Study on Ant Colony Path Selection Models

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Abstract— **Ants, like many other social insects, perform very structured and complex tasks collectively without any central coordinating body in a self-organizing way. They do so by a simple yet robust communication model named stigmergy. The theory of swarm intelligence has extended this robust biological insight into artificial systems. Implementation of ant colony optimization, one of the first types of swarm intelligence, has been proven to be very successful in solving hard combinatory problems in artificial systems and robotics. The ant colony's selection of the optimal solution is dependent on various factors such as pheromone secretion rate, pheromone evaporation rate, population size, and many others. This study is focused on investigating the ant colony's exploratory behavior in food searching and collection tasks by varying these parameters. It runs computer simulation on an agent-based modeling software and presents the ant colony with qualitatively different food sources at a different distance. The study finds that the evaporation rate has a substantial effect on the time taken to complete the food collection task regardless of the diffusion rate and the ant colony size, and the relationship among them is highly non-linear.**

***Keywords*— Swarm intelligence, stigmergy, ant colony optimization, pheromone diffusion and evaporation, agent-based modelling**

I. INTRODUCTION

Social insects like ants show interesting intelligence collectively in the basic life works such as building nest, foraging, sorting and distribution of labor. While an individual ant's activity might seem simple, their collective activities are highly structured and complex, and fascinating to observers, both scientists and laymen [1][2]. Their structured work pattern appears to be highly coordinated and organized, hinting a strong hierarchical - top-down approach- in existence. But, the emergence of this highly organized work pattern is not a result of any hierarchical management system, but a result of multiple interactions of individual ants with limited capability and simple work rules like a distributed intelligence systems [3][4][5]. With a very simple communication model, collectively they outperform complex work.

From the evolutionary perspective, ants have lived for more than 100 million years on the earth and are still thriving as one of the most operative species [3]. This biological insight of robustness has motivated the scientists to investigate how ant colony build nest, find food, transport food from the source, sort and store food, and ultimately manifest emergent behavior of self-organization, apparently at a global level [3][6][7]. The process of achieving self-organizing capability collectively in ant colony is an appropriate motivation for the scientists to study this biological creature for solving computation problem in artificial agents [8][9]. Eminent scientist Marco Dorigo first proposed the Ant colony Algorithm in the 1990s to imitate the biological ant attributes into artificial practical applications. Subsequently, many researchers have designed a considerable number of novel algorithms in solving combinatorial optimization problems in diverse application areas such as multi-agent robot systems, communication networks, traveling salesman problem, graph coloring problems and so on [3][8].

Of different interesting ant colony activities like foraging, division of labor, transportation, nest building, sorting, this study is focused on studying the ant colony's path selection process in food searching and collection. It investigates how the ant colony chooses a food source under various constraints like distance, quality and natural evaporation. In the subsequent sections, literature review and background on the ant colony are discussed along with the description of methodology and experimental setup including computer-based simulation tests. Finally, the findings and results are discussed.

II. BACKGROUND AND PREVIOUS WORKS

A swarm is a large of group of small animals or insects, homogenous in nature, that interact individually with one another and the environment in the absence of a centralized control system[10]. Their interactions, apparently very local in nature, result in the emergence of interesting collective accomplishment. While the individual member of the groups has very limited capability and performs a very simple task based on simple rules, collectively they carry out distributed problem-solving at the global level [9]. The motivation for swarm intelligence in the artificial system is drawn from the evidence of the emergence of self-organizing properties in small animals and social insects. In swarm intelligence, the agents are homogeneous in nature, act asynchronously at the individual level without any central control system, equipped with very limited communication capability - mostly through modification of the environment, and are conscious of small neighbourhood [11]. Multiple interactions at the individual level by these agents result in the emergence of complex self-organizing phenomena that can be extended to solve complex problems in artificial systems.

Swarm intelligence was first introduced as an algorithmic framework for controlling swarm robots by G. Beni and J. Wang in 1989 [10]. M. Dorigo and his colleagues, in 1991, proposed a metaheuristic, Ant Colony Optimization (ACO), for solving complicated combinatory problems inspired by the ant colony's efficiency in finding out the shortest path to food source [12][10][11]. Subsequently, Particle Swarm Intelligence (PSO), inspired by the bird flocking and fish schooling, was introduced by Kennedy and Eberhart in 1995 [13][10][11]. Successful implementation of these nature-based solutions has received greater interest in succeeding decades. Later in 2005, Artificial Bee Colony (ABC) algorithm was proposed by D. Karabago [10]. Swarm intelligence is now increasingly used to solve a variety of problems in artificial systems.

