Università di Catania

HOW A DIFFERENT ANT BEHAVIOR AFFECTS ON THE PERFORMANCES OF THE WHOLE COLONY

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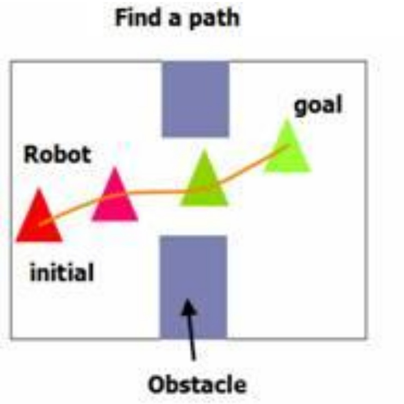
TALK OUTILE

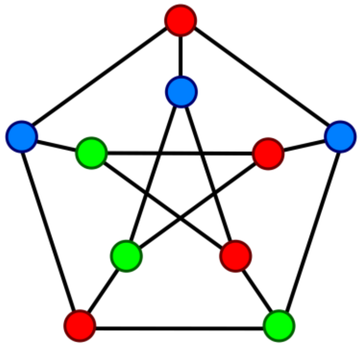
- INTRODUCTION
- THE MODEL
- EXPERIMENTS AND RESULTS
- CONCLUSIONS

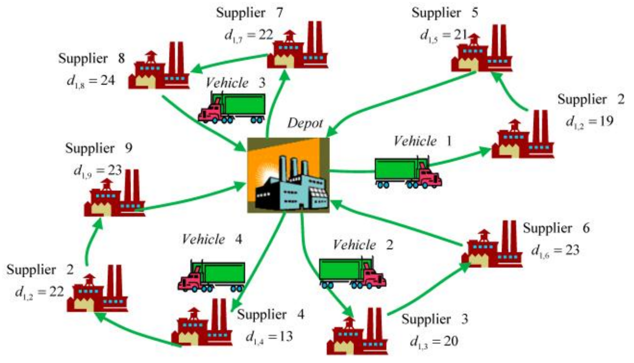
Ant Colony Optimization (ACO) is a metaheuristic that takes inspiration from real ants, which can find the shortest path from their nest to a food source and communicate it to the rest of the colony using chemical signals called pheromones.

Thanks to these properties it has become a powerful **optimization technique** for **solving different kinds of combinatorial optimization problems**, such as:

- scheduling and routing problems[1,2];
- coloring[3];
- robot path planning[4];
- feature selection[5];
- …many others…







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2. Jia, Y.H., Mei, Y., Zhang, M.: A bilevel ant colony optimization algorithm for capacitated electric vehicle routing problem. IEEE Transactions on Cybernetics pp. 1–14 (2021)
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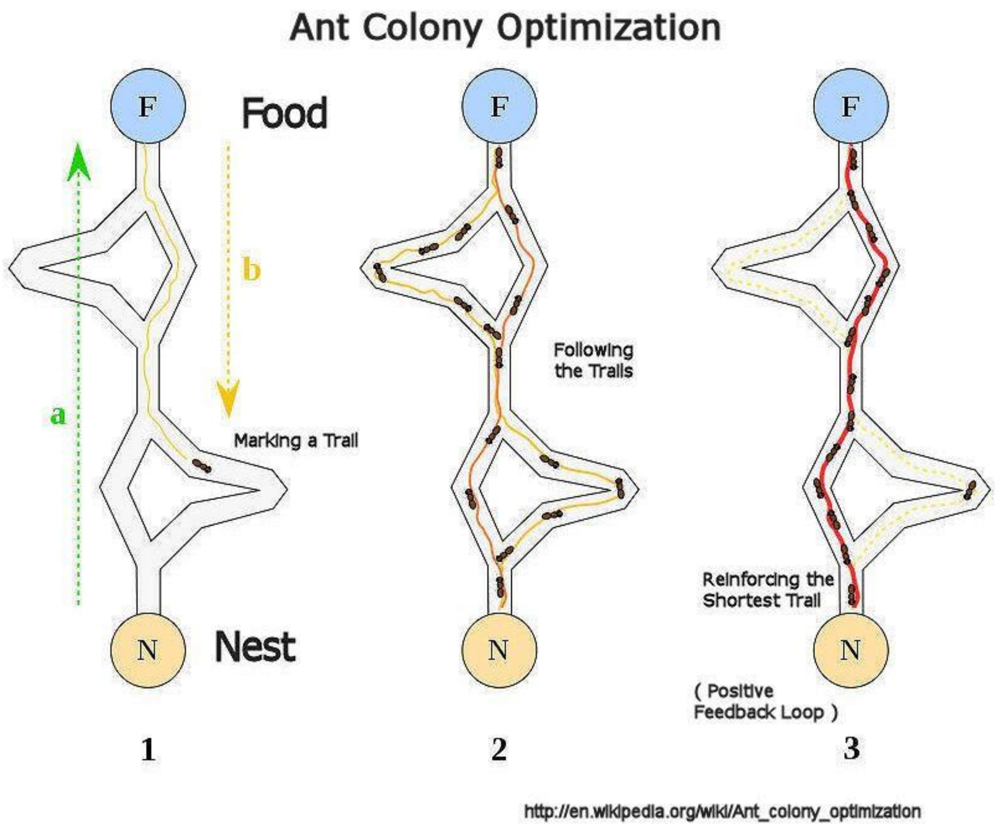
ACO works because **is not the single ant that finds the best solution**, but its **cooperation and interaction with the environment and the rest of the colony** that produces the desired result. In light of this, a natural question arises:



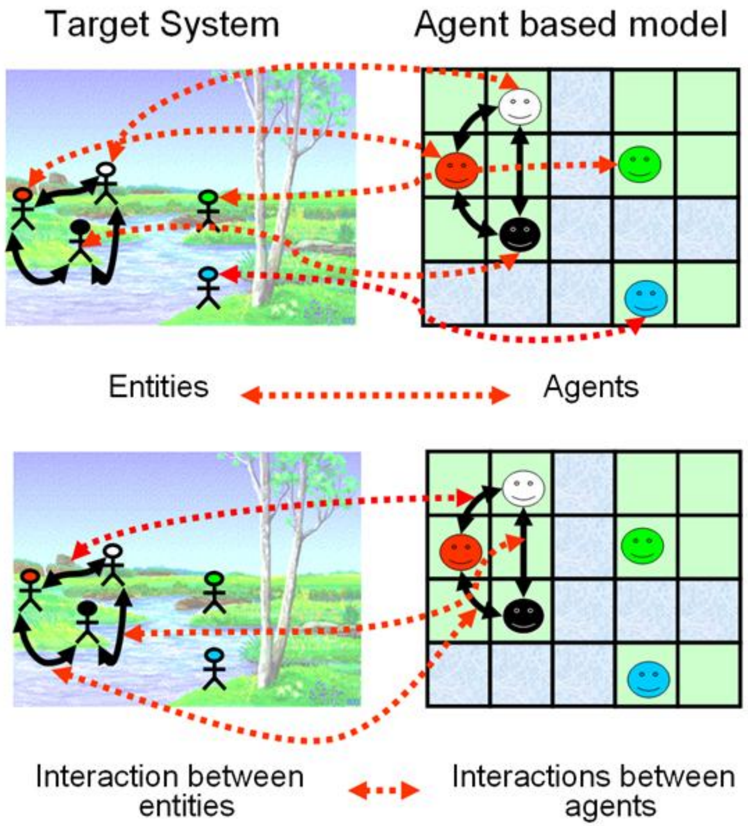
What happens if, in a colony, some ants act in a different way from the others?

This question is the focus of our work.

To try to answer to this question, we have realized **an agent-based model** using NetLogo[6], an agent-based programming language and an Integrated Development Environment (IDE). It consists of **two different kinds of ants**, with different behaviors, that **move into a virtual environment to find a location (exit) from a starting point**.

Their aim is:

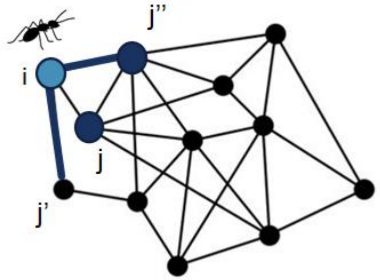
- **finding the best path from the starting to the endpoint;**
- **spending less time as possible to find it;**
- **maximizing the number of ants that do it.**



6. U. Wilensky, "Netlogo," Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, 1999. [Online].Available: http://ccl.northwestern.edu/netlogo/

The ***environment*** is represented as a weighted undirected graph $G(E, V, w)$ where:

- V is the set of vertices,
- $E \subseteq V \times V$ the set of edges;
- $w: V \times V \to \mathbb{R}^+$ is a weighted function that assigns to each edge a **positive cost**.



Proportional transition rule

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{l \in J_i^k} \tau_{il}(t)^{\alpha} \cdot \eta_{il}^{\beta}} & if \quad j \in J_i^k \\ 0 & if \quad j \notin J_i^k \end{cases} \tag{1}$$

- $\tau_{ij}(t)$ **pheromone intensity** on the edge (i, j) at a given time *t*.
- $\eta_{ij}(t) = 1/w_{ij}(t)$ **desirability** of the edge (i, j) at a given time *t;*
- α and β parameters that determine the importance of pheromone intensity with respect to the desirability;
- $J_i^k = A_i \backslash \{\pi_t^k\}$ are all the possible displacements of the ant *k* from vertex *I;*
- $A_i = \{j \in V: (i, j) \in E\}$ is the set of vertices adjacent to vertex *I;*
- $\pi^k(t) = (\pi_1, \pi_2, \dots, \pi_t)$ is the set of vertices visited by the ant *k;*

Reinforcement rule

$$\tau_{ij}(t+1) = \tau_{ij}(t) + K \tag{2}$$

after an ant crosses a link, the pheromone is increased by a constant quantity K (user defined)

Global updating rule

$$\tau_{ij}(t+T) = (1-\rho) \cdot \tau_{ij}(t) \tag{3}$$

every T ticks*, the amount of pheromone decay according to the value of ρ (**evaporation rate**)

*The time unit used that corresponds to a single movement of all agents.

