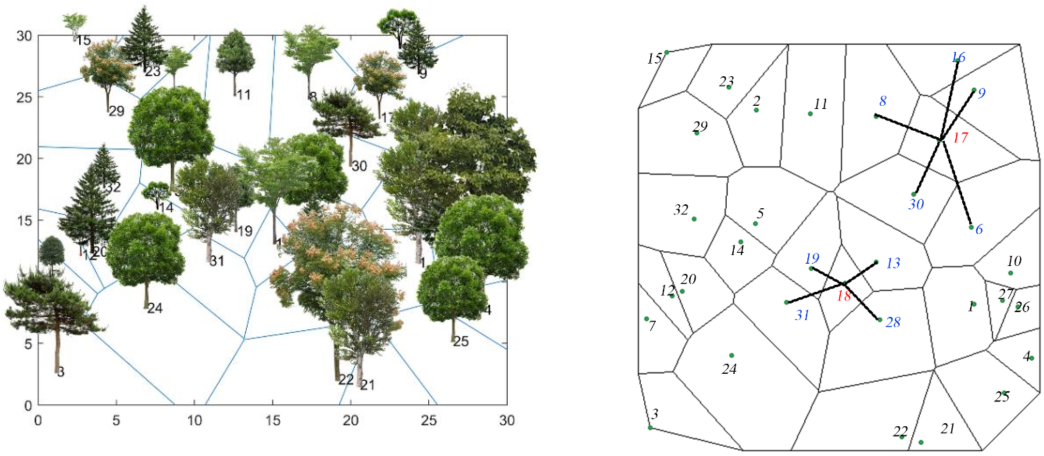

Figure 2. *Spatial distribution of trees based on Voronoi diagram theory*

Scheme for handling edge effects

In this study, a boundary detection method based on Delaunay triangulation was used to identify boundary trees in forest communities. By triangulating tree coordinates, all triangular edges were extracted and the occurrence frequency of each edge was counted. Edges appearing only once were determined as boundary edges, with their vertices identified as boundary trees. For example, the boundary trees in the sample plot below are numbered [3,5,14,15,21,22,28,29,30,36,37,39,45] (*Fig. 3.*). To avoid edge effects, this study stipulates that boundary trees can only serve as adjacent trees for other target trees.

Dynamic neighborhood unit problem

According to forest structural management theory, selective cutting is a core strategy to optimize stand mingling degree. However, after selective cutting, reconstructing the

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stand topological structure via Voronoi theory is required, causing dynamic changes in each tree’s neighborhood units and making the optimization process highly uncertain. Especially for large-scale mixed forest management, the traditional mixed integer programming (MIP) algorithm, relying on implicit enumeration, fails to effectively prune invalid search branches. This leads to exponential growth in solution time as the problem scales up, making it hard for conventional computing devices to handle such tasks. Taking Tree No. 19 as an example, with selective cutting plans [23, 9, 10] or [23, 48, 35], the reconstructed dynamic neighborhoods for target Tree 19 are [16, 31, 44, 35, 33, 40, 48, 26] and [9, 31, 44, 33, 40, 18, 26] (*Fig. 4*), respectively. The mingling degree value varies dynamically according to *Equation 1*. This dynamic recalculation process is embedded within the optimization loop, where every candidate cutting scheme proposed by an algorithm triggers a Voronoi reconstruction that alters the neighborhood structure, thereby updating its fitness.

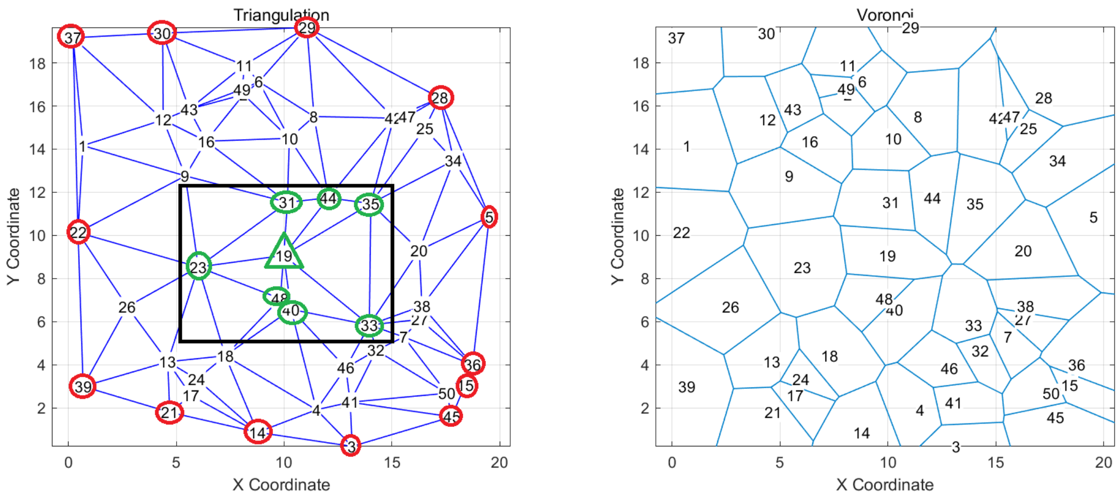

Figure 3. *Schematic diagram of boundary tree identification and neighborhood in forest stands based on Delaunay triangulation*

