

ANT COLONY OPTIMIZATION

Swarm Inspired Methods

- Artificial life
- Social biological systems, group behaviour
- Swarm Intelligence
- Two approaches applying swarm intelligence to optimization problems
 - Ant Colony Optimization
 - Swarm Particle Optimization

Ant Colony Optimization

- Introduced first in 1991 by M. Dorigo, V. Maniezzo, and A. Colorni.
- Inspired from Ant searching for food and finding the shortest path back home.
- Randomly exploring the search space while using the elements from the previous solutions.

Combinatorial Optimization Problems

- $C = c_1, \dots, c_n$ basic components
 S a solution: subset of components
 $F \subseteq \wp(C)$ subset of feasible solutions
 $z: \wp(C) \rightarrow \mathbb{R}$ cost function
- find S^* such that
 $S^* \in F$, and $z(S^*) \leq z(S) \quad \forall S \in F$

Basic Components of AOC

- A set of concurrent computation agents (Ants)
- Each ant moves based on a stochastic local decision based on:
 - trails (globally affected)
 - attractiveness (locally affected)
- Global mechanisms
 - trail evaporation
 - daemon actions

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- Ants iteratively constructs the solution by local choices from state i to state j
 - At each step σ , ant k computes a set of feasible expansions $A_k^\sigma(i)$ from its state.
 - Probability of moving from state i to state j $p_{i \rightarrow j}^k$ depends on:
 - Attractiveness $\eta_{i \rightarrow j}$ of the move
 - trail level $\tau_{i \rightarrow j}$ of the move

Ant System

- The first idea applied
- Each move is based on a local probability value:

$$p_{i \rightarrow j}^k = \begin{cases} \frac{\tau_{i \rightarrow j}^\alpha + \eta_{i \rightarrow j}^\beta}{\sum_{(i \rightarrow l) \notin \text{tabu}_k} (\tau_{i \rightarrow l}^\alpha + \eta_{i \rightarrow l}^\beta)} & \text{if } (i \rightarrow j) \notin \text{tabu}_k \\ 0 & \text{otherwise} \end{cases}$$

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- Trail levels are updated based on the tour length of previous solution and evaporation:

$$\tau_{i \ j}(t) = \rho \tau_{i \ j}(t-1) + \Delta \tau_{i \ j}$$

$$\Delta \tau_{i \ j} = \sum_{k=1}^m \Delta \tau_{i \ j}^k$$

$$\Delta \tau_{i \ j}^k = \begin{cases} \frac{Q}{L_k} & \text{if ant } k \text{ uses arc } (i \ j) \text{ in its tour} \\ 0 & \text{otherwise} \end{cases}$$

Any System Algorithm

1. Initialization

Initialize τ_{ij} and η_{ij} values

2. Construction

foreach ant k (in state i) do:

repeat

choose the state j to move to (with prob.)

Append the chosen move to tabu_k

Until ant k has completed its solution

3. Trail update

for each ant move ($i j$) do:

compute $\Delta\tau(i j)$

update trail matrix

4. Termination

if not end of test, go to step 2

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- Ant system could not produce competitive results:
 - All solutions, good or bad, contribute on the trails.
 - Pressure of transition probability is diverse (uniform probability or single edge takeover)
 - No local improvement
 - Extensions:
 - Elitist Ant System (the elite updates trails at each cycle)
 - Ant Colony System
 - Max Min Ant System (max and min pheromone)

Ant Colony System

- 3 basic changes from Ant System:
 - Pheromone, trail update (best updates)
 - State transition rule (choice of exploration vs. exploitation)
 - Hybridization
- Competitive results (ie. known best values for TSP) found.

ACS: Pheromone

- Ant System: everyone updates pheromone trails globally.
- Ant Colony System: the current best since the beginning updates trails globally at each cycle.
- Search focuses around the current best.
- Local update and evaporation: only if an ant traverses that edge.

$$\tau_{ij}(t) = \rho \tau_{ij}(t-1) + (1-\rho) \tau_0$$

$$\tau_0 = \frac{1}{n L_{nn}}, \quad L_{nn}: \text{base (greedy) solution}$$

- Unvisited edges stays at τ_0 , visited gets smaller.
- Max-Min ant system uses similar upper-lower bounds.

ACS: Transition Rule

- Ant System: probability proportional to trail and attractiveness.
- Ant Colony System: *pseudo-random-proportional*.
- A choice is made among the best transition and probabilistically among others.

$$s = \begin{cases} \max_{(i \rightarrow s) \notin \text{tabu}_k} \{ \tau_{i \rightarrow j}^\alpha + \eta_{i \rightarrow j}^\beta \} & \text{if } q \leq q_0 & (\text{exploit}) \\ \text{proportional to weighted values} & \text{otherwise} & (\text{explore}) \end{cases}$$

q : random value such that $0 \leq q \leq 1$

ACS: Hybridization

- Performing repairs on found individuals
- 2-opt, 3-opt, Lin-Kernighan
- Keep a list of preferred cities at each city (tabu search, etc).