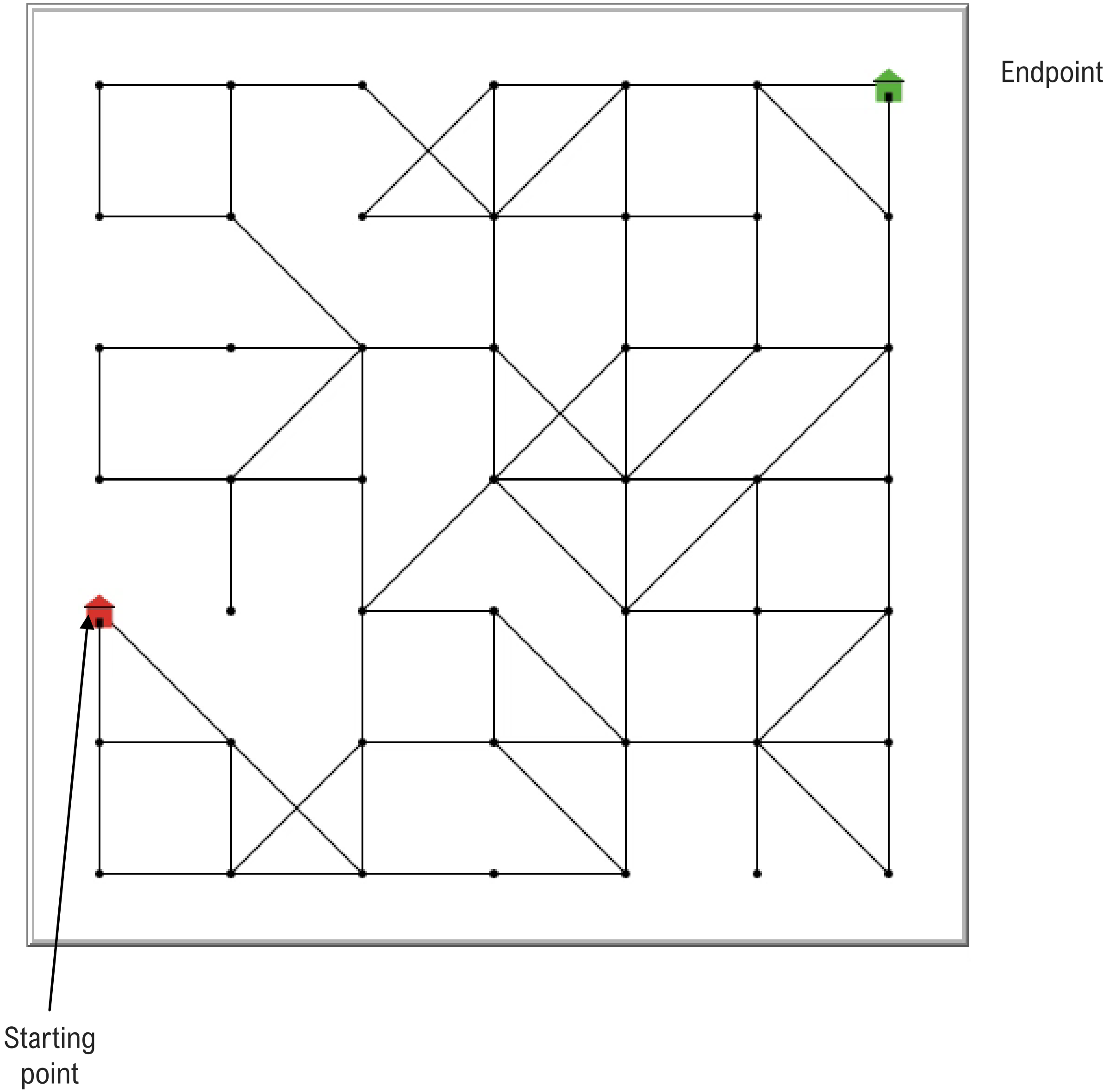
Two kinds of ants

High Performing Ants

- Leave an amount of **pheromone** K after crossing an edge (i,j);
- **Leave an information** $\boldsymbol{\eta_{ij}(t) = 1/w_{ij}(t)}$ on the endpoint after crossing an edge (i,j);
- Repair, with a certain probability $0 \leq \rho_{e,v} \leq 1$, a destroyed edge (i,j) and/or a vertex *i;*
- They work at their best.

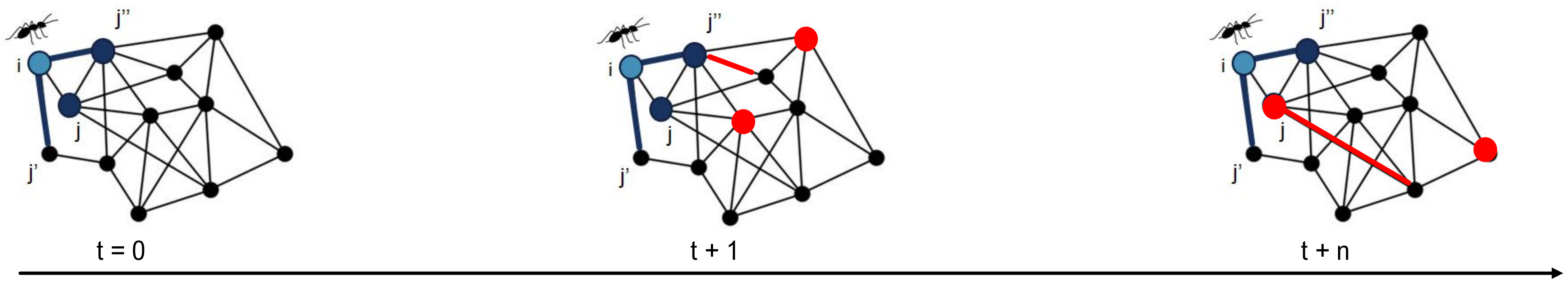
Low Performing Ants

- Leave an amount of pheromone K after crossing an edge (i,j);
- **Don't leave an information** on the endpoint after crossing an edge (i,j);
- Destroy, with a certain probability $0 \leq \rho_{e,v} \leq 1$, an edge (i,j) and/or a vertex *i*;
- They do not work properly.