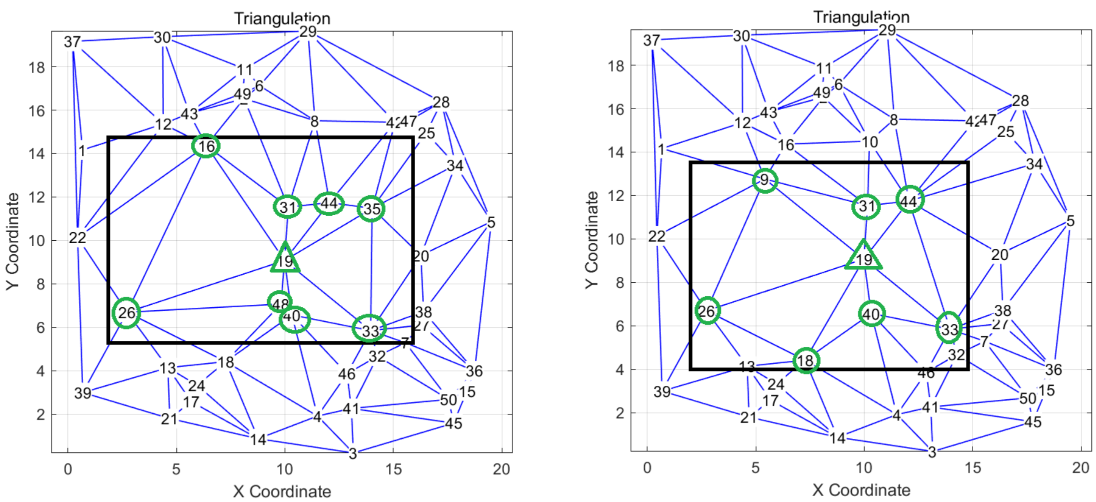

Figure 4. *Example diagram of dynamic neighborhood reconstruction for tree No. 19 under different selective cutting schemes*

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Fitness function mathematical model

Optimization problem statement

This study addresses the problem of optimizing the stand mingling degree under dynamic neighborhood conditions. The objective is to maximize the mean stand mingling degree $\overline{M}$ after selective cutting. The decision variables are the identities of the trees selected for removal, represented by a solution set S. The optimization is constrained by a fixed selective cutting ratio of $\alpha = 0.15$. A defining feature of this problem is the dynamic neighborhood mechanism, whereby the reconstruction of the Voronoi diagram after tree removal dynamically alters neighborhood relations and the objective function value, as detailed in the 'Dynamic neighborhood unit problem' section and illustrated in *Figure 4*.

Rationale for the optimization objective

The mingling degree, which describes the spatial distribution characteristics of forest tree species (with a value range of 0–1), has a significant impact on forest functions such as productivity, biodiversity, and pest resistance (Deng et al., 2021). Since its "optimal range" needs to be determined based on stand type, site conditions, and management objectives, there is currently no unified standard. From the perspective of spatial structure optimization, management measures are often used to improve the mingling degree of stands with low mingling degrees under a specified selective cutting ratio (Huang et al., 2024; Liu et al., 2023). This study sets the selective cutting ratio at 15%, a conservative level that aligns with sustainable forest management practices (Sheng et al., 2024). This intensity effectively optimizes stand structure while minimizing ecological disturbance. The optimization goal is to maximize the stand mingling degree under this constraint. The mathematical model of the fitness function is shown in *Equation 3*.

$$\max\big(f(M_i)\big)\ f(M_i) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{n}\sum_{j=1}^{n}\vartheta_{ij} \quad \text{(Eq.3)}$$

$f(M_i)$ is the fitness function for stand mingling degree, $n$is the number of neighboring trees of the target tree i, and ϑ_{ij} is the variable value. When the j_{th}neighboring tree is of the same species as the target tree i, $\vartheta_{ij} = 0$; otherwise $\vartheta_{ij} = 1$, and N is the total number of trees in the forest stand (excluding boundary trees).

Optimization approaches of intelligent algorithms

In this study, 10 intelligent algorithms are selected, including the genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and artificial bee colony algorithm (ABC), which belong to categories such as evolutionary algorithms and swarm intelligence algorithms. Based on the basic principles of each algorithm, they are applied to the optimization of stand mingling degree to improve its value. Taking PSO as an example for illustration, the approaches of other algorithms for solving the dynamic neighborhood mingling degree optimization problem are not elaborated here due to space constraints.

The basic principle of the PSO algorithm

The Particle Swarm Optimization (PSO) algorithm was proposed by Kennedy and Eberhart in 1995 (Blackwell and Kennedy, 2019), and its core idea is derived from the

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collective intelligent behavior of bird flocks during foraging. In PSO, each particle represents a candidate solution to the optimization problem. By iteratively updating the position and velocity of the particles, the global optimal solution is gradually approached. The update formulas for velocity and position are shown in *Equations 4* and *5*.

$$V_i^{t+1} = \omega \times V_i^t + c_1 \times r_1(P_{besti}^t - X_i^t) + c_2 \times r_2(G_{best}^t - X_i^t) \quad \text{(Eq.4)}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad \text{(Eq.5)}$$

ω is the inertia weight, c_1 and c_2 are the learning factors, $r_1 r_2$ is the random number in the interval ([0,1]), P_{besti}^t is the optimal position of particle *i* in the t-round self-search; G_{best}^t is the global optimal position of all particle swarm in the t-round search. $X_i^t = [x_{i1,}^t x_{i2,}^t \cdots, x_{iD,}^t]$ and $V_i^t = [v_{i1,}^t v_{i2,}^t \cdots, v_{iD,}^t]$ are the position vector and velocity vector of the i^{th} particle in the t^{th} iteration, and *D* is the dimension of the problem.

Since the particle position must correspond to a valid combination of forest tree numbers, the updated X_i^{t+1} needs to adopt repair strategies such as deduplication, completion, and elimination.

Deduplication: $X_i^{t+1} = sort(unique(X_i^{t+1}))$, it is to prevent the generation of identical forest tree numbers.

Supplementation: If the number of trees in group X_i^{t+1} is less than the number of trees to be felled, a certain number of trees will be randomly selected from the remaining numbers.

Elimination: If the number of trees in group X_i^{t+1} is greater than the number of trees to be felled, a certain number of trees will be randomly removed from them.

