Ant Colony Optimization

Part 1: Introduction

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Introduction

Swarm Intelligence

- **Swarm intelligence** (**SI**) is artificial intelligence based on the collective behavior of decentralized, self-organized systems.
- The expression was introduced by **Gerardo Beni** and **Jing Wang** in 1989.
- The natural examples of SI includes the behaviors of certain **ants**, **honeybees**, **wasps**, **beetles**, **caterpillars**, and **termites**

Swarm Intelligence

- Example of swarm intelligence algorithms:
  - **Ant colony optimization**
  - **Particle swarm optimization**
  - **Stochastic diffusion search**
  - **Swarm robotics**

Ant Colony Optimization

- **Ant Colony Optimization (ACO)** is inspired by the foraging behavior of ant colonies
- ACO algorithms are used for solving discrete optimization problems.
- ACO is one of the most successful examples of metaheuristic algorithms.

Ant Colony Optimization

- Examples of ACO algorithms
  - Ant System (AS)
  - Elitist Ant System (EAS)
  - Rank-Based Ant System (ASrank)
  - Min-Max Ant System (MMAS)
  - Ant Colony System (ACS)
  - Approximate Nondeterministic Tree Search (ANTS)
  - Hyper-Cube Framework

ACO Brief History

- **1989 & 1990**:
  - By **Goss et al.** & **Deneuborg et al.**
  - Experiments with Argentine ants
  - The ants prefer the shortest path from the nest to the food source
- **1991**:
  - By **Dorigo et. al.**
  - Ant System (AS) was the first ACO algorithm presented for shortest paths
- **1998**:
  - **Ant Colony Optimization** is the name given by **Dorigo** (Milan, Italy),
  - A class of algorithms whose first member was AS.

ACO Applications

Problem type	Problem name	Main references
Routing	Traveling salesman	Dorigo, Maniezzo, & Colorni (1991a,b, 1996) Dorigo (1992) Gambardella & Dorigo (1995) Dorigo & Gambardella (1997a,b) Stützle & Hoos (1997, 2000) Bullnheimer, Hartl, & Strauss (1999c) Cordón, de Viana, Herrera, & Morena (2000)
	Vehicle routing	Bullnheimer, Hartl, & Strauss (1999a,b) Gambardella, Taillard, & Agazzi (1999) Reimann, Stummer, & Doerner (2002)
	Sequential ordering	Gambardella & Dorigo (1997, 2000)

ACO Applications

Problem type	Problem name	Main references
Assignment	Quadratic assignment	Maniezzo, Colorni, & Dorigo (1994) Stützle (1997b) Maniezzo & Colorni (1999) Maniezzo (1999) Stützle & Hoos (2000)
	Graph coloring	Costa & Hertz (1997)
	Generalized assignment	Lourenço & Serra (1998, 2002)
	Frequency assignment	Maniezzo & Carbonaro (2000)
	University course timetabling	Socha, Knowles, & Sampels (2002) Socha, Sampels, & Manfrin (2003)

ACO Applications

Problem type	Problem name	Main references
Scheduling	Job shop	Colorni, Dorigo, Maniezzo, & Trubian (1994)
	Open shop	Pfahringer (1996)
	Flow shop	Stützle (1998a)
	Total tardiness	Bauer, Bullnheimer, Hartl, & Strauss (2000)
	Total weighted tardiness	den Besten, Stützle, & Dorigo (2000) Merkle & Middendorf (2000, 2003a) Gagné, Price, & Gravel (2002)
	Project scheduling	Merkle, Middendorf, & Schmeck (2000a, 2002)
	Group shop	Blum (2002a, 2003a)

ACO Applications

Problem type	Problem name	Main references
Subset	Multiple knapsack	Leguizamón & Michalewicz (1999)
	Max independent set	Leguizamón & Michalewicz (2000)
	Redundancy allocation	Liang & Smith (1999)
	Set covering	Leguizamón & Michalewicz (2000) Hadji, Rahoual, Talbi, & Bachelet (2000)
	Weight constrained graph tree partition	Cordone & Maffioli (2001)
	Arc-weighted *l*-cardinality tree	Blum & Blesa (2003)
	Maximum clique	Fenet & Solnon (2003)

ACO Applications

Problem type	Problem name	Main references
Machine learning	Classification rules	Parpinelli, Lopes, & Freitas (2002b)
	Bayesian networks	de Campos, Gámez, & Puerta (2002b)
	Fuzzy systems	Casillas, Cordón, & Herrera (2000)
Network routing	Connection-oriented network routing	Schoonderwoerd, Holland, Bruten, & Rothkrantz (1996) Schoonderwoerd, Holland, & Bruten (1997) White, Pagurek, & Oppacher (1998) Di Caro & Dorigo (1998d) Bonabeau, Henavy, Guérin, Snyers, Kuntz, & Theraulaz (1998)
	Connectionless network routing	Di Caro & Dorigo (1997, 1998c,f) Subramanian, Druschel, & Chen (1997) Heusse, Snyers, Guérin, & Kuntz (1998) van der Put (1998)
	Optical network routing	Navarro Varela, & Sinclair (1999)

