

# Behavior Integration for Prometheus using Real World Ant Colony Algorithm

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August 2013

A Thesis submitted to the Faculty of Graduate Studies and Research in partial  
fulfilment of the requirements for the degree of Master of Science

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## ACKNOWLEDGEMENTS

Firstly, I would like to thank my supervisors Mathieu Blanchette and Joseph Vybihal for their invaluable inputs, ideas, patience and most importantly, for lending me a hand when I needed one the most. I am sure I wouldn't have reached this stage if not for their accommodating nature. Secondly, a special thanks to all the socs staff who were available and ready to help every time I approached them. Lastly, I would like to thank my family for their never ending support and my friends in Montreal for just being there.

## ABSTRACT

Prometheus aims to explore artificial intelligence in a controlled but flexible environment by mimicking the properties of the real world using a swarm intelligence implementation. Swarm Intelligence has been used for solving problems in the domain of self organization, complexity and collective intelligence for a group of agents. The collective behavior of the entity considered here - ants, are modeled as a decentralized and self-organized system in which the ants communicate indirectly and thrive by modifying the environment. This novel approach combines the widely established stigmergy theory with real-time fluid dynamics by using Pheromones and the Navier-Stokes equations respectively to subject the environment to natural conditions like wind, and spread and decay of smell thus making the environment more suitable to real time conditions. The chosen real-time fluid dynamics method proves to be computationally fast, robust and far more realistic than traditional approaches. Also, for evaporation, instead of choosing a random fixed value for every timestep, we take into consideration the effect of temperature, vapor pressure, wind and humidity on evaporation and consequences of that. It is hoped that this model will be a step closer to achieving results substantially closer to the real world and also, observing the changes that the aforementioned natural properties might impose on experimental world.

## ABRÉGÉ

Le projet d'intelligence artificielle Prometheus vise à explorer, dans un environnement contrôlé mais flexible, les propriétés du monde réel sur une intelligence en essaim. L'intelligence distribuée a été utilisée afin de résoudre les problèmes dans le domaine de l'auto-organisation, la complexité et l'intelligence collective d'un groupe d'agents. Le comportement collectif de l'entité considérée, ici la fourmi, est modélisé comme un système décentralisé et auto-organisé dans lequel les fourmis communiquent indirectement et prospèrent en modifiant l'environnement. Cette nouvelle approche combine la théorie de stigmergie avec la mécanique des fluides, utilisant respectivement les phéromones et les équations de Navier-Stokes, afin de soumettre à l'environnement des conditions naturelles comme le vent ou encore la propagation et la désintégration de l'odeur. Ainsi l'environnement correspond mieux à des conditions réelles. La méthode de mécanique des fluides en temps réel choisie s'avère être rapidement calculable, robuste et beaucoup plus réaliste que les approches traditionnelles. De plus, pour modéliser l'évaporation, au lieu de choisir une valeur aléatoire fixée pour chaque itération, nous prenons en compte l'effet de la température, de la pression de la vapeur, du vent, de l'humidité de l'évaporation et leurs conséquences. Nous pensons que ce modèle contribuera à l'obtention de résultats nettement plus proches du monde réel et à l'observation des changements que les propriétés naturelles susmentionnées pourraient imposer à l'environnement expérimental.

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## CHAPTER 1 Introduction

### 1.1 Communication among Ants

Ants communicate with each other for performing various tasks like foraging, navigation, defending the territory, building of nests and other activities which require interaction. It has been long established that ants use pheromones to communicate with one another [11]. They use different pheromones for dealing with different tasks [28]. The capability of ants to communicate in this unique manner has given rise to solutions to many complex problems. Though certain families of ants exhibit communication traits that are distinct to their family, it has been proven that self organization has been at the forefront for use by almost all ant colonies [7]. This behavior combined with decentralization and autonomy forms the key to viewing the ant colony as a suitable candidate for swarm intelligence [5, 6] which in simple terms can be defined as collective intelligence concerning a specific group. The approach of sharing knowledge locally between its peers and eventually propagating the knowledge to a global level is one of the main reasons researchers were interested in relating this to intelligent system design. This chapter discusses in detail the aforementioned concepts thus leading to the objective of this thesis and the goal we wish to achieve through that.

## 1.2 Self Organization and Swarm Intelligence

Self organization can be defined as a decentralized process by which a solution to a specific problem is found based on the interaction at the global level as against local interaction. Therefore, this process does not involve any committed attempt by the agent to transfer any kind of information to other agents. Rather, this process, when considered in its entirety can lead to a solution that other agents can use. This behavior can be commonly observed in social insects like bees, ants, wasps etc. This autocatalytic process is complex in its own right and this can be attributed to the stable states the agent can choose from. The agent can then choose from one of these stable states.

A stable state is chosen by selecting one based on the amplification of available random possibilities. In ants, these stable states are chosen based on the pheromones and their densities at a given point. This chosen state is further amplified by other agents which chose this state as the solution state. Dorigo [6] pointed out that self organization consists of four main properties: Positive feedback - helps in the amplification of a state through increased attraction, negative feedback - reduces the attractiveness of an option through insertion of repulsive elements, amplification of random points - results in the exploration of possible solutions thus increasing the possibility of finding a stable state, and multi agent interaction - allows the agents to utilize the information passed on by other agents in addition to its own. These four properties form the cornerstone of collective intelligence of this kind and the way it affects our research will be discussed in detail later. A point worthy of mention here is that self organization in itself does not directly influence the cooperation and

adaptation among the agents. Rather, it is the agents that form a certain solution using self organization that are adaptive or cooperative [7].

A concept that emerged from self organization and that is extensively used in this research is Swarm Intelligence. It can be defined as the collective behavior of simple agents which results in the agents performing some intelligent task. The term swarm intelligence was first used by Gerardo Beni and Jing Wang [5]. With respect to ants, this gives an idea of how the knowledge transfer happens among different ants spatiotemporally thereby resulting in a global solution from several local decisions. One of the advantages of this approach is that the failure of a small number of agents to take part in the experiment will not have any adverse or drastic impact on the way the processing takes place. As regards the problem that we have in hand, this tendency of agents could also lead to further exploration thus encouraging more spatial exploration indirectly. This unique method of information transfer, though not having any major drawbacks, has a clear requirement - the manner in which the information is shared must be clearly outlined. The lack of this could lead to failure in arriving at a complete solution [6].

### **1.3 Stigmergy**

Ants have been successfully thriving on earth for the past 100 million years [29] and that is one of the main reasons scientists have taken special interest in exploiting the communication pattern among them [17]. It has been widely established that ants use a concept named stigmergy to communicate indirectly to one another. The term Stigmergy was coined by Grasse [26]. Stigmergy refers to the modification of environment from its current state to an updated state through the communication

among different entities thriving in the environment [34].

There are two types of stigmergies: Sematectonic and sign-based [47, 48]. In sematectonic stigmergy, communication is initiated through the ants physically changing the shape of the environment by moving things around or building structures (Example: An ant discovering a pattern emerging during the nest building process and consequently, making its contribution to that). In sign-based stigmergy, communication is triggered through the ants adding some kind of sign to the environment that is identifiable to others in the community (Example: Ants spraying chemicals known as pheromones for communication between them). With respect to the foraging process in ants, it is the sign-based form of stigmergy that we will be focusing on.

#### **1.4 Pheromones**

Pheromones can be formally defined as an olfactory or oral chemical signal used for communication among the same species [49]. Different pheromones are known to have been used by ants for performing different activities. In addition, pheromones play a vital role with respect to maintaining the social order in the ant colony. The aspect that we are primarily concerned about here is the foraging behavior of the ants. The use of pheromones by ants for foraging has been well studied [13, 2, 36, 14]. Ants use trail laying/decaying behavior through pheromones to locate the food source and reinforce the path towards that i.e. they mark the trail using pheromones while foraging so that it can help them later while returning to nest or will allow other ants to reinforce the trail towards the food path. Failure to reinforce the path, which usually happens when other ants choose not to traverse the

established path, results in evaporation of pheromones i.e. trail decaying. This kind of trail laying and decaying behavior leads to information being conveyed among the ants without the existence of a conscious attempt to share resources. Moreover, this shows that this kind of behavior comprises positive feedback through reinforcement, and negative feedback through the evaporation of pheromones [17] which makes this kind of communication one of a kind.

### **1.5 Relation to Computational Science**

As regards computational science, there are many reasons why one would be interested in studying this particular behavior of ants and building a foraging model based on that. For one, creating a model will help in proving the different theories that have been formulated and will also help us in finding the importance of different variables involved in the experiment. The inclination for creating such a model are manifold. Given that we know all parameters involved in this process, changing the values of the parameters and comparing the real-time behavior with a theoretical one will give us clues that might lead to building an optimal solution for a problem in hand. As well, this kind of communication is unique in the sense that it encompasses different fields of study in the computational domain such as distributed system, simulation, discrete optimization and complexity theory.

The most common phenomenon of interest observed through this behavior is finding the shortest path between the nest and the food source. Deneubourg et al. [12] and Goss et al. [25] conducted experiments to show that ants almost always choose the shortest path between the nest and the food source in the right conditions. When provided with two paths of equal length, they tend to choose the path randomly

but when provided with two paths of different lengths ants choose the shortest path over a period of time by making use of pheromones. Goss et al. [25] conducted the famous double-bridge experiment which proved to be a cornerstone study for scientists studying the foraging behavior of ants (figure 1-1). In simple terms, the ants choosing the shorter path will be the ones to return to the nest faster since they travel a shorter path both while traveling towards the food source and while returning to the nest. Therefore, over time, the pheromones deposited in this path will become reinforced and this path will become the most favored due to the maximum pheromone concentration. This observation, called the differential length effect [20] led to many ant colony algorithms and optimization algorithms.

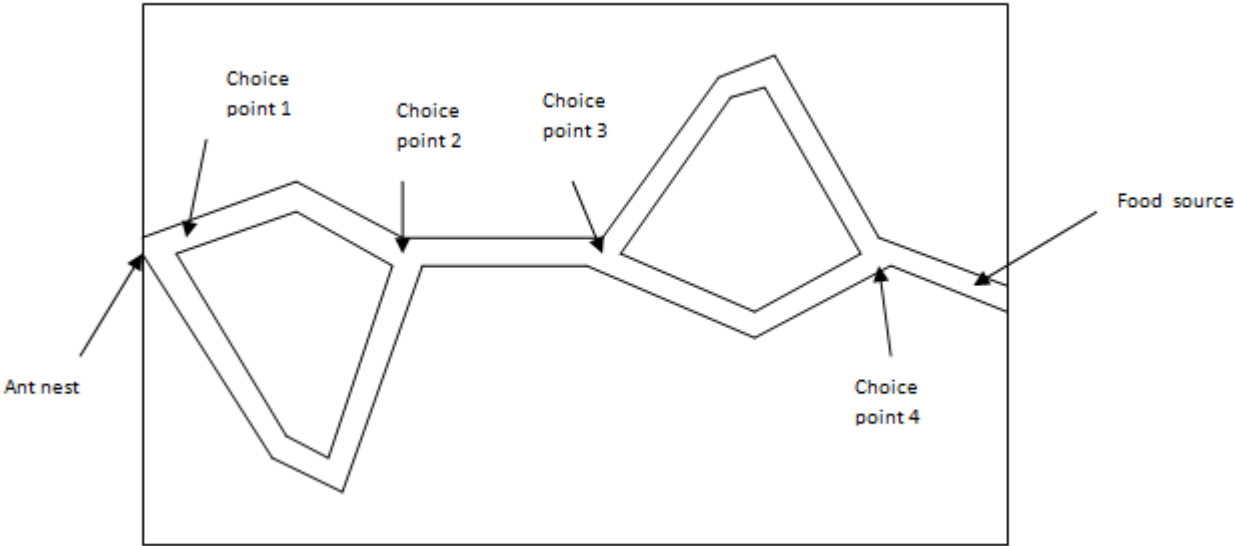


Figure 1-1: A Double-bridge Experiment setup

## 1.6 Existing Implementations

Studying the ant colony system has led to a lot of interesting implementations and models, the most successful of them being the Ant Colony Optimization (ACO) [15]. Ant Colony Optimization, along with its variants, has paved the way for a series of noteworthy applications and quality solutions to NP-Hard problems [16]. ACO has been developed for a number of well known applications which span Ordering problems (Traveling salesman problem, Load balancing in communication networks), Grouping problems (Graph coloring problem), Subset problems (Multiple knapsack problem), Assignment problems (Quadratic assignment problem) and more recently, for improving the accuracy of software quality prediction models [1]. ACO tries to mimic the communication observed in real ants by using artificial ants and finding solutions to the optimization problem that is being considered. Here, the solution by the artificial ants is built based on a graph where the ants traverse from one vertex to another with the condition that the next vertex in the path building process should not be equal to the previously visited vertex.