The problem under investigation can be considered as a **general path problem** but the **shortest path, in this case, is not a good evaluation metric** because:

- The destroy\repair actions make the **network dynamic**;
- A node or a link can be **not crossable** in the timestep *t*, but **becoming crossable** later.



Good evaluation metrics are:

Exit function

must be maximized

$$\max \sum_{g \in G} \sum_{k \in N} k_g \qquad (4)$$

- G number of groups;
- g index of the group to which the ant k belongs;
- k_g ant k that belongs to g group;
- N set of ants.

Path cost and resolution time functions

must be minimized

$$min \sum_{i=1}^{t-1} \boxed{w\left(\pi_i^k, \pi_{i+}^k\right)} + \boxed{\left|\pi^k\right|} \qquad (5)$$

path made by an ant *k*

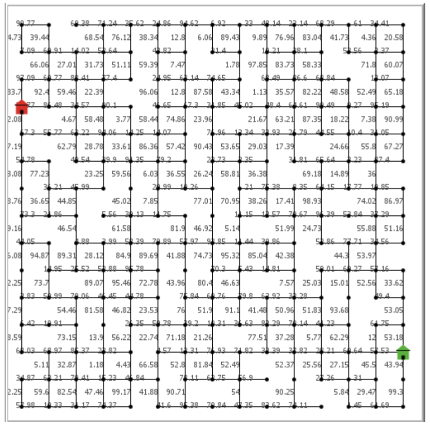
n° **steps** made by ant *k*

- It can be used also as a time term because **each unit of time corresponds to an ant displacement.**
- **the number of nodes visited by an ant corresponds to the resolution time.**

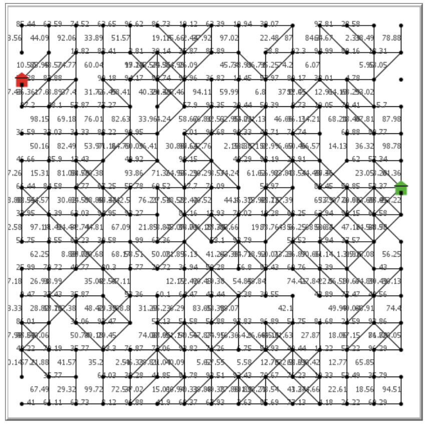
EXPERIMENTS AND RESULTS

We have performed the simulations by using **two networks**:

- **Scenario B1**: rows = 15, columns =15, (|V|= 225) vertices and (|E|=348) edge
- **Scenario B2**: rows = 15, columns =15, (|V|=225) vertices and (|E|=495) edges



B1



B2

and the following v**alue parameters**:

- $\boldsymbol{N = 1000}$ **ants;**
- $\boldsymbol{G = 10}$ **groups**
- $\boldsymbol{N_g = 100}$ **ants;**
- $\boldsymbol{T_l = |V|,}$ **each group is launched after a certain amount of time (**$\boldsymbol{T_l}$ **ticks) from the previous group;**
- $\boldsymbol{T_{max} = 2 \times G \times T_l}$**, all the ants have a limited time to find the exit because of limited time resources**;
- $T_d = 50$ pheromone evaporation decay;
- $\rho = 0.10;$
- $\rho_e, \rho_v = 0.02;$
- $\boldsymbol{0.0 \leq f \leq 1.0}$ **performing factor to define the proportion of HPAs with respect to the LPAs;**
- $s = 10$ independent simulations for every value of f.

We have considered the following cases:

LOW PHEROMONE\TRACE CASE

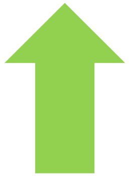
$K = 0.001, \alpha = 1.0, \beta = 0.5$

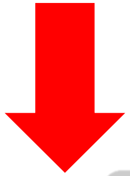
$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{l \in J_i^k} \tau_{il}(t)^{\alpha} \cdot \eta_{il}^{\beta}} & if \quad j \in J_i^k \\ 0 & if \quad j \notin J_i^k \end{cases} \qquad (1)$$

HIGH PHEROMONE\TRACE CASE

$K = 0.1, \alpha = 1.0, \beta = 0.1$

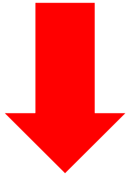
Objective information

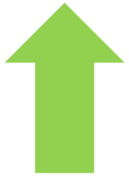




trace\pheromone

Objective information





trace\pheromone

Heat map plots

- x-axis: performing factor
- y-axis: groups
- legend: the lighter the blue is the higher the value of the number of ants is, and vice versa.
- absence of colour: no ants have reached the exit.

