How does the modification of a simulated ant colony affect the ants’ behavioural patterns?

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1. Introduction

Ant colonies are complex and highly organized societies, where individual ants work together to achieve collective goals such as gathering food, which is done using a key characteristic known as pheromone trails, these are trails used to communicate to other ants that a food source has been found and how to get to it (Wikipedia). We can understand the dynamics of ant colonies and the factors that influence their behaviour with the application of a computer simulation that will allow the investigation and manipulation of how ant colonies behave in a controlled environment.

By modifying a simulated ant colony, we can investigate the effects of altering factors such as colony size, resource availability, communication mechanisms, or social structure on the ants' behaviour. For example, increasing the colony size might influence the foraging patterns or division of labour among the ants. Changing the communication mechanisms, such as the pheromone trails used by ants to navigate and share information, could have significant implications for their foraging efficiency and overall coordination.

The ants are designed based on the Ant Colony Optimization Algorithm, an optimization technique inspired by the path finding behaviour of ants when searching for food and also a subset of swarm intelligence. One interesting aspect of ACO is the ability to modify the ant colony to improve its performance. The modification of the ant colony can affect the ants' behavioural patterns, leading to changes in the algorithm's convergence rate and exploration-exploitation balance. For instance, increasing the number of ants in the colony can enhance the diversity of the search process, while decreasing the pheromone evaporation rate can increase the exploitation of promising solutions.

This approach provides a detailed analysis of the cause-and-effect relationship between colony modifications and the upcoming alterations in individual ant behaviour. The initial phase of this study involves a comprehensive description of the agents involved and the environment in which they operate. Furthermore, the methodology employed to address the project's research question, along with the experimental design. The remaining section focuses on the evaluation of the results obtained, highlighting their significance. Additionally, noteworthy observations relating to the acquired results and the learning process are discussed.

1.1 Question

I will be investigating how a simulated colony of ants is affected from different aspects of its environment alongside other traits, aiming to answer the project question:

How does the modification of a simulated ant colony affect the ants’ behavioural patterns?

1.2 Motivation

The main motivation behind creating a project based on ACO is to solve complex optimization problems by mimicking the collective intelligence of ant colonies. In nature, ants can find the shortest path between their nest and food sources by laying down pheromone trails, which attract other ants to follow the same path. ACO algorithms use a similar approach, where artificial ants explore different solutions to a problem and leave pheromone trails to guide the search process.

The effects on the environment and pheromones by ants to facilitate communication and exhibit highly advanced behaviour in nature fascinates me, and hence, I aim to explore whether my simulated ants can learn to procure food sources within different conditions by modifying the ant colony and observe how its performance changes.

Therefore, by understanding how the modification of the ant colony affects the ants' behaviour, we can uncover insights into the abilities of ants to learn and test if whether or not machine learning techniques can be used to replicate these behaviours in artificial environments. This can have applications in various fields, such as logistics, transportation, and telecommunication, where finding optimal solutions is critical for reducing costs and improving performance.

2. Background Research

ACO was the first swarm intelligence-based algorithm (ScienceDirect, 2021), a problem-solving technique that uses decentralized collective behaviour to derive artificial intelligence. A typical application of ACO is using it on combinatorial optimization problems such as the popular Traveling Salesman problem, alongside other popular scheduling, and routing problems.

There are several modifications of the Ant Colony Optimization, with the two main ones being the elitist type and MaxMin. The elitist ACO uses the best global ant at a current time to deposit more pheromones than usual during its pheromone trail creation in order to encourage the rest of the ants to update their search around the same solution that the best ant derived, this ensures that they follow a high-quality record of searches and in turn result in an improved search performance.

The following formula is how the elitist local pheromone update procedure works, where e is used as the parameter that adjust the quantity of extra pheromones given to the elite.

$$\Delta\tau_{ij}^{bs} = \begin{cases} Q/C^{bs} & \textit{if component}(i,j) \textit{ belongs to an elite ant} \\ 0 & \textit{Otherwise} \end{cases}$$

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} + e\Delta\tau_{ij}^{bs}$$

(Lee, 2015)

Similarly, the MaxMin modification takes preference towards the ants that provide the best solutions, however, instead of providing a higher pheromone deposit to the elite ants, it stops all inferior solutions from generating pheromone trails and only lets the best global solution to continue deposit. By having a maximum and minimum range of pheromone trails, we can avoid sub-optimal solutions. This method allows for the exploration of an entire search space, before having to focus on the global optima.