Real Ants

Stigmergy

- Ant colonies, in spite of the simplicity of their individuals, present a highly structured social organization.
- As a result of this organization, ant colonies can accomplish complex.
- Ants coordinate their activities via **stigmergy**

Stigmergy

- Stigmergy is a form of **indirect communication** mediated by modifications of the environment.
  - an individual modifies the environment
  - other individuals respond to that change at a later time
- The environment mediates the communication among individuals
- A foraging ant deposits a chemical on the ground which increases the probability that other ants will follow the same path.

Pheromones

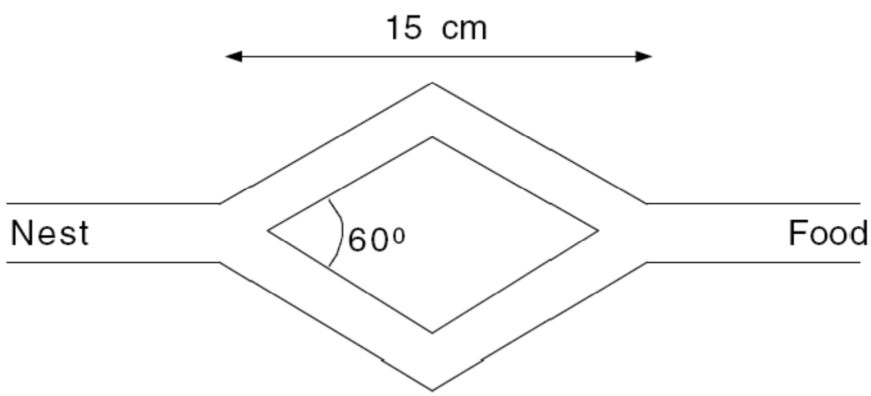
- The communication among individuals, or between individuals and the environment, is based on the use of chemicals produced by the ants.
- These chemicals are called **pheromones**.
- **Trail pheromone** is a specific type of pheromone that some ants use for marking paths on the ground, for example, paths from food sources to the nest.

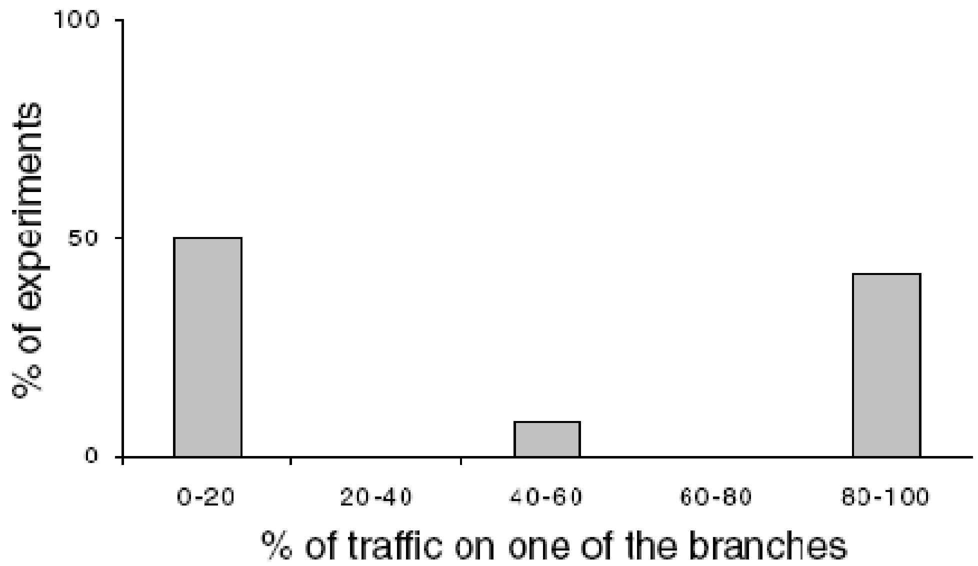
Double Bridge Experiments

- **Deneubourg** and colleagues have shown that foraging ants can find the shortest path between their nest and a food source
- They used a double bridge connecting a nest of ants and a food source.
- They ran experiments varying the length of the two branches of the double bridge.