Particle coding and fitness function design

(1) Particle coding

The core of stand mingling degree optimization is to select k trees from n trees to remove, thereby maximizing the mingling degree of the remaining stand. Therefore, the position of a particle is set as $X_i^t = [x_{i1,}^t x_{i2,}^t \cdots, x_{iD,}^t]$, where x_{xj}^trepresents the number of the tree to be removed, satisfying condition $x_{xj}^t \in \{1,2,\cdots,n\}$, and all numbers are distinct.

(2) Fitness function design

The fitness function is defined as the average mingling degree of the remaining stand, as shown in *Equation 6.*

$$fitness(X_i) = \frac{1}{m}\sum_{i=1}^{m} M_i \quad \text{(Eq.6)}$$

m is the number of non-boundary trees remaining after tree felling; M_i is the mingling degree value of the i-th tree; X_i is the combination of numbers of the felled trees.

The process of solving stand mingling degree optimization using the PSO algorithm

Input: Original stand data *T*, selection cutting proportion α, number of particles N_P, maximum number of iterations T_{max}, parameters ω, c_1, c_2.

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Output: Optimal felling scheme G_{best}^{t}, maximum stand mingling degree value $\overline{M}_{max}$, convergence times, and convergence time.

Initialization: Calculate the initial mingling degree according to *Equations 1* and *2*. Initialize the number of selected trees *(k)*. Initialize the particle swarm $\{X_i^0\}_{i=1}^{N_p}$, whose value is a random k-dimensional vector without repetition, and initialize the particle velocity$\{V_i^0\}_{i=1}^{N_p}$. Calculate the initial fitness value $f_i^0 = fitness(X_i^0)$ according to *Equation 6*. Set $P_{besti}^0 = X_i^0$and $G_{best}^0 = maxf_i^0, i\epsilon\{1,2,\cdots,N_p\}$.

Design of iterative optimization process

$for\ t = 1\ to\ T_{max}$
$for\ i = 1\ to\ N_p$
Calculate the velocity V_i^t *of the particle according to formula (4), where* $r_{1,}r_2 \sim U(0,1)$*in the formula.*
Update the positionX_i^t *of the particle according to formula (5), and rectify the validity of the position through operations such as deduplication, completion and elimination.*
Calculate the new fitness value$f_i^t = fitness(X_i^t)$
$if\ f_i^t > f(P_{besti}^{t-1}), P_{besti}^t = X_i^t$
$if\ f_i^t > f(G_{best}^{t-1}),\ G_{best}^t = X_i^t$
$Endfor$
Record the current global optimal fitness value $f(G_{best}^t)$*, Convergence time and convergence times*
If the convergence condition is satisfied or the maximum number of iterations is reached, the loop shall be terminated.
$Endfor$

Evaluation indicators

To evaluate the efficiency of 10 intelligent algorithms in optimizing the mingling degree of dynamic neighborhood forest stands, the experiment sets a consistent number of cycles for each algorithm under the same problem scale. To eliminate interference from random effects, each algorithm is repeatedly executed 30 times in each sample plot, and indicators such as improvement amplitude (IA, *Eq. 7*), convergence, and stability (coefficient of variation, CV, *Eq. 8*) are selected as the main evaluation metrics. An algorithm is determined to have converged when the change in the global optimal fitness during 40 consecutive iterations is less than 1e^{-6}.

$$IA = \frac{FMDA - IMDA}{IMDA} \times 100 \quad \text{(Eq.7)}$$

$$CV = \frac{SD}{MEAN} \times 100 \quad \text{(Eq.8)}$$

SD is the standard deviation, Mean is the mean, *IA* is the improvement amplitude, *FMDA* is the final mingling degree value after optimization, and *IMDA* is the initial mingling degree value before optimization.

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Results

Algorithm operating environment and core parameters

To ensure the scientific validity of the experiment and the reliability of the results, all 10 intelligent algorithms were tested under the same operating environment (*Matlab(noParallelpool), CPU(Intel(R) Core(TM) i7-7700HQ 2.81GHz), RAM (16GB)*). The Mixed Integer Programming (MIP) baseline was implemented using an exhaustive search algorithm coded in MATLAB R2021a. As an exact enumeration method, it guarantees global optimality for all small-scale stands by evaluating all possible tree removal combinations. Algorithm Basic Parameter Settings in *Table 4*, Each algorithm was executed repeatedly 30 times in each sample plot, with their core parameters shown in *Table 5*.

Table 4. *Algorithm basic parameter settings*

Scale	Population Size	Number of Iterations
Small-scale	50	300
Medium-scale	70	600
Large-scale	100	1000

Table 5. *Core parameter settings of each algorithm*

Algorithm	Core parameter
ABC (Artificial Bee Colony)	limit = 100
ACO (Ant Colony Optimization)	alpha = 1, beta = 2rho = 0.5; Q = 100; initial_pheromone = 0.1;
AIA (Artificial Immune Algorithm)	clone_rate = 5; mutation_rate = 0.2; memory_size = 10; affinity_threshold = 0.9
BA (Bat Algorithm)	A = 0.5*ones(num_bats,1); r = 0.5*ones(num_bats,1); alpha = 0.9; gamma = 0.9; fmin = 0; fmax = 2
DE (Differential Evolution)	F = 0.8; CR = 0.9
GA (Genetic Algorithm)	crossover_rate = 0.8; mutation_rate = 0.1; elite_rate = 0.1;
GWO (Grey Wolf Optimizer)	a_decrease = 2
PSO (Particle Swarm Optimization)	c1 = 2; c2 = 2; w = 0.7
TS (Tabu Search)	tabu_size = 15; aspiration_threshold = 0.01
WOA (Whale Optimization Algorithm)	a_decrease = 2

The “algorithm convergence criteria” refers to: an algorithm is deemed to converge when, over 40 consecutive iterations, the change in global optimal fitness is less than $1e^{-6}$ and the position change is less than 0.05; the parameters in *Table 5* are all conventional settings for each algorithm in the stand mingling degree optimization scenario, so as to ensure the stable exertion of the algorithms' original characteristics

Small-scale sample plot

Solution quality

Table 6 shows in small-scale problems, the ABC algorithm exhibits the optimal solution quality, with an average improvement rate of 29.68%. It is consistent with the absolute optimal solution obtained by the MIP algorithm, and the convergence rate of the absolute optimal solution reaches 100.00%. This indicates that in small-scale scenarios, the algorithm can stably converge to the global optimal solution. In contrast, the BA algorithm performs the worst, with an average improvement rate of only 24.44% and an absolute optimal solution convergence rate of 86.67%. It lags significantly behind other algorithms in both solution improvement capability and global optimal solution acquisition capability.