In nature, ants like other small animals and social insects have limited direct communication capability. They communicate indirectly through the environment. This was first explained by Pierre-Paul Gasse in 1959 by introducing the term stigmergy[14][3]. It refers to a mechanism of communication by modification of the environment. Stigmergy is a stimuli-response communication model in the social insects where both quantitative and qualitative stigmergy is observed. In case of quantitative stigmergy, individual responses to a particular stimulus that does not change qualitatively; on the other hand, for qualitative stigmergy, the stimuli changes qualitatively by instigating different response for a different quality of stimuli [14]. The concept of stigmergy was an important contribution in explaining the emergence of self-organization in biological systems.

Besides being limited in direct communication skills, biological ants have very limited capability. Ants leave out their nest and wander randomly in search of their food. An ant lays down a volatile chemical, called pheromone, during its travel to food and nest. This chemical can be sensed by other ants with their antennae and it acts as stimuli for the other ants to follow the chemical trail [10][14][15]. As many ants start to follow the trail, the chemical deposition on the path gets reinforced. The frequency of traveling by other ants acts as positive feedback and the concentration of the ant colony increases along the chemical path. In some species, the amount of chemical secretion by an ant depends on the quality of the food. However, this does not mean a qualitative stigmergic response, rather refer to more amount of chemical secretion. The chemical trail gets reinforced, and trail construction becomes stable and continuous until the food is exhausted. Interestingly enough, this chemical evaporates in nature [2][1][3]. The property of evaporation is so critical for the foraging activities of ants that without evaporation they would get trapped to the chemical trail even after the exhaustion of the food. The phenomena of evaporation act as negative feedback, and ultimately provides a balance transition for ants to explore alternative food sources [14].

Ants behavior in chemical laying and following has been of great interest to many scientists. One of the landmark experiments with real ants to study these trail-laying and trail-following behavior was carried out by Deneubourg, Goss and their colleagues in 1989 [16][2]. A colony of Argentine ants, Iridomyrmex Humilis, was presented with two bridges from their nest to a food source in the experiment. They ran multiple experiments in three basic settings: (1) colony was offered with two equal-length and equal-shaped bridges at the same time from the nest to food source (refer to Figure 1)[2]; (2) colony was presented with two bridges, the length of one is double the other (refer to Figure 2) [16][10]; (3) short branch of the bridge was presented after 30 minutes from the commencement of the experiment (refer to Figure 3) [16][10]. The results of the experiments were very insightful. For the first setting, ants chose arbitrarily any one of the paths and reinforced the chemical deposition by frequent travel on the route. In the

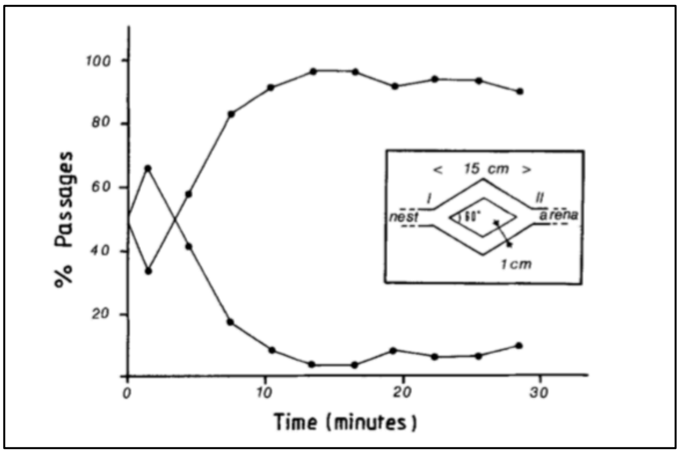


Figure 1: Percentage of ants per 3-min period passing on the two equal branches of the bridge (inset). Colony of 1000 ants. Taken from Deneubourg et al. [2]

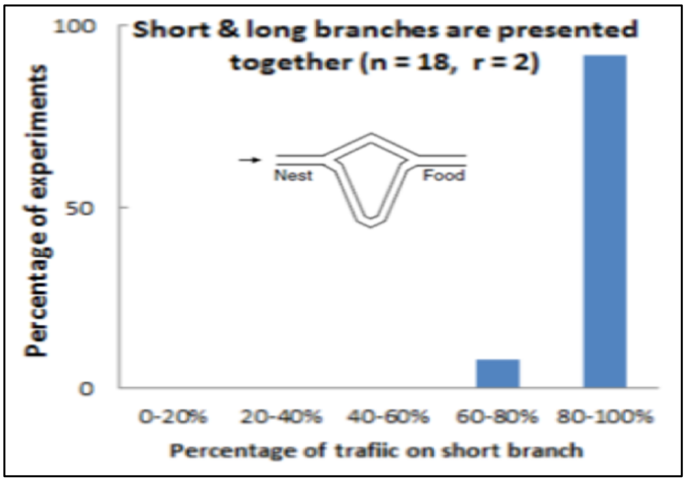


Figure 2: Distribution of ants for the 2nd experiment when the short and longer branches presented at the beginning of the experiment. Adapted from Goss et al [16] and taken from Ahmed et al. [10]

second setting, out of two alternatives, ants colony chose the shortest path; this is because travel in shorter bridge required half the time of the longer bridge. While initially, ants chose both the paths arbitrarily, the ants traveling on the shortest path

