

# Effects of Different Dynamics in an Ant Colony Optimization Algorithm

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**Abstract**—Finding shortest path in a labyrinth, made up of roads, crosses and dead ends, and where entrance and exit dynamically change during the time, is an important and challenging optimization task especially in emergency scenarios, such as earthquakes, volcanic eruptions, and/or hurricanes. In this research work we present a study on the effects of cooperative and competitive strategies in an agent-based model using an Ant Colony Optimization (ACO) algorithm for the solution of labyrinth problem. Two different ants' search strategies in the colony have been designed: those that acts competitively and selfishly, damaging some crossings (i.e. nodes) on the path, and cooperative ones, which instead attempt to repair them. The purpose of both strategies is finding a path from the entrance to the exit in order to gain the highest number of some resources positioned appropriately at the exit and bound to be collected if and only if both types of ants reach it via the shortest path. This research work has a twofold aim, that is, finding obviously the shortest path in the labyrinth (then maximize the resources gained), as well as analyzing the effects of both strategies on the overall ACO performances, and inspecting how one strategy affects the other by motivating it to improve its performances and its efficiency. From the overall outcomes, indeed, it emerges that the existence of the competitive ants is a strong incentive for cooperative ones to improve themselves.

## I. INTRODUCTION

Taking inspiration from the ants' ability to find the shortest path from the anthill to the source of food, we have seen in the literature a development of different models and algorithms which have been successfully applied in recent years for solving optimization problems on graphs [1], [2], such as routing problem [3], robot path planning [4], coloring [5], traveling salesman problem [6], and many others. It is known that the ability of the colony to find the shortest path depends on the capacity of a single ant to share and follow the pheromones on the path [7]. And it is also known that the ants behavior is the best example in nature of Complex Adaptive Systems (CAS), that can live and reproduce simply cooperating each other [8]. Several studies have been carried out in the last years to try to understand the role of the cooperation among the CAS [9]. On the other hand, the role of competition among the same systems is still not so clearly understood. This important gap in literature motivated us to study and present some novel features, in which are analyzed the effects of two different dynamics in an Ant Colony Optimization (ACO) algorithm based on a revisited shortest path problem. In particular, how cooperative and competitive dynamics differ from another and

the impact of each of them on the performances of the colony are analyzed and inspected.

The revisited shortest path problem consists in a labyrinth, that is a structure made up of a series of roads and dead ends through which the agents travel to get to the exit starting from a given entrance. The aim of each agent is then to find the shortest path from the entrance to the exit in a dynamic environment. Being able to design efficient algorithms capable to find the shortest path inside a labyrinth for moving from a starting point to a target one, especially when this last can change in the time, is an important and crucial in emergency tasks, such as for instance earthquakes, volcanic eruptions, or hurricanes.

In this paper, cooperative and competitive ants from a colony are put in competition with each other, with the aim of analyzing and understanding whether such competition stimulates both, or one of them, to be better and more efficient. From the analysis of the outcomes, it emerges that the presence of competitive and selfish ants, which act in a totally different way, is a spur for the cooperative ones to perform better and more efficient performances.

## II. THEORETICAL BACKGROUND

One of the first algorithms applied for searching optimal paths in a graph was proposed in [10] and draws inspiration own from the behavior that ants exhibit when looking for a path between any food source and their anthill. It has been observed, in fact, that they are able to identify the shortest paths and communicate it to the others through chemical signals released along the path, called pheromones. From the mathematical point of view, one can imagine the environment in which the ant moves as a graph  $G = (V, E)$  with  $V$  set of nodes and  $E$  set of links. The probability  $p_{ij}^k(t)$  with which an ant  $k$  placed on a node  $i$  chooses as destination one of its neighbor nodes  $j$  at the time  $t$  is defined as the following proportional transition rule:

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

where  $J_i^k$  are all the possible displacements of the ant  $k$ ,  $\tau_{ij}(t)$  is the pheromone intensity on the edge  $(i, j)$  at a given iteration,  $\eta_{ij}$  is the desirability of state transition (a *priori* available information), typically defined as the inverse of the distance between two nodes, while  $\alpha$  and  $\beta$  are two parameters that determine the importance of pheromone density with

respect to the desirability of a path. The amount of pheromone deposited by ant  $k$  is expressed by the following formula:

$$\Delta\tau_{ij}^k(t) = \begin{cases} \frac{Q}{L^k(t)} & \text{if } (i, j) \in T^k(t) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where  $T^k(t)$  is the path made by an ant  $k$  at the time  $t$ ,  $L^k(t)$  is the length of the path and  $Q$  is a constant. At the end of each iteration the amount of deposited pheromone will be updated in according to the following global updating rule:

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k(t) \quad (3)$$

with  $\tau_{ij}(t)$  quantity of pheromones on the edge  $(i, j)$  in the previous step,  $\rho$  is the pheromone decay parameter and  $m$  number of ants used for iteration.

