

Modeling Dynamic Change Tolerance in Ant Colony Optimization

Robert Gomez, Gibson Olbrys

Abstract

Ant colony optimizations are often used as effective approximations for difficult pathfinding problems such as the traveling salesman problem. In these problems either a single colony, or in special cases, multiple colonies are modeled. The strength of these algorithms is derived from their quick convergence to an approximately correct solution. However, when dynamic change occurs in their environment and some subset of solutions no longer become viable, these simulations can lose productivity and be forced to completely re-explore their environments. This paper demonstrates characterizes the effect on shared information between colonies such that best solutions on a colony-by-colony basis are propagated to the other colonies with the hope that this provides redundancy to the solution set in the case of dynamic environmental change.

Introduction

Ant colonies have often been used as a source of inspiration for various algorithmic models. Rather than having a colony of individuals making independent decisions based solely on their physical surroundings, ants are able to lay chemical signals for each other called pheromones to use as a form of collective guidance. Paths with higher levels of these pheromones are then preferred by some new ant deciding which direction to travel. As a result, ants have a sort of self-reinforcing collective behavior where paths that have more ants travel on it will have higher concentrations of pheromones, leading to more and more ants to use this path and thus raise its pheromone concentration. The key to making this system effective and efficient is the idea that the colony's objective is to minimize the distance and time it takes for an ant to leave the colony, explore, find food, and return to the colony. It then follows intuitively that if all ants drop pheromones at, ostensibly, the same rate then those who best achieve the objective, such as finding the shortest path to food and back, will leave behind the highest concentrations of pheromones for others to converge on.

Ant Colony Optimization Algorithms

Consequently, Ant Colony Optimization algorithms (ACO's) have become an effective approximation technique for difficult exploration and pathfinding problems such as the traveling salesman problem. For these problems, it is most common to utilize a *single colony* ACO approach, wherein there is one colony with some n number of agents all seeking to optimize over a single, common objective function. Thus, ants are allowed to explore their environment, laying pheromones, and making movement decisions based on a probabilistic model that weights a heuristic together with pheromone concentrations. In this *single colony* example, the expected behavior for the colony is that, over time, the ants will all converge on to a single approximated solution based where divergence is highly unlikely. The speed at which this convergence occurs is based upon the rate of pheromone dissipation, balance between heuristic and pheromone concentration value, the number of ants in the colony, and the size of their environment.

However, the *single colony* approach is not the only way in which ACO's appear. Similarly, there exists the concept of the *multi-colony* approach. In this approach there are simply some m number of colonies, each with n ants, and each colony's ants have a pheromone that is uniquely layed and detected by ants from that respective colony. By utilizing multiple colonies that possibly are located at different locations, the ACO algorithm will now converge to a set of approximately good solutions rather than a single solution such as the case of the *single colony* example. The usual hyperparameters of pheromone dissipation, heuristic and pheromone balancing, and environment size are still relevant here as they were in the *single colony* scenario.

Dynamic Environmental Change

Up to this point, convergence to a solution is exactly what makes these algorithms viable. However, as will be discussed, this ends up being what makes these algorithms susceptible to pitfalls when the concept of dynamic change is introduced to these models. Dynamic environmental changes appear in real life that we may wish to model like mapping when traffic changes occur such as accidents, road closures, or slow downs. As a result, it is then natural to ask how tolerant the solutions that are produced by these *single colony* and *multi-colony* models are in response to dynamic change.

Evaluating the *single colony* model, it quickly becomes clear that the single model does not, intrinsically, respond well to dynamic changes. Take for instance the following scenario. Let there be some environment where, from the location of the colony, there are exactly two paths that lead to two completely disjoint, intricate sub-environments with exactly one food source in each sub-environment. Without loss of generality, let one of the food sources be accessible by a path that is notably longer than the other. Naturally, the model will converge to a single solution such that the ants travel to the sub-environment where the path is shortest to the food source. Consequently, after sufficient time, pheromones outside of that solution will dissipate to a measure zero concentration. Then, let some change occur such that the food source they are currently accessing is no longer reachable. Now, the colony will essentially be forced to restart their exploration process to converge onto a solution that reaches the other food source. In the meantime, there will be some expected drop in the amount of food that can be accumulated by the colony.

Similarly, in the *multi-colony* model, assume the same setup but now introduce two colonies. Place one colony closer to one food source and the one closer to the other. When the dynamic change occurs in this setting, one of the colonies will be entirely unaffected by the change. However, the other colony will incur the same drop in productivity and exploration cost as was discussed in the *single colony* example.