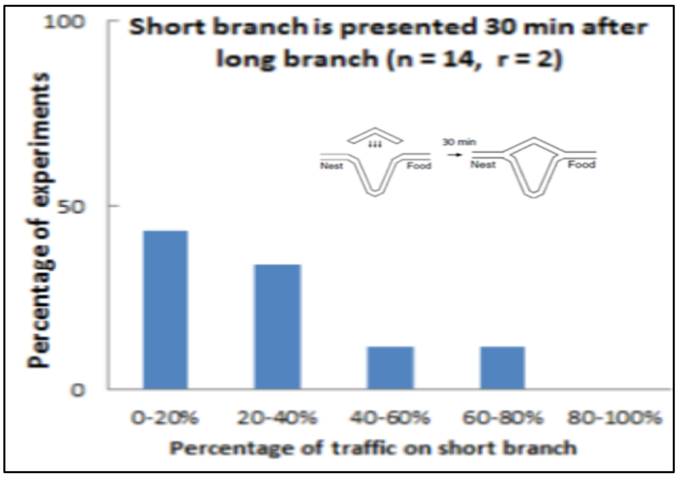


Figure 3: Distribution of ants in the 3rd experiment when the short branch is presented after 30 minutes after the long branch. Adapted from Goss et al [16] and taken from Ahmed et al. [10]

ultimately returned in half the time, reinforcing the chemical deposit. Eventually, most of the ants concentrated on the shortest path. In the third experimental setting, the result was quite intuitive as by the time the shortest branch was presented, ants have already established a chemical trail on the longest branch. In the absence of any evaporation of the chemical, ants continued to choose the longest path, leaving the shortest path unexplored [17].

The result of this experiment has drawn a lot of interest in extending ant colony behavior into solving diversified complex optimization problems in computation. After the introduction of ACO by Marico Dorigo, it has been further extended and used by the researchers in solving classification problems [18][19], traveling salesman problem [20], shortest path problem [21], vehicle routing problem [22], robot path planning [23][24][25][26], assignment problems [17], scheduling problem[17], cooperative transportation by robots [5] [27], optical network routing[17] and many other hard combinatory problems.

To study this interesting behavior in ant colonies, modeling biological ants in computer-simulated programs has greater benefits, as constraints are only limited by technology and researchers' inspiration [10]. Essentially, there exist some basic differences between biological ants and artificial ants. In biological ants, an individual updates its actions asynchronously, but in most of the simulated programs, artificial ants update their local conditions synchronously [11]. Biological ants lay down pheromone both way i.e. during travel from nest to food and vice versa, but artificial ants deposit pheromone only during return travel from the food to the nest. A memory characteristics like 'Nest-scent' is used to direct the ants to their nest [11]. More so, evaporation of the chemical in nature is often a slow process which is generally regulated in artificial ants to avoid converging into a wrong solution [10]. However, these differences in many cases are dependent on the research objectives. Given the technological flexibility in modeling artificial ants in computer-simulated programs, this study attempted to observe the emerging pattern that results from changing different parameters such as diffusion rate, evaporation rate, size of the ant colony, number of food sources, the distance between nest and food source, dimension and size of the space.

The ant colony's path selection pattern and exploratory behavior depend on different parameters that can affect the outcome. One of the important parameters is the rate at which evaporation of chemicals takes place[10][28]. Higher evaporation rate may restrict the formation of a workable chemical trail; on the contrary, a very low evaporation rate may reinforce the establishment of a chemical trail on a wrong solution. Again, the amount of chemicals deposited by the ants is also a deciding factor for converging on the right solution. When both diffusion rate and evaporation rate at various degrees act in the ant colony's food collection, the outcome can be very unpredictable. Besides, the size of the ant colony is another vital parameter when the time for quick completion of the task is important. The distance between the nest and food source and the quality of food can also affect the time taken by the ant colony to collect the whole food. In the subsequent paragraphs, the experimental setup and method are described.

