Lecture Series on

Intelligent Control

Lecture 28
Ant Colony System Algorithm

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ANT COLONY SEARCH ALGORITHMS IN POWER SYSTEM OPTIOMIZATION

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K. Y. Lee and M.A. El-Sharkawi (Editors)
IFAC Tutorial on Evolutionary Computation Techniques for Power System Optimization, Seoul, Korea, September 15-18, 2003, Chapter 6.

K. Y. Lee and M.A. El-Sharkawi (Editors)
Modern Heuristic Optimization Techniques, Wiley-Interscience, 2008, Chapter 5, pp. 89-100.

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Outline of Presentation

1. INTRODUCTION
2. BEHAVIOUR OF REAL ANTS
3. A SIMPLE ANT COLONY ALGORITHM
4. MAJOR CHARACTERISTICS OF ANT COLONY SEARCH ALGORITHM
5. CASE STUDY
6. CONCLUSIONS

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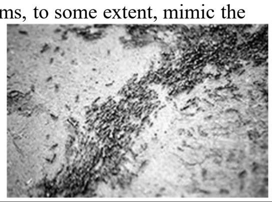
1. INTRODUCTION

Ant Colony Search (ACS) studies artificial systems that take inspiration from the behavior of real ant colonies and are used to solve function or combinatorial optimization problems.

Ant colony search algorithms, to some extent, mimic the behavior of real ants.



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2. BEHAVIOUR OF REAL ANTS

- As is well known, real ants can find *shortest path* from food sources to the nest without using visual cues.
- They are also capable of *adapting to changes* in the environment, for example, finding a new shortest path once the old one is no longer feasible due to a new obstacle.

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2. BEHAVIOUR OF REAL ANTS

- The studies by ethnologists reveal that such capabilities ants have are essentially due to what is called "pheromone trail," which ants use to communicate information among individuals regarding path and to decide where to go.
- Ants deposit a certain amount of *pheromone* while walking, and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one.

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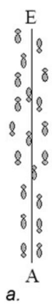
2. BEHAVIOUR OF REAL ANTS



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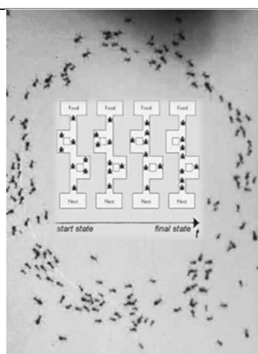
2. BEHAVIOUR OF REAL ANTS



The main quality of the colonies of insects, ants or bees lies in the fact that they are part of a self-organized group in which the keyword is simplicity.

Every day, ants solve complex problems due to a sum of simple interactions, which are carried out by individuals.

The ant is, for example, able to use the quickest way from the anthill to its food simply by following the way marked with pheromones.

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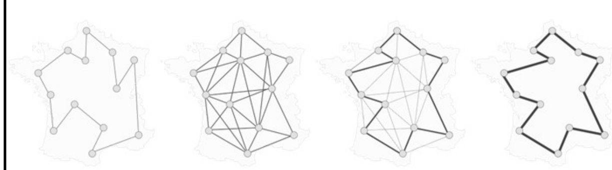
2. BEHAVIOUR OF REAL ANTS



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The ant colony optimization of the travelling salesman problem *Author:* Johann Dréo (User:Nojhan) *Date:* 29 may 2006 *Notes:* 1) an ant choose a path among other, and lay a pheromonal trail on it. 2) all the ants are travelling some paths, laying a trail proportionnal to the quality of the solution. 3) each edge of the best path is more reinforced than others. 4) evaporation ensures that the bad solutions disappear.

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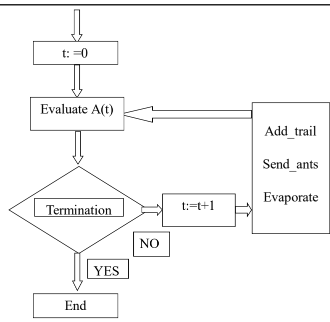
3. A SIMPLE ANT COLONY ALGORITHM



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3. A SIMPLE ANT COLONY ALGORITHM

Major steps of ACSA:

(1) Initialize A(t): The parameters to be optimized are encoded as a real number. Before each run, the initial populations (Nest) of the colony are generated randomly within the feasible region which will crawl to different directions at a radius not greater than R.

(2) Evaluate A(t): The fitness of all ants are evaluated based on their objective function.

(3) Add_trail: Trail quantity is added to the directions the ants have selected in proportion to the ants' fitness.