Alternatively, there are more complex methods of applications of Ant Colony Optimization such as network coding resource minimization where a tabu-table based path construction method is used which supports a better collaborative performance of ants (Zhaoyuan, 2015).

All these methods rely around ACO by using different modifications that in turn provide different effects/performance which is what I will be exploring in this project.

3. The Environment

The field is represented as a two-dimensional space. Each point is identified by a unique pair of coordinates (x,y). On top of the field there are different layers that are used to represent different properties of the environment, this would be the colony nest which always remains at the centre where ants spawn from and deposit food found, the pheromones and the food sources. I have chosen to scale it as 1280x720 pixels, so it was calculated to have a 16:9 aspect ratio, providing us with a large search space for the simulation to take place. Additionally, the field has no borders so instead of the ants bouncing off from the walls, they show up at the opposite side of each border.

3.1 Colony Nest

The Nest Layer is a crucial component of the Ant Colony Optimization algorithm, as it represents the location of the ants' nest. The nest serves as a central hub for the ants to return their collected food. It is represented as a circular cell located at the centre of the field.

It is important to note that the colony nest is read-only and is not modified past execution. This means that the information contained within the colony nest is static and does not change during the execution of the algorithm. This feature ensures that the ants always have a reliable location to return to with their food and allows the algorithm to maintain consistency in its execution.

On top of the colony nest is a label which indicates how much the ants have stocked up the colony from their food search using an integer value as shown in figure 1.

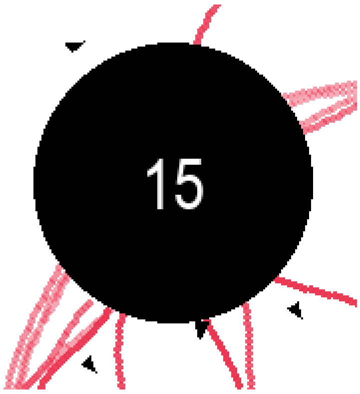


Figure 1 - Colony Nest

3.2 Pheromones Layer

In an ant colony optimization algorithm, pheromones serve as a crucial component for the ants to navigate and communicate with each other. Pheromones are classified into two different types, namely food and home. When an ant is searching for food, it is naturally attracted to food pheromones and will release more of this type of pheromone after reaching the food source. The primary purpose of the pheromones is to help other ants locate the same food source quickly.

On the other hand, home pheromones play a role in helping ants locate the nest. The scent helps the ants determine the location of their nest and ensures they do not lose their way back. These pheromones are released by the ants on their way back to the nest after they have collected food. It is worth noting that ants are selective in the pheromones they search for, and they are only interested in the type that matches their current task. For example, an ant looking for food will only be affected by food pheromones, and it will ignore home pheromones.

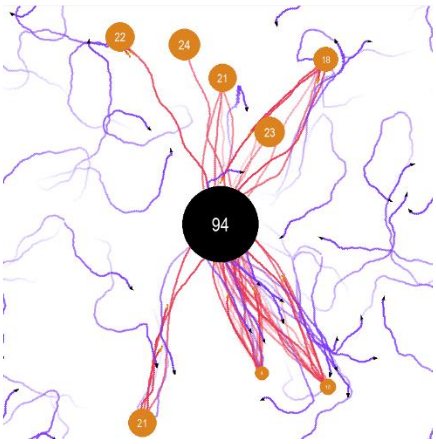


Figure 4 - Pheromones

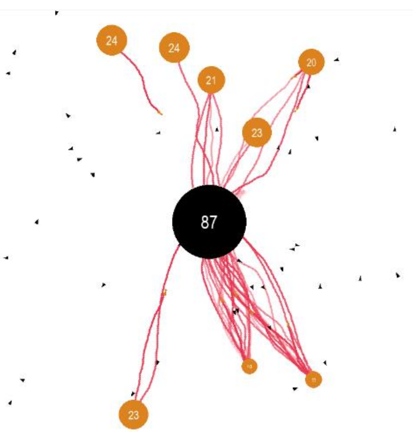


Figure 3 - Food Pheromones(Red)