The simplest version of algorithm built is the Simple Ant Colony Algorithm (SACO) [21] which basically tried to implement the double-bridge experiment model. The variables considered here were the number of ants, amount of pheromones deposited, and the probability with which an ant chooses a position to move to, as a function of the the amount of pheromones found at neighboring vertices. The Ant System designed by Dorigo et al. [19] was based on SACO and served as the basis for most of the future algorithms designed. This algorithm was applied to Traveling Salesman Problem in order to find desirable solutions and prove its feasibility. The major difference



between SACO and AS was that AS assumed that the ant agents have some kind of memory associated with them which was implemented by using a tabu list [24] - a data structure that's used to record each point visited by ants. As well, AS used a state transition rule known as the random-proportional rule which is a rule followed by ants to move to the next point. Some of the well known algorithms which were built based on the AS and tried to improve on that are given as follows: Max-Min Ant System [46] tried to handle the premature stagnation problem - a phenomenon by which all ants start following the same path too soon without much exploration having occurred - in AS by making sure that pheromones are added only to the best solution during the updating process; Antabu [41] uses a local search based on tabu search and uses a method by which the contribution made by each ant depends on a fitness solution; AS-Rank [8] uses an elitist strategy by which importance is given to the best solutions and by taking into account only the best ants - the ants that have managed to find the best path so far after every timestep - for the model; ANTS [33] was another algorithm that was tried on the Quadratic Assignment Problem and improved on the performance with regard to the quality of the best solution found by using a different approach for stagnation handling and probability distribution. Another well known algorithm built based on AS was the Ant Colony System (ACS) which suggests some improvements for AS by using a different state transition rule, a different pheromone update rule, introducing local pheromones, and using candidate lists for more complex problems.

## 1.7 Motivation for the Research

All the algorithmic approaches that we discussed were based on the graph based implementation using stigmergic variables and used similar parameters: the total number of ants, the amount of pheromone deposited for positive feedback, and the presence and degree of evaporation (not considered in all algorithms) for negative feedback. An important aspect that has been ignored so far is the role played by real-world properties in the model to exploring/establishing a path between the food source and the nest. It has been already mentioned that the pheromones are olfactory or oral chemical signals that the ants use to exchange information. Therefore, there is always a possibility that the pheromone deposits are affected by natural phenomena such as sun, rain, vegetation, wind, and the resulting spread and decay. This in turn can bring about drastic and unexpected changes with respect to how the environment evolves as a whole. These effects, when ignored will be tantamount to analyzing the ant behavior in an enclosed space which leaves a void with respect to achieving real-world simulation results. For example, the natural conditions can have an impact on the decaying time of a food source or wind acting along a particular direction can result in an ant altering the path in which it is traveling due to change in the strength of the smell. A simulation considered with the aforementioned effects can alter the observed results with respect to foraging activity in more ways than one and this is the area that we would like to concentrate on with this research. It is also hoped that this can give us an insight into how much an effect wind can have on the spread of pheromones, and to what level it can affect the decision making process of the ant agent and the consequences on the foraging behavior of the colony.

Hence, the goal of this experimental approach is to test the assumptions of the model that has already been established and to suggest that wind as a parameter, if taken into consideration could alter the results. From a real-world perspective, this can be seen as a step closer to achieving a mimicking behavior that's more in line with the natural conditions. When seen from a modeling perspective, this could be another parameter added to the given set that we have; subsequently, this can be used to explore different possibilities which may not be commonly observed in the real world. This in turn can find its use in discovering an optimal solution to a given foraging problem or could even lead to a new variant of the class of optimization algorithms.

## **1.8 Overview**

In chapter 2, we introduce the custom-designed ant colony algorithm known as the Real World Ant Colony Algorithm (RWACA) used for the experiments along with the different parameters concerned. In chapter 3, we present the model that was chosen to simulate the effect of wind and incorporated into the RWACA. In chapter 4, we discuss the effect of evaporation on the foraging process of ants. In Chapter 5, we present the workflow along with the experimental setups and the corresponding results. The future work and conclusion are given in chapter 6.

## **CHAPTER 2**

### **Real World Ant Colony Algorithm**

In this chapter, we introduce our own version of the ant colony algorithm called Real World Ant Colony Algorithm which can be seen as a variant of the ant colony algorithm approaches. Here, the attributes and environment are chosen in such a way that the foraging behavior of the recruiters and recruits can be subjected to real world properties that were already discussed. A brief description of these attributes is given before explaining the algorithm.

#### **2.1 Properties and Parameters**

Owing to the wide ranging applications of collective intelligence combined with heuristic algorithms, the need to replicate the behavior of social insects and understand their lifestyle became more and more prominent. This resulted in a plethora of ant-based algorithms (AA) structured accordingly to the needs of the research. In the same way, the formal model that is going to be designed for this research will be tailor made for incorporating the modeling of real world processes that we are going to consider. Before explaining the algorithm, a brief introduction to the properties and parameters taken into consideration in line with those used for ACO algorithms and key differences between them are given here.

##### **2.1.1 Convergence time**

The convergence time is defined as the elapsed time from the beginning of the simulation to the moment the solution path has been found, i.e. when a particular

path has been reinforced to such an extent that the majority of the ants start following the same path in order to reach the food source and return to the nest. The desired characteristic would be being able to find an optimal path and strengthening it by making the ants choose it. Obtaining this state is not always possible as sometimes a sub-optimal path is found and the ants stick to this sub-optimal path. This phenomenon is referred to as premature convergence. Another possibility would be that the ants simply fail to reinforce any path thus leading to non-convergence.

### **2.1.2 The number of ants (recruiters and recruits)**

There are two types of ants to be considered here - recruiters and recruits. The recruiters are responsible for establishing the path between the nest and a food source whereas the recruits help in reinforcing the chosen path. It has been shown empirically that the number of recruiters and recruits in the given environment influences convergence to a great extent [12]. A small number of ants could mean that it would take more time for the algorithm to converge and a larger number of ants could mean faster convergence. Therefore, choosing the number of ants here is directly related to achieving the right balance between premature convergence and non-convergence. Also, the number of recruiters and recruits influence the path establishment and path reinforcement strategies. The roles of recruiters and recruits are explained later in this chapter.

### **2.1.3 Pheromone deposit**

Pheromone deposit can be defined as the amount of pheromones deposited by the agents when a recruiter/recruit moves from the current position to the next position. Ant Colony algorithms usually use different initial pheromone deposit values as one of

the parameters to influence the path searching process. Here, it is assumed that both the recruiters and recruits deposit the same amount of pheromones since any bias arising out of differential pheromones deposit values are not taken into consideration.

#### **2.1.3.1 Pheromone depositing pattern**

As regards the pheromones depositing trait in ants, there are two patterns commonly observed: some ants start depositing pheromones only when they find the source i.e. always a path is established only from the food source to the anthill and never the other way. Another pattern found is the ants start depositing pheromones as soon as they leave the nest. Our assumption here is that the ants start depositing pheromones as soon as they leave the anthill. This is advantageous due to the fact this could help in preventing the same zone being explored more than once and also help the returning recruiter to arrive at the nest without having to perform another exploration. This kind of collective exploration and marking behavior is only found in certain species of ants such as *Linepithema humile* (formerly *Iridomyrmex humilis*) [25].

#### **2.1.3.2 Evaporation**

In a real world case, evaporation might play a role in the food foraging process as the pheromones may be impacted by natural parameters like temperature, wind speed, humidity etc. The effect of evaporation on pheromones has been well debated and more on this is presented in chapter 4. The rationale behind including evaporation for consideration in ant colony algorithms was to encourage the agents to increase the exploration and also to avoid premature convergence [21]. Therefore, in

the paths that are not traversed frequently, the pheromone deposits will start evaporating whereas the intensity of pheromone deposits in the favorable paths will keep increasing because deposits are renewed by ants traveling them. The rate of evaporation could influence the possibilities of premature convergence and non-convergence, i.e. if there is no evaporation, then the convergence time may be increased whereas a large evaporation rate might lead to too fast a convergence or non-convergence. As a result, the rate of evaporation can also act as a parameter to find the right balance between premature convergence and non-convergence.

The parameters used for evaporation are applied to the pheromone deposits at every timestep in order to ensure that each path experiences evaporation to some degree. The evaporation rate was set to some constant and based on the exploration and convergence requirements of the algorithms. This feature can be seen as an indirect form of negative feedback since the ants not traversing a particular established path will result in the pheromones in that path getting evaporated slowly and will eventually disappear completely.

#### **2.1.4 Agent Memory**

Though it has been found that some species of ants utilize memory in the foraging process [3, 4, 27], it hasn't been proved that all species of ants use the memory in the same way nor does any concrete proof exist to show that all species have memory. The ant agents are assumed to have no memory here since all the actions performed by ants are based on the information gathered using the collective behavior and stimuli. Generally, some kind of limited memory would be required for the artificial ant to store the position during transition towards the food source (forward

phase) so that this memory can be used to trace back to the nest during the backward phase. In the case of the Real World Ant Colony Algorithm, the action behavior of the agent during the backward phase is the same as the behavior observed during the forward phase and therefore, this effectively wipes out the need for the agent to have any kind of memory.

## 2.2 Movement of Agents

It is imperative to see to it that the ants' movement is not restricted in as many ways as possible. As a part of this effort, instead of reducing the considered space to a set of discrete points and restricting the spatial movement of ants to either of the two points that lie ahead (as commonly done in Ant Colony Algorithms), the ant is allowed to move to any vector position in the forward direction. Thus, by doing so, we are not introducing any spatial constraints to the ants which is a step closer towards the real-world conditions.

### 2.2.1 Exploration strategy - Monte Carlo Simulation

Here, we will be restricting ourselves to the species of ants that lay pheromones both towards the food source and while returning to the nest. Some examples of species which are known to mark the substrate in both directions are *I. humilis*, *Messor rufitarsus*, and *Myrmica sp.* [3]. This type of ant species can be broadly categorized based on their foraging behavior: the ones that prefer using individual memory for exploration (ex: *Lasius niger*) and ones that use collective exploration strategies for searching without using any individual memory (ex: *Linepithema humile*) [3]. The main difference between the two different categories is based on the



movement of the recruiter: In case of the ants that use individual memory, the recruiter does not start marking the substrate until the food source is found whereas in latter case, the recruiters start marking the substrate the moment they begin exploring. The algorithm created here is comparable to the typical behavioral pattern of the Argentine ant (*Linepithema humile*) which uses collective exploration strategies for trail laying and trail following behavior. A lot of research has been done trying to understand the decision making behavior of the argentine ant [25, 12, 39]. Based on this effort, the following exploration strategy is defined. Firstly, there are two types

---

**Algorithm 1** Real World Ant Colony Algorithm

---

- 1: Initialize ant objects - recruiters and recruits - and other necessary parameters
  - 2: **repeat**
  - 3: recruiter algorithm
  - 4: **until** recruiters have completed the journey establishing the paths
  - 5: **repeat**
  - 6: recruit algorithm
  - 7: **until** an established path (optimal/sub-optimal) is reinforced
- 

of agents - recruiters and recruits - and two different phases - the initial exploration phase and the path following phase - considered here. As shown in algorithm 1, the recruiters are entrusted with finding a path between nest and food source whereas the recruits help in strengthening the established path. In the initial exploration phase, as shown in algorithm 2, the recruiter starts from the nest and starts exploring the temporal space without any a priori knowledge. Therefore, to mimic this behavior in the best possible way, we will be using Monte Carlo simulations of the model whereby every successive vector position in the forward direction is determined randomly. While the recruiter is exploring the region, it leaves pheromone

deposits as it moves from one point to the next. This behavior of recruiter leaving pheromone trails can help the whole process in many ways: Firstly, it can serve as a cue for other recruiters conveying that a certain region in the environment is already being explored by one recruiter and therefore, a recruiter which detects a pheromone trace may want to deviate from the path already being explored thus encouraging greater exploration in lesser time. Secondly, it can also serve as a guide for recruiters wanting to return to nest once they find the food source. A recruiter can be sure of arriving back to the nest since all the recruiters start from the nest and start leaving pheromone deposits once they begin the journey. It is to be noted here that what we are trying to do is not an optimization approach but a proof of the concept approach. Therefore, the path which will eventually be established by one of the recruiters, though the right one, may not be the shortest one all the time. The recruiter, after finding the destination returns home by taking cues from the path established by itself or other explorers. During this phase, the recruits are in a dormant state waiting for cues from a recruiter to begin the trail following.

After a specific period by which time some of the recruiters would have successfully returned home, as shown in algorithm 3, the recruits start going in search of the food source signaling the start of the path following phase. The recruits gradually start showing preference for the path with higher pheromone intensity since they have a higher probability of leading to the food source. The reason for the gradual preference is that initially, when the recruit starts traveling from the nest after a path has been established by a recruiter, the set of next possible positions would have similar pheromone deposits and hence, there shouldn't be any preference shown

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**Algorithm 2** Recruiter

---

```
1: for all recruiters that have not completed the journey do
2:   if the destination is food source then
3:     select the next transition vector position based on randomness
4:   else if the destination is nest then
5:     if feasible neighborhood (vector position with pheromone deposit) is found
6:       then
7:         move to selected vector position
8:       else
9:         select the next transition vector position based on randomness (to-
10:        wards the nest)
11:       end if
12:     end if
13:   Increase the pheromone deposit in the current vector position and move to
14:   the selected vector position
15: end for
```

---

initially. After a while, when some points are more pronounced than others, that is when the recruits will start showing a clear preference. If  $Max_N$  represents the pheromone deposit values of  $N$  points that the recruit has to choose from in order to make its next move, and  $Max_1$  and  $Max_2$  represent the two highest pheromone deposit values from  $N$  points, then the probability  $P$  of choosing  $Max_1$  is given by:

$$P(Max_1) = \begin{cases} Maximum & \text{if } Max_1 \gg Max_2 \\ High & \text{if } Max_1 > Max_2 \\ Equally likely & \text{if } Max_1 = Max_2 \end{cases} \quad (2.1)$$

Therefore, the next position  $Y$  of the agent from the current position  $X$  is determined by the weight of the pheromone present in each of the possible points. The most important observation in the exploratory pattern while conducting the simulation is

that the weight of the pheromone at each point will be equal to the number of ants that have traversed that area. This metaheuristic phenomenon can be likened to the traditional reinforcement learning techniques where an agent tries a particular action and is rewarded based on the consequence of its action leading to the path towards the destination. The destination here is the food source and the weight of the pheromone at each point is linked to the reward that the agent will be getting moving into that particular position. It is worth mentioning here that the path established by the first recruiter may not be the path followed by all the other recruits because the recruits blindly follow the path that leads them to the food source based on the weight of the pheromone at each point. In accordance with the mechanisms involved, there are two constraints involved here [12] - all the recruiters and recruits must lay pheromone while traversing a temporal space irrespective of whether they are moving towards the food source or arriving back home, and there must be a minimum number of ants leaving the nest. These constraints make stronger the possibility that the paths are formed and reinforced. Also, unlike the method used by Pasteels et al. [38], here we assume that the degree of attraction to an unexplored branch for a recruit is minimum. Therefore, the recruit chooses a path with no pheromone deposit only if it is not able to find a path with any pheromone deposit. As well, the autocatalytic process is not affected largely because of this.