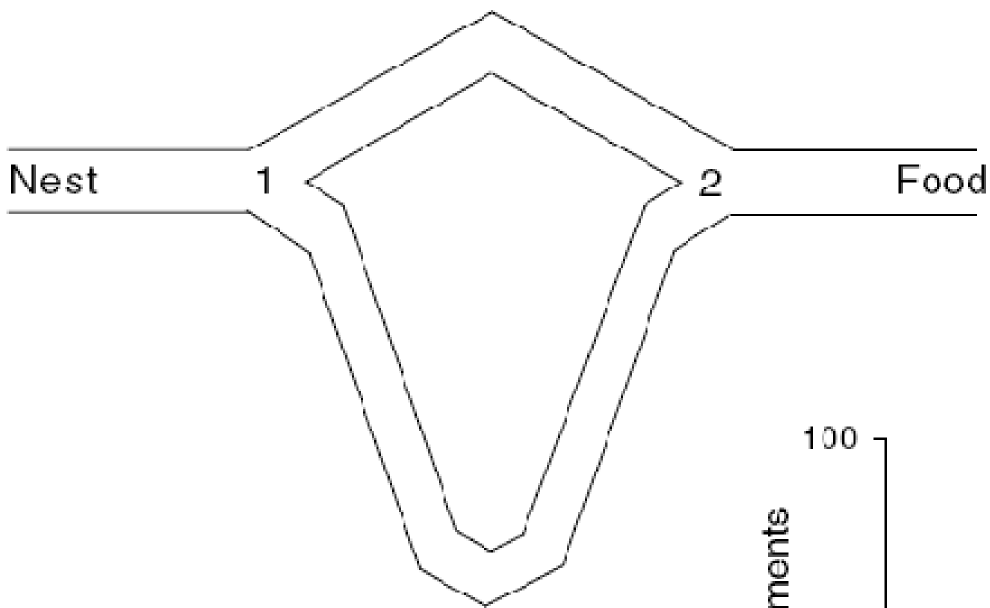
Double Bridge Experiments

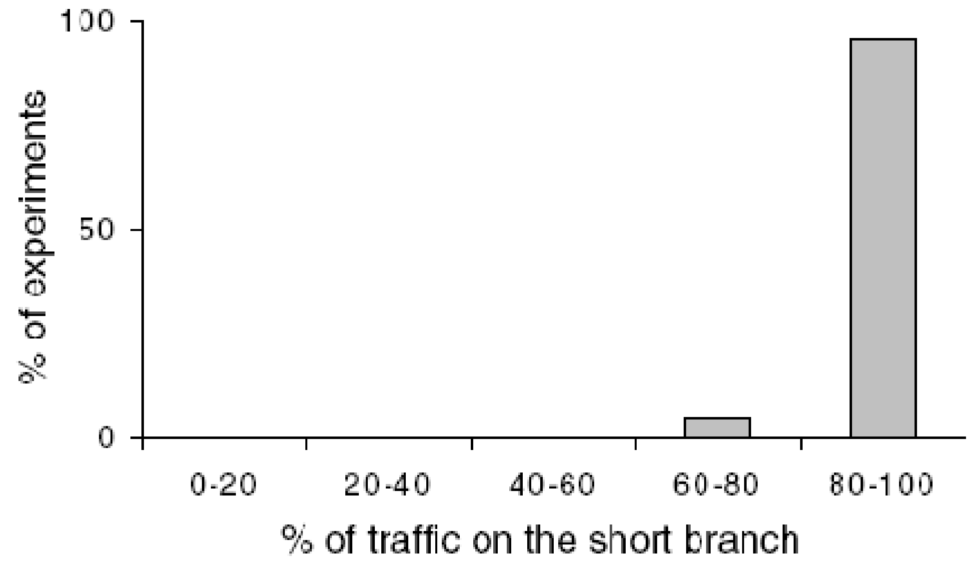
First Experiment



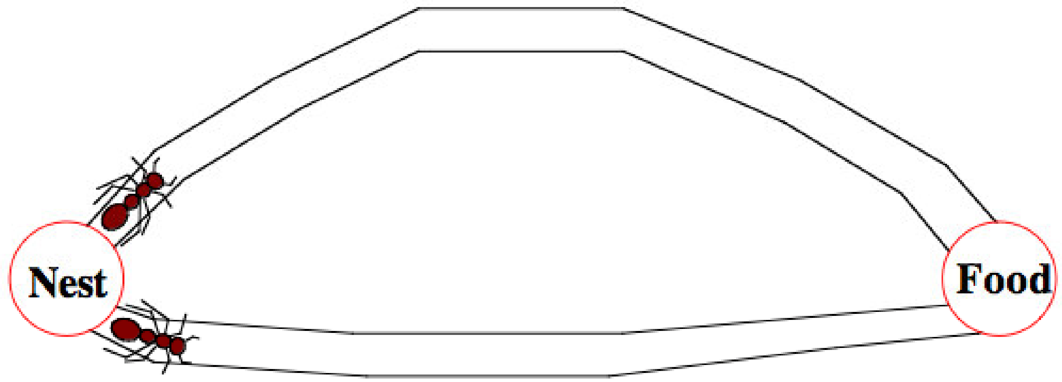


Second Experiment



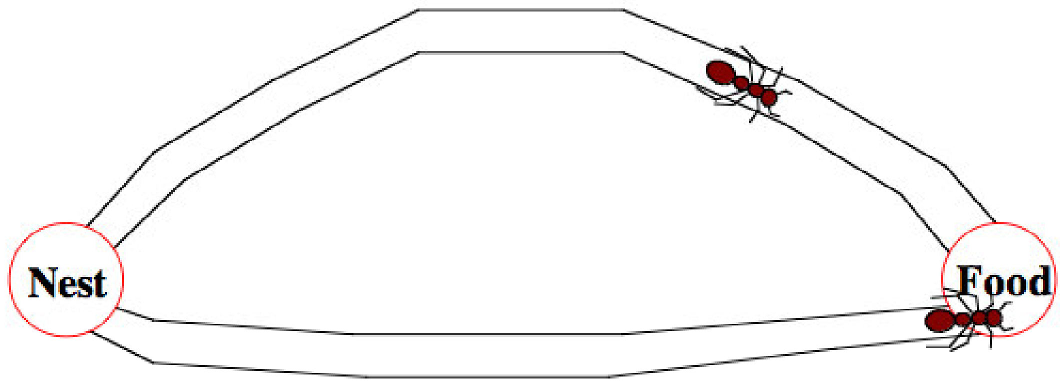


Foraging behavior of Ants