### III. THE MODEL

The realization of the model is carried out using NetLogo [11]. Firstly, we created the labyrinth modifying an existing model [12]. This model implements an iterative method called *Recursive Backtracker*, a slightly modified version of the depth-first search. It was originally provided for the possibility of creating different, simple and random labyrinths in according to the values of certain parameters. We modified it by fixing the seed of the random numbers to make sure we could repeat our simulations under stable conditions (at each run, the same labyrinth is regenerated). Secondly, we created a network underneath the labyrinth and realized more complex labyrinths. Our modified procedure can add other links between some nodes with at least two first neighbors and other nodes also with at least two first neighbors. This particular choice was made to prevent the loss of the dead ends. We selected one edge node on the left part of the labyrinth to be the entrance and one edge node on the right part to be the exit and put on it some resources to be gained by the ants of the colony.

The colony is composed of two kinds of ants:

- **competitive:** they always act competitively, as soon as they arrive at the exit, they block a random node on the path and get a resource only when they find the shortest path.
- **cooperative:** they always act in a cooperative way, if they find a damaged node near their path, they repair it and take a resource only when the find the shortest path.

The number of ants that act in a cooperative way is defined by the *cooperation factor*  $f \in [0, 1]$ .  $f$  represents the proportion of cooperative ants with respect to the colony. So, once the proportion of cooperative ants is defined, the others will act in a competitive way.

A general ACO algorithm consists of a proportional transition random rule (that describe how an ant move from one node to another) and a global updating rule (that describe how the amount of pheromone levels change over time). In this model, the proportional transition random rule has been defined as follow: at the first iteration the pheromone trails

are the same for all  $(i, j) \in E$  and ants will move randomly exploring the available space. The first one that arrives at the exit releases a trace of pheromone along its path. After that, the other ants of the same kind die, and a new generation is launched. The rule take place only at this point, i.e. when the initial pheromone levels of the paths has been changed and for this model it is defined as follow:

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}(t)}{\sum_{l \in J_i^k} \tau_{il}(t)} & \text{if } j \in J_i^k \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

with  $\tau_{ij}$  quantity of pheromone present on the link  $(i, j)$ , while  $J_i^k$  is the set of allowed links. The 4 is specific case of the 1 where  $\eta_{i,j}$ ,  $\alpha$  and  $\beta$  are all 1. In this way the transition from node  $i$  to node  $j$  depends only on the pheromone on the link  $(i, j)$ .

The global update rule has been inserted in a procedure which updates the pheromone levels at the end of each tour of the winning ant. All pheromones on the links are updated according to the follow rule:

$$\tau_{ij}(t+1) = (1 - \alpha) \cdot \tau_{ij}(t) + \Delta\tau_{ij} \quad (5)$$

where  $\alpha$  is the evaporation rate,  $\tau_{ij}$  is the amount of pheromone on the link at the previous step and  $\Delta\tau_{ij}$  is the amount of deposited pheromone by the winning ant. For this model this quantity is constant and it is fixed at 1.5. To prevent the stagnation of the algorithm around a local optimum and let the colony be able to explore the rest of the labyrinth, the pheromone trail on a link cannot be lower than a value greater than zero.

The aim of the ants is to explore the labyrinth and find the shortest path from the entrance to the exit orienting themselves using the amount of pheromones on the paths. To evaluate the impact of different strategies we have also put a limited amount of resources on the exit that can be taken if and only if they reach it by the shortest path. When there are no more resources on the exit node, a new node will be selected as exit, with a new amount of resources. Contrarily to the classical *Shortest Path Problem*, our model tries to figure out what happens in a dynamic case in which not only the ants must be able to find the exit from the maze through the shortest path, but from time to time, they must also have the ability to organize themselves for a new objective that gives the opportunity to collect new resources.