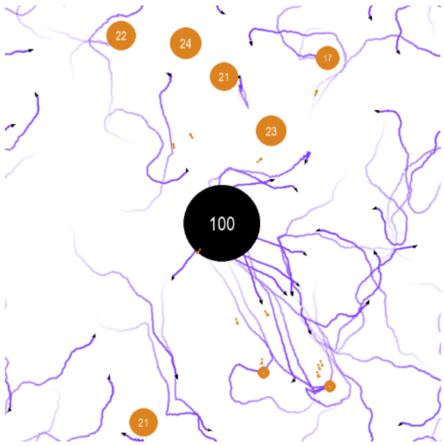


Figure 2 - Home Pheromones(Purple)

3.3 Food Layer

In the food source layer of the Ant Colony Optimization algorithm, the landscape consists of evenly spaced cells of food arranged randomly. These blobs are placed randomly during initialisation to ensure an equal amount and a consistent distribution. This approach results in an optimal distribution of food sources. Food sources decrease in size as ants remove food from them, until the food cell total food count reaches 0 and disappears.

It is worth noting that the food sources are not placed over the entire area, which allows for further optimization in future implementations of the algorithm.

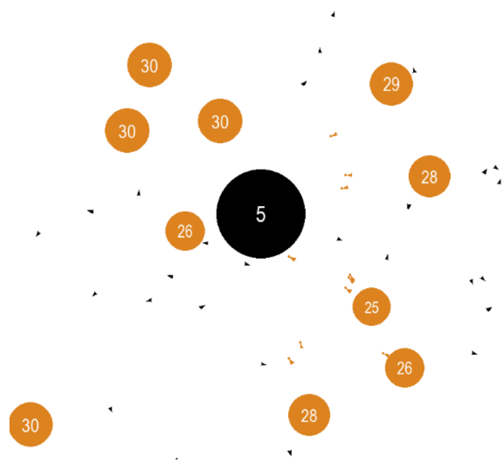


Figure 5 - Food Sources (Orange Cells)

4. The Agents

The environment is inhabited by a colony of ants whose population size can be adjusted by the user. Each ant exhibits individual behaviour and decision-making, which can be influenced by pheromones from other colony members. An ant's behaviour is characterized by a simple routine: leaving the nest to search for food, upon discovery of a food source the ant picks it up and returns home. During the search, the ant may either exploit existing information such as following an existing trail of pheromones or explore the environment randomly to locate food sources from new paths while ignoring pheromones.

4.1 Sensors

The ants have sensors which provide with information such as their distance from other ants' pheromone trails. The sensors start from the ant and end at a fixed distance. We have a set of n artificial ants, each represented by a vector p_i = (x_i, y_i). We use the GetDistance method of our Vector class to calculate the distance between any two ants (i, j) using Euclidean Distance:

$$d_{ij} = |p_i - p_j| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

(Euclidean Distance formula)

The distance is computed as the magnitude of the vector difference between the points, which is represented by subtracting the coordinates of the two points and computing the square root of the sum of their squares.

We can then use a proximity function to check if two points are within a certain distance to each other:

$$(p_i, p_j, r) = \{1 \quad \text{if } |p_i - p_j|^2 \leq r^2 \ 0$$

(Proximity Function formula)

It returns 1 if the squared Euclidean distance between two points is less than or equal to the squared radius, meaning that the two points are within the reach. Otherwise, it returns 0 which means that the two points are outside of the area and so the ant is not within range of a food source or a pheromone trail.

This is then used as a heuristic for the ants to decide on which path, they should choose to reach their destination

More frequently, the ants will be in the exploitation strategy, but it may transition to an exploration strategy under certain circumstances. These circumstances include detecting a local pheromone trail or autonomously deciding to explore based on randomness. The latter prevents the ant from becoming trapped in a local optimum and allows them to discover new paths that may be superior. Additionally, this is also done to avoid an ant mill or also known as a death spiral which occurs when ants lose a pheromone track and being to follow one another in a spiral (Ant Mill, 2003).