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In terms of the coefficient of variation of the improvement rate, the ABC algorithm has a coefficient of 0.00, indicating that its solution improvement capability shows almost no fluctuation across different test cases, with extremely strong stability. The ACO algorithm has a coefficient of variation of 5.70 for the improvement rate, showing the largest fluctuation and poor consistency in solution improvement performance.

Convergence

All algorithms can converge, but there are differences in convergence time. The TS algorithm has an average convergence time of 5.15 seconds, performing optimally. It demonstrates strong fast convergence capability and can well meet the needs of scenarios with time efficiency requirements. Although the MIP method can obtain the absolute optimal solution, its average convergence time is as long as 2435.55 s, which is much higher than that of meta-heuristic algorithms, showing obvious disadvantages in time efficiency (*Table 6*).

Table 6. *Comparison of optimization performance of various algorithms for small-scale stands*

Algorithm	Avg. improvement rate (%)	CV of improvement rate	Avg. convergence time (s)	CV of convergence time	Conv. rate of abs. optimal sol. (%)
MIP	*29.68*	/	*2435.55*	/	*100.00%*
ABC	*29.68 ± 0.00*	0.00*	13.01 ± 3.74	28.71	*100.00%*
ACO	26.34 ± 1.50	5.70	8.05 ± 2.26	28.03	90.00%
AIA	28.24 ± 1.01	3.59	9.46 ± 1.77	18.75	96.67%
BA	24.44* ± 2.42	*9.91*	7.91 ± 2.82	*35.65*	86.67%
DE	27.71 ± 1.07	3.85	7.12 ± 1.71	23.98	93.33%
GA	27.59 ± 0.61	2.21	18.65 ± 4.97	26.63	95.33%
GWO	26.72 ± 0.80	2.99	7.12 ± 2.08	29.27	85.93%*
PSO	28.17 ± 0.82	2.92	5.68 ± 1.16	20.46	96.67%
TS	28.78 ± 0.46	1.60	5.15* ± 0.40	7.85*	96.67%
WOA	26.80 ± 1.33	4.98	5.47 ± 1.33	24.35	87.40%

* denotes the minimum value of the corresponding indicator, and italicized values represent the maximum value of the corresponding indicator

Medium-scale

Solution quality

The average improvement rate of the TS algorithm reaches 27.42, higher than that of other compared algorithms. Moreover, its coefficient of variation for the improvement rate is only 0.73, the lowest among all algorithms. The AIA algorithm ranks second with an average improvement rate of 26.93, while maintaining a low coefficient of variation of 1.28, demonstrating a good balance between optimization effect and stability. The GWO algorithm performs the worst, with the lowest average improvement rate (16.25), which is only about 60% of that of the optimal TS algorithm; additionally, its coefficient of variation is 4.67, and its stability is also at a downstream level (*Fig. 5*).

Convergence

In medium-scale scenarios, all algorithms converge but differ in convergence efficiency: The average convergence times of PSO, GA, and ABC are 147.67 ± 61.11,

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167.27 ± 34.17, and 184.52 ± 46.61, respectively; those of GWO, WOA, and ACO are significantly lower, at 27.27 ± 16.34, 39.25 ± 35.90, and 46.50 ± 37.59.

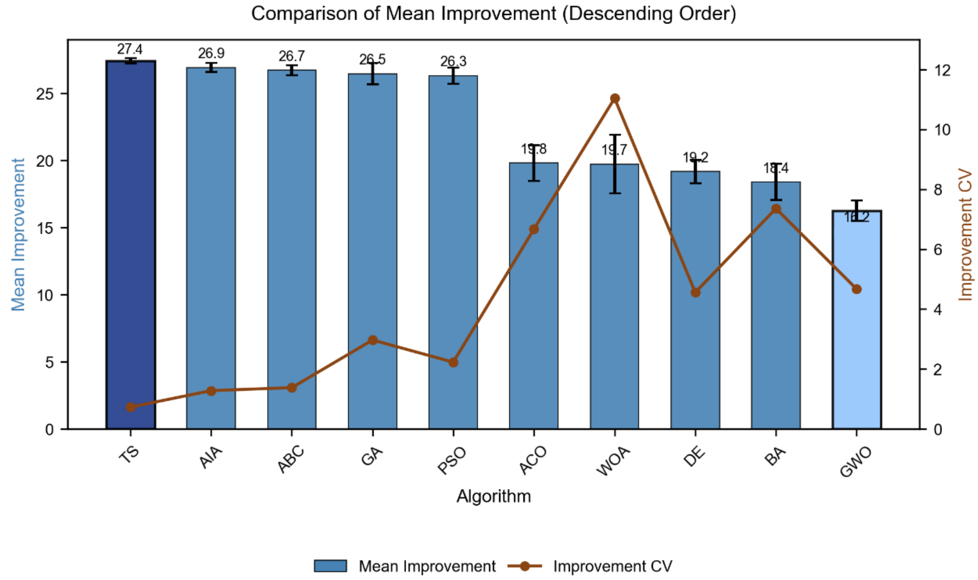

Figure 5. *Comparison of average improvement rate and stability of various algorithms for medium-scale stands*

In terms of single-sample solution accuracy: ABC performs best in M1 and M2, with maximum fitness values of 0.78 (vs. GWO's 0.73) in M1 and 0.56 (vs. GWO's 0.50) in M2; TS is optimal in M3 and M4, with maximum fitness values of 0.55 and 0.58, respectively. Additionally, despite fewer convergence times, GWO, WOA, and ACO have weak global search capabilities, leading to poorer optimal solution quality (*Fig. 6*).