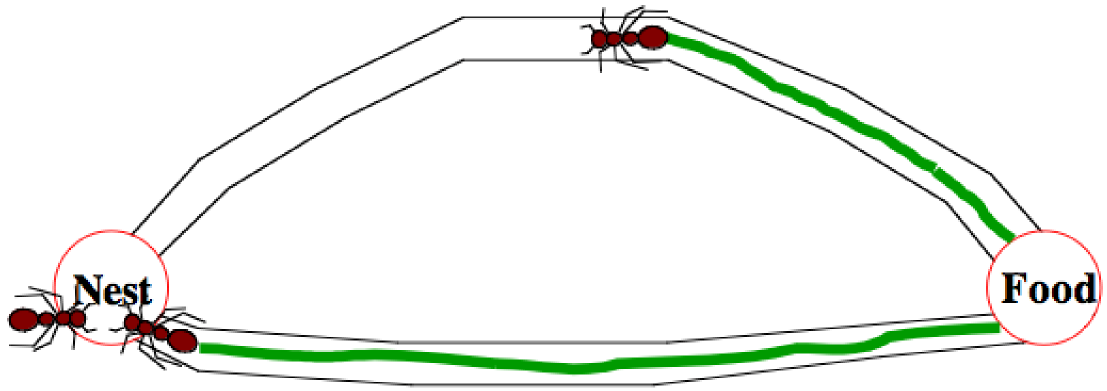
- 2 ants start with equal probability of going on either path.

Foraging behavior of Ants



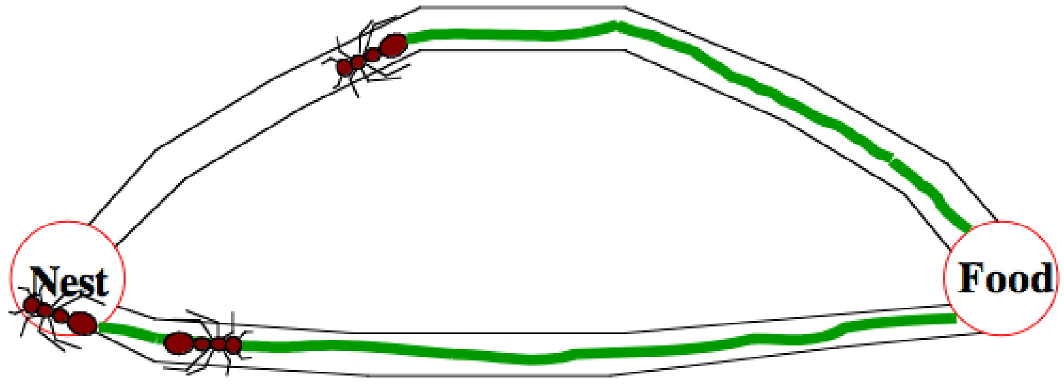
- The ant on shorter path has a shorter to-and-fro time from it’s nest to the food.