III. Experiment Setup and Method

As discussed, an ant colony's exploration for food is a function of the time, the distance between the food source and nest, the dimension of space/ world, size of the ant colony, velocity of ants, pheromone diffusion rate and evaporation rate. This experiment was set up to study how the ant colony chooses a particular path, close or distant, with respect to different parameters of the function. Randomness in the path selection with different paraments in an ant colony is stochastic in nature. Therefore, experiments were designed to sweep parameters and averaging the result to get the data.

The experiments were carried out with the 'Ant' model [29] in Netlogo 6.10.0 [30][31], which is an agent-based modeling software. Ants in the model are represented by the 'turtles' agent of the software, and nest and food sources are represented by the 'patches' agent. In addition to in-built primitives for both 'turtles' and 'patches', the software allows users to define variables and add functionalities according to study requirements. The virtual world in which 'turtles' and 'patches' interact is a two-dimensional grid that can be extended or reduced to meet the experimental requirements [30][15]. For the purpose of this study, 'Ant' model in the Netlogo software was modified to fit the three experimental settings of the study: (i) two food sources with equal amount of food placed at equal-distant from the nest; (ii) two food sources with equal amount of food, one is placed at the double-distant from the nest than the other source; (iii) one food, qualitatively better than the other one in equal amount placed double-distant from the lower quality of food from the nest. Ants in this model were designed to perform two simple tasks: look for food and return to the nest with food. To accomplish these tasks ants were capable of wiggle (move randomly), lay down chemical, follow the chemical and the nest-scent.

Experiment 1 setup in the software was below:

Environment (space): 101 X 101, Non-toroidal
Nest location: (0, 0)
Nest size: (4 X4)
Food source 1 location and size: (15, 0) and (4 X 4)
Food source 2 location and size: (-15, 0) and (4 X 4)

Experiment 2 and 3 setup in the software was below, except in case of experiment 3, ants were asked to deposit double amount of chemical for the longest path food source:

Environment (space): 101 X 101, Non-toroidal
Nest location: (0, 0)
Nest size: (4 X4)
Food source 1 location and size: (15, 0) and (4 X 4)
Food source 2 location and size: (-30, 0) and (4 X 4)

For all the experimental setup, simulations were carried out by sweeping three parameters: the size of the population, diffusion rate, and evaporation rate. All the parameters were varied for each setup, and 5 data readings of time taken were recorded and averaged. Time steps required to finish collecting the whole food was recorded and averaged to get a single data point.

Ant population :	{ 50, 100 }
Diffusion rate :	{ 0, 20, 40, 60, 80 }
Evaporation rate :	{ 0, 5, 10, 20, 40 }
Simulation run :	250

IV. RESULTS

Results of simulation run for three experimental setup are given in subsequent paragraphs.

A. Equal-distance Food Source (Experiment 1)

During simulations run with both the population size of 50 and 100, ants chose both the food source almost at an equal time interval and concentrated on the pheromone trail to collect the food. Figure 4 shows the snapshot of ants taking two paths to food sources (blue – path 1 and green – path 2). Figure 5 shows that the ant colony distributed equally into both the food sources, and taken approximately the same amount of time interval to complete the food regardless of changing evaporation rate and diffusion rate. For the diffusion rate set at 0, the time taken by the ant colony was found much higher as no feedback system was present.

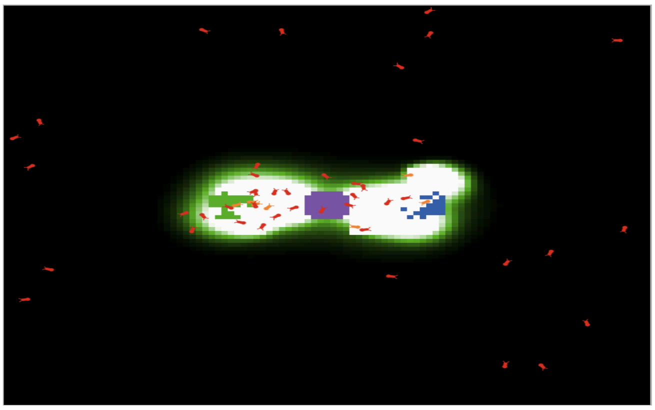


Figure 4: Snapshot of simulation of experiment 1. Two equal amount of food source (blue- path 1 and green – path 2) placed at equal distance from the nest where two food sources are selected by ants almost at equal times