In terms of convergence time (*Fig. 7*), the WOA algorithm has the shortest average convergence time (41.17 s), showing a significant advantage in computational efficiency; however, its coefficient of variation in convergence time is as high as 48.68, indicating poor stability in time consumption. Although the GA algorithm has the longest average convergence time (296.35 s), its coefficient of variation in convergence time is the lowest (18.53), demonstrating the characteristic of "low efficiency but high stability". The TS algorithm has an average convergence time of 96.04 s and a coefficient of variation in convergence time of 38.59. Although it does not have an absolute advantage in a single indicator, it achieves a balance between computational efficiency and time-consuming stability.

Large-scale

Quality of solutions

In terms of solution optimization effect, the TS algorithm performs the best, with an average improvement rate of 19.12%, and the coefficient of variation of its improvement rate is only 1.05, indicating that the algorithm not only has a significant optimization effect but also exhibits extremely strong stability in multiple solutions (*Fig. 8*). AIA (18.96%), GA (18.51%), and ABC (18.10%) follow closely, all maintaining an average improvement rate of over 18% with coefficients of variation below 2.04, thus forming a

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cluster of efficient and stable optimization algorithms. In contrast, the GWO algorithm has the lowest average improvement rate (5.38%); although the WOA algorithm reaches 10.52%, its coefficient of variation is as high as 14.53. Both have obvious disadvantages in terms of optimization effect and stability.

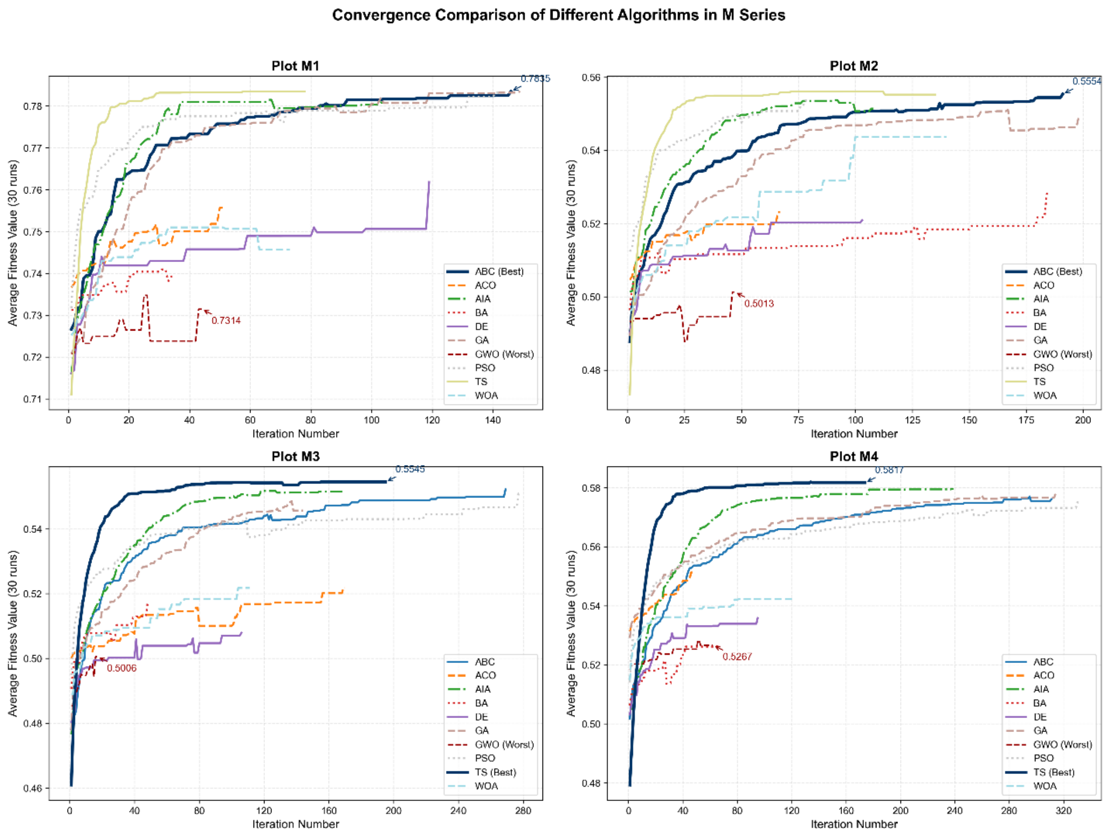

Figure 6. *Comparison of convergence curves of various algorithms in medium-scale plots*