4.2 Actions

The ants are capable of performing different actions within the environment. These are the following:

Travelling Forward	The ant moves forward in the current direction at a max speed of 3
Deposit Pheromones	The ant will lay pheromones as it travels, upon finding a food source it will then lay stronger pheromones.
Turn	The ant will rotate using its 180 degrees field of view accordingly to the desired vector
Return to nest	Upon collecting food from a source, it turns itself 180 degrees and returns to the nest position

5. Experiments & Findings

In order to perform the experiments and analyse the results, it is worth considering the question at hand first. “How does the modification of a simulated ant colony affect the ants’ behavioural patterns?” As it is a rather open question, to answer it, we will be looking to find insights into how the ant agents act upon the environment through the increase or decrease of parameter values over a specified time period.

5.1 Challenges met

One of the significant challenges encountered in this project was the amount of time required for the simulation to take place. The implementation of the project was carried out entirely in Python due to its easy coding syntax, useful libraries, and the vast number of resources available for this language. However, Python has a drawback of being relatively slow, which led to the simulation crashing at various times when using certain parameters that my computer could not handle. Therefore, there is a need to consider alternative optimization techniques to improve the overall performance of the algorithm. Ideally, I would’ve preferred to have tackled this experiment with a much larger population and other large values for different properties of the simulation as more could’ve been explored. However, at the current state, the code would crash or take extremely long to show results.

Additionally, there were times where too many food sources would spawn too close to the colony’s nest so I had to rerun the code to hopefully spawn a more dispersed set of sources.

5.2 Experiments

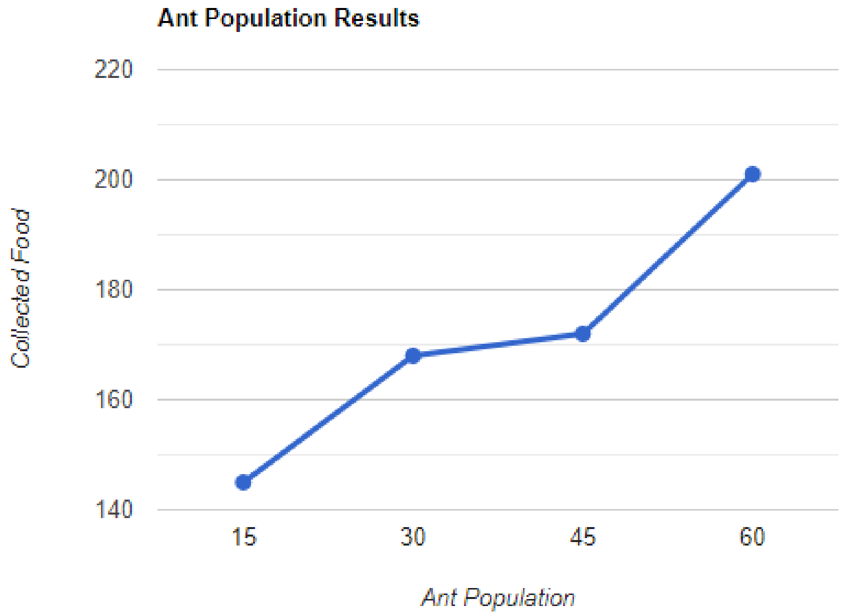
In the experiments conducted, parameters were modified by incrementing it over four different times. During each increment, the experiment was conducted for a 5-minute period. This approach allowed for the observation of the behaviour of the ants under different parameter values for an extended period of time. By incrementing the parameter, the effect of incremental changes on the behaviour of the ants could be observed, and patterns in the data could be identified. The 10-minute period for each test ensured that sufficient data was collected while still keeping the experiment at a manageable length.

The total amount of food per source will remain with a value of 8 to remain balanced, additionally, outside of the ant colony population size parameter experiment, ants total will be set to 30. When carrying out the experiments, all parameters in bold black will remain with the values suggested, while the parameters in bold red will be altered.

Ants Parameters		
Parameter	Description	Suggested
ANT_TOTAL	Ant Colony Population Size	25
ANT_SIZE	Size of each individual ant	8
ANT_SMELL_RADIUS	Olfactory detection radius	30
ANT_TRIGGER_RADIUS	Trigger radius for the ants to follow a pheromone or go to a food source	20
ANT_SPEED	The ant’s max speed	2