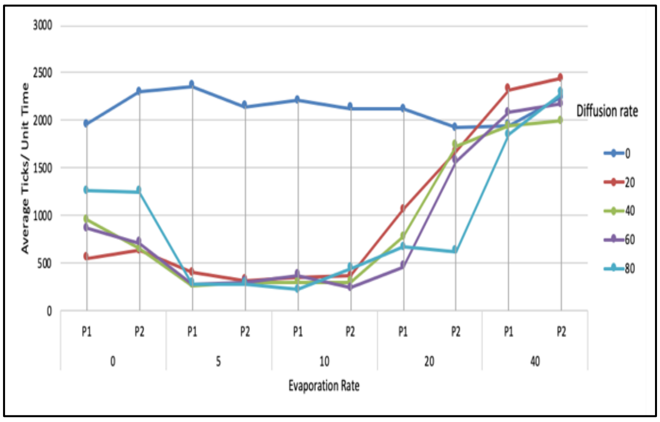


Figure 5: Time required to complete food collection on both paths (blue- path 1 and green – path 2) with changing evaporation rate and diffusion rate

B. Double-distance Food Sources of Equal Quality

Figure 6 shows the simulation snapshot where concentration of ant colony was along the closest food source. Ant colony could not sustain chemical gradient for the path 2 until the completion of closest food source.

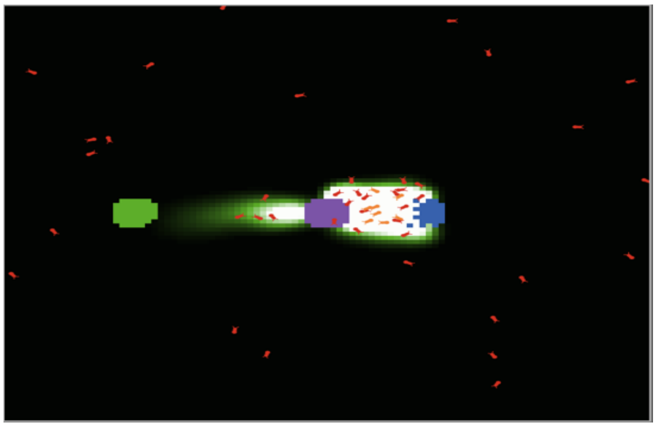


Figure 6: Snapshot of simulation of experiment 2. Two equal amount of food sources (blue- path 1 and green – path 2), but placed at different distance (length (Path 2) = length (2 X Path 1))

In the case of two food sources placed at double-distant, ants colony choose the closest path (path 1 to blue food source) for 121 times out of 125 simulation cycle. Only 4 times they selected the longest path to complete the food when diffusion rate was set to 0. Figure 7 shows the result of this simulation.

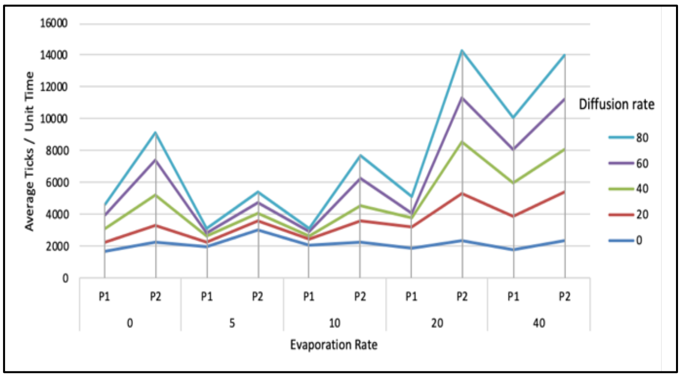


Figure 7: Two equal amount of food source (blue- path 1 and green – path 2) placed at different distance (length (Path 2) = length (2X Path 1))

Figure 8 and 9 show effect of evaporation rate on the time taken to complete the collection of closest food source for 50 and 100 ant colony size respectively.

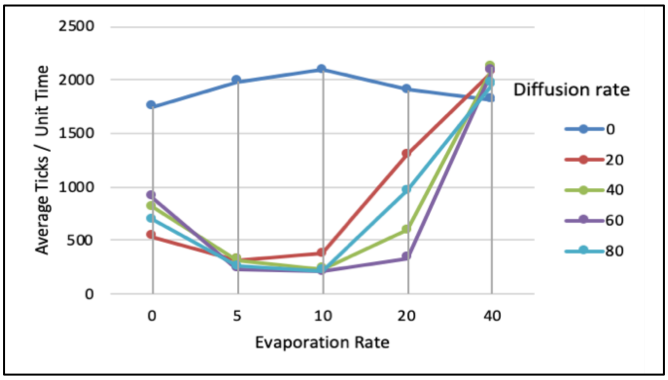


Figure 8: Effect of evaporation rate on time taken to complete food with changing diffusion rate for blue food source, path 1 (For Ant Colony size 50)