Foraging behavior of Ants



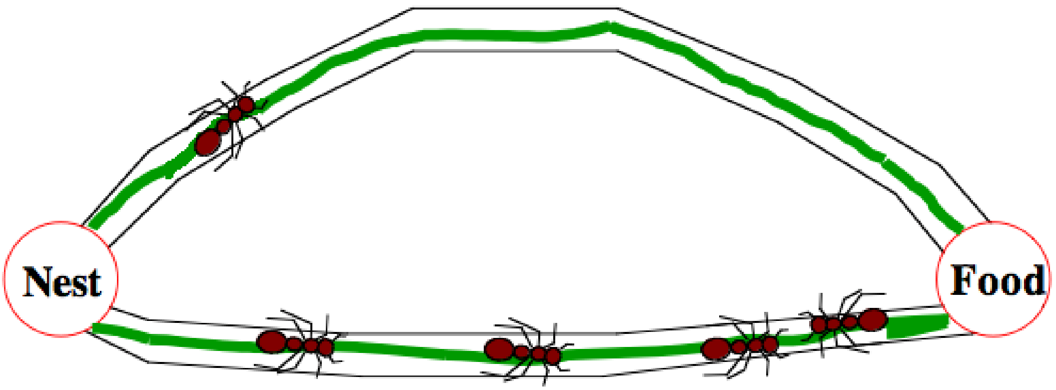
- The density of pheromone on the shorter path is higher because of 2 passes by the ant (as compared to 1 by the other).

Foraging behavior of Ants



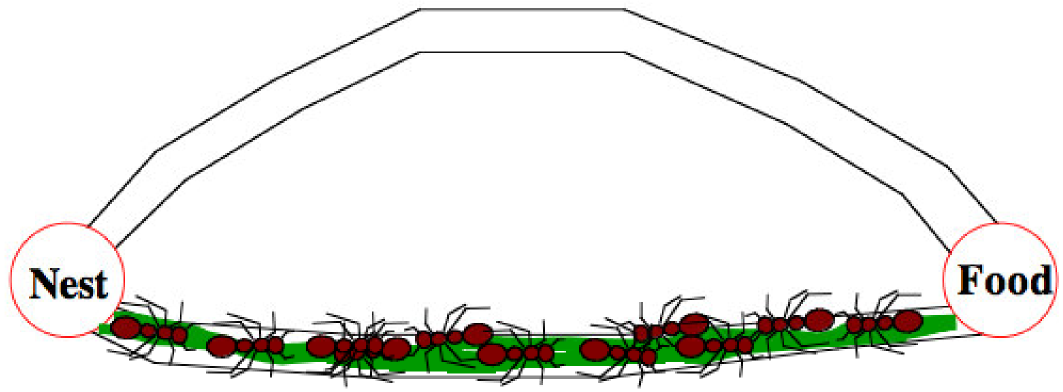
- The next ant takes the shorter route.

