Modelling the Social Interactions in Ant Colony Optimization

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Abstract. Ant Colony Optimization (ACO) is a swarm-based algorithm inspired by the foraging behavior of ants. Despite its success, the efficiency of ACO has depended on the appropriate choice of parameters, requiring deep knowledge of the algorithm. A true understanding of ACO is linked to the (social) interactions between the agents given that it is through the interactions that the ants are able to explore-exploit the search space. We propose to study the social interactions that take place as artificial agents explore the search space and communicate using stigmergy. We argue that this study bring insights to the way ACO works. The interaction network that we model out of the social interactions reveals nuances of the algorithm that are otherwise hard to notice. Examples include the ability to see whether certain agents are more influential than others, the structure of communication, to name a few. We argue that our interaction-network approach may lead to a unified way of seeing swarm systems and in the case of ACO, remove part of the reliance on experts for parameter choice.

Keywords: Swarm Intelligence · Swarm-based algorithms · Ant Colony Optimization · Interaction network · Social interactions.

1 Introduction

Swarm intelligence algorithms have been successfully applied to solve a wide range of optimization problems due to the simultaneous use of multiple artificial agents on high dimensional search problems [5,4]. Even though they are effective, the usability of swarm-based algorithms is limited by the lack of knowledge on why the interaction of simple reactive agents lead to such a complex system. Another challenge is the diversity of algorithms inspired by different animals such as ants, bees, fish, wolves and birds. Knowing what is the best swarm-based algorithm and its initialization to each type of problem requires deep expertise.

Bratton and Blackwell [1] proposed a simplified version of the Particle Swarm Optimization (PSO) algorithm [3] by removing the randomizing factors from the equations of the algorithm. Their simplification gives insight into the swarm behavior and helps us understand what makes PSO an effective algorithm. However, this still could not quite capture why the social behaviour emerges from the simple rules.

In our previous works, we showed the value of using an interaction network to analyze the social interactions occurring during executions of swarm-based algorithm [7,8,9,10]. In this paper, we show that applying the same principles of analyzing social interactions to Ant Colony Optimization can provide a better way to initialize the algorithm for higher usability and understanding. This paper contributes to the literature in ACO and Interaction Networks because it is the first work that tracks social interaction even though these interactions are indirect via stigmergy.

2 ACO and TSP

Ant Colony Optimization (ACO) is a meta-heuristic technique inspired by the behaviour of ants [2]. In nature, ants solve complex problems by indirectly communicating via the environment (stigmergy). While an ant travels to a food source, it drops an amount of pheromone along the path that other ants can follow. Then, the ants that come next choose a path probabilistically; the paths already taken by previous ants are more likely to be selected because the pheromone amount is longer. Given that ACO was extensively used in TSP, we also chose the TSP to model the interaction network in ACO.

Artificial ants move on a fully connected graph where the vertices represent cities and the edges represent the paths to go from one city to another. The goal for each ant is to find the shortest path that visits each city and returns back to the origin city. During the tour of the cities, an ant is presented with many choices on which city to visit next. As the ants travel through the cities, they drop pheromone on the path allowing them to use it and make decisions on which city to go to next. The pheromone τ_{ij} associated with the edge joining cities i and j, is updated as follows:

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \ , \tag{1}$$

where ρ is the evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}(t)$ is the amount of pheromone dropped by ant k on the edge (i, j) at iteration t calculated based on a heuristic that represents the goodness of the path taken.

Ants drop more pheromone on edges which lead to good solutions, and the pheromone from sub-optimal solutions is evaporated over time. Thus, an ant k going from city i chooses city j using the following probability equation:

$$p_{ij}^{k}(t) = \frac{\tau_{ij}^{\alpha}(t) \cdot \eta_{ij}^{\beta}(t)}{\sum_{u \in \mathcal{N}_k(t)} \tau_{iu}^{\alpha}(t) \cdot \eta_{iu}^{\beta}(t)}, \qquad \text{if } j \in \mathcal{N}_k(\text{t}), \tag{2}$$

where $\mathcal{N}_k$ is the list of cities that the ant k has not yet visited, and $\eta_{ij} = 1/d_{ij}$ is the visibility, where d_{ij} is the distance between cities i and j. The parameters α and β control, respectively, the importance of pheromone and edge visibility.

3 Interaction Network

Swarm-based algorithms, like ACO, consist of artificial agents interacting with each other and with the environment [2]. These algorithms are useful tools to solve real-world problems [4,5]. Despite their effectiveness, they lack *explainability*; we are still unable to explain the dynamics that make these techniques useful [10]. Notably, the pivotal feature in these algorithms is the social interactions enabling the system to solve problems. Indeed, each algorithm has its own rules defining the way agents interact with others and determining how they change themselves as result of interaction. This interplay among agents leads to the emergence of a network of interaction which provides a mezzo-level perspective of swarms [10].

