Swarm Intelligence: Concepts, Models and Applications

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Outline

Introduction

- Swarm intelligence studies how simple agents can produce intelligent collective behaviour.
- The system works without central control.
- Global behaviour emerges from local interactions.
- Typical natural examples include ant colonies, bird flocks, and bee swarms.

Source: [R1]

Why Swarm Intelligence Matters

- It offers a decentralized way to solve complex problems.
- It is robust, adaptive, and scalable.
- It is useful for optimization in engineering and computer science.
- It has applications in routing, scheduling, machine learning, and bioinformatics.

Source: [R1]

Key Concepts

- **Emergence**: complex global behaviour from simple local rules
- **Self-organization**: order without central coordination
- **Direct interaction**: communication through signals
- **Indirect interaction**: communication through the environment
- **Stigmergy**: coordination through environmental changes

Source: [R1]

Historical Development

- **1989**: "Swarm Intelligence" introduced by Beni and Wang
- **1991**: Ant Colony Optimization (ACO) introduced
- **1995**: Particle Swarm Optimization (PSO) introduced
- Later, other SI models were also proposed, such as:
  - Artificial Bee Colony
  - Bacterial Foraging
  - Cat Swarm Optimization
- In this presentation, the main focus remains on **ACO** and **PSO**.

Source: [R1]

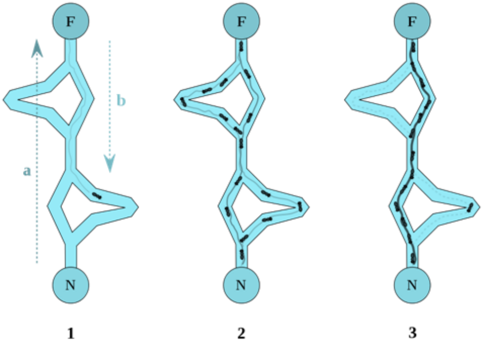
Ant Colony Optimization (ACO): Inspiration

- ACO is inspired by the foraging behaviour of ants.
- Ants communicate using pheromone trails.
- Frequently used paths receive stronger pheromone reinforcement.
- Pheromone evaporation helps the colony adapt to change.

Source: [R1]

Double Bridge Experiment

- Ants travel between the nest and a food source using two alternative branches.
- At the beginning, both branches appear similar, so ants choose randomly.
- Ants using the shorter path return earlier and reinforce it sooner.
- As pheromone accumulates, the colony gradually converges to the shorter route.



Double bridge experiment showing collective shortest-path selection

Source: [R1]

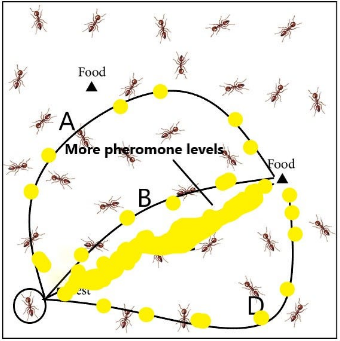
What Does the Experiment Show?

- Positive feedback helps ants discover good paths.
- Early reinforcement can strongly influence later decisions.
- Too much reinforcement can trap the colony in a suboptimal path.
- Evaporation is essential to balance exploration and exploitation.

Source: [R1]

Basic Framework of ACO

1. Represent the problem as a construction graph
2. Initialize pheromone values
3. Let ants construct candidate solutions
4. Update pheromone trails
5. Repeat until convergence or stopping condition



Conceptual visualization of ACO search and pheromone-guided path formation

Sources: [R1], [R8]

ACO Transition Rule

- Each ant builds a solution step by step on a **construction graph**.
- The probability of choosing the next component depends on:
  - **pheromone trail** τ_{ij}
  - **heuristic information** η_{ij}
- α: importance of pheromone
- β: importance of heuristic information

$$p_{ij}^{(k)}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in N_i^{(k)}} [\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}}$$

where $N_i^{(k)}$ is the feasible neighbourhood of ant k at node i.

Source: [R1]

ACO Pheromone Update

- After all ants construct solutions:
  1. pheromone evaporates
  2. good solutions deposit new pheromone
- Evaporation avoids overcommitting to old paths.
- Reinforcement increases the probability of reusing good components.