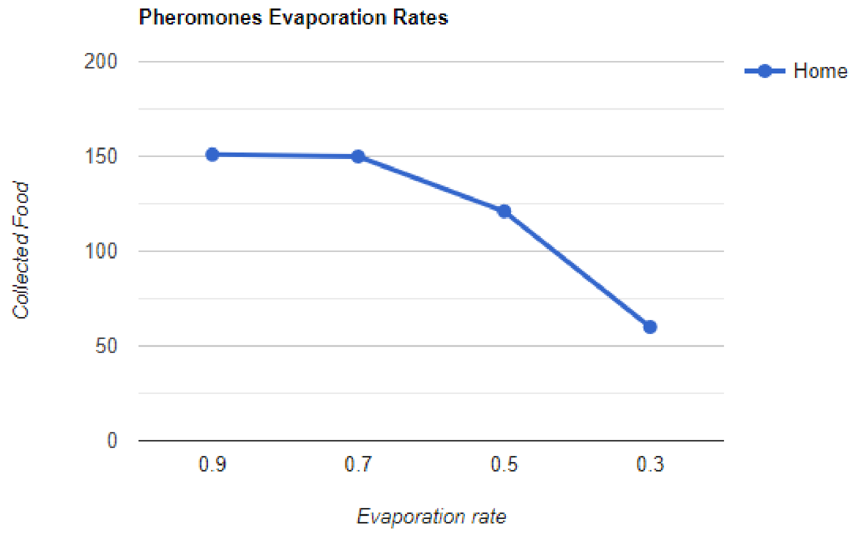
Pheromones Parameters		
Parameter	Description	Suggested
PHEROMONE_RADIUS	Size each pheromone cell	2
PHEROMONE_LAY	The drop discount factor	1
HOME_PHEROMONE_EVAPORATION RATE	Evaporation rate of pheromone trail when the ant is exploring	0.9
FOOD_PHEROMONE_EVAPORATION_RATE	Evaporation rate of the pheromone trail when the ant has food	0.2

Field Parameters		
Parameter	Description	Suggested
WIDTH	Width of the field	1280
HEIGHT	Height of the field	720
FOOD_SOURCE_TOTAL	Total amount of food sources present on the field	8
FOOD_UNITS	Total amount of food per food source	50