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3. A SIMPLE ANT COLONY ALGORITHM

(4) Send_ants A(t): According to the objective function, their performance will be weighed as fitness value, which influences the level of trail quantity addition to the directions the ants have selected. (The details will be given.)

(5) Evaporate: Finally, the pheromone trail secreted by an ant eventually evaporates and the starting point (nest) is updated with the best tour found.

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3. A SIMPLE ANT COLONY ALGORITHM

The details of step (4):

Each ant chooses the next node to move considering two parameters:

- the visibility of the node
- the intensity of trail previously laid by other ants.

The *send_ants operation* sends ants by selecting directions using Tournament selection based on the two parameters.

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3. A SIMPLE ANT COLONY ALGORITHM

The details of step (4):

The *k*-th ant starting from node *i* decides to move to node *j* on the basis of *Probability,* defined as follows:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in \text{allowed}_k \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

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3. A SIMPLE ANT COLONY ALGORITHM

Where: visibility

$$\eta_{ij} = |\mu - \Delta F| \quad (2)$$

Move value, ΔF = original total cost - new total cost

μ, α, β are the heuristically defined parameters.

μ is used for cost setting,

$0 < \alpha < 1$ is a pheromone decay parameter

β is a parameter which determines the relative importance of pheromone versus distance.

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3. A SIMPLE ANT COLONY ALGORITHM

Trail Intensity $\tau_{ij}(t)$ on edge (i,j) at time t.

Each ant at time t chooses the next node, where it will be at time t+1. For 1 iteration of ant colony search algorithm, m moves are carried out by m ants in the interval (t, t+1), then for every n iterations of the algorithm each ant has completed a *tour*. At this point the trail intensity is updated as:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij} \qquad (3)$$

where: ρ is a coefficient of persistence of the trail during a cycle which is heuristically defined.

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3. A SIMPLE ANT COLONY ALGORITHM

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \qquad (4)$$

where: $\Delta\tau_{ij}^{k}$ is the quantity of substance laid on edge (i,j) by the k-th ant between time t and $t+n$.

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4. MAJOR CHARACTERISTICS OF ANT COLONY SEARCH ALGORITHM

Some attractive properties of ant colony search algorithm:

(i) *Distributed Computation* - Avoid Premature Convergence:

The power of the *massive parallelism* in ACSA can deal with incorrect, ambiguous or distorted information which are often found in nature. The computational model contains the dynamics which is determined by the nature of local interactions between many elements (artificial ants).

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4. MAJOR CHARACTERISTICS OF ANT COLONY SEARCH ALGORITHM

(ii) Positive Feedback - Rapid Discovery of Good Solution:

As the search proceeds, the new population of ants often containing the states of higher fitness will affect the search behavior of others and will eventually gain control over other agents, while at the same time actively exploiting inter-ant communication by mean of the pheromone trail laid on the path. The artificial ant foraging behavior dynamically reduces the prior uncertainty about the problem at hand.

Therefore, the emerging collective effect is in a form of *autocatalytic behavior*, in that the more ants following a particular path, the more attractive this path becomes for the next ants. It can give rise to global behavior in the colony.

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4. MAJOR CHARACTERISTICS OF ANT COLONY SEARCH ALGORITHM

(iii) Use of Constructive Greedy Heuristic - Find Acceptable Solutions:

It uses *only* the objective function to guide the search, and does not need any other auxiliary knowledge.

Such capabilities are essentially due to what is called "pheromone trails," which ants use to communicate information among individuals regarding path and to decide where to go.

Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one.

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5. CASE STUDY

Case Study 1 - Short-term generation scheduling of thermal units.

Objective function : $F = \sum_{j=1}^{T}\left[\sum_{i \in G} f_i(P_{ij}) + C(j,k)\right]$

where, G : number of generating units

T : the time horizon of interest (24 hours)

$f_i = a_i + b_i P_{ij} + c_i P_{ij}^2 \, [\hbar / hr]$

P_{ij} : real power output of the *i*-th unit in the *j*-th stage

$C(j,k) \in \{C_T(j,k), C_P(j,k)\}$

$C_T(j,k)$, $C_P(j,k)$: transition and penalty cost from stage *j* to *k*

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5. CASE STUDY

Subject to:

(a) Real power balance constraint

$$\sum_{i \in G} P_{ij} = P_{Dj} + P_{Lj} \quad , j \in T$$

where, P_{Dj}, P_{Lj} are the total demand and the transmission loss in the area at the j-th stage

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5. CASE STUDY

(b) Real power operating limits of generating units

$$P_i^{\min} \le P_{ij} \le P_i^{\max} \quad , i \in G, j \in T$$

where, $P_i^{\min}, P_i^{\max}$ are the minimum and the maximum real power outputs of the i-th unit

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5. CASE STUDY

(c) Spinning reserve constraint

$$\left(\sum_{i=1}^{G} u_{ij} P_i^{\max} - P_{Dj}\right) / P_{Dj} \ge 0.1, j \in T$$

where, u_{ij} is the status index of the i-th unit at the j-th stage (1 for up and 0 for down).