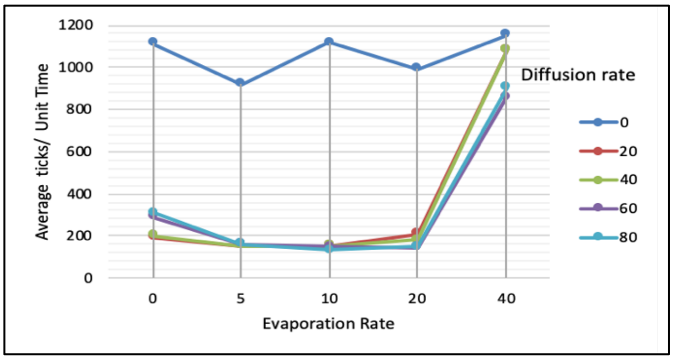


Figure 9: Effect of evaporation rate on time taken to complete food with changing diffusion rate for the closest food source : blue food source, path 1 (For Ant Colony size 100)

Figure 10 and 11 show the effect of evaporation rate on the time taken to complete collection of the longest food source for 50 and 100 ant colony size respectively.

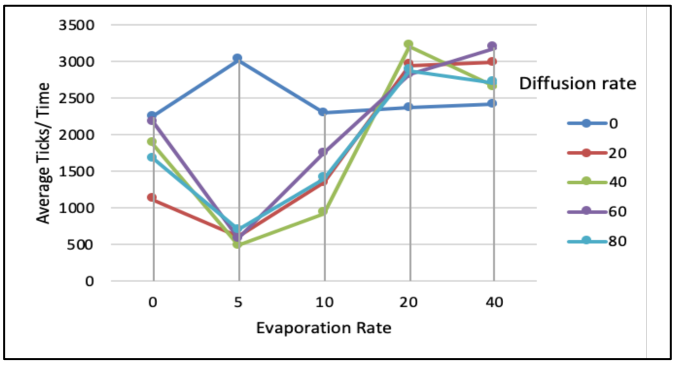


Figure 10: Effect of evaporation rate on time taken to complete foods with changing diffusion rate for the longest food source : green, path 2 (For Ant Colony size 50)

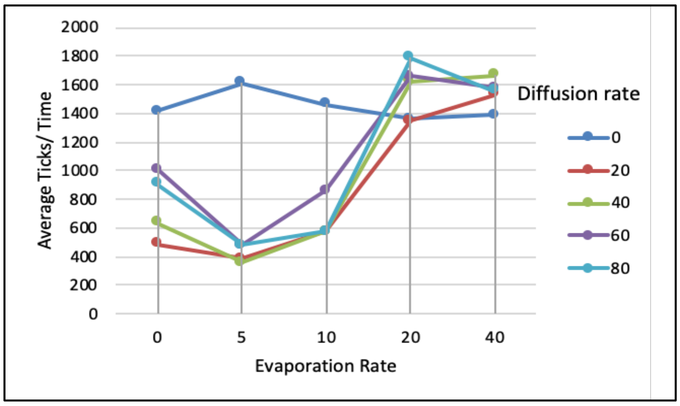


Figure 11: Effect of evaporation rate on time taken to complete food with changing diffusion rate for the longest food source : green, path 2 (For Ant Colony size 100)

C. Double-distance Food Sources of Different Quality

Snapshot of experiment 3 simulation where in the longest distant food source ants deposited double amount of pheromone is given at figure 12. The ant colony could establish a thin chemical gradient for the better food source though placed at double distant. Ant colony in all simulations choose the closest food source, despite depositing double amount of chemical (Figure 13).

Figure 14 and 15 show the effect of evaporation rate on the time taken to complete the collection of furthest food source, where double amount of chemical was deposited by the ant colony of 50 and 100 respectively.

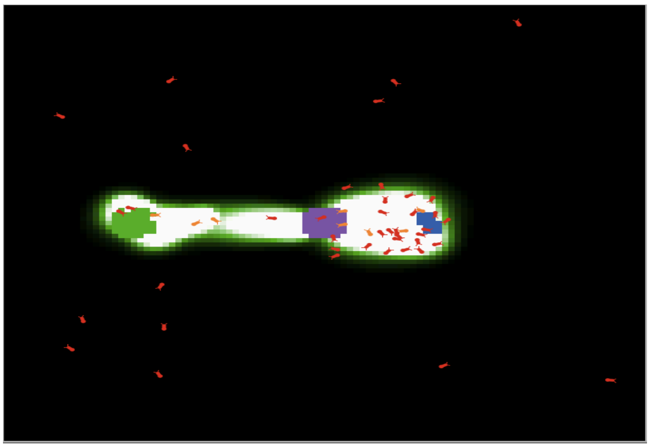


Figure 12: Two equal amount, but qualitatively different food sources. Closest food (blue- path 1) has lower quality and furthest food source (green – path 2) has quality better, placed at double the distance of the closest food source.