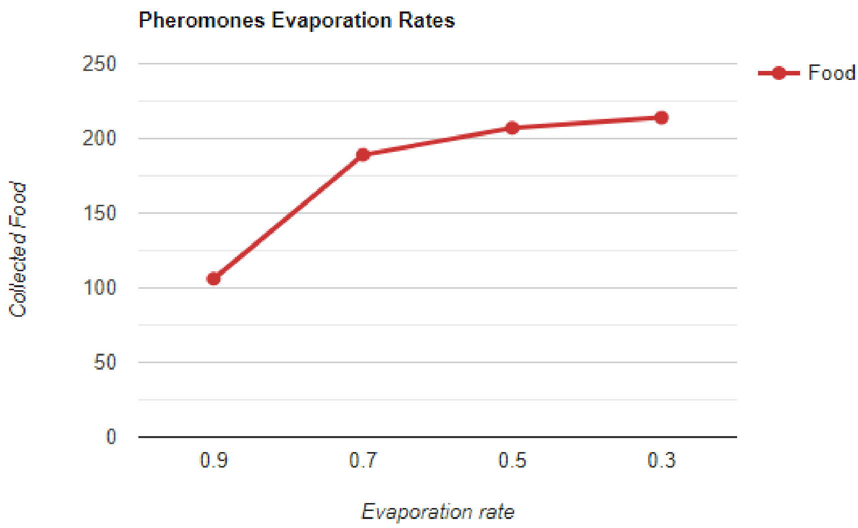
Graph 1 - ANT_TOTAL Results

Total Ant Population	Food Collected
15	145
30	168
45	172
60	201



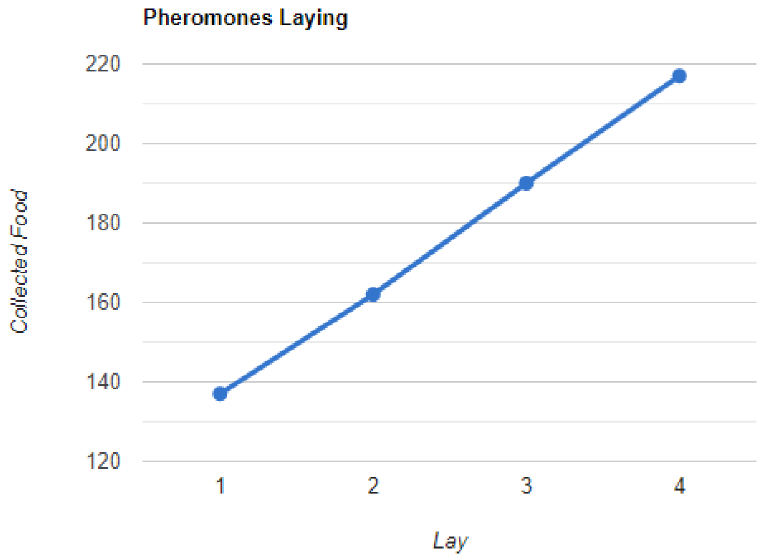
Graph 2 - Home Evaporation Rate Results

Home Evaporation Rate	Food Collected
0.9	151
0.7	150
0.5	121
0.3	60



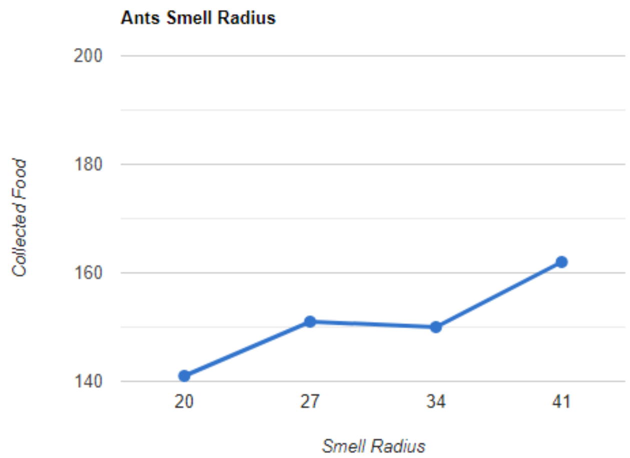
Graph 3 - Food Evaporation Rate results

Food Evaporation Rate	Food Collected
0.1	106
0.3	189
0.5	207
0.7	214



Graph 4 - Pheromones Laying Steps Results

Pheromones Laying Steps	Food Collected
1	137
2	162
3	190
4	217



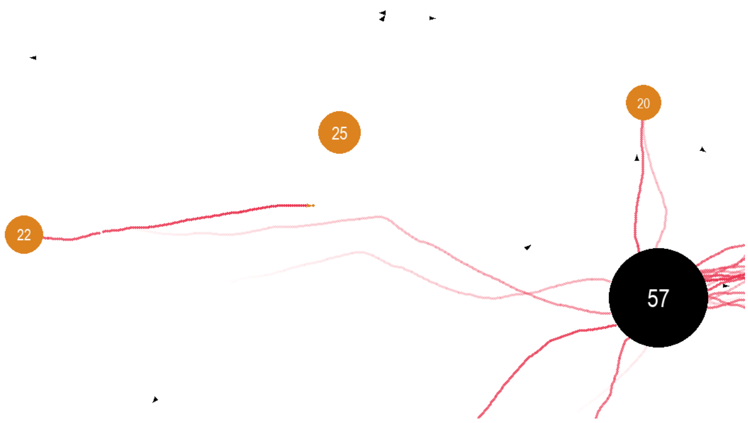
Graph 5 - Ants Smelling Radius Results

Ants Smell Radius	Food Collected
20	141
27	151
34	150
41	162

5.3 Results and Analysis

The first finding is involved increasing the number of ants in the colony from 15 up to 60. The results of the experiment showed that with more ants, the search process became more efficient, and the food collection rate increased significantly. The ants were able to cover a larger search space, and as a result, the probability of finding new food sources increased.

It was also found that a slower rate of pheromone evaporation leads ants to being more likely to follow established pheromone trails, resulting in greater exploitation of food sources. Conversely, a faster rate of pheromone evaporation will lead to ants exploring more, resulting in a more balanced exploitation-exploration trade-off, but also result in a lower total amount of food collected by the colony.



Additionally, we found that when the evaporation rate was set to a high value, the pheromone trails leading to distant food sources were not stable and the ants were unable to form a reliable route to the food source. This resulted in the ants being unable to efficiently collect food from the distant sources and, in some cases, completely abandoning the search for those sources.