Such network-based viewpoint was first introduced by Oliveira et al. in the context of Particle Swarm Optimizers [7,9] and then extended to swarm-based algorithms in general [10]. The concept of *interaction network* enables the analysis of social influence among the agents in the swarm [10]. The approach unveils the dynamics of swarm systems via tracking the evolution of social interactions.

In the interaction network $\mathbf{I}(t)$ nodes represent the agents and links (or edges) between the nodes represent the influence between the agents. This network allows us to capture the social behavior of the swarm at different points in time during an execution of the algorithm. Formally, the network $\mathbf{I}(t)$ at iteration t is represented by an adjacency matrix where each element of the matrix can be defined by the presence, 1, or the absence, 0, of influence between the artificial agents *i* and *j*. However, this definition only tells us whether or not two artificial agents in a swarm interacted with each other over time. Oliveira et al. [7] developed an expanded version of the interaction network that keeps track of the history of information exchanges, by creating a separate interaction network for each iteration and summing all of them up at the end to get an accurate picture of all the interactions that took place among the artificial agents in the swarm. The matrix resulting from this sum is a weighted interaction network $\mathbf{I}_t^w$ as shown in Eq. 3:

$$\mathbf{I}_t^w = \sum_{t'=1}^{t} \mathbf{I}(t') \tag{3}$$

The weighted interaction network $\mathbf{I}_t^w$ allows us to analyze the history of interactions of each agent in a swarm, and determine if there are any particular agents that had a major influence on the interactions of other agents. Moreover, we can analyze different time windows to identify the peculiarities of swarm-based techniques.

To capture the structure of the information flow within the swarm, Oliveira et al. also proposed a metric called *Interaction Diversity* (ID) to measure how quickly the interaction network can be destroyed by removing the edges from the network. The precise definition of ID can be found in [8]. If the graph becomes completely disconnected with the removal of only a few edges, it indicates that the swarm lacked diversity in its interactions. On the other hand, if the graph remains well connected even after the removal of edges, it indicates higher diversity in the interactions that occurred among the agents.

4 Interaction Network in ACO

In the Ant System (AS-ACO) [2], the decision-making of each ant (Eq. 2) considers the aggregated pheromone deposited by all ants. Given that ants indirectly communicate with one another, the interaction network for ACO algorithms attempts to estimate the interaction between ants based on the pheromone they deposit on the environment and how this pheromone is used by other ants.

Kromer et al. [6] previously defined an interaction network for the Ant System. According to their definition, the interaction between two ants depends on the similarity of their current tours. In this sense, it ranges from 0 (i.e., disjoint tours) to 1 (i.e., identical tours). This definition, however, neglects the fact that pheromone deposited in previous iterations still enables ants to influence each other in subsequent iterations regardless of the similarity of their current tours. Technically, having similar tours at a specific iteration does not necessarily imply ants exerted influence on each other towards the decision-making that led to their final tours. It implies that at the end of such a tour, ants will similarly deposit pheromone on the constituting edges of that tour, which in turn will influence ants in the subsequent interactions.

Conversely, our definition of the interaction network for the Ant System accounts for the effective interaction between ants as measured by the pheromone they leave on the environment. It captures how the decision-making of an individual ant is effectively influenced by other ants in terms of their deposited pheromone. This definition considers that the pheromone existing between cities i and j is actually an aggregation of pheromones deposited by all ants. If not completely evaporated, pheromone deposited at previous interactions can still influence the decision-making of ants at current iteration.

The interaction I_{kl} between ants k and l is formally defined as

$$I_{kl}(t) = \sum_{(i,j)\in\mathcal{T}_k(t)} \tau_{ij}^{l}(t), \tag{4}$$

where $\mathcal{T}_k(t)$ is the set of edges visited by ant k at iteration t, and $\tau_{ij}^{l}(t)$ is the cumulative pheromone deposited by ant l between cities i and j at iteration t after evaporation. Although it accumulates past pheromone, the interaction network does not necessarily become denser with more iterations because the cumulative pheromone of less visited edges tends to decrease (due to ρ in Eq. 1).

5 Analysis of ACO's Interaction Network

The AS algorithm was applied to the Symmetric Traveling Salesman Problem. As the TSP has been widely replicated in optimization problems, we argue that this work may refrain from the analyses of its fitness performance. We evaluated our implementation against four different instances of the TSP (Groetschel): 17 cities, 21 cities, 24 cities and 48 cities[1]. The considered initial parameters for the simulation of AS-ACO was 2,000 iterations, Q (used in the calculation of $\Delta\tau_{ij}^{k}(t)$ of Eq. 1) is 1.0, $\alpha = \beta = 0.85$

[1] https://github.com/pdrozdowski/TSPLib.Net

and five different values for $\rho : \{0.0, 0.3, 0.5, 0.7, 1.0\}$. The ρ value reflects the amount of memory each ant carries, so the five different values for ρ were chosen in order to test how different levels of memory affect the finding of the solution. The weighted degree analyzed in this section was normalized to ensure that the values are scaled to the same range for all the four problems.