### IV. RESULTS

In this section all simulations performed are presented. We have performed these simulations by using two different labyrinths, both with same number of nodes ( $|V| = 77$ ) and links ( $|E| = 128$ ) but different distribution of the links. In particular, a first labyrinth was generated via a non-uniform distribution, and labelled as *A*, while a second one via a uniform distribution, labelled instead as labyrinth *B*. For both type of labyrinths, a colony of 100 ants was used. The cooperation factor  $f$  goes from  $f = 0$  (that define a colony of just competitive ants) to  $f = 1$  (that define a colony of just

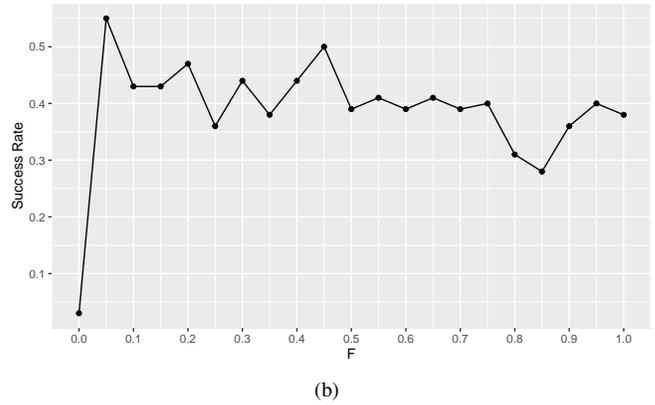
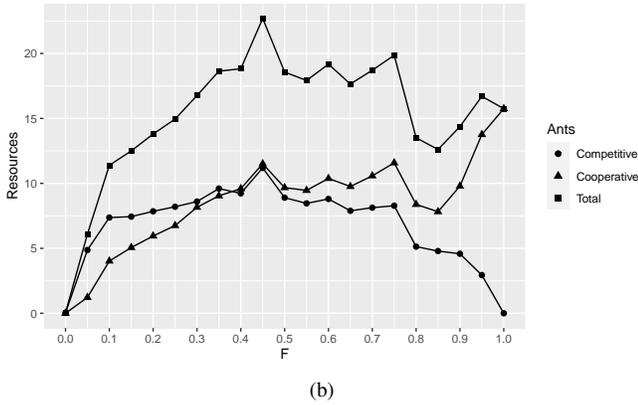
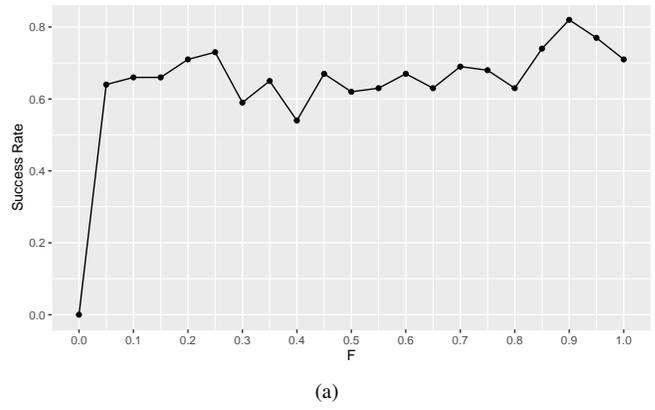
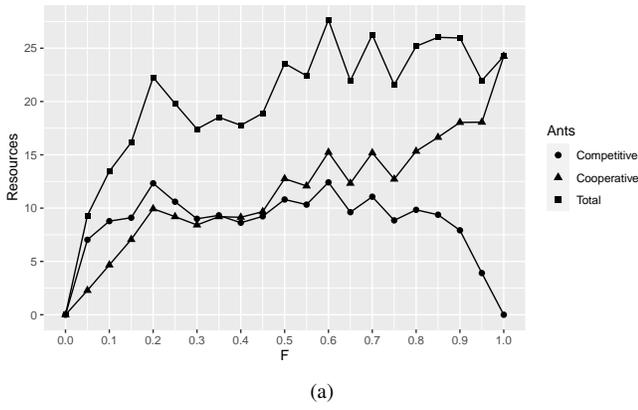


Fig. 1: Average of the resources earned by the colony on network A (a) and network B (b) calculated over 100 simulations.

Fig. 2: Success rate of the colony on network A (a) and network B (b) calculated over 100 simulations.

cooperative ants) with step of 0.05. The initial pheromone trail on the links is set to 1.0, while the evaporation rate  $\alpha$  is set to 0.1. For all simulations performed, the maximum number of generations was fixed to 100. The setting of all parameters presented above, and used in this section in general, was determined via preliminary dedicated experiments.