Foraging behavior of Ants



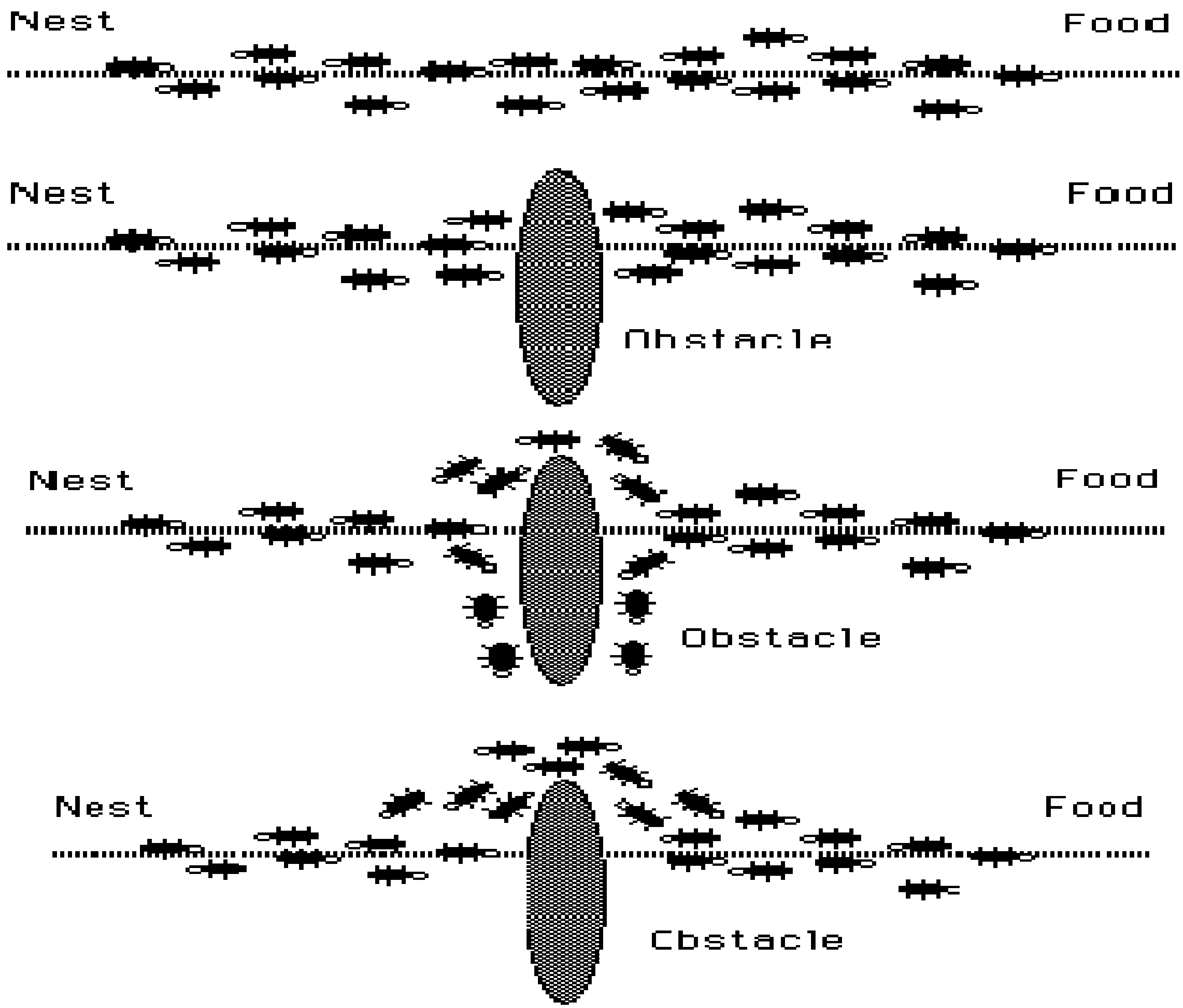
- Over many iterations, more ants begin using the path with higher pheromone, thereby further reinforcing it.

Foraging behavior of Ants



- After some time, the shorter path is almost exclusively used.

Foraging behavior of Ants



Inspiring Source of ACO

- This collective trail-laying and trail-following behavior whereby an ant is influenced by a chemical trail left by other ants is the inspiring source of ACO.

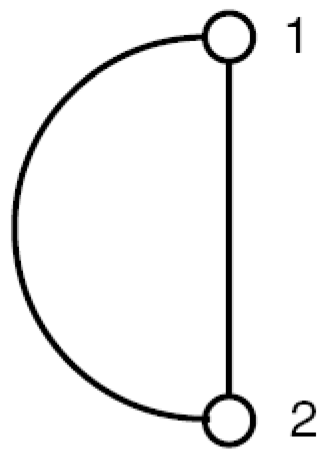
Artificial Ants

Artificial Ants

- The **double bridge experiments** show clearly that ant colonies have a built-in optimization capability
- By the use of probabilistic rules based on local information they can find the shortest path between two points in their environment.
- It is possible to design **artificial ants** that, by moving on a graph modeling the double bridge, find the shortest path between the two nodes corresponding to the nest and to the food source.

Artificial Ants

- As a first step toward the definition of artificial ants, consider this graph



- The graph consists of two nodes (1 and 2, representing the nest and the food respectively)

Artificial Ants

- The nodes are connected by a **short** and a **long** arc
- In the example the long arc is **r times** longer than the short arc, where r is an integer number.
- We assume the time to be discrete (t = 1, 2, …) and that at each time step each ant moves toward a neighbor node at constant **speed of one unit of length per time unit**.

Artificial Ants

- Ants add **one unit of pheromone** to the arcs they use.
- Ants move on the graph by choosing the path probabilistically:
  - $P_{is}(t)$ is the probability for an ant located in node i at time t to choose the short path, and
  - $P_{il}(t)$ the probability to choose the long path.
- These probabilities are a function of the pheromone trails φ_{ia} that ants in node i

Artificial Ants

- The probabilities

$$p_{is}(t) = \frac{[\varphi_{is}(t)]^{\alpha}}{[\varphi_{is}(t)]^{\alpha} + [\varphi_{il}(t)]^{\alpha}}$$

$$p_{il}(t) = \frac{[\varphi_{il}(t)]^{\alpha}}{[\varphi_{is}(t)]^{\alpha} + [\varphi_{il}(t)]^{\alpha}}$$