In certain ways, this approach borrows certain traits from the ACO in that each ant's position is updated in an iterative fashion and the focus will be on convergence but the duration for convergence is generally not deterministic. It differs largely

---

**Algorithm 3** Recruit

---

```
1: for all recruits that have not completed the journey do
2:   if the destination is food source then
3:     if feasible neighborhood (vector position with pheromone deposit) is found
       then
4:       move to selected vector position
5:     else
6:       select the next transition vector position based on randomness (to-
       wards the food source)
7:     end if
8:   end if
9:   if the destination is nest then
10:    if feasible neighborhood is found then
11:      move to selected vector position
12:    else
13:      select the next transition vector position based on randomness (to-
       wards the nest)
14:    end if
15:  end if
16:  Increase the pheromone deposit in the current vector position and move to
  the selected vector position
17: end for
```

---

from ACO in that it is not an optimization algorithm but a plain concept explanation approach. Therefore, here our objective does not look to achieve any kind of optimization. This can be quite evident from the fact that the path that will be established and reinforced by the explorers is not guaranteed to be the shortest path and the focus would always be on the agent behavior in the given environment.

There are certain observations to be made here. Firstly, as mentioned before, since the ants don't have memory, the only factor that influences their path selection decisions is the pheromone deposit. These pheromones deposits are registered using a global pheromone table which is updated every time an ant agent moves from its current position. It could be observed that this is quite similar to a frequency based memory used in Tabu search [24] with the only difference being that this memory consists of points which the ant agent should consider as being favorable while searching for a feasible neighborhood. Secondly, it is assumed here that evaporation acts uniformly on all the pheromone deposits. Thirdly, the pheromones deposited on all points are constant. The next chapter discusses the real-world properties and how they are incorporated into our algorithm, which is the cornerstone of this project. This incorporation of real-world properties is key to witnessing a reinforced path that might be different from the path established by the explorer initially due to changes brought to the weight of pheromone at a particular position by natural factors that we experience in the real world.

## CHAPTER 3

### Wind Simulation

#### 3.1 Introduction

An important property that we are forced to consider when we think of wind is its effect on spreading the smell from a single source point to many other points in space. With respect to the pheromones, it has already been mentioned that ants respond to the odour rather than the visual cues. In that case, it naturally follows that this odour and its intensity, when considered as an entity, will certainly be impacted by the direction of the wind and the period for which it lasts. Therefore, this leaves us with the need to come up with an implementation for the simulation of wind and the impact it will leave on spreading the odour. Here, we hypothesize that the effect that wind will have on odour will lead to an ant choosing a point which it would not have if not for the consideration of wind and its natural effect on spreading odour. This in turn could lead to a different path being reinforced by the recruit than the one established by the recruiter. This hitherto overlooked factor could lead to more accurate results when compared to the ones which have totally ignored the effect of wind on odour, and to a greater extent against the implementations which have completely ignored evaporation and its effects. Several existing solutions were considered for including this effect to our algorithm.

The approach selected is based on the real time fluid dynamics (RTFD) approach by Jos Stam [45]. With regard to the needs of this research, this method has several

advantages over the other ones which will be discussed later. A detailed explanation about Stam's approach and the way it is being incorporated into our approach is given as follows.

### **3.2 Motivation**

Building a physics model is by far the best approach to simulating a real time fluid motion. With regard to the model that we require for our simulation, it is imperative that the model that we consider must fit into the algorithm that we already have. Traditionally, models created for simulation involving fluids were based on either grids or particles. Both have their own advantages and disadvantages and the choice of method depends upon the requirements of the problem. Particle based approaches are good in the way that visualization in real time is possible but looks artificial visually. Grid based approaches have proven to be successful creating models but on the flip side, computation on them is typically very expensive [43]. While Navier-Stokes equations are widely accepted as the right model to use for flow of fluids [44], it was Foster et al. [22] who first showed that it is possible to use Navier-Stokes equations for simulation of fluid like motion. This eventually led to many models being implemented based on that but all the models developed had one common problem: the simulations developed were unstable meaning that there was a chance that the simulation would become unstable for larger timesteps. Therefore, this introduced the limitation that the simulations might have to be run in smaller timesteps.

Jos Stam came up with a new improved method using the Navier-Stokes equation and by making it stable meaning that it can run for larger timesteps. This method proved



to be a much easier alternative in terms of ease of use and understanding. As well, this model stands out from the other implementations due to the fact that it involves both grid based and particle based approaches. Another important difference is that a Lagrangian scheme of reference is used instead of the Eulerian scheme of reference. A brief explanation of the algorithm and how this is used with respect to spreading the pheromone in a particular direction is given here. A complete explanation of the algorithm can be read from [45, 44].

### 3.3 Navier-Stokes equations

The Navier-Stokes equations [10] give us an idea of how the velocity field with respect to an object changes over a period of time. When we consider a fluid like air, it would be computationally expensive to consider every particle separately. Therefore, the particles are replaced by a smoke density - a continuous function in space which gives us the amount of particles present at every point. RTFD method solves the following set of partial differential equations. The first equation describes the variation of the density of a medium, under the effect of the velocity vector field. The second equation is a compact vector form of the simplified Navier-Stokes equations governing the motion of non-compressible viscous or inviscid fluids:

$$\frac{\partial \rho}{\partial t} = -(u \cdot \nabla) \rho + k \nabla^2 \rho + s \quad (\text{Eqn 1: Density through velocity field}) \quad (3.1)$$

$$\frac{\partial u}{\partial t} = -(u \cdot \nabla) u + \nu \nabla^2 u + f \quad (\text{Eqn 2: Incompressible Navier - Stokes}) \quad (3.2)$$

where

$u = u(x, y, z, t), v(x, y, z, t), w(x, y, z, t)$ : velocity vector field

$\rho = \rho(x, y, z, t)$ : particle density scalar function

$\vartheta$ : coefficient of kinematic viscosity

$\kappa$ : coefficient of diffusion

$s = s(x, y, z, t)$ : external density sources

$f = f(x, y, z, t), g(x, y, z, t), h(x, y, z, t)$ : external velocity sources

The structure of both equations is very similar. The rightmost term on the right hand side (RHS) models the external sources. The middle term on the RHS models diffusion: gradual smoothing of the density map, or the velocity field, in time. The left term on the RHS models advection: the transport of density along the existing velocity field, or of the fluid itself (self-advection). A brief overview of the algorithm is given in the following section.

### 3.4 Algorithm

The algorithm starts with setting initial values for the velocity and density, and recalculating their values iteratively based on the changes brought in by external factors and the movement, if any, of the density source. The updated values are calculated for every timestep and the current values of density and vector fields will depend on their previous values calculated during the past iterations. Here, computations are performed on a uniformly discretized space, forming an  $N \times N$  grid. Each iteration involves computing the new velocity and density grids  $u[i,j]$  and  $\rho[i,j]$  at time  $t = t_0 + t$ , from the current values  $u_0[i,j]$  and  $\rho_0[i,j]$ , at time  $t = t_0$ . Given the similarity of the differential equations, both density and velocity calculations involve similar computation steps per iteration as shown in the figure 3-1.

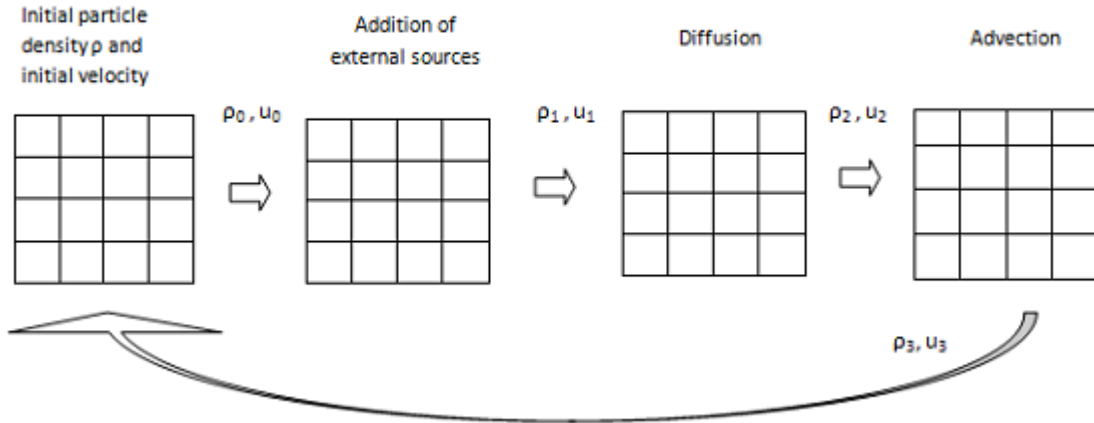


Figure 3–1: *RTFD method - Algorithm steps: The diagram shows the different steps involved in the RTFD method and its influence on the density and velocity grids after each step as given in the algorithm - Initial density and velocity values  $(\rho_0, u_0)$ , Addition of external sources  $(\rho_1, u_1)$ , Diffusion  $(\rho_2, u_2)$ , and Advection  $(\rho_3, u_3)$ .*

### 3.4.1 External source addition step and Diffusion step

In external source addition, as the name implies, an external source grid ( $f[i,j]$  or  $s[i,j]$ ) is simply added to the current grid ( $u_0[i,j]$  or  $\rho_0[i,j]$ ) to form the updated grid ( $u_1[i,j]$  or  $\rho_1[i,j]$ ).

The diffusion step can be defined as the process of spreading the density into neighboring cells. The diffusion is performed backwards in time (semi-Lagrangian numerical scheme) using Gauss-Seidel relaxation to solve the resulting system of linear equations.

#### 3.4.1.1 Backtracing

The diffusion step in RTFD solves the terms  $\kappa \nabla^2 \rho$  and  $\vartheta \nabla^2 u$  in the equations for the density and the velocity. The diffusion process of exchanging particle densities, in the former case, or exchanging fluid densities, in the latter case, between cells,

can be explained as follows: for every iteration, each cell will lose some part of its density to its neighbors while at the same time gaining density from the neighbors. The density at a given point can be given as

$$\rho[i, j] = \rho_0[i, j] - (\Delta t \kappa N^2) (\rho_0[i - 1, j] + \rho_0[i + 1, j] + \rho_0[i, j - 1] + \rho_0[i, j + 1] - 4\rho_0[i, j]) \quad (3.3)$$

Though this method appears fairly straightforward, there is a serious drawback associated with it - it can become unstable for larger timesteps. Hence a work-around for this problem would be to use semi-lagrangian method by tracing back in time. This results in a system of linear equations that can be solved using an iterative method. The iterative method used here is Gauss-Seidel relaxation and the way it is used here is given as follows.

### 3.4.1.2 Gauss-Seidel Relaxation

Gauss-Seidel relaxation is an iterative method for solving a system of linear equations which is represented as  $Ax = b$  such that  $A$  is a sparse matrix.

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \quad (3.4)$$

where the solution for  $x_i$  can be given as:

$$x_1 = \frac{1}{a} (b_1 - bx_2 - cx_3) \quad (3.5)$$

$$x_2 = \frac{1}{e} (b_2 - dx_1 - fx_3) \quad (3.6)$$

$$x_3 = \frac{1}{i} (b_3 - gx_1 - hx_2) \quad (3.7)$$

The value of  $x_i$  is updated every iteration accordingly based on the following approach:

$$x_1^{new} = \frac{1}{a} (b_1 - bx_2^{old} - cx_3^{old}) \quad (3.8)$$

$$x_2^{new} = \frac{1}{e} (b_2 - dx_1^{new} - fx_3^{old}) \quad (3.9)$$

$$x_3^{new} = \frac{1}{j} (b_3 - gx_1^{new} - hx_2^{new}) \quad (3.10)$$

The advantage of using Gauss-Seidel relaxation here is that the values are updated iteratively and the updated values are used for subsequent computations. Here, the convergence depends on the form of the matrix  $A$  and the total number of iterations is fixed.