Thus, we intend to introduce the concept of shared information as a proposed solution to the lack of tolerance of these models to dynamic change. Intuitively, it seems obvious that in the previously described example where one colony was not affected by the dynamic change but the other was forced to restart exploration entirely, this drop in productivity could be reduced if there were some ability for the affected colony to leverage the solution set already developed by the unaffected colony. As a result, in this paper we explore the effectiveness of balancing the value an ant places on the pheromones from its own colony and the value of those from a shared pheromone that is propagated to all colonies.

Background

Ant colony optimization models that rely on shared information typically employ the use of self reinforcing pheromone trails to elucidate and solidify the shortest path found by the ants. This is done by having ants lay pheromone trails that evaporate at the same rate, making the pheromone scents from more recently completed (and thus shorter) trails more prominent,

creating a feedback loop. This pheromone reinforcement is the guiding principle to most ACO's. This pheromone feedback loop happens when ants find pheromone trails from members of their own colony, but, when multiple colonies are added to the simulation, ants can also interact with pheromone trails from other colonies. This is implemented as a global pheromone trail. Global pheromones are placed whenever ants find a new shortest path to their destination, and ants now factor this global pheromone into their decision of where to move next. The addition of a global pheromone presents an increase in complexity for the simulation. But this increase in complexity can lead to great improvements in the ants navigational efficiency.

When multiple colonies are added, the colony's interactions with each other present a lot of opportunities for research. We decided to add multiple colonies to our simulations because we thought that the added complexity brought about by having multiple colonies in our simulations mirrored the real world factors present in ant colonies. The colonies' local and global interactions with pheromone trails create a great amount of individually controllable interactions, and research has been done into making behavioral changes to individual colonies, and how that affects the ants overall navigational efficiency. (Mavrovouniotis et. al. 2014). Due to the complexity introduced by changing an individual colony's behavior, we plan to keep all colony's decision procedures homogenous. Changing individual colonies behaviors would have made the model more realistic, as ants often interact with ants from different species, but the added complexity in the model deterred us from adding these changes to our project.

Ant colony optimization as a modeling approach has been used to solve many different optimization problems, including the traveling salesperson problem and even protein folding problems. ACO's are a randomized approach to solving these problems, they operate like a Monte Carlo algorithm to find the optimal solution through continuous random exploration. This mechanism of randomized action is the source of their versatility as a tool for solving optimization problems. But this source of randomness is also prone to inconsistencies in the models results. Since the simulation is entirely random, results are unique and can be hard to recreate even with the setup standardized.

Modeling

In general, we take two approaches to model this problem with several shared aspects. The first approach we take is to set up the environment in terms of a bi-directional weighted graph. The second approach we take is to implement the environment in terms of a $r \times c$ grid. We will subsequently detail the unique portions of these approaches. However, first, we will detail the commonalities between the two approaches.

Movement

First, the way in which we model the choice of movement direction by ants is kept common. For this, we use a probabilistic model to determine a distribution across the available locations to move and randomly draw from that distribution to determine where a given ant will move. The distribution can be seen in **Figure 1**. To break down this equation we need to introduce some simple notation. Let $p(i)$ denote the probability that a given ant moves to location

i . Let τ_i denote the pheromone concentration at location i for the ant's respective colony pheromone table. Similarly, let τ_i^g denote pheromone concentration at location i for the global pheromone table. Next let c_i, c_i^g follow similarly denoting the heuristic value at location i . We then introduce hyperparameters α, β to tune the weight of the heuristic and the pheromone concentration have on the distribution. Furthermore, we introduce hyperparameter w to denote the weight on local colony information versus global information. Finally, we let j denote some other adjacent location that the ant has the option to move to.

$$p(i) = \frac{w((\tau_i)^\alpha * (c_i)^\beta) + (1 - w)((\tau_i^g)^\alpha * (c_i)^\beta)}{\sum_{\forall j} w((\tau_j)^\alpha * (c_j)^\beta) + (1 - w)((\tau_j^g)^\alpha * (c_j)^\beta)}$$

Figure 1. Probabilistic model for ant movement.

Global Propagation

Furthermore, we keep the technique of propagation to the global pheromone table common between both approaches. We do this by tracking when an ant has achieved the shortest path yet seen for its respective colony. While it still holds the record for this shortest path for its own colony it is then allowed to lay both its regular local pheromone as well as a pheromone that can be sensed by all ants. Once an ant for that colony has achieved a shorter path, the previous ant will no longer lay global pheromones and the new one will. After each dynamic change that occurs, the shortest path is reset due to the possible removal of edges such that the path can no longer be used.