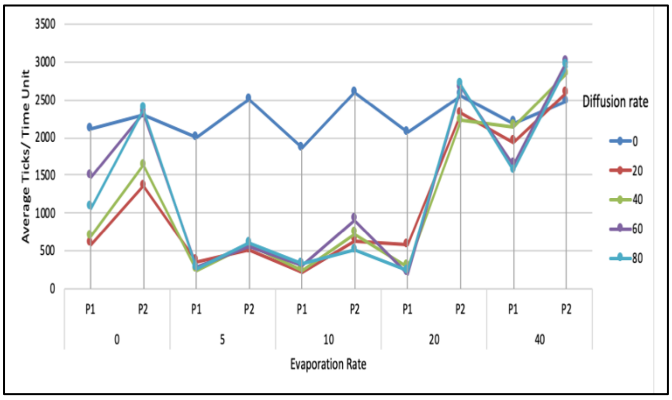


Figure 13: Two equal amount, but qualitatively different food sources. Closest food (blue- path 1) has lower quality and furthest food source (green – path 2) has better quality, placed double the distance of closest food source.

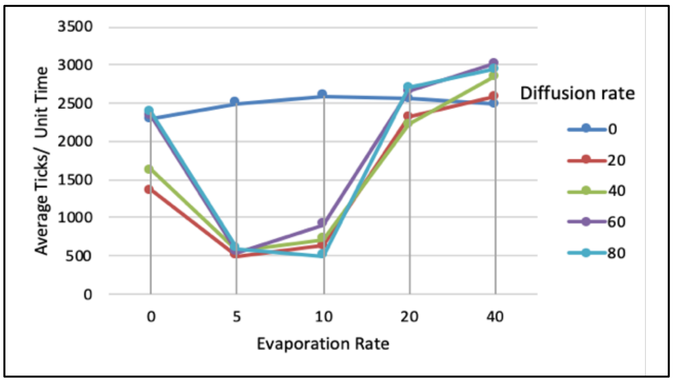


Figure 14: Effect of evaporation rate on the time taken to complete food with changing diffusion rate for the longest food source : green, path 2 (For Ant Colony size 50)

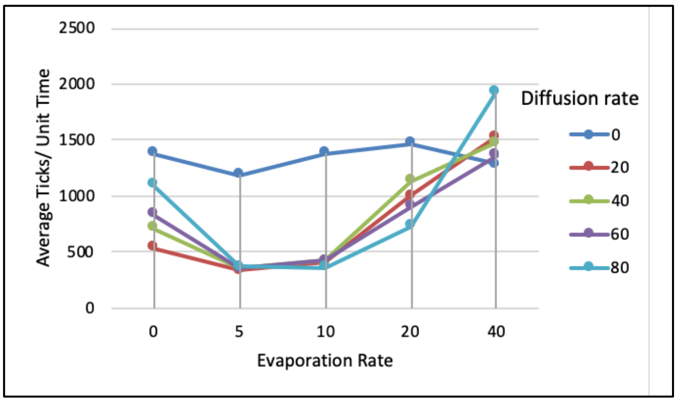
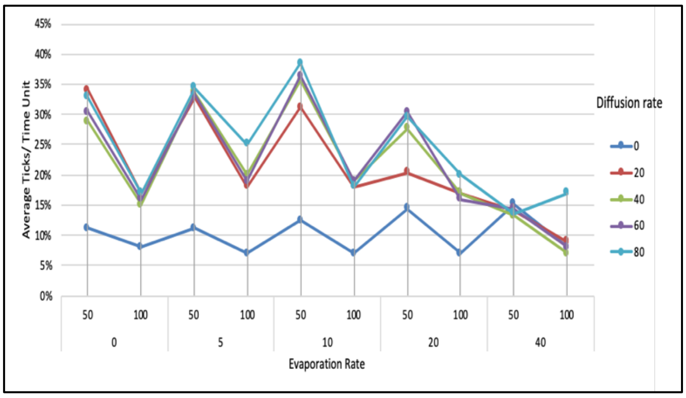


Figure 15: Effect of evaporation rate on the time taken to complete food with changing diffusion rate for the longest food source : green, path 2 (For Ant Colony size 50)

Figure 16 Maximum number of ants active in food collection



V. Discussions

The ant colony, when offered with two equal quality of food sources at equal distance, chose both the food sources randomly (refer to Figures 4 and 5). The time taken to complete the food collection was approximately equal, except few cases due to the randomness in the movement of ants. The pattern of chemical gradients established by the ants was the same. However, when the same quality food sources were placed at different distances, the ant colony always chose the closest food source first, established the chemical trail, and then completed the collection of food (refer to Figures 6 and 7). The high evaporation rate and distance of the food sources from the nest did not allow the construction of a steady chemical gradient (refer to Figures 10 and 11).