Artificial Ants

- Trail update on the two branches is performed as follows:

$$\varphi_{is}(t) = \varphi_{is}(t-1) + p_{is}(t-1)m_i(t-1) + p_{js}(t-1)m_j(t-1),$$
$$(i = 1, j = 2; i = 2, j = 1),$$

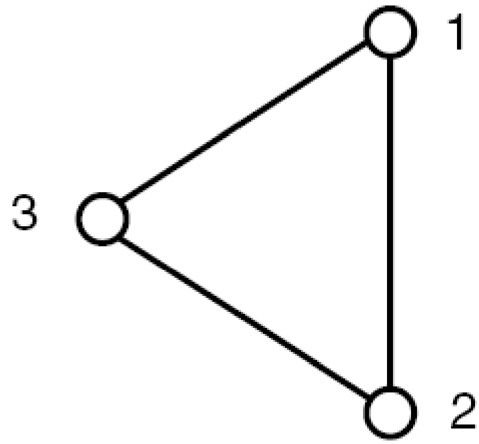
$$\varphi_{il}(t) = \varphi_{il}(t-1) + p_{il}(t-1)m_i(t-1) + p_{jl}(t-r)m_j(t-r),$$
$$(i = 1, j = 2; i = 2, j = 1),$$

  – Where $m_i(t)$ the number of ants on node i at time t, is given by

$$m_i(t) = p_{js}(t-1)m_j(t-1) + p_{jl}(t-r)m_j(t-r),$$
$$(i = 1, j = 2; i = 2, j = 1).$$

Artificial Ants

- Another way of modeling:

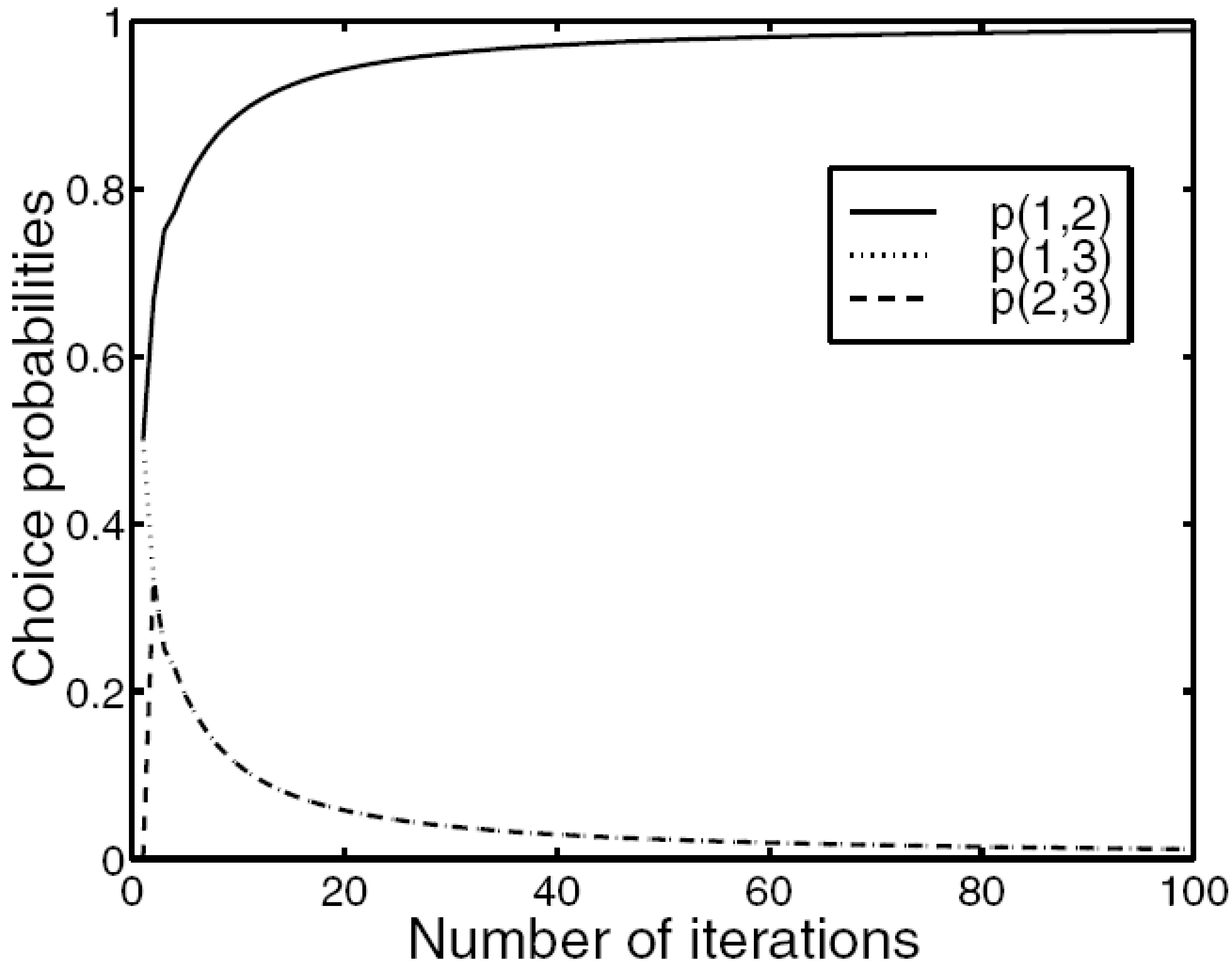


- In this model each arc of the graph has the same length, and a longer branch is represented by a sequence of arcs.
- In the figure, for example, the long branch is twice as long as the short branch.

Artificial Ants

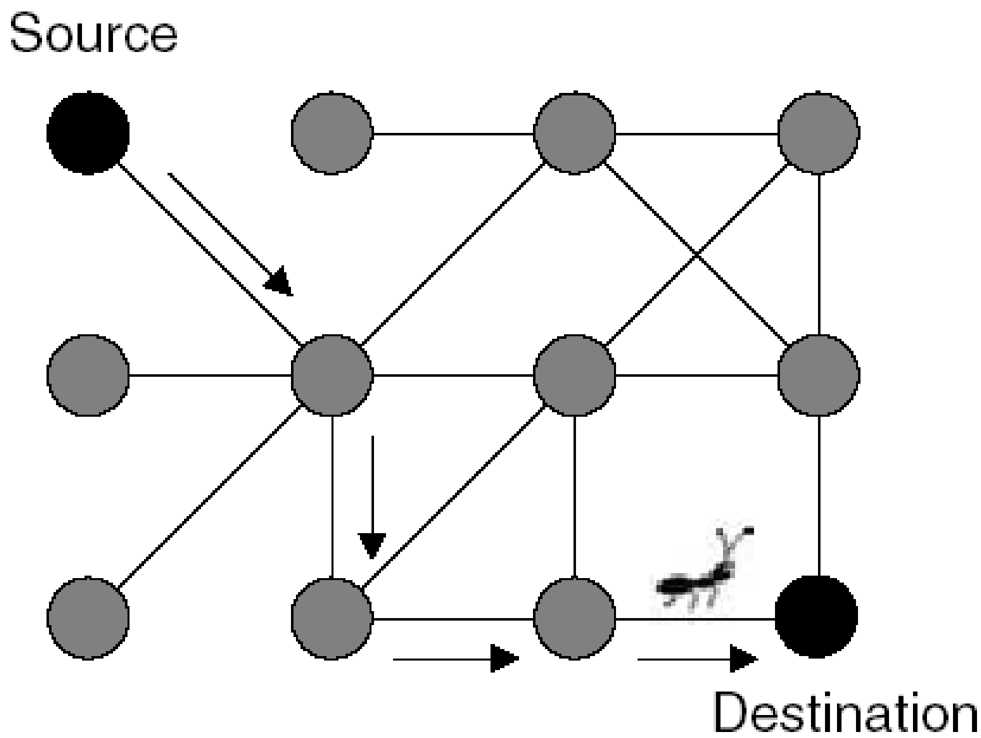
- Pheromone updates are done with one time unit delay on each arc.
- The two models are equivalent from a computational point of view, yet the second model permits an easier algorithmic implementation when considering graphs with many nodes.
- By setting the **number of ants to 20**, the **branch length ratio** to r=2, and the **parameter α** to 2, and t=100, the system converges rapidly toward the use of the short branch.

Artificial Ants



Artificial Ants

- Let us consider a static, connected graph $G = (N, A)$, where N is the set of nodes and A is the set of undirected arcs connecting them.



Artificial Ants

- **Artificial ants** whose behavior is a straightforward extension of the behavior of the real ants, while building a solution, may **generate loops**.
- As a consequence of the forward pheromone trail updating mechanism, loops tend to become more and more attractive and ants can get **trapped** in them.

Artificial Ants

- Artificial ants are given a **limited form of memory** in which they can store:
  - The **paths** they have followed so far, and
  - The **cost** of the links they have traversed.
- Via the use of memory, the ants can implement a number of useful behaviors

Artificial Ants

- The artificial ants have these behaviors:
  1. Probabilistic solution construction biased by **pheromone trails**, without forward pheromone updating
  2. Deterministic backward path with **loop elimination** and with pheromone updating
  3. **Evaluation of the quality** of the solutions generated and use of the solution quality in determining the quantity of pheromone to deposit

References

References

- M. Dorigo and T. Stützle. **Ant Colony Optimization**, MIT Press, Cambridge, 2004.

The End