Returning to backtracing process, the equation can be rewritten as

$$\rho_0[i, j] = \rho[i, j] - (\Delta t \kappa N^2) (\rho[i-1, j] + \rho[i+1, j] + \rho[i, j-1] + \rho[i, j+1] - 4\rho[i, j]) \quad (3.11)$$

This results in a set of linear equations which can be solved by Gauss-Seidel relaxation. In order to solve this using Gauss-Seidel relaxation, the equation is written as

$$\rho[i, j] = \frac{1}{(1 + 4(\Delta t \kappa N^2) (\rho_0[i, j] + (\Delta t \kappa N^2) (\rho[i-1, j] + \rho[i+1, j] + \rho[i, j-1] + \rho[i, j+1])))} \quad (3.12)$$

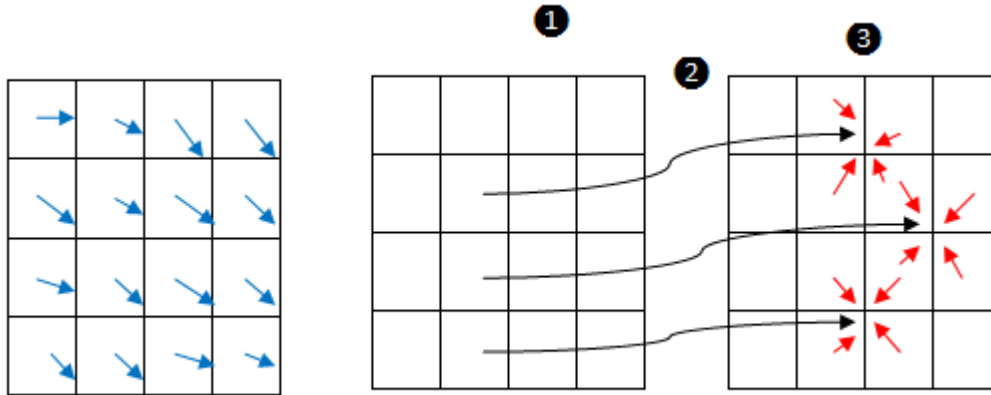


Figure 3-2: A sample vector field and Advection step: (left) A sample vector field: The path traveled by the density particles will depend on these established vector fields. (1), (2) and (3) show the order through which the advection step traces back to the previous timestep, calculates the interpolated values of the neighboring cells, and updates the current density value.

As discussed above, based on the Gauss-seidel relaxation, the values of  $\rho[i,j]$  are computed for every iteration and used for subsequent calculations. The method used for diffusion in the velocity is quite similar to what was explained above with the only difference being that velocity calculation involves the processing of both velocity vector components, and kinematic coefficient of viscosity  $\vartheta$ .

### 3.4.2 Advection

In fluids, advection can be defined as transfer of particle substances under the influence of the fluid velocity vector field. The advection step in RTFD solves the terms  $-(u \cdot \nabla) \rho$  and  $-(u \cdot \nabla) u$  in the equations for the density and the velocity. Here, advection is also performed backwards in time, with linear interpolation as shown in figure 3-2. The process is explained as follows. The assumption made here is that density is to be treated as a set of particles. Therefore, with the velocity field

that we already have in place, we have to channel these density particles through the already established vector field. The method used here is to identify all the particles that are on the the centers of the grid cells and obtaining the density values of these particles based on the interpolated values of the four neighboring cells during the previous timestep. Consequently, this can be imagined as having two grid cells with one grid containing the old values and the other grid containing the new values based on the values obtained in the old grid. One of the advantages of using this backtracking approach is that it ensures stability, as the values calculated for the new grid cells can never be greater than the values calculated for the previous grid cells.

### 3.4.3 Projection

There is an important addition to be made after this step with respect to the velocity field. This method makes the velocity mass conserving. The velocity field should always be mass conserving or divergenceless but after the advection step, it loses that property and this forces a correction to be made through this additional step. It is to be noted that this same step is performed once after the diffusion step as well in order to add stability to this algorithm. The projection step involves the use of Helmholtz-Hodge decomposition theorem [44] according to which every vector field can be denoted as a sum of a mass conserving or divergenceless component and a gradient-field/irrotational component. From this relation, the mass conserving component can be obtained by computing the gradient-field and subtracting it from the non-mass conserving velocity field thus obtaining a mass conserving field. Helmholtz theorem states that any sufficiently smooth vector field can be expressed as a sum

of an irrotational (curl-free) and solenoidal (divergence-free, mass-conserving) component vector fields and can be expressed as

$$F = \nabla\varphi + \nabla \times A \quad (3.13)$$

where

$F$  : a smooth vector field

$\varphi$ : a scalar function

$A$  : a vector potential function

After the advection step of RTFD the velocity field  $u$  does not respect the mass-conservation condition of having a zero divergence:  $\nabla \cdot u = 0$ . From the above theorem, it can be written as

$$u = \nabla\varphi + u_{MC} \quad (3.14)$$

where

$u$ : non-mass conserving velocity field

$u_{MC}$ : mass conserving velocity field

$\nabla\varphi$ : gradient field

The required velocity field,  $u_{MC}$ , can be obtained by subtracting a gradient field  $\nabla\varphi$  from  $u$ .

To find the required gradient field, the following equation must be solved:

$$\nabla \cdot u = \nabla \cdot (\nabla\varphi + u_{MC}) = \nabla^2\varphi \quad (3.15)$$



This is Poisson's equation  $\nabla^2\varphi = f$ , where  $f = \nabla \cdot u$

The discretized form of the Poisson's equation using finite difference numerical method is:

$$\nabla^2\varphi_{i,j} = \frac{1}{dx^2} (\varphi_{i+1,j} + \varphi_{i-1,j} + \varphi_{i,j+1} + \varphi_{i,j-1} - 4\varphi_{i,j}) = f_{i,j} \quad (3.16)$$

Written as a system of linear equations,  $A\bar{\varphi} = \bar{f}$ , it can be solved using the iterative techniques, such as Gauss-Seidel relaxation, because the coefficient matrix A is sparse. Once the potential  $\varphi$  is found, computing its gradient and subtracting it from u yields  $u_{MC}$ , the mass-conserving velocity field:  $u - \nabla\varphi = u_{MC}$

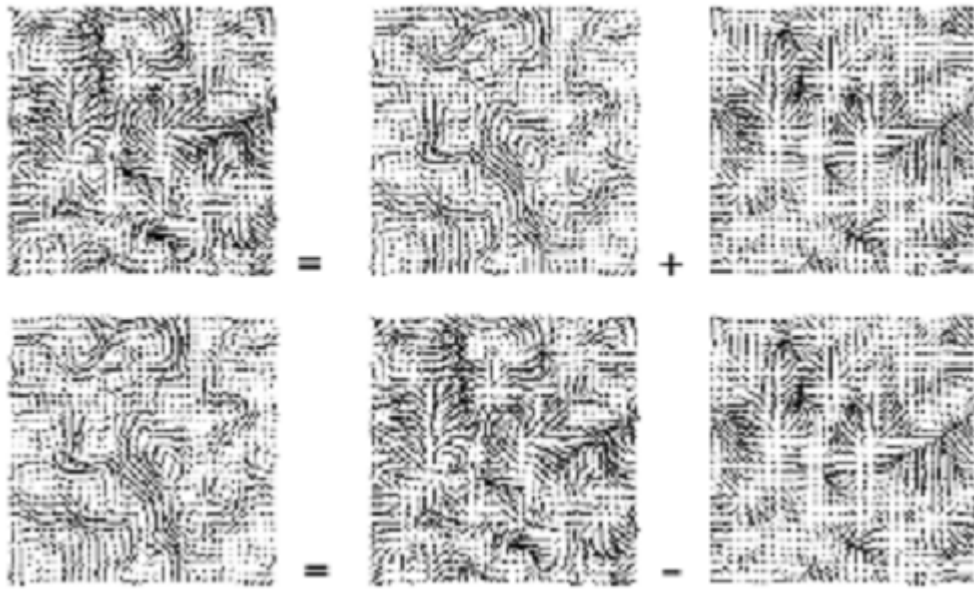


Figure 3-3: *Helmholtz decomposition (Taken from [45]). (Top)  $u =$  mass-conserving field + gradient field (Bottom) mass-conserving field =  $u$ -gradient field*

Thus, in sum, the following steps compose the projection procedure in RTFD:

- Find the divergence of  $u$ , after the advection step.
- Solve the Poissons equation by using Gauss-Seidel relaxation technique to find the gradient potential  $\varphi$ .
- Compute the gradient of  $\varphi$ .
- Subtract it from  $u$ , to obtain a mass-conserving velocity field.

### 3.5 Integration into RWACA

Now that the mathematics behind wind simulation and the movement of density particle components have been explained, we turn our attention towards how these concepts are incorporated into the real world ant colony algorithm. Firstly, the velocity field is mapped onto the terrain that we have in place for the ants to navigate. Therefore, here the density particle components will be the pheromones deposited by the ant agents which will be dissipated over a certain range of space based on the vector fields and whose values will depend on the interpolated values of its neighbors during the previous timestep. Thus, we have the artificial agents foraging for food in an atmosphere affected by wind. The point where the pheromone is dropped will be the strongest point of attraction for ants. The areas in vicinity may also be points of attraction (with lesser intensity) and that depends on whether the wind is blowing over those points. Therefore, in effect, it can be said that the pheromone deposits follow all the basic laws of fluid motion with respect to transporting the particles or through a fluid.

---

**Algorithm 4** Integration into RWACA

---

```
1: repeat  
2:   velocity-step  
3: until the velocity values settle  
4: for all recruits/recruiters that have not completed the journey do  
5:   find the next position to travel (feasible neighborhood)  
6:   if feasible neighborhood found then  
7:     if the position is within the velocity field then  
8:       repeat  
9:         determine the pheromone densities at the given point and the  
           neighboring points based on the velocity field established using velocity-step  
10:      until the density values settle  
11:     else  
12:       spread the pheromone deposit to neighboring points using gaussian  
           distribution  
13:     end if  
14:   end if  
15: end for
```

---

## CHAPTER 4

### The Effect of Evaporation

#### 4.1 Evaporation

The effect of evaporation on pheromones though not actively a part of real time experiments, has played a major role in ant colony optimization algorithms. The reason for this is that, as mentioned before, it acts as a parameter for indirectly enforcing negative feedback during the experiment. As regards real-time experiments, evaporation's role has been rather subdued due to the lack of clear evidence. Perna et al. [39] conducted experiments on pheromones and implied that evaporation may not be a factor to consider when conducting real-time experiments. But a look at the given experimental setup can give way to some interesting observations. It has already been mentioned that ants react to the odor from the pheromones in order to explore and establish a path between the food source and nest. Since the aforementioned experiments were conducted in an enclosed environment, it would be safe to assume that they apparently ignored the fact that the rate of evaporation is affected by various real world properties like pressure, temperature, wind speed, surface area etc. Also, the fact that ambiance certainly plays a role here can be shown by the following observation: in an enclosed space, as the water molecules evaporate into vapor, some escaping molecules collect at the top as vapor and return to the liquid state through the process of condensation. The rate of this reverse process depends on how close the enclosed space is and resulting pressure and density created at the

top. When this forward and reverse process reach a state of balance, which is called equilibrium, there will not be any more changes to the temperature and density of the liquid. Therefore, when we consider the same simulation being performed in an environment with real world properties and also the effect of the ambiance, they might have an impact on the rate of evaporation and consequently in the establishment of a path between the nest and the food source.

The primary factors affecting the rate of evaporation are the temperature, the wind, the surface area that is exposed to other real world properties, and humidity. Of the four, temperature and the direction of the wind are the ones that could largely influence the rate of evaporation and these are the ones that we will be retaining for discussion. The reason for not considering all the factors is that the focus is not on accuracy here but rather to see if evaporation as an entity could play a certain role in our experiment.

## **4.2 Temperature and Vapor Pressure**

When the temperature of the substance being considered is increased, the interaction between the molecules increases as more heat is absorbed. As a result, more molecules start to evaporate from the liquid surface and this leads to higher rates of evaporation. Therefore, as the temperature increases, the rate of evaporation also increases. In a real world scenario, the liquid temperature reaches constant value once the equilibrium state has been reached. This equilibrium state is directly related to the vapor pressure of the system, which is equal to the pressure experienced by the closed system due to the vapor. From the definition, it can be seen that the vapor pressure is directly proportional to the temperature. The relationship between the

equilibrium state and the vapor pressure is given by Clausius-Clapeyron relation as:

$$\ln \left( \frac{P_2}{P_1} \right) = -\frac{\Delta H_{vap}}{R} \left( \frac{1}{T_2} - \frac{1}{T_1} \right) \quad (4.1)$$

where,

$P_1, P_2$ - vapor pressure at the temperature  $T_1, T_2$

$\Delta H_{vap}$ - Enthalpy of Vaporization

R - Universal gas constant ( $8.3144621 \text{ JK}^{-1}\text{mol}^{-1}$ )

We can make use of this relation to find the vapor pressure at the required temperature once we know the vapor pressure at a given temperature.

S. E. Van Vorhis Key et al. [31] proves that (Z)-9-hexadecenal (Z9-16:ALD) is a trail pheromone component of *Iridomyrmex humilis*, the ant whose traits are closest to the ones that we have decided to take into consideration for this project. From the

Table 4–1: Properties of (Z)-9-hexadecenal (Z9-16:ALD)

Properties	Values
<b>IUPAC Name</b>	(Z)-Hexadec-9-enal
<b>Molecular Formula</b>	$C_{16}H_{30}O$
<b>Molecular Weight</b>	238.4088
<b>Index of Refraction</b>	1.451
<b>Surface Tension</b>	30.2 dyne/cm
<b>Density</b>	0.84 g/cm <sup>3</sup>
<b>Flash Point</b>	161.5 °C
<b>Enthalpy of Vaporization</b>	57.36 kJ/mol
<b>Boiling Point</b>	330.9 °C at 760 mmHg
<b>Vapour Pressure</b>	0.000161 mmHg at 25°C
<b>Storage temp</b>	-20°C

table 4–1, it can be seen that its enthalpy of vaporization is 57.36 kJ/mol and the vapor pressure at 25°C is 0.000161 mmHg. Therefore, based on the data that we

have, we can find the vapor pressure at any given temperature which will be an indicator of the rate of evaporation at the given time.