Graph Approach

Next, we will detail what portions of the approaches were held to be strictly unique from each other, starting with the graph approach. In total, we will cover the initialization, use of heuristic, and movement constraints.

Initialization

To initialize the environment in the graph approach, the following parameters were necessary: number of nodes, connection ratio, food source count, colony count, and colony size. Their definitions are as follows respectively: the number of nodes to be used in the graph, the approximate ratio of edges that should exist of all possible edges, the number of nodes to be designated as food sources, the number of colonies used in the simulation, and the number of ants to exist in each colony. To construct the environment, for each possible edge, we draw from a biased coin flip where the probability of success is the connection ratio and set whether the edge exists accordingly. We enforce that a node may always be connected to itself and that all edges are bidirectional. Next, we draw uniformly from all the nodes for each colony to have

its location assigned, and similarly, for each ant, we draw uniformly for where their starting location will be.

Heuristic

Furthermore, the heuristic must be defined slightly differently for the graph approach than grid approach. Here we define the heuristic function to simply be the minimum distance that must be traversed from some given node to the point of interest most relevant to the ant at the time of the decision. The distinction here would be that ants that are currently carrying food hope to minimize the distance to their colony, while ants who are not carrying food want to minimize the distance to a food source. Thus the calculation is slightly different between the two contexts.

Dynamic Changes

To model the dynamic change in this environment, we set some parameter for how often a change should occur. Then, when it should occur, we drop some number of the most used edges at random. This technique is used to attempt to elicit emergent behavior exactly in similar circumstances to those outlined in the introduction where a colony sees its converged solution made no longer viable due to a dynamic change.

Movement Constraints

Finally, we wish to simulate some form of ‘traffic’ in an effort to elicit some emergent behavior under constrained flow conditions. To do so, we impose on the graph approach that a parameter must be set to determine the maximum number of ants allowed at a given node at a given time. Additionally, this creates the potential logistical pitfall that ants who have their next movement calculated first are at a disadvantage as they might be rejected from movement into a node that is currently occupied but may not be occupied later in the queue of ant movements. To address this, we make it such that the order in which ants have their next movements calculated is randomized at each timestep.

Grid Approach

Next we will provide the details for the Grid implementation of the simulation. This approach was in some ways more realistic because the ants have complete freedom of movement, but is limited in other ways such as the computational complexity required to run it. We will explain the Initialization, Heuristic, and movement constraints of using this model.

Initialization

The initialization of the grid approach utilizes the following input parameters: `grid_size`, `number_of_colonies`, and `ants_per_colony`. For `grid_size` the grid environment is always a square and as such, the `grid_size` input variable is a single integer representing the length of one side of the grid. `Number_of_colonies` represents the number of colonies in the simulation. And `ants_per_colony` is the variable controlling how many ants are added to each colony at model startup.

Heuristic

The heuristic for the grid approach was implemented differently than for the graph approach. In the grid approach the heuristic is defined as the euclidean distance between the cell that is being considered and the ants destination goal. For ants not carrying food this destination is the food source, for ants laden with food the destination is their respective colony home. The global heuristic is implemented as colonies begin to complete deliveries. It takes the number of steps taken to complete the delivery, and then recreates a path that takes that number of steps.

Movement Constraints

In order to simulate a maximum “flow” through the environment, the grid approach utilized a maximum ant occupancy per cell. If an ant chooses a cell that is full, the ants movement opportunity is skipped and it must wait until the next simulation update. At smaller values of `grid_size` this can create a “grid-lock” around cells that change the direction of the ants heuristic, while this was not an issue with larger grid sizes, it can be remedied by randomizing which ants positions are updated first.

Results

Although the implementations vary between the grid and the graph approach, both models sought similar goals regarding the analysis of parameter sweeps over w and the number of colonies. A similar analysis of results between the approaches allowed us to directly compare the effectiveness of the different implementations.