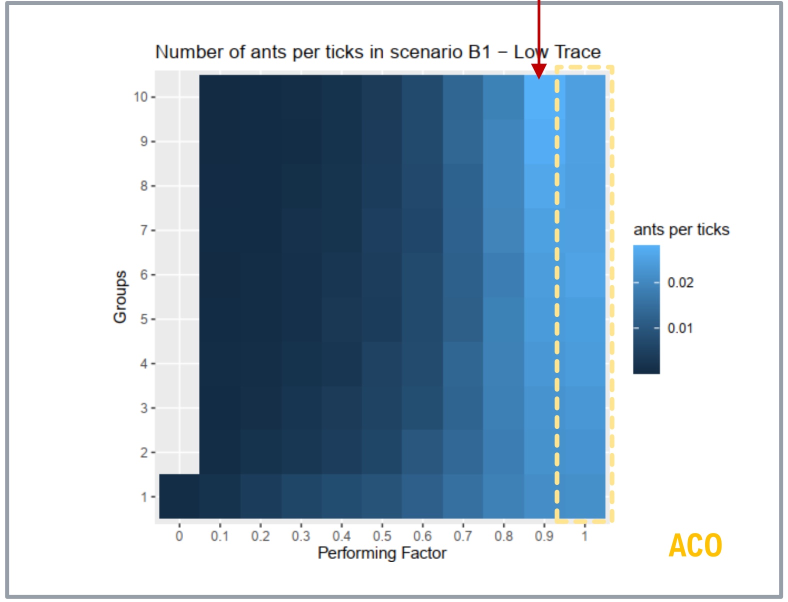
LOW TRACE CONFIGURATION

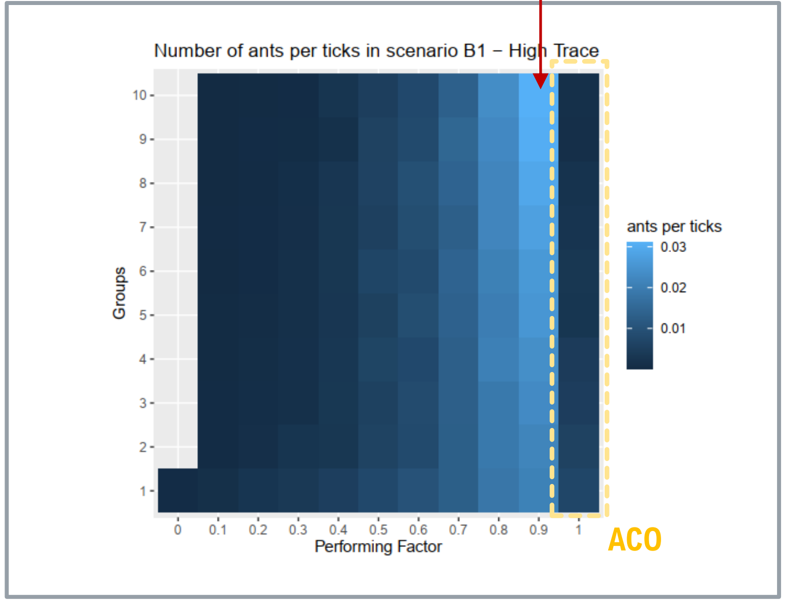
- best results are for $f = 0.9$ in B1 and $f = 1.0$ in B2;
  - **the more HPAs are present the better the performances of the colony will be;**
  - last groups exploit better the information left by the first in B1 and not in B2.