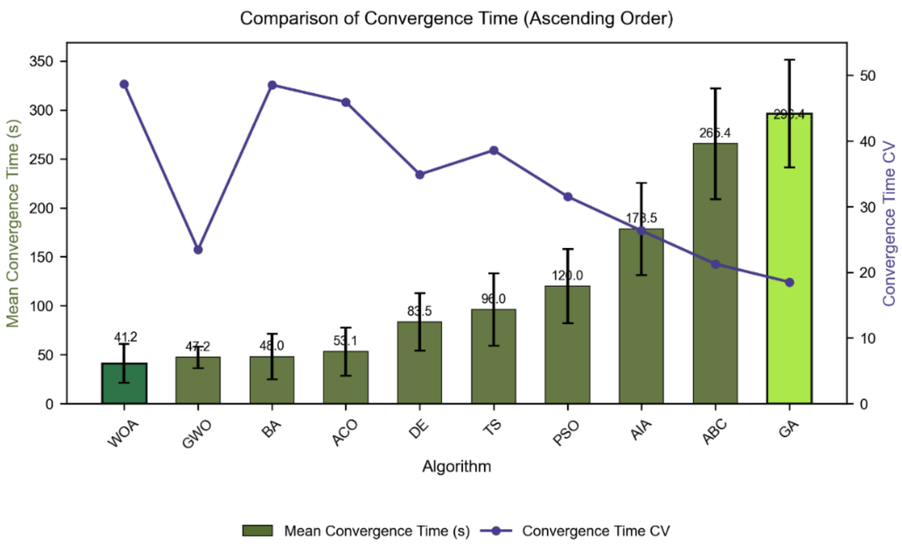

Figure 7. *Comparison chart of average convergence time and time-consuming stability of various algorithms in medium-scale forest stands*

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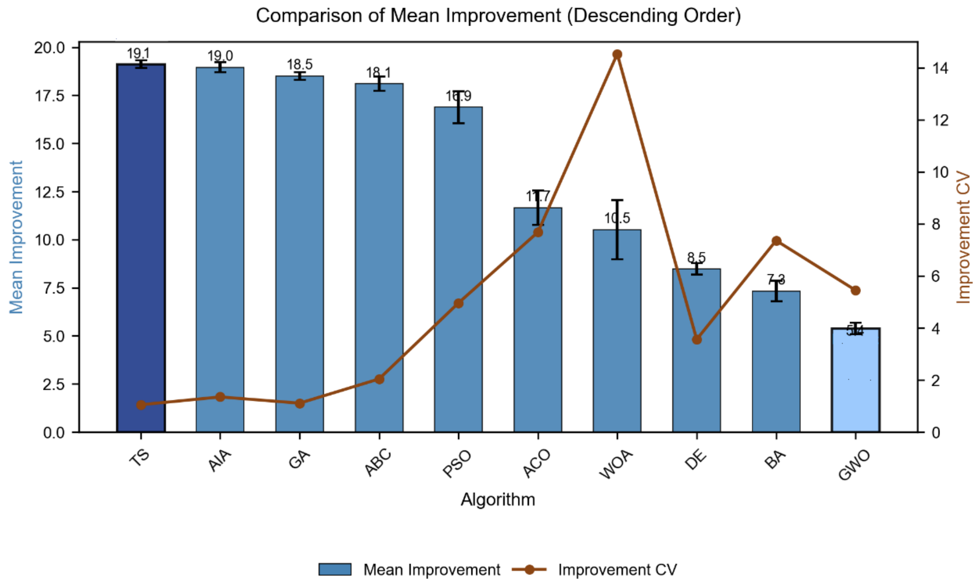

Figure 8. *Comparison of average improvement rate and stability of various algorithms in large-scale forest stands*

Convergence

All algorithms can converge in large-scale scenarios, but with significant efficiency differences. ABC, AIA, GA and PSO converge slowly, e.g., ABC and AIA have average convergence times of 477.75 ± 122.55 and 418.04 ± 115.28 respectively; GWO, BA, DE, ACO and WOA have superior convergence speed, e.g., GWO and BA only 20.73 ± 17.51 and 34.33 ± 18.6. These algorithms approach convergence quickly in early iteration, showing “accuracy” in local search but with the risk of premature convergence.

In terms of solution accuracy of individual plots, TS, AIA and ABC perform well in H1-H4 plots, with fitness values rising rapidly and remaining high; while low-convergence algorithms like GWO and BA have average optimal fitness values of only 0.66 (GWO) and 0.67 (BA). Due to insufficient breadth and depth in solution space exploration, the quality of optimal solutions is limited (*Fig. 9*).

In terms of convergence time (*Fig. 10*), the GWO algorithm performs best with an average convergence time of 185.01 s; BA (226.49 s), WOA (411.57 s) and ACO (467.53 s) are all within 500s, belonging to fast-converging algorithms. However, GA (4975.38 s) and ABC (3728.81 s) have significantly longer convergence times, with GA taking about 27 times as long as GWO, resulting in excessive time costs in large-scale forest stand optimization. In terms of convergence stability, BA (22.64) and GWO (30.92) have low coefficients of variation in convergence time, with controllable time fluctuations; while ABC (38.34) and PSO (41.38) show more obvious fluctuations.

The comparative performance of the algorithms was assessed for statistical significance using Kruskal-Wallis tests on the improvement amplitudes from 30 independent runs. The tests confirmed significant differences among the algorithms across all stand scales ($p < 0.001$). Overall, the TS algorithm has significant comprehensive advantages across all stand scales and is the first choice for dynamic neighborhood stand mixed-degree optimization; the AIA performs steadily in medium and large-scale scenarios, suitable for

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stability-priority needs; the GWO and WOA perform inadequately in medium and large-scale scenarios and should be used with caution.