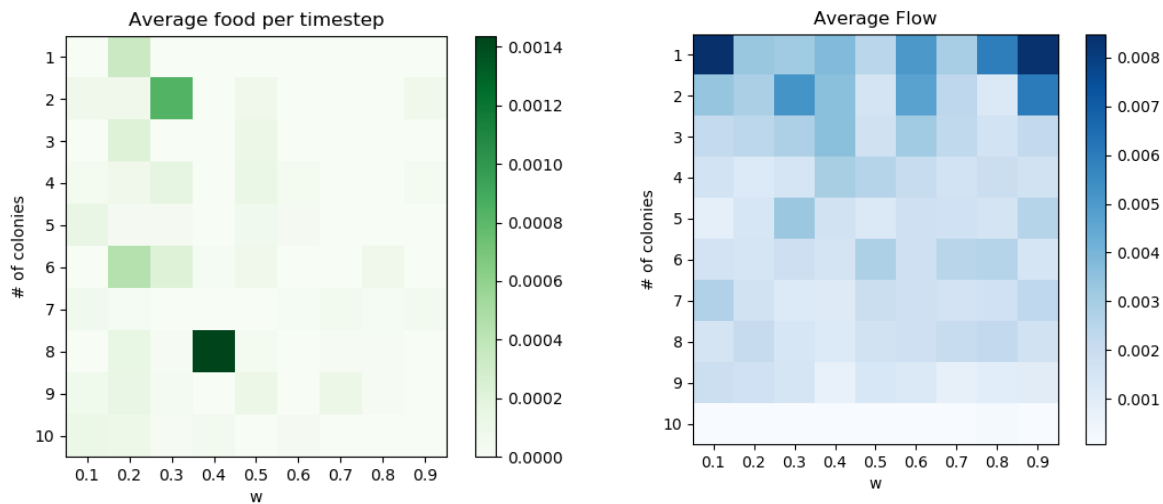
Graph Approach

Now we may detail the results of our parameter sweeps over the variables of w , value on local information, and the number of colonies used in the simulation. We note here that a previous parameter sweep yielded acceptable ranges for α and β to be set at without having dramatic effect on the performance of the algorithm. Thus, those have been controlled and set to 2.2 and 3.7 respectively. Next we note that the following experiments took place with 50 nodes, a connection ratio of 0.3, 2 food sources, an evaporation rate of 0.2 (thus multiplying pheromones by 0.8 each timestep), and a dynamic change occurring every 400 timesteps of the total 10000 timestep allowed for the simulation.

Hypothesis

Our hypothesis is that ants will prefer some medium balance between the local and global pheromone tables to better handle the dynamic changes. Thus we believe that at medium values of w , we should expect to see higher values for the average amount of food brought in per colony per timestep. Next, we hypothesize that since the effect of the dynamic change will be less, we should see higher average flow rates at those values of w as well. Finally, we predict

that at the extremes of the colony counts we should see lowered values of average food per colony per timestep. This is based off of the intuition that we should expect to at least outperform the single colony example with some notion of shared information, as well as the idea that with too many colonies we should see a dilution in the quality of the global pheromone table thus being less helpful to individual colonies. Finally, we hypothesize that the flow will naturally decrease with the increase of the number of colonies simply because the positive effect of shared information will not outweigh the dramatic increase in the number of ants introduced with each new colony.



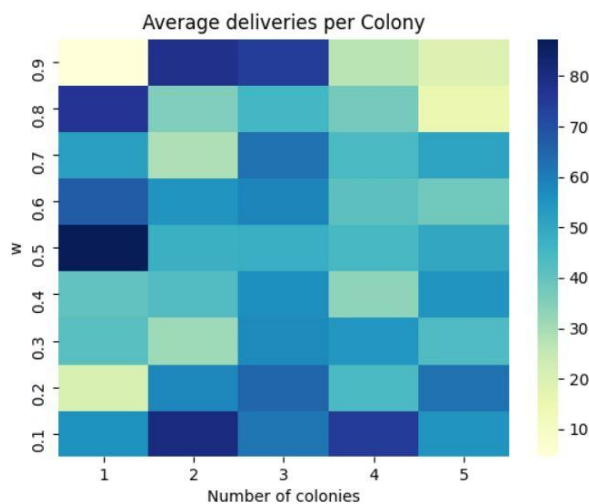
Above, two heat maps are included for the parameter sweeps over our desired variables. In green, the metric displayed is the average amount of food that one colony is able to acquire per timestep. We use this as a proxy for efficiency of the colony. We notice that in that green figure, the results somewhat align with our hypothesis as it is clear that the average food per colony per timestep is maximized under the conditions where there is some notion of shared information. Interestingly, it seems that for values of w that are too high, the productivity is notably lower than when w is low in value. This may be explainable under the logic that the higher w is set, the closer the setup begins to reflect a single colony setup. However, more robust simulation may be necessary to have a more certain result.