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5. CASE STUDY

(d) Minimum up time of units

$$(u_{ij} - u_{i,j-1})(w_{i,j-1} - \tau h_i) \leq 0, i \in G, j \in T$$

where, τh_i is the minimum up time of the *i*-th unit and

$$w_{ij} = u_{ij}(w_{i,j-1} + 1)$$

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5. CASE STUDY

(e) Minimum down time of units

$$(u_{ij} - u_{i,j-1})(q_{i,j-1} - \tau l_i) \geq 0, i \in G, j \in T$$

where, τl_i is the minimum down time of the *i*-th unit and

$$q_{ij} = (1 - u_{ij})(q_{i,j-1} + 1)$$

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5. CASE STUDY

(f) Maximum operating time of units

$$u_{ij,}(v_{i,j-1} - \tau u_i) \leq 0, i \in G, j \in T$$

where, τu_i is the maximum operating time of the *i*-th unit and

$$v_{ij} = u_{ij}(v_{i,j-1} + 1)$$

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5. CASE STUDY

To consider all the constraints mentioned above, the generation scheduling problem could be modeled in a form of dynamic process as follows:

$$F_j\,({}^{j}U^{l}) = Min.\{\Phi^{l}_{j}\,({}^{j-1}U^{k}, {}^{j}U^{l})\},\, j \in T \quad (17)$$

Subject to the constraints (a) -(f)

where,

$$\Phi^{l}_{j}({}^{j-1}U^{k}, {}^{j}U^{l}) = \sum_{i\in G} f_i(P_{ij}) + \sum_{i\in G} SC_i(q_{i,j-1}) + \\ + \sum_{i\in G} DC_i + C_P(k,l) + F_{j-1}({}^{j-1}U^{k}) \quad (18)$$

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5. CASE STUDY

The ACSA works in this application as follows:

a) form the traveling salesman type of search space for the Generation Scheduling Problem (GSP)
b) *m* ants are initially positioned on *n* states chosen according to some initialization rule
c) each ant builds a tour by repeatedly applying the state transition rule
d) while constructing its tour, an ant changes the amount of pheromone on the visited edges by applying the local updating rule

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5. CASE STUDY

e) once all ants have terminated their tour, the amount of pheromone modified again by applying the global updating rule.
f) seek the best tour using the solution process, in which ants are guided in building their tours by both heuristic information and by pheromone information. An edge with a high amount of pheromone is a very desirable choice
g) the pheromone updating rules are designed so that they tend to give more pheromone to edges which should be visited by ants

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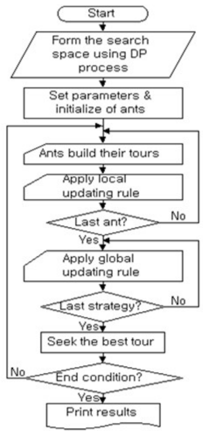

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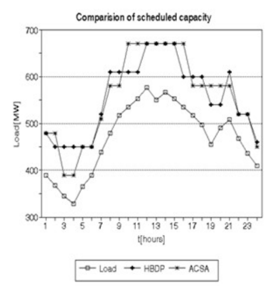
5. CASE STUDY

The results of the proposed algorithm to 6-unit model power system are presented.



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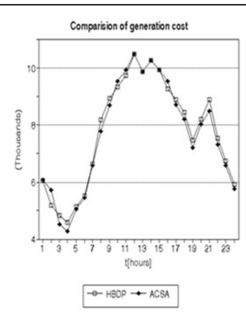
5. CASE STUDY



Comparison of generation costs of the 6-unit system

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5. CASE STUDY

Case Study 2 - Combined heat and power dispatch

The combined heat and power (CHP) dispatch problem in a system is to determine the unit heat and power production so that the system production cost is minimized while the heat and power demands and other constraints are met.