Fig. 1 compares the evolution of shortest paths found in the simulations for several problems, and several evaporation rates for the problem with 48 cities. Fig. 1(A) shows that in each problem, the shortest path is found within the first hundred iterations. In Fig. 1(B), it can be noted that the excess of evaporation is not positive for the system because it removes the memory of the system.

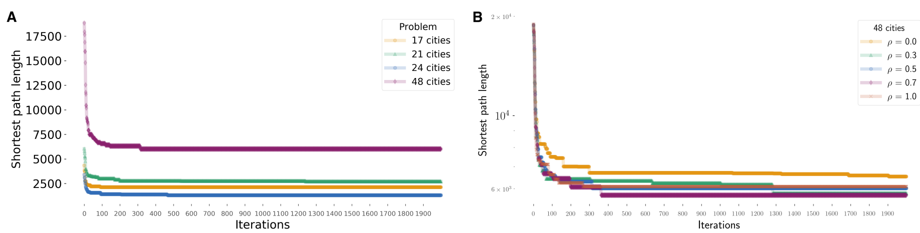

Fig. 1. (**A**) Fitness evolution of all the problems using the evaporation rate equal to 0.5. (**B**) Fitness evolution of the 48 cities problem varying the evaporation rate as 0.0, 0.3, 0.5, 0.7 and 1.0.

Fig. 2 depicts the Empirical Distribution Function (EDF) from the final interaction network in each problem simulated using $\rho = 0.5$, and the final interaction network in the problem of 48 cities simulated using ρ equals to 0.0, 0.3, 0.5, 0.7 and 1.0. All the distributions are a Gaussian distribution which means that the majority of ants display similar behaviour but a few of the ants can be seen as hubs or in the periphery. In Fig. 2(A), we can observe that the values of weighted degree change based on the magnitude of the paths. In Fig. 2(B), the excess of pheromone evaporation changes the distribution of weighted degrees, as the memory of system is removed as defined in Eq. 1.

In Fig. 3, both cumulative interaction networks from 24 and 48 cities are displayed at 200 and 2000 iterations. The red, orange, yellow, green and blue are the representations from the highest to the smallest amount of interaction. Each row indicates the strength of influence of each ant, and each column indicates how much an ant was influenced by another ant. The presence of homogeneous lines demonstrates that the ants influence more equally than are influenced. We observe that the lack of pheromone history has a different impact on both problems. On 24 cities, accounting a percentage of memory decreases the ants interaction. However, on 48 cities, the opposite is identified, the ants strength increases. As the presence of memory is positive for the system, the heatmaps for ρ equal to 0.5 are better for the problem. In this way, the high presence of more hubs seems to be benefit only for the 48 cities problem. As the majority of ants start to follow the same path over time, the contribution of pheromone could be more similar between them. However, some ants get lost in the process and they usually are less influenced by the other ants, which are perceived as blue dots/lines on the heatmap.

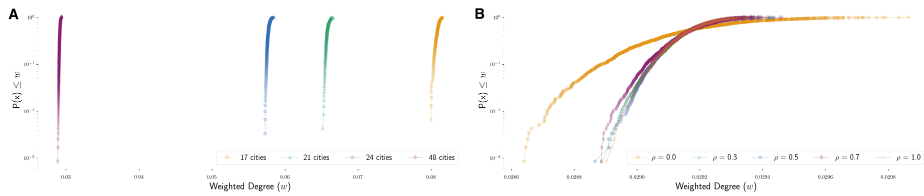

Fig. 2. (**A**) Empirical Distribution Function (EDF) of the weighted degree from the final interaction network on the problems: 17, 21, 24 and 48 cities using the evaporation rate set to 0.5. (**B**) Empirical Distribution Function (EDF) of the weighted degree from the final interaction network on the problem of 48 cities. The important issue here is that the interaction network allows us to get a deeper understanding of the execution of the algorithm. Note that by studying such behaviour, one can make better decisions about the parameters in Eqs. 1 and 2.

In the beginning, some ants are more likely to contribute more because some ants might find first a good path than the others.