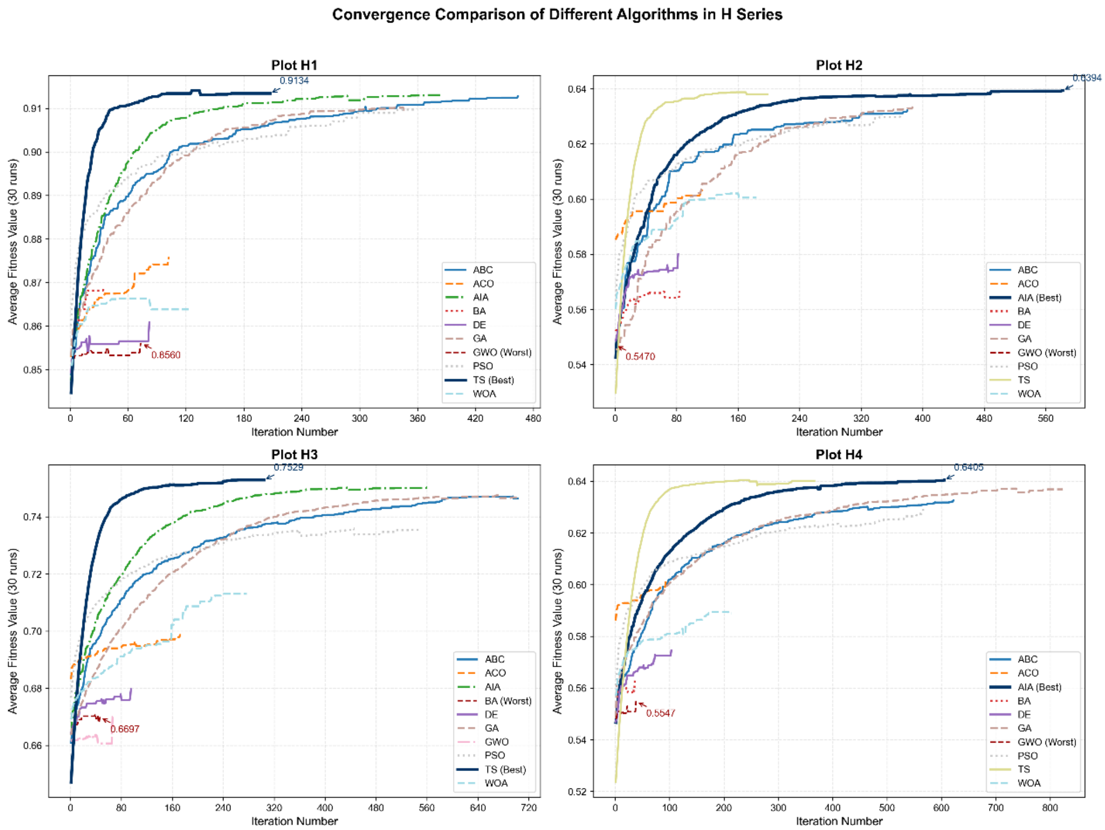

Figure 9. *Comparison of convergence curves of various algorithms in large-scale plots*

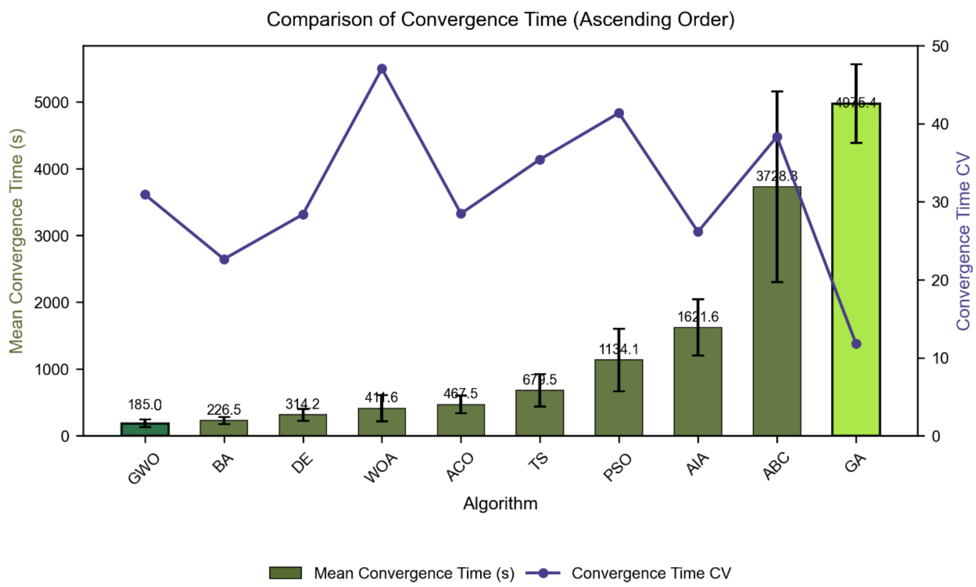

Figure 10. *Comparison of average convergence time and stability of various algorithms in large-scale forest stands*

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Discussion

Performance mechanism of intelligent algorithms on stand mingling degree optimization

The Tabu Search (TS) algorithm shows comprehensive advantages of "high optimization effect-strong stability" across all stand scales: the average improvement amplitude reaches 28.78% in small-scale stands, 27.42% in medium-scale stands, and 19.12% in large-scale stands, with the coefficient of variation of the improvement amplitude all below 1.60. The Artificial Immune Hybrid Algorithm (AIA) follows closely, maintaining an average improvement amplitude of over 18% in medium and large-scale stands, and its stability (coefficient of variation < 2.04) is close to that of the TS algorithm. This result is closely related to the core mechanisms of intelligent algorithms: the TS algorithm avoids repeated searches through a tabu list and combines the amnesty criterion to jump out of local optima, and its neighborhood search strategy is highly compatible with the demand for "topological relationship reconstruction after selective cutting" in dynamic neighborhoods (Li et al., 2025; Zhang et al., 2023). The AIA algorithm, based on the optimization logic of antibody clonal mutation, can quickly adapt to the dynamic changes in tree neighborhood relationships (such as Voronoi neighborhood reconstruction after selective cutting) (Ahmad et al., 2018; Tavana et al., 2016).