Secondly, in the blue figure, the metric being measured is the average proportion of total ants that are able to leave their current node for a new node which we use as a proxy for flow. In this result we can see another confirmation of our hypothesis as flow generally follows a pattern where the more colonies that are introduced, the more natural congestion. In general we do not see much discernable gradient across different values of w having a noticeable effect on the flow. We may expect a more accurate estimate on the effects on flow with a more robust way of simulating the geometry of ants as well as actual slow-down characteristics under congested conditions than our rather rudimentary approach.

Grid Approach

As in the graph approach, initial parameter sweeps were run to establish primary values for different input variables. Alpha and beta were set to both set to 1, grid_size was set to 20, max_occupancy was set to 20, ants per colony was set to 50. Rate of evaporation was set to .9 and the strength of pheromone trails left by ants was set to 1. Each combination of parameters was run 5 times for 100 time steps to get an average, this was done to smooth over outliers since the simulation has a large random component.

The hypothesis for these parameter sweeps for the grid approach was largely the same as our hypothesis for the graph approach. We hypothesized that the middle values of w would produce the best delivery count since it factored in both heuristics. We also expected the extremes of the colony count to perform poorly, the lower values doing so because they simply have less ants to complete deliveries, and the higher values because with more ants in the environment, the ants would face problems with cell occupancy.



Above is the heatmap produced by varying w and the number of colonies. The chart displays the average total food delivered per colony as a function of w and number_of_colonies. We can see that our hypothesis is partially correct, values of w which are balanced between both heuristics produce generally higher average delivery counts, the exception to this is very low values of w which seem to produce above average delivery counts. What is surprising about this chart is that the number of colonies seems to have little effect on the average food delivery per colony, this suggests that the ants had little trouble with occupancy limits. Lowering the occupancy limit for the simulation might give the number of colonies a greater impact on food deliveries since more colonies would mean more competition for cell space, given an equal sized grid.

Discussion

Overall we are pleased with the results we got from our models, especially considering the number of factors we considered while building the models. Values of w in the middle of the range producing more food proves that a balance of the local and global heuristics provides the ants with the best information for path finding. As it stands it would be interesting to implement the global pheromone differently, the global heuristic could be changed to reflect a different

aspect of the ants navigation, for example you could build a simulation that included both positive and negative pheromones, where negative pheromones would deter ants from following certain paths.

One cool concept that could be used in future research is the idea of competition between colonies. For example you could give ants territorial behavior relating to food locations, so if ants found ants from other colonies are near what they would consider "their colonies" food source, they would attack the ants. You could even have ants from separate colonies fight whenever they made contact. Another interesting direction for future research would be manipulating the colonies behavior individually, for example one colony could be more focused on exploring new paths (maybe through a lower value of alpha which would decrease the input from the heuristic) while other colonies could be more focused on collecting food.

Contributions

In general reference to all of the proposal, slides, implementation, analysis, and writeup, use the following rules for determining who contributed it:

1. If it has to do with the graph model: Robert Gomez
2. If it has to do with the grid model: Gibson Olbrys
3. If it has to do with anything more general: Equally shared

References

Awan-Ur-Rahman. "The Inspiration of an Ant Colony Optimization." Medium, Towards Data Science, 26 Apr. 2020, towardsdatascience.com/the-inspiration-of-an-ant-colony-optimization-f377568ea03f.

Burd, Martin, et al. "Traffic dynamics of the leaf-cutting ant, *Atta cephalotes*." The American Naturalist 159.3 (2002): 283-293.

Couzin, Iain D., and Nigel R. Franks. "Self-organized lane formation and optimized traffic flow in army ants." Proceedings of the Royal Society of London. Series B: Biological Sciences 270.1511 (2003): 139-146.

Gambardella, M. D. L. M., Mauro Birattari Alcherio Martinoli, and Riccardo Poli Thomas Stützle. "Ant colony optimization and swarm intelligence." 5th international workshop, Springer. 2006.

Mavrovouniotis, Michalis, Shengxiang Yang, and Xin Yao. "Multi-colony ant algorithms for the dynamic travelling salesman problem." 2014 IEEE Symposium on Computational Intelligence in Dynamic and Uncertain Environments (CIDUE). IEEE, 2014.

Peters, Karsten, et al. "Analytical and numerical investigation of ant behavior under crowded conditions." Advances in Complex Systems 9.04 (2006): 337-352.