The plots in Fig. 1a and Fig. 1b represent the average number of resources earned by cooperative ants, competitive ants and the entire colony, calculated over 100 simulations. The trend of the data follows what we expected: the mean value of gained resources increase as the value of  $f$  increase. As we can see, as the fraction  $f$  of cooperative ants increases, the colony has better performances in both labyrinths, which means it can gain more resources. This would lead to a maximum gain for  $f = 1$  but the data shows something different. The maximum of earned resources is not where there is the maximum value of cooperation but at lower values of  $f$ .

To better understand this behavior, we have also plotted in Fig. 2a and in Fig. 2b the success rate of the colony. In this case, the success rate is simply how many times in 100 simulations the colony finds the shortest path at least one time. As previously, we have found that the highest values of success rates are not the ones calculated for  $f = 1$ , that means when all ants of the colony act cooperatively. We would

be led to say that even a small fraction of cooperation could potentially improve the performances of the algorithm but we have also noticed, in our analysis, that the standard deviation of these data results to be very high (Fig. 3). So, this data set is susceptible to statistical fluctuations and the position of the data points could be different from the ones presented here.

Comparing the results for the earned resources in Fig. 1, with the success rate in Fig. 2 and with the corresponding data distribution in Fig. 3 for labyrinths *A*, seems that for  $f = 0.90$  there are the better performance, both in term of resources earned and successes rate. For this value the colony earned 25.96 resources on average and obtained the best success rate (82%). This value corresponds also to the only boxplot without outliers. For the labyrinth *B*, instead, the best values were obtained for  $f = 0.45$ , with 22.70 resources earned on average, but with a 50% of success rate.

The correctness of our results is also validated by a better correspondence between the average value of the earned resources by the colony and its median. The box-plot graph shows, in fact, that in this case the median value and the mean value are very close but only for the labyrinth with configuration *A*. The second configuration, on the contrary, shows a median value equal to zero for all the values of  $f$ . In our opinion this fact doesn't represent a problem because it just could be linked with the lower values of the success rate.

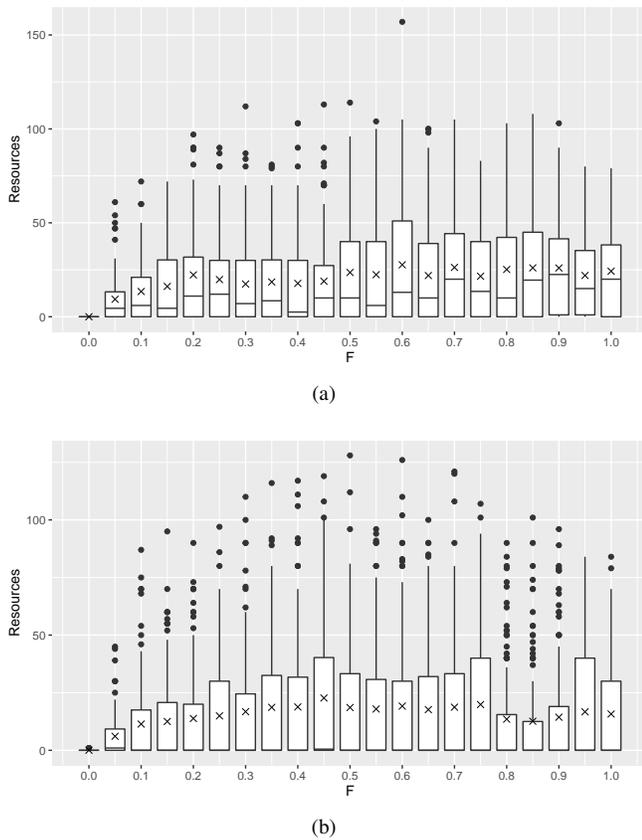


Fig. 3: Distribution of resources earned by the colony in network A (a) and network B (b) calculated over 100 simulations.

## V. CONCLUSIONS

The presented study suggests a beneficial role of competition for the colony. From the data analysis, it seems that a small fraction of competitive agents can be useful and advantageous for the entire colony. In fact, as the previous figures show, the colony reaches better results not when it is composed of just one kind of agents (the cooperative ones) but when some agents act differently. A possible explanation of this counterintuitive result could be due to the fact that when a competitive ant reaches the exit, it blocks a node of the path and this action can be useful because it forces the rest of the colony to change its behavior and search other alternative paths. Although this is still a preliminary study that needs a careful and rigorous investigation, it is our opinion that this could open new paths of research in the field of the natural computation with agent-based models, as well as in complex systems.

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