A simple example of the calculation involved in finding the vapor pressure at a particular temperature(32°C) based on the given data is given below:

$$\ln \left[ \frac{P_2}{0.000161} \right] = \frac{-57.32}{8.31} \left[ \frac{1}{32} - \frac{1}{25} \right]$$

$$\Rightarrow P_2 = 0.000173mmHg$$

### 4.3 Wind speed and its effect on evaporation

The water molecules that are bound tightly together need some kind of force in order for them to break up and speed up the conversion from droplets to vapor. The wind, when acting on the surface of water with the required force, breaks the water molecules and thus eases the conversion process from the liquid state to the gaseous/vapor state. Therefore, it can be seen that the rate of evaporation increases with the increase in wind speed. One important factor that we are ignoring here is surface area of the pheromone concentration (since the wind acts only on the surface of the liquid). The total exposed area will be related to the total amount of molecules affected by the wind acting at a particular direction in a given point of time.

### 4.4 Updating the Pheromone Weight

Based on the formula presented in [18], we can update the weight of the pheromone at a given point as

$$\zeta(e) = \begin{cases} (1 - \rho) \cdot \zeta(e) & \text{if no new pheromones deposited} \\ (1 - \rho) \cdot \zeta(e) + \text{newPheromone} & \text{otherwise} \end{cases} \quad (4.2)$$

where  $0 \leq \rho \leq 1$  is the rate of evaporation for the given time step,  $\zeta(e)$  is the amount of current pheromone deposit, and *newPheromone* is the value of the new pheromones deposited. The greater the value of  $\rho$ , the greater the rate of evaporation. For the effect of wind speed, we can use the observed pheromone concentration at a particular point and the wind direction to set different pheromone values for different points with the effect being maximum near the wind source and minimum near the waning point of the pheromone. Therefore, the pheromone evaporation rate can be updated as:

$$F(\rho_1) = \begin{cases} \rho & wc = 0 \\ \rho + wc & wc > 0 \end{cases} \quad (4.3)$$

where  $wc$  is a value directly proportional to the wind current value.

Similarly, for the effect of temperature, since we already know that the vapor pressure increases with the increase in temperature of the substance which in turn increases the rate of evaporation, the pheromone evaporation rate can be updated based on the vapor pressure value as follows:

$$F(\rho_2) = \begin{cases} \rho_1 & vp = 0 \\ \rho_1 + vp & vp > 0 \end{cases} \quad (4.4)$$

where  $vp$  is a value associated with the vapor pressure at the given temperature.

Thus, the weight of the pheromone at a given point is updated based on the calculated evaporation rate  $\rho_2$  whose value is affected by the temperature of the substance and the wind speed.



## CHAPTER 5

### Experimental Evaluation

For the experimental evaluation, a simulator was built and all the parameters were set according to the needs of the respective experimental setups. First, the simulator along with the different parameters is described. This is followed by the four different experimental setups. The first experimental setup is a 'proof of concept' approach done by constructing a double-bridge based on that proposed by Goss et al. [25] and comparing the results obtained. In the second experimental setup, the efficiency and the effectiveness of the algorithm is tested by introducing the agents in an environment with obstacles placed between the food source and nest. The third experiment can be seen as an extension of the second experiment with wind introduced to the same landscape. Then, the same setup is tried with evaporation considered as a pheromone decay parameter and comparisons are made to derive conclusions. The final setup serves as an epilogue discussing the behavior of agents in a more hostile environment.

#### 5.1 Simulator

This section explains the workflow of the experiment using the simulator and the different parameters that are set before the start of the experiment. The simulator and the solvers were built using jMonkeyEngine 3 (SDK RC2) and Java. Firstly, the scene needs to be set before starting the simulation based on the values of the parameters that are entered. This is done using the *simpleInitApp()* in jMonkeyEngine

which initializes the scene and the variables. This is where the ant objects, the values entered for the parameters and the listeners (if any) are initialized. First, the ants are created using a *Spatial* - an abstract data structure that serves as a base class - and attaching a *RigidBodyControl* - a class that can be used to create dynamic objects and add physical properties to them - to it. We then set the textures and the initial location of the agent. After creating the ant agent and adding physical properties to it, we add light to the scene by attaching a directional light. The sky is created using the *SkyFactory* - a spatial which can be used to add sky to the scene. The landscapes were constructed using height-field based *TerrainQuad*. The nest and food source are defined by a fixed vector position ranges at opposite ends. The water filled obstacle is constructed using the *SeaMonkey* Water Filter. An *AnalogListener* is added to introduce recruits while the simulation is running i.e, while the program is in the update loop. Also, the camera angle can be changed along all three axes using the sliders at any time during the simulation while the program is running. A snapshot of the simulator is shown in figure 5-1 and the parameters used in the simulation are explained below:

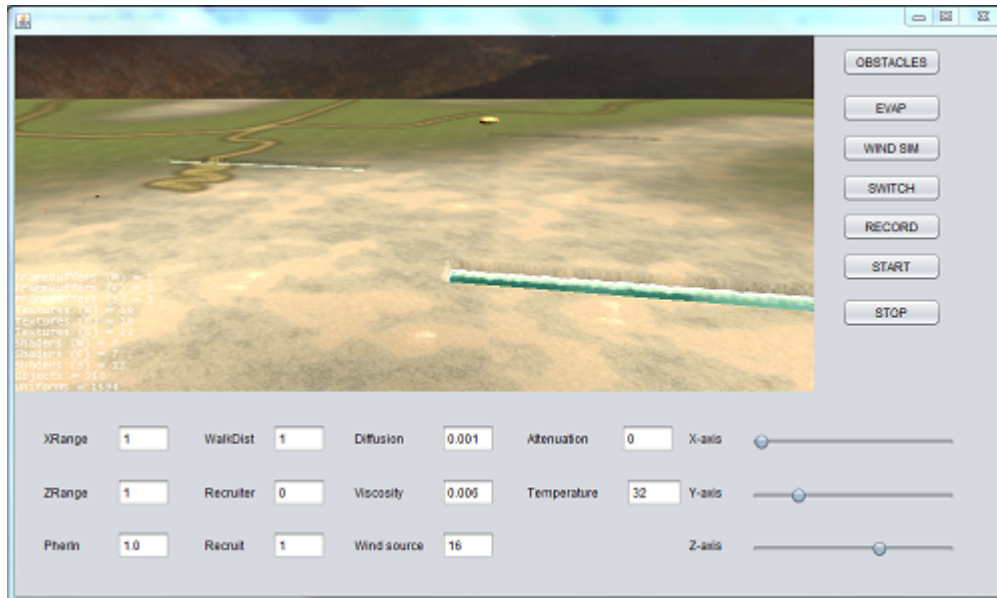


Figure 5–1: *Simulator Snapshot: A snapshot of the simulator*

- XRange, ZRange - Defines the range that the ant can scan searching for pheromone deposits along the x-axis and z-axis
- PherIn - Pheromone weight
- WalkDis - The vector distance covered by the ant agent every iteration
- Recruiter - Number of recruiters
- Recruit - Number of recruits
- Diffusion - Diffusion of the density
- Viscosity - Viscosity of the fluid
- Wind source - Density that will be deposited
- Attenuation - Attenuation of the fluid
- Temperature - The temperature of the surface in which the agents thrive (assumed to be constant for the entire duration of the experiment)

The configuration for the given set of parameters are given as follows: XRange and ZRange are kept as constant for the entirety of the analyses (Xrange - four vector positions on either sides, Zrange - one vector position ahead) so that it can be assumed that all the recruits/recruiters have similar range of areas to scan for pheromones when they are trying to find pheromone deposits in the vicinity and hence the probability that an agent manages to find a pheromone deposit will remain undisturbed because of this. The reason for including pheromone weight as a parameter is that though it is kept constant here, it might prove helpful in prospective experimental conditions where we might be looking at ulterior motives. For example, we might want the recruits to follow a path established by a specific recruiter in which case the pheromone weight of that particular recruiter alone will be several folds more than that of the other recruiters. As mentioned before, the number of recruiters and recruits considered will certainly play a role in the foraging process and here, the numbers are kept constant throughout all experimental setups to facilitate comparison of results. This is explained in detail in section 5.2. Attenuation, viscosity, and diffusion are the parameters that can be used to change the degree of dissipation of pheromones and we will be using viscosity and attenuation for our experiments. More on this is explained in section 5.4. The temperature parameter is solely used for the calculation of evaporation rate and for our experiments, the temperature is fixed at 32°C.

After initialization of the objects and parameters in accordance with the required setup of the experiment, we enter the update loop named *SimpleUpdate()* which is where the RWACA is implemented. The position of the ants and the corresponding

pheromone weight are entered as key-value pairs in a global hashtable. Therefore, we use this update loop to move the ant agents every timestep. With reference to our experiment, the initial number of recruits is always zero since recruits start traveling only after at least one of the recruiters have returned home. This is where we use the *AnalogListener* to release certain number of recruits for every fixed interval of time. It is to be noted that the pheromone trails of the recruiters are marked by blue dots and the pheromone trails of the recruits are marked by red dots. The simulation is stopped by the user manually the moment all the ants (excluding the recruiters that have already arrived back home and the recruiters/recruits that have gotten lost) are seen following the reinforced path.

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**Algorithm 5** Simulator Workflow

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1: function SIMPLEINITAPP()                                ▷ Initialize the scene
2:   Set initial location for camera
3:   Initialize key binding
4:   Create light                                           ▷ Add directional light to the scene
5:   Create sky                                             ▷ Add a static horizon as backdrop
6:   Create terrain                                         ▷ Add a height-field based terrain system
7:   Create food source                                     ▷ create a fixed vector space for food
8:   Create nest                                           ▷ create a fixed vector space for nest
9:   Create obstacles ▷ Introduce obstacles by reducing the height of terrain and
   adding a water processor
10:  Create ants ▷ Create ant objects and attach control and physical properties
   to them
11:  Initialize parameters to the values based on the user input
12: end function
13: function SIMPLEUPDATE()                                ▷ The update loop
14:  Update camera axes
15:  Apply evaporation and update the pheromone deposit table
16:  RWACA() ▷ Update the pheromone table after every ant moves to the new
   vector position
17: end function

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## 5.2 Experimental setup - I

This experimental setup as shown in figure 5–2 is a replica of the double-bridge experiment used by Goss et al. [25] to prove that the ant agents manage to find the best path between the nest and the food source. Here, the ants are allowed to go in search of food placed at the opposite end of the world compared to the nest through a landscape that requires the ants to choose one path from two at two different points. The landscape is made more pronounced by increasing the height-field and is surrounded by water on all sides. In order to avoid any bias towards a particular direction, the shorter branches are placed on either sides at the two points. Initially, the 24 recruiters are allowed to go in search of food. The recruits are not allowed to move until the first recruiter arrives back home having found a food source. Here, the probability that an ant will find a food source is one since the position of the food source is such that it is accessible irrespective of the length of the paths chosen.



Figure 5–2: *Experimental Setup - I : Feasibility Test: A replica of the double bridge experiment created to test the feasibility of our model*

After the first recruiter returns, 5 recruits are allowed to move from the nest every five seconds until 100 recruits have left the nest. The probability that a recruit chooses a path increases only gradually with increasing differences between the pheromone deposit values scanned and therefore the recruits don't show strong bias towards a particular path initially. This can be observed from the graph shown in figure 5-3 where the number of ants in the to-be established path gradually increases. After some time, it was observed that the recruits slowly started showing bias towards a particular path. According to the observed behavior of Argentine ants in the double-bridge experiment, this process would lead to the shortest path being established between nest and food source with the ants gradually preferring the shorter branches at both points in the landscape. Here, it was observed that of the 15 times the experiment was conducted, the ant agents chose the shortest path 11 times with a sub-optimal path being chosen the remaining 4 times. A sub-optimal path here refers to the established path containing at least one longer branch.