Global update:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{(k)}(t)$$

Deposit rule:

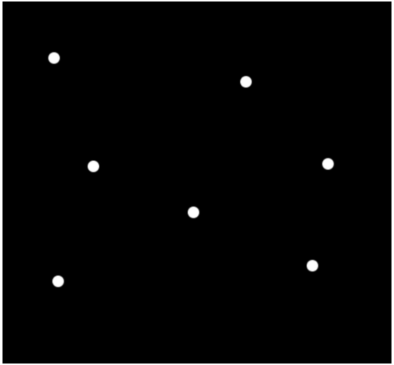
$$\Delta\tau_{ij}^{(k)}(t) = \begin{cases} \frac{Q}{L_k(t)}, & \text{if ant } k \text{ used edge } (i,j) \\ 0, & \text{otherwise} \end{cases}$$

where ρ is the evaporation rate, Q is a constant, and $L_k(t)$ is the cost of ant k's tour.

Source: [R1]

ACO Example: Traveling Salesman Problem

- Cities are represented as graph nodes.
- Distances are represented as edge weights.
- Each ant constructs a complete tour.
- The goal is to find the shortest possible route.



ACO demo

Source: [R1]

ACO: Strengths and Limitations

Strengths

- Effective for combinatorial optimization
- Distributed and adaptive
- Good at path-finding and ordering problems

Source: [R1]

Limitations

- Sensitive to parameter settings
- Can stagnate on suboptimal solutions
- May struggle when many paths have similar quality

Particle Swarm Optimization (PSO): Inspiration

- PSO is inspired by bird flocking behaviour.
- Birds move collectively without central control.
- They adapt their motion based on neighbouring individuals.
- This social behaviour is modeled as a search strategy.

Source: [R1]

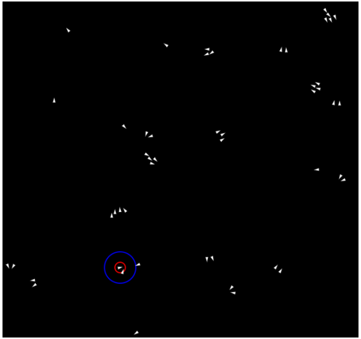
Bird Flocking Rules

- **Cohesion**: move toward nearby flockmates
- **Separation**: avoid collisions with neighbours
- **Alignment**: match direction and speed with nearby individuals

Key idea

Simple local interaction rules can produce coordinated global motion without central control.

Source: [R1]



Flocking behavior simulation

Main Idea of PSO

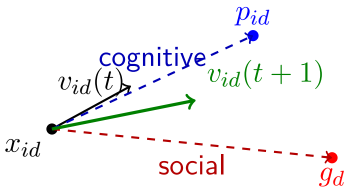
- A **particle** represents a candidate solution.
- Its **position** represents the current solution.
- Its **velocity** controls how it moves in the search space.
- Each particle remembers its **personal best** position.
- The swarm also tracks the **global best** position.

Source: [R1]

Basic Framework of PSO

1. Initialize particle positions and velocities
2. Evaluate the fitness of each particle
3. Update each particle's personal best
4. Update the swarm's global best
5. Update velocities and positions
6. Repeat until stopping condition

Source: [R1]



PSO movement is guided by inertia, personal best, and global best.

PSO Core Equations

Velocity update:

$$v_{id}(t+1) = v_{id}(t) + c_1 r_1 (p_{id} - x_{id}(t)) + c_2 r_2 (g_d - x_{id}(t))$$

Position update:

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1)$$

where:

- $x_{id}(t)$: position of particle i in dimension d
- $v_{id}(t)$: velocity of particle i
- p_{id}: personal best position
- g_d: global best position
- c_1, c_2: cognitive and social parameters
- $r_1, r_2 \in [0, 1]$: random factors

Source: [R1]

Interpretation of the PSO Velocity Equation

$$v_{id}(t+1) = \underbrace{v_{id}(t)}_{\text{Inertia term}} + \underbrace{c_1 r_1 \left(p_{id} - x_{id}(t)\right)}_{\text{Cognitive term}} + \underbrace{c_2 r_2 \left(g_d - x_{id}(t)\right)}_{\text{Social term}}$$

- **Inertia term**: keeps the particle moving in its current direction
- **Cognitive term**: pulls the particle toward its own best position
- **Social term**: pulls the particle toward the swarm's best position
- Random factors r_1 and r_2 add variation to the search

Source: [R1]

Why Were Refinements Added to PSO?

- The original PSO is simple and effective, but it may suffer from:
    - overly large particle movements,
    - premature convergence,
    - weak balance between exploration and exploitation.