Figure 6 - Distant food source losing its pheromone trail

This finding highlights the importance of balancing the evaporation rate in the algorithm. While it may be tempting to set a high evaporation rate in order to avoid the formation of stable pheromone trails leading to distant food sources, doing so can have a negative impact on the efficiency of the algorithm as a whole, leading it to being unbalanced and potentially worse solutions. Therefore, it is important to carefully tune the evaporation rate to ensure that the pheromone trails are stable enough to guide the ants to the food sources, but not so stable that the ants become stuck in local optima.

However, referring back to the increase in number of ants modification, it also had an effect on the formation of stable pheromone trails. With more ants in the colony, the pheromone trails were denser, and they tended to be more stable, even for food sources located far away from the nest.

Upon experimenting with the ant's smell radius, the results show that the food collection rate increases alongside it, suggesting that the ants can effectively search for food over longer distances and avoid the possibility of missing a food source nearby, additionally, with a smaller radius, the algorithm takes longer to achieve an optimal solution. Making it too small leads to the ant's search process becoming sort of random and much more difficult to collect food.

Although there were several parameters explored, due to the nature of the algorithm, there are other several properties that influence the performance and behaviour of the ants which could be investigated further. However, these are seen to have a greater influence in the algorithm' behaviour.

6. Conclusion

6.1 Successful Observations

The ant colony tends to optimize its food collection process by following a hierarchical order, starting with the food source that is closest to the nest and progressing towards the farthest one. However, the process of trail formation becomes increasingly challenging for the ants as the distance between the nest and the food source increases. This is because the pheromone trail marking the path has more time to evaporate before being used, making it more difficult to establish a stable trail.

Once the ant colony has collected the food from the nearest source, the pheromone trail leading to it naturally fades away, allowing ants to redirect their efforts towards collecting other food sources. However, by using a larger number of ants, we can reinforce the pheromones and create a more stable trail that can be used.

6.2 Limitations

A significant limitation of ACO algorithms is scaling to large problem sizes. The size of the search space increases exponentially with the number of decision variables, which can make the algorithm infeasible for large-scale problems, however, several approaches have been proposed to overcome this challenge, such as parallelization and hybridization with other metaheuristic algorithms (Gonz, 2022).

6.3 Future Directions

There are several areas of improvement that could be touched on, one such area is the need for code refactoring and optimization as currently the performance slows down there more trails that are made and the more ants that are present. Refactoring can improve the code's readability, maintainability, and extensibility, while optimization, on the other hand, can improve the algorithm's efficiency and reduce the time it takes to find a solution.

Another area of improvement is the possible inclusion of a velocity multiplier by delta time. Multiplying the velocity by delta time can help maintain the consistency of the algorithm across different computer systems and time steps. In the future, with more time available, I would've liked to explore the idea of implementing obstacles/barriers and creating mazes to answer the question of what the impact is caused by them within the environment on the ants' behavioural patterns and search performance. With these improvements, the Ant Colony Optimization Algorithm can become more robust, efficient, and accurate in solving complex optimization problems.

6.4 Final Conclusion

The experiments demonstrated that modifications to the simulated ant colony can have a significant impact on the ants' behavioural patterns. By modifying the pheromone updating rule, we were able to increase the exploratory behaviour of the ants, resulting in the discovery of more efficient paths. However, this also came at the cost of reduced overall efficiency, highlighting the importance of striking a balance between exploration and exploitation in the ACO algorithm.

References

Gonz, P. (2022). *Parallel ant colony optimization*. Retrieved from Science Direct: https://www.sciencedirect.com/science/article/pii/S0957417422013586

Lee. (2015, May). Retrieved from The Project Spot.

ScienceDirect. (2021). *Ant Colony Optimization*. Retrieved from ScienceDirect: https://www.sciencedirect.com/topics/engineering/ant-colony-optimization#:~:text=2%20Ant%20colony%20optimization,interactions%20and%20communications%20among%20ants.

Wikipedia. (2003). *Ant Mill*. Retrieved from https://en.wikipedia.org/wiki/Ant_mill

Wikipedia. (n.d.). *Pheromone*. Retrieved from https://en.wikipedia.org/wiki/Pheromone

Zhaoyuan, W. (2015, July). *A Modified Ant Colony Optimization Algorithm for Network Coding Resource Minimization*. Retrieved from https://nottingham-repository.worktribe.com/output/756748