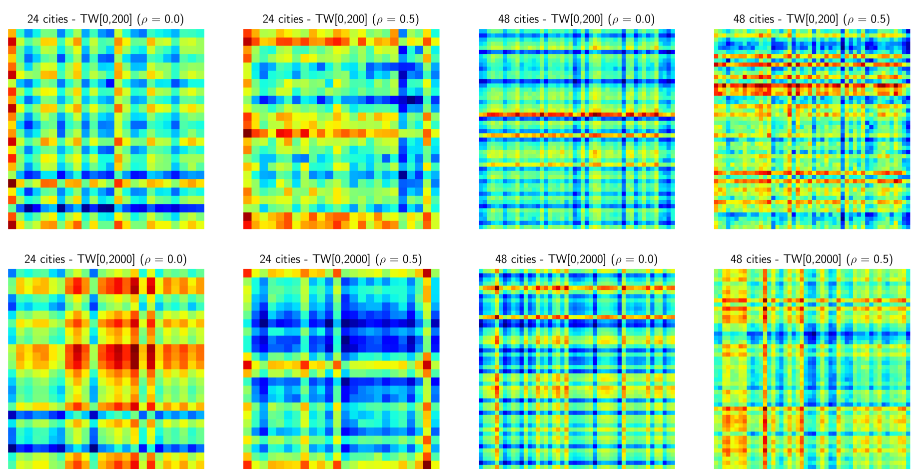

Fig. 3. Cumulative interaction network from different time windows on the problems 24 and 48 cities using the evaporation rate (ρ) set to 0.0 and 0.5.

In order to understand the exploration-exploitation balance of the system, we analyzed the Interaction Diversity of the interaction networks in Fig. 4. In the beginning of the process, the interaction diversity goes down quickly. This decrease might be caused by the rules of the system because even when we remove the memory of previous iterations, we still notice such behaviour. In Fig. 4(A), we observe that the total evaporation of pheromone makes the convergence of the swarm more difficult by adding on the swarm a constant growth of exploration. When the evaporation rate gets bigger than 0.0, as in Fig. 4(B), the exploitation is maintained which helps on the convergence of

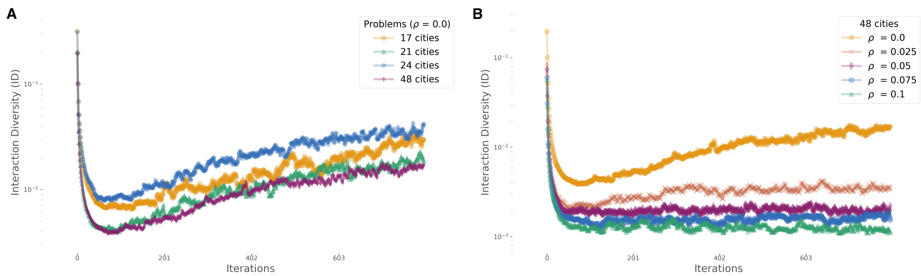

Fig. 4. Dynamics of Interaction Diversity (ID). (**A**) Problems with 17, 21, 24, and 48 cities, using the evaporation rate (ρ) as .0. (**B**) Problem with 48 cities using ρ equals to .0, .025, .05, .075, and .1. The ID is calculated over the weighted degree interaction network with time windows equal to [10, 20, 30, 40, 50, 100, 150, 200].

the swarm. The 48 cities problem can be highlighted by its dynamic behaviour of increasing and decreasing the ID. If we increase the evaporation rate for bigger than 0.1, we identified that the dynamic behaviour gets smaller. Moreover, in 24 cities, we could notice that the dynamicity is higher than the other problems. In summary, we can observe that the memory of the system is important for the convergence of the swarm, and that different problem sizes may show more deviation on the interaction diversity.

6 Conclusion

Swarm-based algorithms are computational models containing multiple agents simultaneously searching for optimal solutions while sharing with each other the solutions they find. Though swarm-based algorithms are effective, they depend on the appropriate adjustment of their parameters, and such adjustment requires significant knowledge about the algorithm. Previous research has demonstrated that the dynamics of these algorithms can be characterized and better understood by the social interactions among individuals and that, by changing the parameters of a swarm-based algorithm at the micro level, we actually create different conditions for social interactions to occur at the mezzo level which, in turn, can ultimately improve the overall performance of the algorithm at the macro level. In this work, we sought to answer the question of whether it would be possible to extract the social interactions of the Ant System—a well-known Swarm Intelligence algorithm—even though the communication in this system is based on stigmergy (indirect communication). We show that indeed the use of an Interaction Network framework can help us understand how to properly adjust its parameters without deep knowledge of the algorithm.

In order to show the effectiveness of the Interaction Network approach, we analyzed the social interactions occurring among ants of an Ant System while they solve four different instances of the Traveling Salesman Problem (TSP). Then, we examined the Ant System with different rates of pheromone evaporation. For future works, we argue that further experiments should be performed to understand the impact of other parameters to the interaction network. Also, we want to further explore why the current influence strength as measured by the weighted degrees in the network seems to be homogeneously distributed around a well-defined typical value. Such type of distribution implies that ants tend to exert similar levels of influence on each other and might prohibit the algorithm to appropriately balance the extent of exploration and exploitation.

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