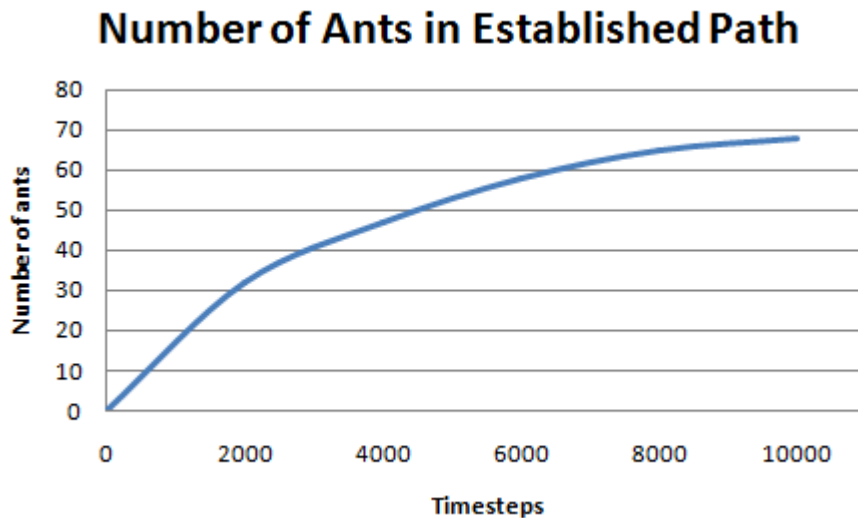


Figure 5–3: *Number of Ants Vs. Timesteps: The total number of ants that are traveling along the established path at different timesteps (out of 24 recruiters and 100 recruits). It could be seen as proof that ants don't show an immediate preference to a particular established path as the pheromone weights of all the established paths will be similar initially. The reinforcement process happens gradually and it is only after certain timesteps that we can observe that most of the recruits start following the same path. This explains the differential length effect [17].*

### **5.3 Experimental setup - II**

Now that the feasibility of our approach has been shown, the next step was to test the approach in a more demanding environment - a landscape filled with more complex obstacles and evaluating the effects of wind eventually. The goals of this experiment are two fold: to demonstrate that the behavior of the agents was designed in such that a way that it was also suitable for maneuvering obstacles of different forms and not confined to the previous design. Secondly, these obstacles, when seen as an attribute that obstructs the flow of air currents in the direction of mapped velocity field, will lead to the air currents moving around the obstacle instead of passing through them. More on this is explained in the next experimental setup. In that aspect, this experimental setup could be seen a precursor of the next experiment setup. Therefore, the landscape should be chosen in such a way that the full potential of the wind simulation can be realized. It was decided to place obstacles between the food and nest.



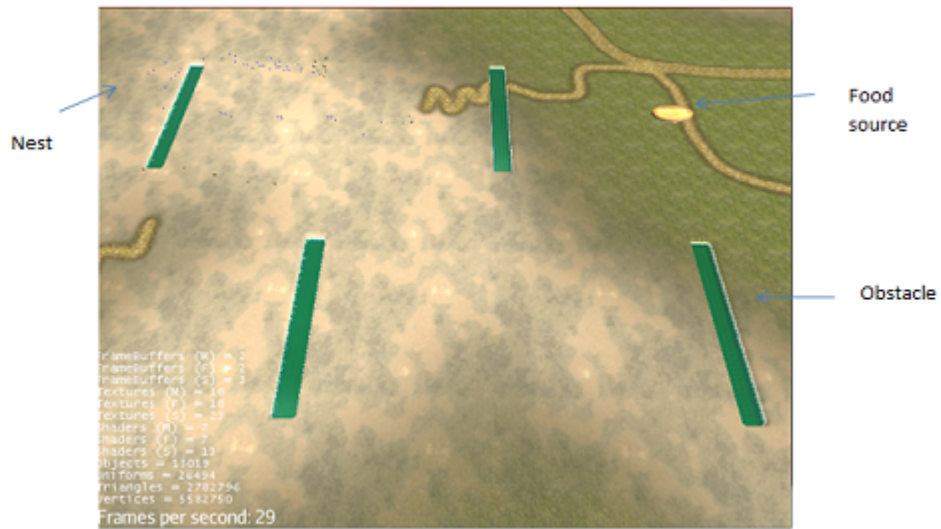


Figure 5-4: *Experimental setup - II: An aerial view of the terrain with obstacles introduced between the nest (left) and the food source (right).*

Here, the obstacles used are introduced by installing trenches at four different places as shown in figure 5-4 and are placed in such a way as to discourage the agents from finding a straightforward path from the nest to the food source. When faced with an obstacle, the ants move around the obstacle in either directions with equal probability which results in a similar behavior as implemented in [19].



Figure 5-5: *Initial Reinforcement Phase: The pheromone deposits of the recruits are shown by red dots and the pheromone deposits of the recruiters are shown by blue dots. This snapshot shows recruits following the pheromone trails established by the recruiters. During this phase, the recruits will have just started and that's been reflected by the fewer number of red dots. The blue dots present all over represent the different routes taken by the recruiters. Here, it can be seen that initially the recruits don't show any preference any of the recruiters' paths as it only happens gradually.*

As regards the foraging process, the procedure is same as the one considered for the previous experiment - the recruiters and recruits are released in the same fashion as it was done for the previous experiment. In line with the explanation provided before, the recruits are introduced once a recruiter returns to the nest. As shown in the figure 5-5, when a recruit starts to move trying to reinforce a path, it will be presented with several paths initially. Towards the end of the simulation, it could be observed that a particular path has been reinforced based on the movement of recruits and inclination shown towards a particular set of pheromone deposits by them (figure 5-6). It was seen that the agents were able to find the best path 10 out of the 15 times the experiment was conducted.

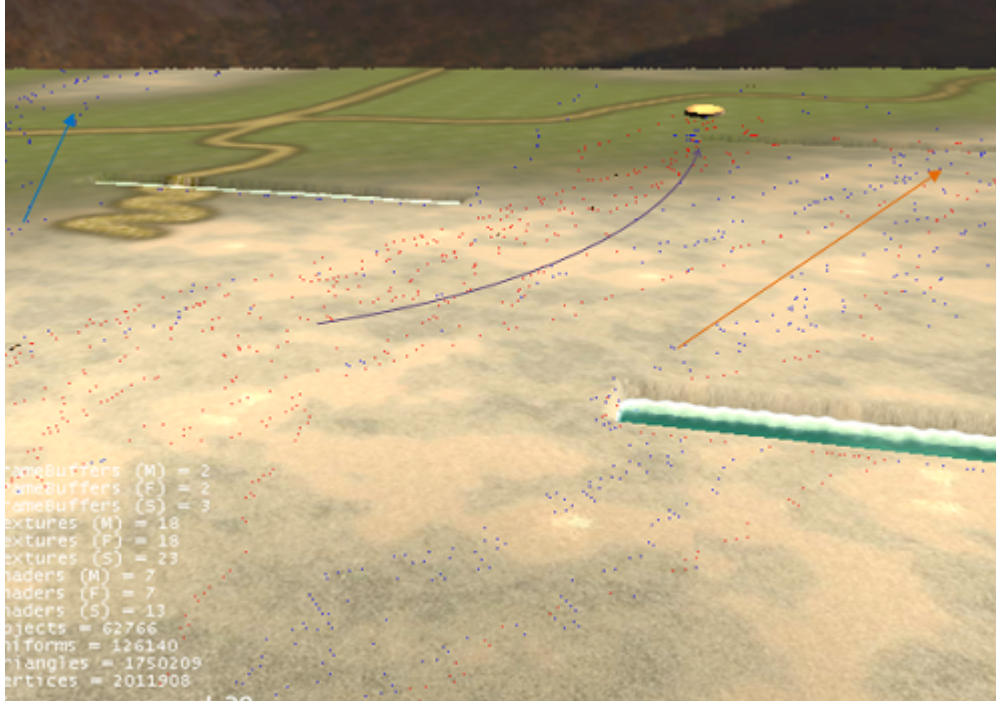


Figure 5–6: *Formation of Best Path:* (Red markings - recruit, Blue markings - recruiter) This snapshot shows the best path being gradually chosen between the nest and food source (shown by a purple arrow). It can be seen that a sub-optimal path was also established (to the right of optimal path - shown by blue dots along an orange arrow) but was not reinforced though a few recruits chose that path initially. This can be observed by the presence of a few red markings (pheromone deposit of recruits) along the sub-optimal path . The fact that all recruiters don't reach the food source can be shown here by blue markings to the left of optimal path (shown by a blue arrow) meaning those certain recruiters did not find the food source.

#### 5.4 Experimental setup - III

The third experimental setup was dedicated to testing the effect of wind in the same environment that we have defined in the second experimental setup. In terms of evaluation of the experimental results, this experiment is the most important one for our research. Before discussing this experimental setup, it is imperative to see to it that the effects of including wind are clearly explained so as to get the right perspective. In order to do this, a small custom experiment named the 'stationary ant experiment' was conducted to explain the ramifications of considering wind blowing along different directions and the role played by obstacles.

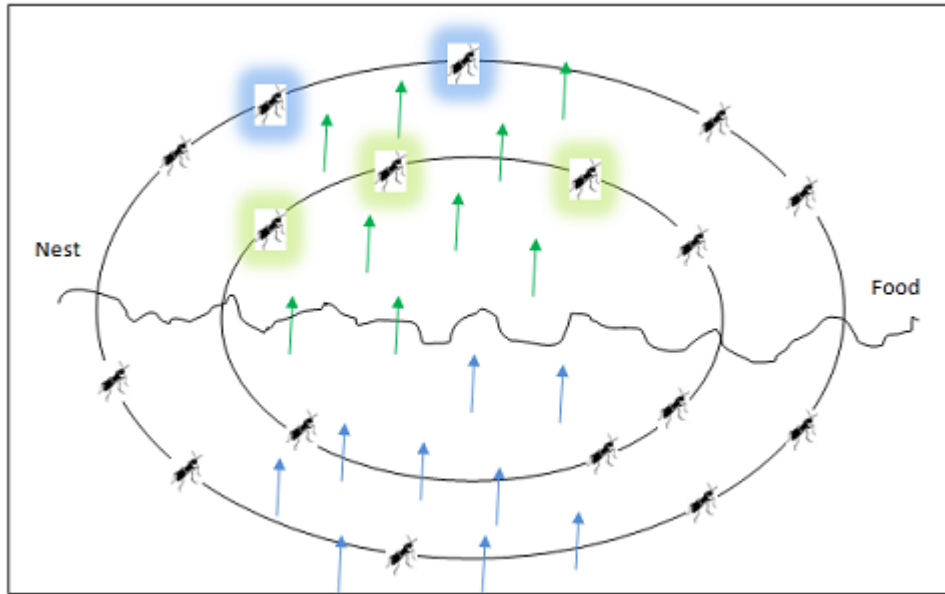


Figure 5–7: *Effect of Wind - I: The arrows represent the wind acting in a direction perpendicular to the the established path. The blue arrows represent the air current before encountering the path and the green arrows represent the wind carrying dissipated pheromone traces with them. The inner ellipse represents a distance that's closer to the path between the nest and food source and the outer ellipse represents a farther distance from the nest-food source path. The ants marked in green, being in closer distance from the path, have been influenced by the presence of pheromones whose smell has been carried over to them by the wind blowing through them. This might not be the case if there was no wind present in which case those ants would have remained stationary. The ants marked in blue, being in farther distance from the path, may or may not be influenced and that depends on the degree of dissipation of pheromones.*

#### 5.4.1 Stationary ant experiment

This experiment was mainly designed to analyze the effect that the wind with a directional bias will have on the path reinforcement process. To begin with, a set of stationary recruits are placed randomly within a specific range on a landscape where the velocity field of the wind is already mapped (figure 5–7). Then, a recruiter is allowed to move within this specified range of landscape leaving pheromone trails behind with stationary recruits placed on both sides. The recruits that smell the

pheromone deposits will start moving towards the deposits with greater attraction shown for stronger pheromone deposits. Therefore, the direction of movement of the every recruit here will solely depend on the weight of pheromone deposits around them. Also, for the sake of this experiment, the probability that an ant will get attracted to a pheromone trace will be one and in case of more than one pheromone deposit found in the neighborhood, the strongest deposit is chosen. The recruits that don't smell pheromone deposits in the nearby area would remain stationary. The most important observation here would be that the recruits may start advancing to other neighboring positions even though there might not be direct contact with pheromone deposits due to the dissipation of pheromones from one point to the neighboring points based on the direction in which the wind is blowing. In order to substantiate this claim, the same experimental setup was created using the simulator as shown in figure 5–8, and 400 stationary recruits were placed in the landscape with arrangement as explained before.





Figure 5–8: *Effect of Wind - II: This diagram shows the random distribution of stationary recruits within a specific range. A recruiter will be made to pass through this range.*

First, the experiment was conducted without considering the effect of wind. It was observed that, as the recruiter started moving, only those recruits that were directly influenced by the pheromone deposits started moving and blindly following the recruiter as it went ahead forming a path (13 recruits in total). Now, the experiment was conducted with the effect of the wind included (figure 5–9). For experimental purposes, wind blowing in two different directions were considered: one that is parallel to the direction in which the path is being formed (west here) and the other in a direction that is perpendicular to the path (south here). It was found that when the wind was blowing in the westward direction with the recruiter moving in the south-north direction, the stationary recruits which were placed to the left of the path being formed were also attracted to the pheromone deposits in addition to the ones attracted by the direct influence of the pheromone deposits (87 recruits). In case of the wind blowing in the southward direction with the recruiter moving

the south-north direction, the number of ants attracted was larger than when there was no wind considered but less than when the wind was blowing in the westward direction (36 recruits).