In the case of two different kinds of food sources, depicted by asking ants to deposit double amount of chemical in one of the food sources, the behavior of the ant colony has changed in terms of the amount of time they took to the complete collection task. Due to the diffusion of a double amount of chemical on the path of the better quality food sources, ants established a thin chemical gradient in most cases. However, ants completed the collection of food from the closest one first, despite being lower in quality which was because the distance was double from one to another, and they had equal velocity. Thus, even after establishing a chemical gradient, the time taken to collect all of the food took longer time (refer to Figures 12 and 13).

A. *Effect of Evaporation Rate*

The evaporation rate of the chemical affects the time required to complete the collection of food. For the equal distant food sources, a lower evaporation rate has no impact due to the small distance between the nest and the food sources, allowing ants to establish a continuous chemical gradient along the path. Ants could return to the food source and reinforce the chemical trail before the chemical got disappeared due to the slow evaporation rate. But, for higher evaporation rate, the chemical trail becomes intermittent, thus engaging the ants in the search task and increasing the time taken to complete the collection task. When offered with food sources at different distances, low evaporation has less effect on the time in the case of the shortest path/ closest food source. For a lower number of population, the evaporation rate up to 10 has less effect on time regardless of varying diffusion rate. On the other hand, with an increased population (ant colony size 100) evaporation rate up to 20 showed a low effect on time. Due to an increased number of population on the chemical trail, a higher evaporation rate could not completely dissolve the chemical (refer to Figures 8 and 9). This allowed completing the food collection task with the shortest possible time.

In the case of the longest path, the presence of the chemical trail was not continuous for any evaporation rate beyond 5. Even with an increased colony size of 100, the scenario did not change (refer to Figures 10 and 11). Double distance between the nest and the food source did not allow the formation of a continuous chemical trail for the ants, and thus, ants had to return to their search task before collecting the food. However, when the ants deposited a double amount of the chemical along the longest path in experiment 3, the degree of evaporation rate's effect increased up to evaporation rate of 10 (refer to Figure 15). The increased amount of chemical on the longest path allowed the formation of a thin chemical gradient (Refer to Figure 12); thus, turning only a few ants for the search task and majority into the collection task.

In all the cases where evaporation rate was set to 0, meaning that no evaporation of chemical in the model, increased the time to collect all the food. In the absence of evaporation, the chemical trail towards the food expands largely and trap the ants inside the chemical trail rather than transporting the food to the nest.

B. *Effect of Diffusion Rate*

Increasing the rate of chemical diffusion does not lower the time required to collect all foods, rather the collection time remains approximately unchanged. With a higher evaporation rate of the chemical, increasing chemical diffusion does not lower the time required for collection.

A relative increment in the chemical diffusion rate, as in Experiment 3, where ants deposited a double amount of chemical on the farthest food source than that of the closest one, reduces the effect of a higher evaporation rate, and decrease the collection time. Ants could establish a thin chemical trail despite higher evaporation that allowed them to move along to collect food.

C. *Effect of Ant Colony Size*

The size of the ants' world (space) regulates the colony's search task and controls the number of ants that are active in collection work. With the limited number of the food options (two food sources, placed within one-third of the space from the center), the maximum number of ants in the colony get engaged in search task due to randomness in their movement. Since the velocity of all ants was equal and sensing of the chemical trail or nest-scent is limited to a specific position, the ants that crossed away from the food source randomly can only return after being bounced back from the last extent of the space or by random turning. Thus, regardless of the size of the ant colony, one-third of the ants were engaged in the actual task of collecting food (refer to Figure 16).

VI. CONCLUSIONS

Swarm intelligence has been drawing increasing interest in artificial systems due to its powerful and robust problem-solving capability. To understand the interplay working in the biological life and regulate the desire solution, computer-simulated agent-based modeling is a useful tool. In this work, the artificial ant colony's exploratory behavior in food source selection and collection were studied by sweeping 3 most important parameters: population size, chemical diffusion rate, and chemical evaporation rate. The colony was offered qualitatively different food sources at different distances, and time taken to select and complete the food was recorded and evaluated. The result demonstrated that the low evaporation rate has less effect on different diffusion rates and time while a higher evaporation rate significantly increases the time, regardless of the increment in diffusion rates. The relationship among them is highly non-linear. To distinguish between the quality of foods, a greater amount of diffusion rate is necessary while keeping the evaporation rate at low. This particular result may be useful in designing collaborative swarm robots for collection and transportation tasks. However, further study on how the ant colony negotiates stationary and moving obstacles with different diffusion and evaporation rate can provide further important insights.

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