The Particle Swarm Optimization (PSO) algorithm performs balanced in small-scale stands (average improvement amplitude 28.17%, convergence time 5.68s), but its performance declines in large-scale stands, which may be related to its "swarm intelligence update" mechanism. When the stand scale expands (e.g., the number of trees reaches 600), the dimension of the particle position vector increases, and the cumulative error of random factors in the velocity update formula may lead to a decrease in search accuracy (Zhao et al., 2023; Qaraad et al., 2024), which is consistent with the phenomenon observed by Qiu et al. (2023) in multi-objective forest harvest models that "PSO is prone to falling into local optima in high-dimensional problems". In contrast, the Genetic Algorithm (GA) still maintains an average improvement amplitude of 18.51% in large-scale stands, but the convergence time is as long as 4975.38 s, which is related to its evolutionary mechanism relying on crossover and mutation. Under complex topological relationships, the effective recombination probability of chromosome coding decreases, requiring more iterations to achieve optimization (Li, 2012; Aghdam et al., 2023; Kılıç et al., 2020).

The Grey Wolf Optimization (GWO) algorithm and Whale Optimization Algorithm (WOA) perform poorly in large-scale stands (GWO average improvement amplitude 5.38%, WOA coefficient of variation 14.53), possibly because such algorithms rely on group hierarchy update mechanisms (such as the α, β, δ wolf guidance strategy of GWO), making it difficult to quickly adjust the search direction when tree neighborhood relationships change frequently in dynamic neighborhoods (Li et al., 2022; Guo et al., 2020; Liu et al., 2022).

Ecological and management significance of dynamic neighborhood optimization

Increasing the stand mingling degree is of great significance for enhancing the stability of forest ecosystems, promoting biodiversity, improving productivity, enhancing soil health, and strengthening the stress resistance of forests (Xu et al., 2024; Trogisch et al., 2021; Hertzog et al., 2021). For example, the TS algorithm increases the mingling degree

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of large-scale stands by 19.12%. This result provides a quantitative basis for "directional regulation of mingling degree" in forest management and demonstrates the application potential of intelligent algorithms in solving the optimization problem of stand mingling degree. From the perspective of dynamic management, the adaptability of intelligent algorithms to the reconstruction of neighborhood relationships after selective cutting (such as the rapid convergence of the TS algorithm under the selective cutting schemes and solves the pain point of traditional methods (such as MIP) where "solution time grows exponentially" in dynamic scenarios. In medium-scale stands, the convergence time of the TS algorithm (96.04s) is only 1/25 of that of MIP, and the optimization effect is close to the theoretical optimum, which makes "real-time stand management decision-making" possible. In the future, intelligent algorithms can be combined with multi-objective regulation of forest management to further expand the optimization dimension (Merganič et al., 2020; Lucash et al., 2023).

Research limitations

Firstly, the optimization framework focuses solely on the immediate, short-term reorganization of neighborhood structures following selective cutting. It does not incorporate long-term forest dynamics, such as tree growth, mortality, and recruitment. For instance, interannual variations in growth rates under climate change could significantly alter competitive relationships and neighborhood topology over time. The absence of these long-term dynamic variables means that the current optimization schemes are static in a temporal context and may not remain optimal throughout a full forest rotation.

Secondly, the parameters for all algorithms were set to conventional values from the literature to ensure a fair comparison of their baseline performance. Consequently, we did not conduct a formal parameter sensitivity analysis. Differences in stand types (e.g., coniferous vs. broadleaf mixed forests) and initial structures might necessitate algorithm-specific parameter tuning for optimal performance, an aspect not explored here. Furthermore, the optimization objective was solely the maximization of the mingling degree. While crucial, this single-objective approach does not integrate the coupling relationships between mingling degree and other forest functionalities like carbon storage or water conservation, potentially making it challenging for the resulting schemes to balance multiple ecological goals in practical management.

Future research should focus on integrating growth and yield models to enable multi-temporal optimization, conducting comprehensive parameter sensitivity analyses to develop adaptive tuning rules for different forest types, and formulating multi-objective optimization frameworks that can simultaneously maximize mingling degree and other critical ecosystem services.

Conclusions

This study developed a "small-scale-medium-scale-large-scale" stand test system to systematically evaluate the effectiveness of 10 intelligent algorithms in optimizing the mingling degree of dynamic neighborhood stands, revealing the scale dependence of algorithm performance and the dynamic neighborhood adaptation mechanism. Overall, the Tabu Search (TS) algorithm, with its strong adaptability to dynamic neighborhoods and stability across all scales, is recommended as the preferred algorithm for optimizing the mingling degree of dynamic neighborhood stands. The other main conclusions are as follows:

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(1) In small-scale stands (25-40 trees), the Artificial Bee Colony (ABC) algorithm yields results consistent with those of Mixed Integer Programming (MIP) and exhibits optimal stability; the Tabu Search (TS) algorithm has the shortest convergence time, balancing efficiency and accuracy. In medium-scale stands (80-200 trees) and large-scale stands (300-600 trees), the TS algorithm is the optimal choice; the Grey Wolf Optimization (GWO) algorithm performs the worst as it struggles to adapt to complex neighborhood relationships.

(2) The TS algorithm marks invalid neighborhoods via a tabu list to avoid ineffective searches and breaks through local optima by means of the amnesty criterion, thereby achieving stable effectiveness across all stand scales; the AIA algorithm adaptively responds to neighborhood changes through antibody clonal mutation, showing robust performance in medium and large-scale stands. However, algorithms relying on group guidance (such as GWO and WOA) see a significant decline in effectiveness in large-scale stands, as they struggle to adjust their search direction quickly.

(3) For different stand management objectives, the Tabu Search (TS) algorithm is recommended for rapid decision-making in small-scale forest stands, while the Artificial Bee Colony (ABC) algorithm is suitable for precise optimization of the stand mingling degree; the Tabu Search (TS) is the optimal choice for mingling degree optimization across medium and large-scale forest stands, while the Artificial Immune Algorithm (AIA) is recommended for stability-prioritized scenarios. However, the Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA) should be used with caution when optimizing the stand mingling degree in medium-to-large-scale forest stands with dynamic neighborhoods.

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