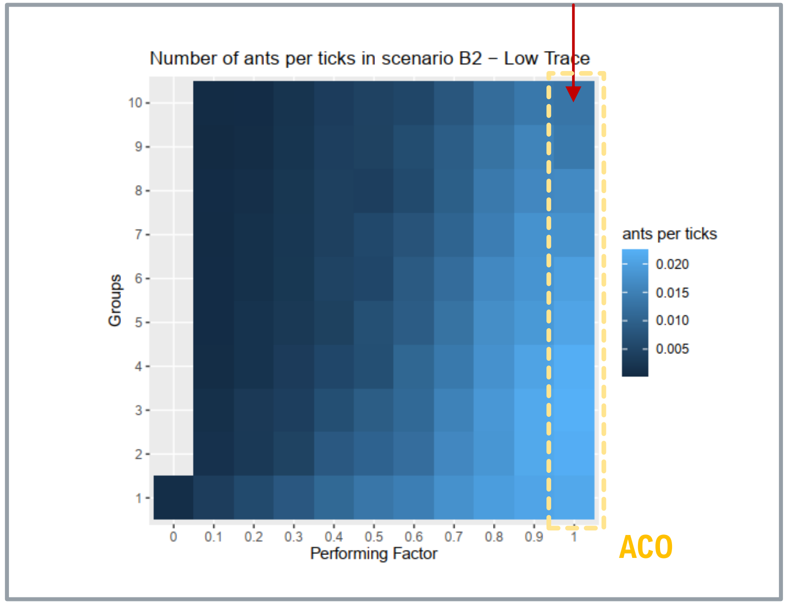
HIGH TRACE CONFIGURATION

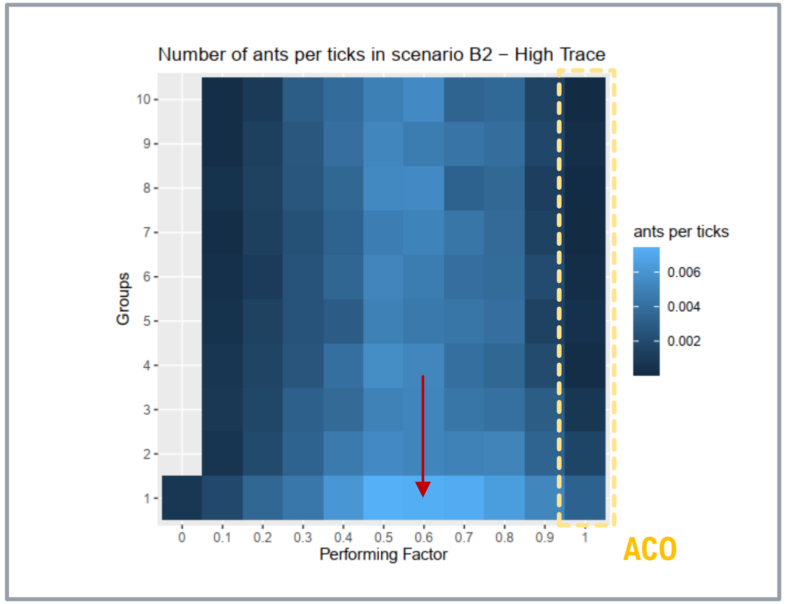
best results are for values of $f \neq 1.0$

- ($f = 0.9$ in B1 and $f = 0.5$ in B2);
  - the more HPAs are present the better the performances of the colony will be;
  - **the presence of LPAs helps the colony to achieve better results.**









$K = 0.001, \alpha = 1.0, \beta = 0.5$

$K = 0.1, \alpha = 1.0, \beta = 1.0$

Plots and inset plots (5)

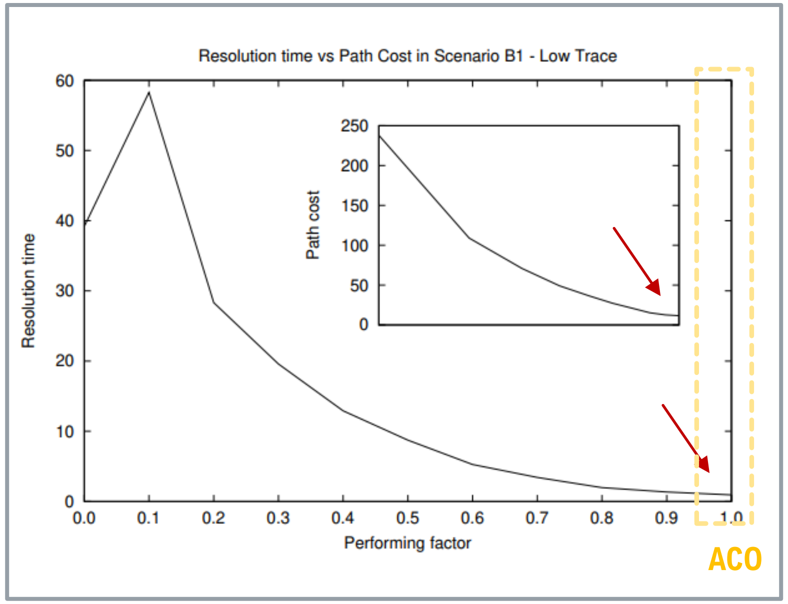
- x-axis: performing factor
- y-axis: resolution time\path cost