The power outputs of electricity units and heat units are restricted by their own upper and lower limits. The combined heat and power dispatch problem can be formulated as follows:

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5. CASE STUDY

Minimize $\sum_{i=1}^{n_p} c_i(p_i) + \sum_{j=1}^{n_c} c_j(h_j, p_j) + \sum_{k=1}^{n_h} c_k(h_k)$

S.T. $\sum_{i=1}^{n_p} p_i + \sum_{j=1}^{n_c} p_j = p_d$

$$\sum_{j=1}^{n_c} h_j + \sum_{k=1}^{n_h} h_k = h_d$$

$$p_i^{\min} \le p_i \le p_i^{\max}, i = 1,\dots,n_p$$

$$p_j^{\min}(h_j) \le p_j \le p_j^{\max}(h_j), j = 1,\dots,n_c$$

$$h_j^{\min}(p_j) \le h_j \le h_j^{\max}(p_j), j = 1,\dots,n_c$$

$$h_k^{\min} \le h_k \le h_k^{\max}, k = 1,\dots,n_h$$

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5. CASE STUDY

A test system containing a set of 4 generators is used to illustrate the performance of the proposed method.

Unit 1 is for power generation only and unit 4 for heat generation only. Units 2 and 3 are co-generation units. There corresponding production cost functions are given below.

$$c_1 = 50 p_1$$

$$c_2 = 2650 + 14.5 p_2 + 0.0345 p_2^2 + \\ + 4.2 h_2 + 0.03 h_2^2 + 0.031 p_2 h_2$$

$$c_3 = 1250 + 36 p_3 + 0.0435 p_3^2 + 0.6 h_3 + \\ + 0.027 h_3^2 + 0.011 p_3 h_3$$

$$c_4 = 23.4 h_4$$

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5. CASE STUDY

The constraints for units 1 and 4 are

$$0.0 \le h_4 \le 2695.2MWth$$

$$0.0 \le p_1 \le 150MW$$

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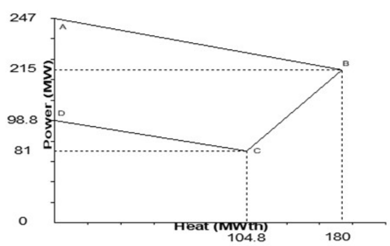
5. CASE STUDY

The constrains for units 2 and 3:



Heat-power feasible region for the co-gen. unit 2.

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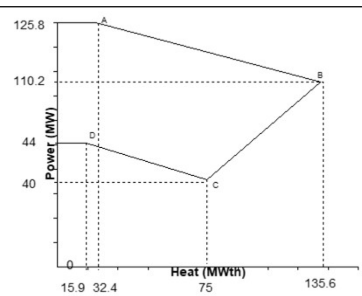
5. CASE STUDY



Heat-power feasible region for the co-gen. unit 3.

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5. CASE STUDY

The following ACSA parameters are chosen for this problem:

Number of ants =10;
Max Generation number=100;
Number of intermediate steps=5,

α = 0.5,
β = 0.05,
μ = 10,
q = 0.5,
Q = 50.

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5. CASE STUDY

Table 1 Test results in comparison with a GA-based approach.

	Unit 1 power	Unit 2 power	Unit 2 heat	Unit 3 power	Unit 3 Heat	Unit 4 heat	Total Power	Total Heat	Total Cost ($)
GA[9]	0.00	160.00	40.00	40.00	75.00	0.00	200.00	115.00	9527.00
ACSA	0.08	150.93	48.84	49.00	65.79	0.37	200.00	115.00	9452.20

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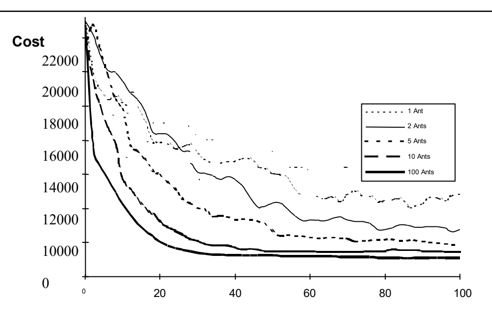
5. CASE STUDY



Evolutionary process of ACSA for different number of population

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6. CONCLUSIONS

- This paper presents the applications of a search methodology - Ant Colony Search Algorithm - based on a distributed autocatalytic process.
- The individual ants are rather simple, however, the entire colony foraging towards the bait site can exhibit complicated dynamics resulting in a very attractive search capability.

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6. CONCLUSIONS

- The results obtained clearly show the Ant Colony Search Algorithm converges to the optimum solution through an autocatalytic process. The massive parallel agent co-operation makes the ants able to jump over the local optimum and to identify the right cluster easily, hence, a good solution can be found.
- Two examples demonstrate the algorithm's feasibility in power system optimization.

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