- **Velocity clamping**: limits particle speed to avoid swarm explosion
- **Inertia weight**: controls the trade-off between global and local search
- **Neighborhood topology**: controls how quickly information spreads through the swarm

Source: [R1]

PSO: Strengths and Limitations

Strengths

- Simple to implement
- Fast convergence
- Uses memory and social learning

Limitations

- Not suitable for every problem representation
- Can converge prematurely
- Original PSO tends to focus on one optimum

Source: [R1]

ACO vs PSO: Technical Comparison

Aspect	ACO	PSO
Natural inspiration	Ant colonies	Bird flocking
Communication	Indirect (stigmergy)	Direct information sharing
Search space representation	Construction graph	n-dimensional solution space
Candidate solution	Path / tour	Particle position
Search mechanism	Probabilistic path construction	Velocity and position update
Main memory	Pheromone trails	Personal best + global best
Originally designed for	Discrete problems	Continuous problems
Typical examples	TSP, routing, scheduling	Function optimization, tuning, control

Source: [R1]

Applications of ACO and PSO

ACO

- Routing
- Scheduling
- Traveling Salesman Problem
- Bioinformatics sequence-related tasks

Source: [R1]

PSO

- Continuous optimization
- Neural network training
- Image analysis
- Biomedical and engineering optimization

How ACO Has Evolved

- To address **stagnation**, **parameter sensitivity**, and weaker performance in **dynamic settings**, later ACO research moved beyond the original formulation.
- **Adaptive / self-adaptive ACO**: adjusts search behaviour during the run
- **Collaborative / multi-population ACO**: improves diversity and robustness
- **Hybrid / memetic ACO**: combines ACO with crossover, local search, or learning
- **Dynamic ACO**: targets changing environments such as dynamic routing

Some Examples of Recent ACO Variants

- Self-Adaptive Ant Optimization (SAAO) [R3]
- Collaborative habitat-based ACO [R5]
- Learning-assisted / memetic ACO [R6], [R7]

Broader ACO evolution context: [R2]

How PSO Has Evolved

- To address **premature convergence**, **loss of diversity**, and weaker performance on **multimodal or high-dimensional problems**, later PSO research introduced richer update and learning strategies.
- **Adaptive PSO**: dynamic control of inertia and learning parameters
- **Comprehensive / heterogeneous learning**: richer learning than the classical pBest–gBest scheme
- **Multi-swarm PSO**: preserves diversity and improves search on hard landscapes
- **Hybrid PSO**: integrates PSO with other optimization strategies

Some Examples of Recent PSO Variants

- Learning-strategy PSO variants [R4]
- Adaptive benchmarked PSO [R9]
- Recent PSO innovations and trend synthesis [R10]

Broader PSO evolution context: [R4], [R10]

Performance Improvements Reported in Recent Studies

Family	Variant / year	Test setting	Metrics used	Reported improvement
ACO	SAAO (2026)	Dynamic multi-criteria TSP benchmark	Offline performance, comparative experiments, statistical validation	15–22% offline-performance improvement over four state-of-the-art algorithms
PSO	Adaptive PSO (2025)	14 benchmark functions, 30 runs	Mean, standard deviation, best value, convergence curves	Better solution accuracy than standard PSO on most tested functions; faster convergence in the reported curves

ACO evidence: [R3]

PSO evidence: [R9]

Current Trends Today

- The field has shifted from basic variants to **adaptive**, **hybrid**, and **problem-specific** designs.
- Modern ACO focuses on better pheromone control, cooperation, and dynamic optimization.
- Modern PSO focuses on richer learning strategies, diversity preservation, and scalability.
- The original ACO and PSO are still foundational, but many current methods build on them rather than using the earliest versions directly.

Sources: [R2], [R4], [R10]

Conclusion

- Swarm intelligence shows how simple local rules can produce intelligent global behaviour.
- ACO and PSO are two major swarm intelligence models with different search mechanisms.
- The original paper remains important as a foundation, but both algorithms have evolved substantially.
- Modern variants mainly aim to improve stability, adaptability, diversity, and convergence.
- ACO is more natural for path-based and combinatorial problems, while PSO is more natural for vector-based and continuous optimization.

Sources: [R1], [R2], [R4], [R10]

References

R1 Ahmed, H., & Glasgow, J. (2012). *Swarm Intelligence: Concepts, Models and Applications*. Technical Report 2012–585, Queen's University.

R2 Blum, C. (2024). Bibliometric review of ant colony optimization and its development trends.

R3 Recent self-adaptive ACO study (2026) on dynamic multi-criteria TSP; reports 15–22% offline-performance improvement.

R4 Recent review of PSO learning strategies (2025) with comparative experimental evaluation.

R5 Recent collaborative habitat-based ACO variant (2026).

R6 Recent learning-assisted ACO variant (2026).

R7 Recent memetic ACO variant (2026).

R8 Visualize It – Ant Colony Optimization simulation (educational visualization).

R9 Recent adaptive PSO benchmark study (2025) using mean, standard deviation, best value, and convergence curves.

R10 Recent PSO innovations / trends survey (2026).