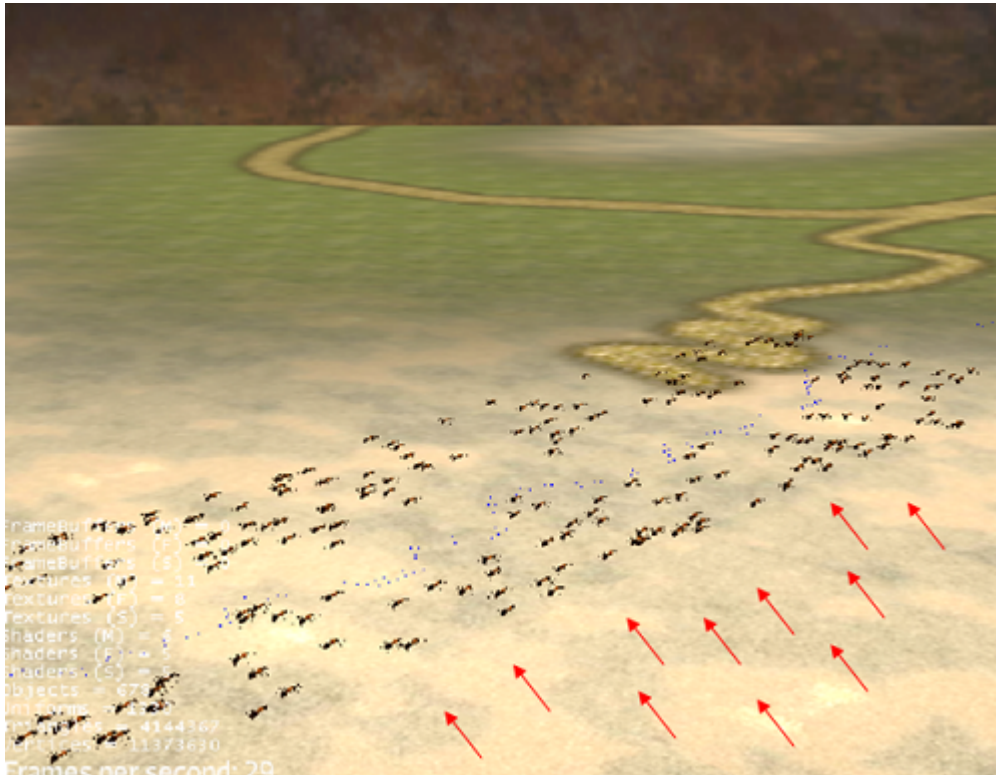


Figure 5–9: *Effect of Wind - III: This diagram explains the effect of diffusion of pheromones. The wind is blowing in the westward direction and is indicated by red arrows in the figure. It can be seen that the area to the immediate left of the pheromone trail shown by blue dots does not have any recruits. This can be explained by the presence of pheromone deposits which in addition to directly influencing the stationary recruits along the path also attract the neighboring recruits present on the left of the pheromone trail (since the wind is blowing in the westward direction here). It is to be noted here that if not for the presence of wind, only those recruits which are directly influenced by pheromones will have started moving and the neighboring recruits would have remained stationary.*

This could be explained by the diffusion of pheromones which appears to be greater when the wind is blowing in the direction perpendicular to the establishment of path. This could be seen as the most important reason we are interested in analyzing the effect of wind with directional bias in the path convergence process.

Now that we have shown that it is worth our while to place emphasis on wind in the path formation and reinforcement process, there's another aspect that, in some ways, could influence the path convergence indirectly - Obstacles. While it can be gathered easily that obstacles directly affect the path establishment process, the role played by obstacles in the path reinforcement process is not quite as obvious in the sense that in addition to hindering the movement of ants, it alters the velocity field when it is being mapped on to the landscape. As shown in the figure 5-10, it can be seen that in the presence of a physical obstacle, wind currents will be forced to move around it. Therefore, it would be interesting to observe the role played by obstacles in deflecting the diffused pheromone deposits. The given setup was replicated using the simulator with the same number of stationary recruits placed and an obstacle added in the same fashion as previously done (shown in figure 5-11). For the purpose of simplicity, the same obstacle model used in the previous experiment are used here and it is assumed that the wind doesn't pass through them. Therefore, this trench can be imagined as an obstacle that blocks the flow of air within its perimeter. A recruiter was allowed to move through the given range in the south-north direction with the wind acting in the westward direction. It was found that the observation was in agreement with our hypothesis. It can be seen from the figure 5-12 (and comparing it with the figure 5-11) that the stationary recruits placed on the flank



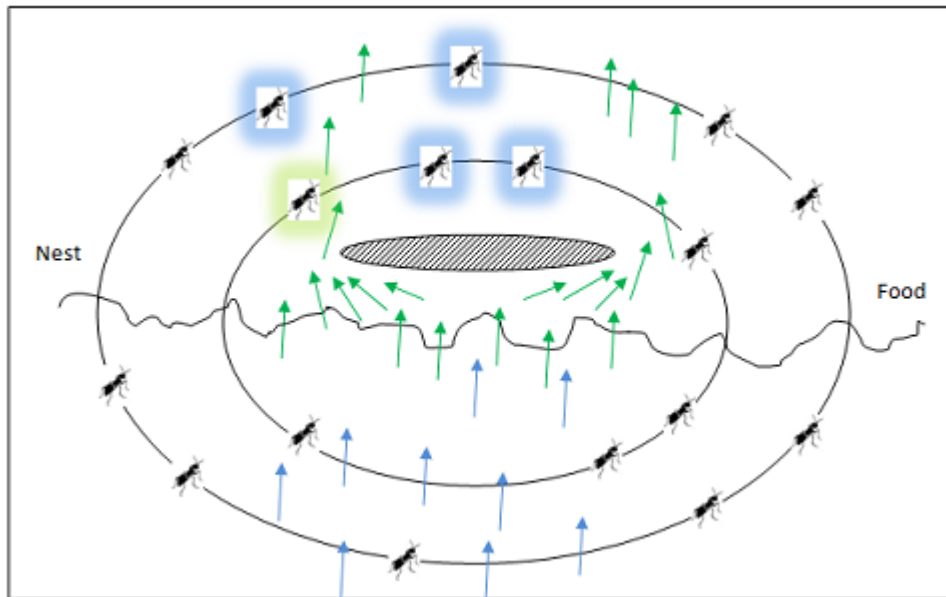


Figure 5–10: *Effect of Presence of Obstacle - I: This explains the effect that an obstacle might have in a recruit getting attracted towards the path established by the recruiter. The recruits marked in green are influenced by pheromones whereas the recruits marked in blue may or may not be influenced by pheromones. It can be seen here that the recruits behind the obstacles will not sense any pheromone trace whereas the pheromone traces reach the recruits on the flanks. If not for the presence of obstacles, the recruits marked in blue in the inner circle would have got attracted and started moving towards the path.*

of the obstacle have reacted to the pheromones deposited while the recruits placed behind the obstacle have not reacted since the air currents containing the dissipated pheromones have been blocked from reaching the recruits by the obstacles. This can be seen as clear evidence for obstacles playing a role in our experiments through the landscape and the motion of deflected air currents. Now that we have shown the effect of wind and obstacles, we move ahead to the planned experiment of analyzing the effect of wind with the second experimental setup. Here, the same landscape and obstacles as described in the previous setup were used. The nest and the food source are placed in the south-north direction. Before the start of the experiment, the velocity field is mapped onto the entire landscape. The velocity field could be



Figure 5–11: *Effect of Presence of Obstacle - II: A setup similar to the previous one with an obstacle placed in the middle.*

mapped as flowing in any one of the four directions. Now, when the agent moves through the velocity field mapped landscape and deposits pheromones after moving to a new position in space, the pheromone is spread in the direction of the velocity mapping. The rate of spreading depends on attenuation, density source, viscosity of the fluid and diffusion of density. Therefore, when an agent is in the vicinity of another agent's pheromone deposit, it might start moving towards that vector position depending on the attractiveness of that position, i.e. the pheromone weight of that particular position. This means that when a recruit starts the foraging process and finds a heavily formed pheromone path, it blindly starts following the path. In effect, the number of positions marked by pheromones will be larger in case of wind acting on the surface and what kind of direction based relation will that hold to the path establishment and reinforcement process is what this experiment will throw light on.



Figure 5–12: *Effect of Presence of Obstacle - III: When compared with the snapshot showing the setup, it can be seen here that the recruits which were placed along the flanks of the obstacle have reacted to the pheromone trail (denoted by blue dots) and started following the path while the recruits placed behind the obstacle have remained stationary.*

## 5.5 Results

### 5.5.1 Effect of Pheromone Dissipation

The results obtained here were compared with the results obtained from the previous experiment to see if the addition of wind simulation has any impact on the foraging process. In total, five experimental results are compared - windless, northward, southward, eastern and western wind. The previous experiment conducted without wind was set as base. In the first case, the experiments were conducted with little dissipation of pheromones (attenuation=0.15, viscosity=0.006) and in the second case, the pheromones were allowed to dissipate by altering kinematic coefficient of viscosity and attenuation of the fluid (attenuation=0.02, viscosity=0.015). It was seen from the graph (figure 5–13) that the number of timesteps taken for convergence with little dissipation was comparatively higher than the timesteps taken for

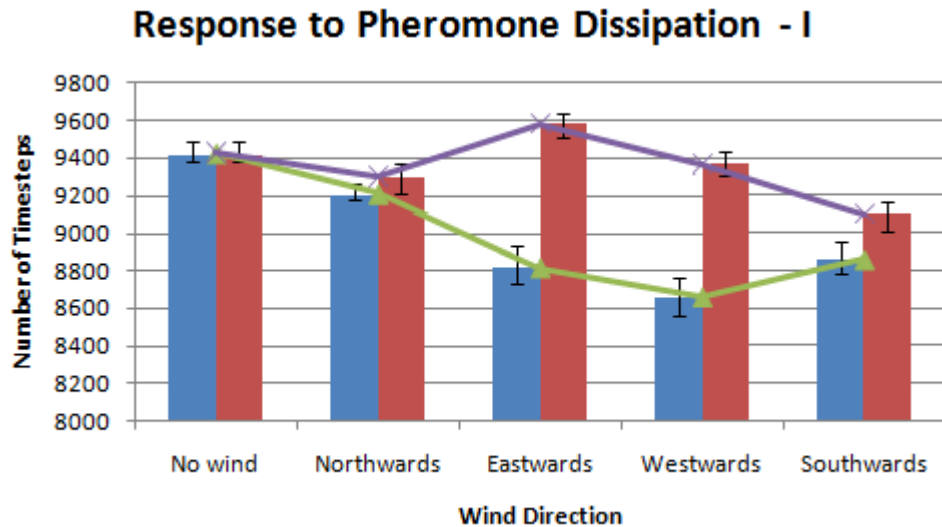


Figure 5–13: *Response to Pheromone Dissipation - I*: The graph shows results obtained from two different cases (averaged values obtained from each experiment conducted 5 times, with errors bars containing positive and negative error values): In the first case (Brown column), the experiments were conducted with little dissipation of pheromones (attenuation=0.15, viscosity=0.006) and in the second case (Blue column), the pheromones were dissipated to a certain range (attenuation=0.02, viscosity=0.015). The simulation conducted without wind is kept as base here (extreme left values of brown and blue columns). It could be seen here that when the pheromones are dissipated, the timesteps obtained for eastward and westward directions are the smallest.

simulations held with dissipation. Another observation that could be made here was that, when the pheromone values were dissipated, the number of timesteps taken for northward and southward wind was larger than that for eastward and westward wind directions. This phenomenon can be explained by the direction of the nest and food source being the same as the direction in which the wind is blowing. Because of this, the dissipation of pheromones will either be in forward or backward direction without much diffusing towards the sides. Therefore, the knowledge transfer range is effectively reduced due to this. In case of the wind blowing in the perpendicular direction, eastward or westward in this case, it can be seen that the total number

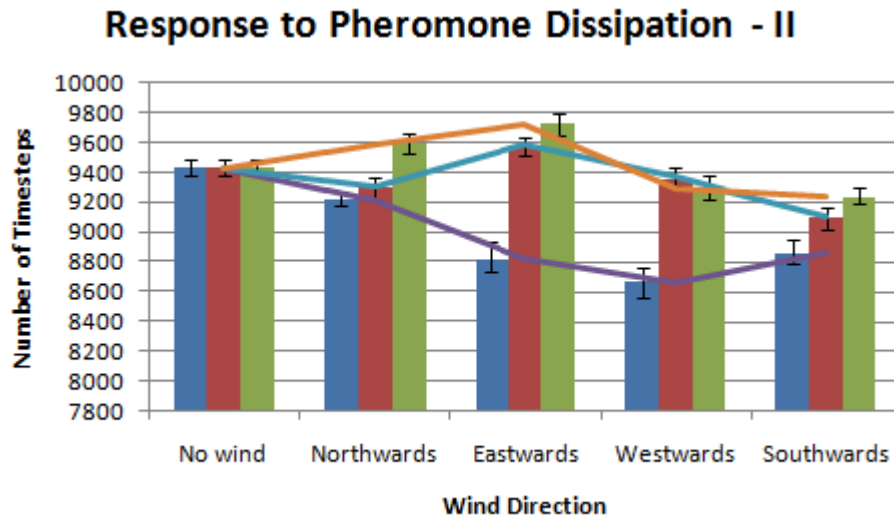


Figure 5–14: *Response to Pheromone Dissipation - II*: This graph (averaged values obtained from each experiment conducted 5 times, with errors bars containing positive and negative error values) compares the results obtained with further dissipation of pheromones (attenuation=0.01, viscosity=0.025) represented by green bars as against the previous results shown in 5–13. When the pheromones are dissipated further, it loses its ability to act as a catalyst in the foraging process. This can be inferred from the observation that the timesteps relating to the green bars are more aligned with the timesteps recorded for little dissipation (brown columns).

of timesteps taken is lower than all others. This goes on to say that ants on either side of the path being established have had greater attraction towards that path and hence are involved in the reinforcement process to a greater extent than all other cases. This can be seen as a clear proof that wind has had an impact on the environment that we have defined.