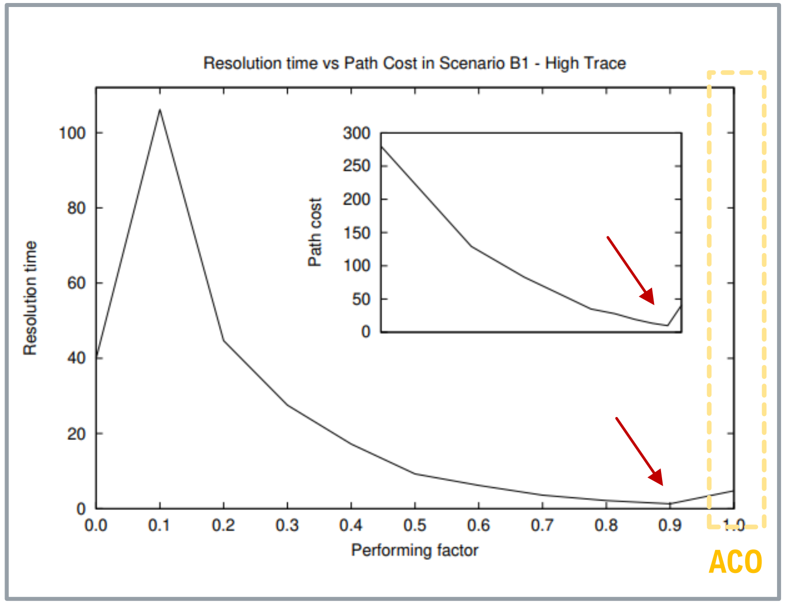
LOW TRACE CONFIGURATION

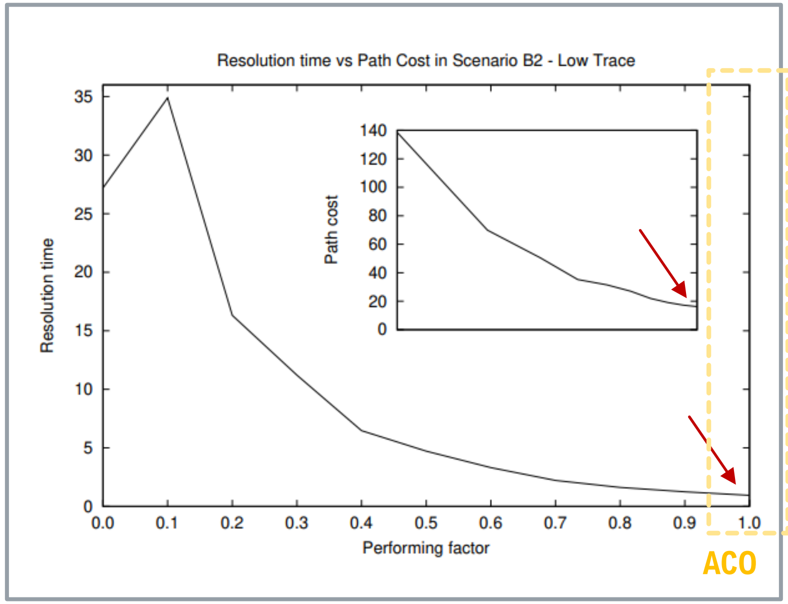
- the resolution time and the path cost are minimum for $f = 1.0$;
  - **a colony of HPAs has the best performances.**

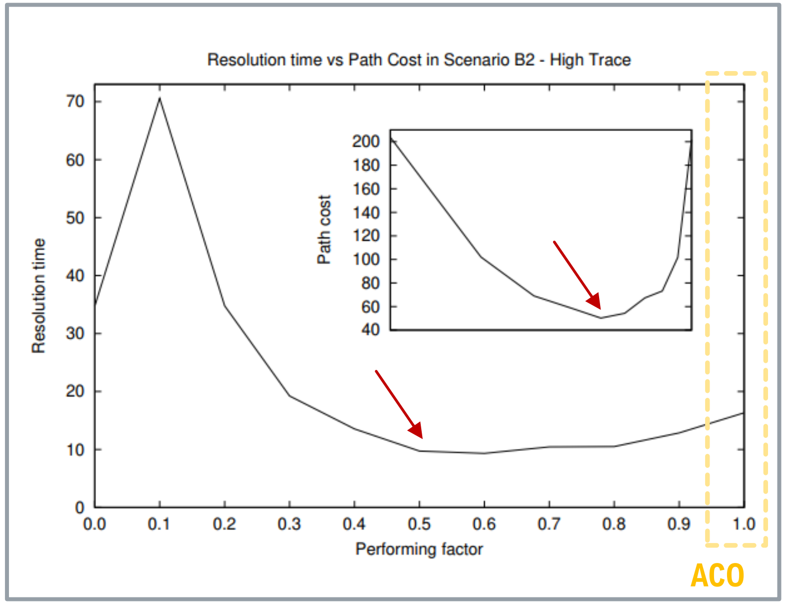
HIGH TRACE CONFIGURATION

- **the resolution time and the path cost are minimum for values of $\boldsymbol{f \neq 1.0}$** ($f = 0.9$ for the resolution time and the path cost in B1, $f = 0.5$ for the resolution time in B2 and $f = 0.6$ for the path cost in B2);
  - the more HPAs are present the better the performances of the colony will be;
  - **the presence of LPAs helps the colony to achieve better results.**









$K = 0.001, \alpha = 1.0, \beta = 0.5$

$K = 0.1, \alpha = 1.0, \beta = 1.0$

Plots (4)

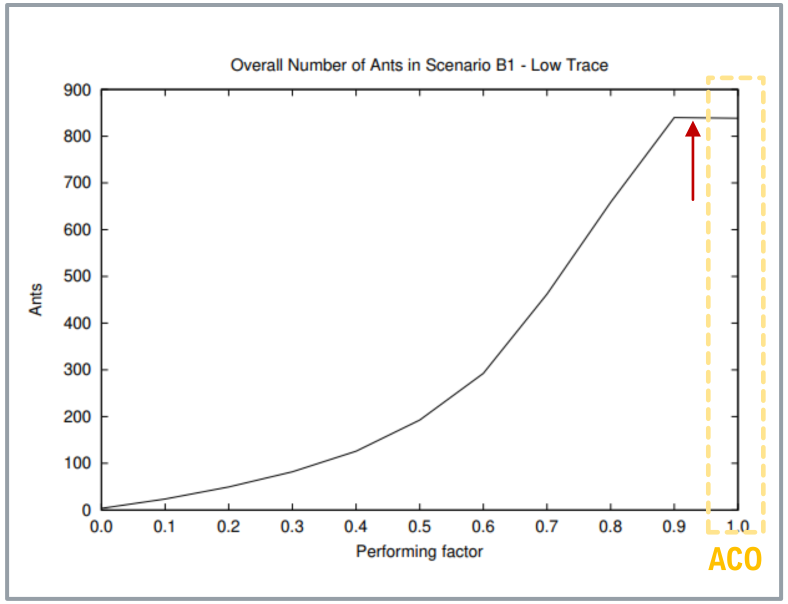
- x-axis: performing factor
- y-axis: number of ants

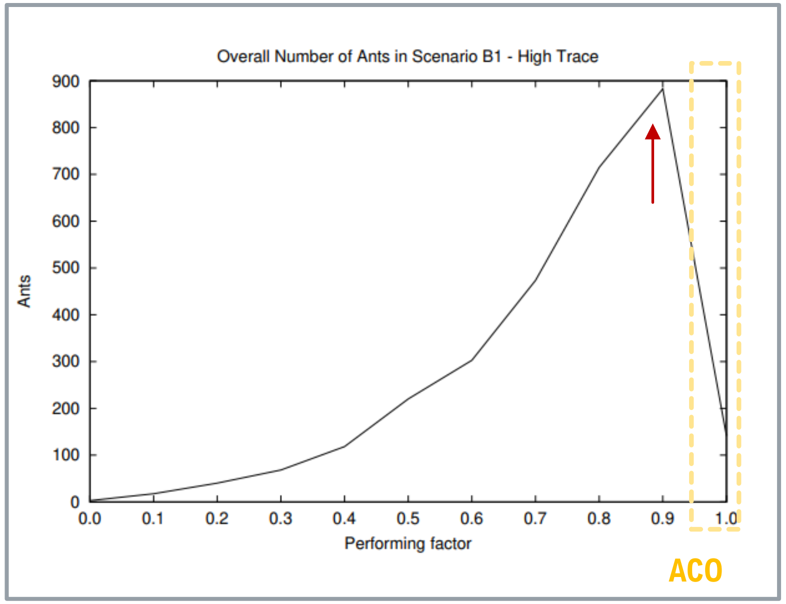
LOW TRACE CONFIGURATION

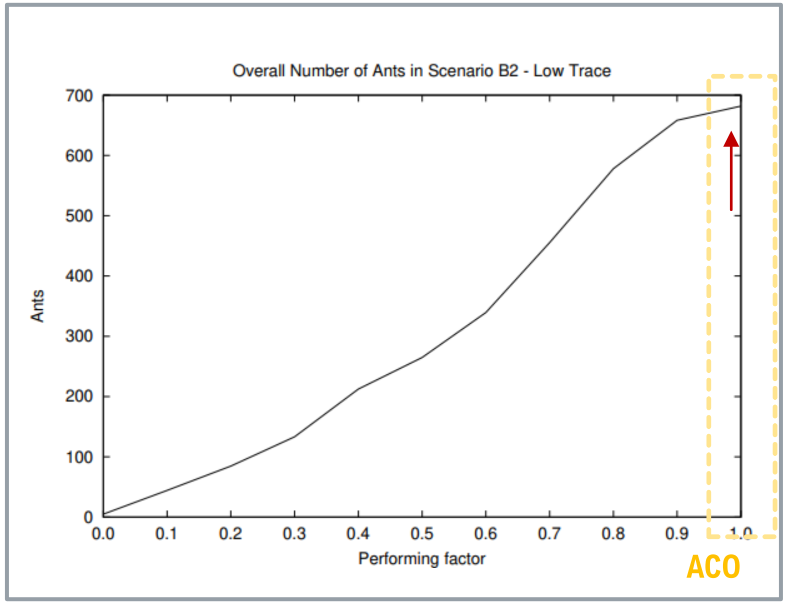
- the overall number of ants exited is maximum for $f = 0.9$ and $f = 1.0$ in B1 and for $f = 1.0$ in B2.
  - **a colony of HPAs has the best performances.**

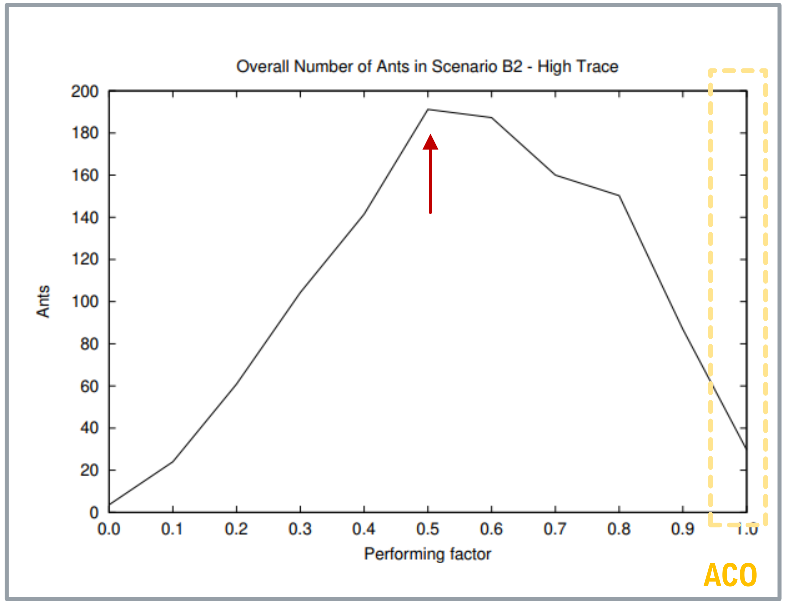
HIGH TRACE CONFIGURATION

- the overall number of ants exited is maximum for $f = 0.9$ in B1 and for $f = 0.5$ in B2.
  - the more HPAs are present the better the performances of the colony will be in B1 but not in B2;
  - **the presence of LPAs helps the colony to achieve better results.**









$K = 0.001, \alpha = 1.0, \beta = 0.5$

$K = 0.1, \alpha = 1.0, \beta = 1.0$

From data analysis, emerges that:

- the **presence of ants with different behaviours** (LPAs) is **useful** when there is a condition of **high-level trace**;
- **the actions performed by the LPAs** (destroy nodes and\or links) **stimulate the rest of the colony** to search for other paths;
- an **excess of trace is self-defeating for the ants.**

Future works:

- simulations on network with more complex topology;
- simulations with different values parameters;
- tests on real combinatorial optimization problems.

THANKS FOR YOUR ATTENTION

ANY QUESTIONS?

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