In order to see if the same observation can be made when the pheromone deposits are allowed to spread further, the same experiments were repeated with the pheromone deposits spread to wider areas. As shown in figure 5–14, it was observed that somewhat surprisingly, the number of timesteps recorded was much closer to the values

obtained when there was no dissipation at all. The reasoning behind this observation is, here the agents detected more pheromone deposits diffused over too wide a range and hence the gradual reinforcement process took more time than it should have taken. To see if this observation holds, the same set of experiments were conducted with the pheromone deposits dissipated further more (attenuation=0.01, viscosity=0.035) and as shown in figure 5–15, it was found to corroborate the previous observation’s results meaning the further dissipation of pheromone did not have an impact on the path formation process.

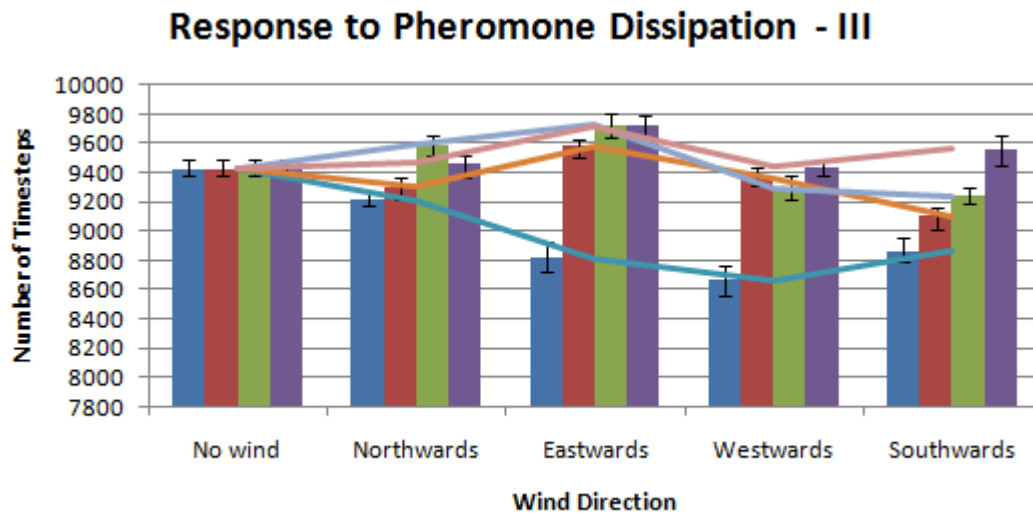


Figure 5–15: *Response to Pheromone Dissipation - III: In comparison to the other timestep values (averaged values obtained from each experiment conducted 5 times, with errors bars containing positive and negative error values), it can be seen here that the results obtained with the pheromones dissipated even further (attenuation=0.01, viscosity=0.035) cling on to the similar range of timesteps (shown by violet columns) that were obtained for the previous two pheromone dissipation setups.*

### 5.5.2 Evaporation for pheromone decay

Experimental setup - III with dissipation (attenuation=0.02, viscosity=0.015) was conducted with and without evaporation and it was observed that evaporation did not have any considerable impact on the path that was being established.

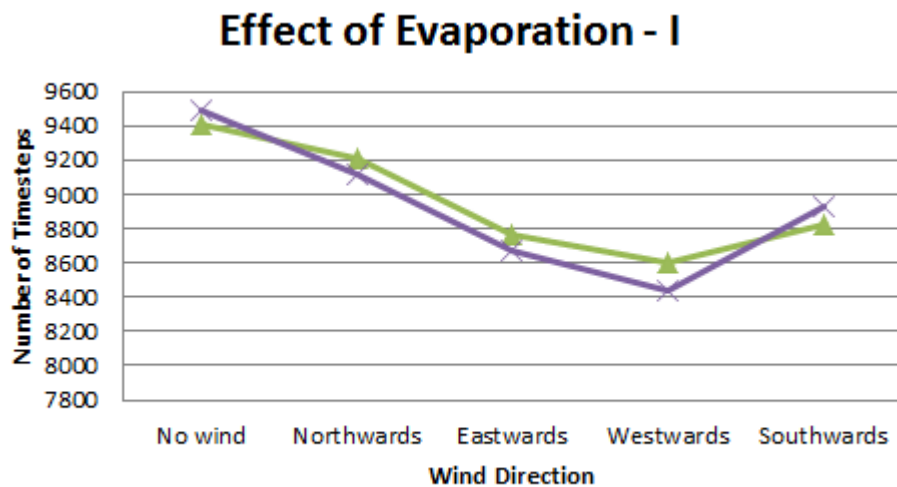


Figure 5-16: *Effect of Evaporation - I : Experimental setup - III (with dissipation) tried with (violet line with markers) and without (green line with markers) evaporation. It could be seen here that applying evaporation has not had any effect here.*

To see if evaporation could play any part when wind was taken into consideration with lesser dissipation values, experimental setup - III with lesser dissipation (attenuation=0.15, viscosity=0.006) was tried with and without evaporation. It was found that the calculated value of evaporation seemed too small to cause any kind of impact with its only use being erasing off the paths that were established by the recruiters but not traversed and strengthened by the recruits.



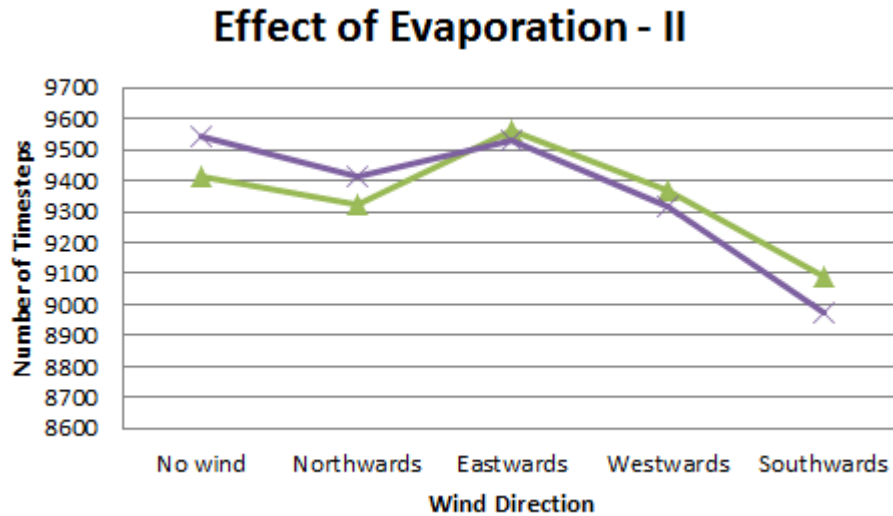


Figure 5–17: *Effect of Evaporation - II : Experimental setup - III (with lesser dissipation) tried with (violet line with markers) and without (green line with markers) evaporation. From the data obtained, it could be seen that evaporation did not have any impact here as well.*

## 5.6 Multiple Obstacles

One obvious thought for furthering the previous experiment would be to use multiple obstacles and see if the previously observed behavior holds when the number of obstacles are increased. Therefore, the landscape containing multiple obstacles (figure 5–18) was chosen for the agents to thrive. In the same way as it was done for the previous experiments, initially, the recruiters were allowed to establish a path followed by the recruits trying to strengthen a path.





Figure 5–18: *Multiple Obstacles: A snapshot of landscape with randomly placed obstacles.*

Contrary to expectation, it was found that, the path reinforcement process in itself was not guaranteed to occur all the time. In one case, the agents were either still found to be navigating along more than one established path and in another, almost all of the agents had got lost - this suggests that though the reinforcement process started, it did not end as the ants lost the path they were trying to reinforce. In total, of the 6 times the experiment was conducted, there were two times where a clear path selection was not made even after 15000 timesteps, all the recruits got lost twice and a path was reinforced two times. But even during the two times path reinforcement was observed, the reinforced path was not the same and the strengthened paths were on either sides of a few obstacles though the time taken for path reinforcement were similar (9953 and 10037 timesteps).

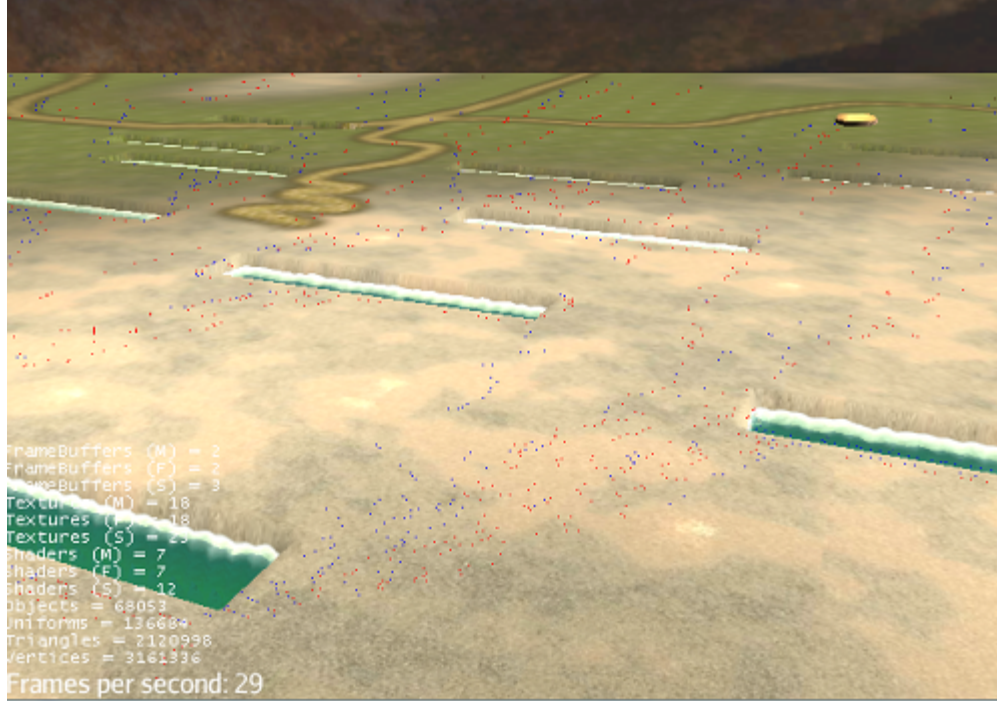


Figure 5–19: *Absence of Path Reinforcement:* It can be seen from this snapshot that there is no clear formation of path formed towards the food source. Though it can be seen that multiple recruiters and recruits have managed to find the food source here, no single path was strengthened thus proving the absence of path reinforcement.

It was observed that due to the presence of multiple obstacles, the probability for formation of a clear-cut best path was greatly reduced. As well, due to the same reason, the possibility of finding the food source and reinforcing the path became less obvious. Therefore, the reason behind the failure to observe results similar to the ones achieved using a simple obstacle model could be that this experiment, in more ways than one, could be viewed as an 'N-bridge experiment'. As a result, not only many more paths between the nest and food source were established but also some paths formed were very similar in distance. In order to check further for the existence of any patterns, as was done before, the same setup was tried with wind blowing in different directions and increasing the degree of dissipation by lowering the attenuation (Att) and increasing the viscosity (Vis) values. The results obtained are given in table 5–1. Though the results looked randomized initially, a closer look

Table 5-1: Results with Multiple Obstacles

<b>Direction</b>	<b>Att=0.15, Vis=0.006</b>	<b>Att=0.05, Vis=0.010</b>	<b>Att=0.02, Vis=0.015</b>
<b>North</b>	Left	Right	Two paths
<b>East</b>	Right	Two paths	Two paths
<b>West</b>	Right	Two paths	Two paths
<b>South</b>	Left	Right	Two paths

Here, 'Left' and 'Right' represent the paths formed along the respective sides of a few obstacles, and 'Two paths' represent both right and left paths (with similar distances) being traversed even after 15000 timesteps.

gives us some insight into how things have taken shape. The first generic observation to be made here is that without wind the agents had got lost 2/6 times whereas in case of wind, they had not got lost even once out of twelve attempts. With this, it can be said here there's some role played by the wind through dissipation which partly helps in convergence. The next observation to be made is in the outcome where a single path reinforcement was not observed even after 15000 timesteps. The results obtained clearly demonstrate that the attenuation and viscosity values altered have played some role in keeping more than one path being favored. This has happened in spite of the number of obstacles acting as a limiting agent obstructing the flow of air currents. The extent to which the obstacles play a limiting role depends on the different factors like the number of obstacles, size of obstacles, and angle in which the obstacles have been placed. Therefore, we can conclude that while it is certain that wind plays a positive role in spite of the presence of multiple obstacles, the extent to which these obstacles play a role is something that requires further research. In comparison to the results obtained from the previous experiment, another interesting observation here is that higher dissipation rates which created a somewhat negative

impact by increasing the time taken for path reinforcement have played a positive role here in helping the ant agents to find the established paths and stay within the foraging range.

## CHAPTER 6

### Conclusion and Future Work

#### 6.1 Conclusion

The conclusions that can be derived from the simple obstacle setup are as follows: Firstly, wind as a parameter does have an impact on the foraging process with the time taken for path formation considerably lower when compared to a windless simulation. This observation becomes pronounced when the direction considered was perpendicular to one in which ant agents were moving. Secondly, the parameter loses its trait when pheromone deposits are dissipated to wider areas. Thirdly, another important conclusion that can be derived is that, as against initial observations, the number of pheromone deposited is not always proportional to the time taken for the path establishment process.

In sum, we can say that wind can be included as a parameter in ant colony algorithm to speed up the path establishment and reinforcement process without disturbing the convergence rate i.e., not being at the cost of optimal solution. It could also be said that dissipation has a gradient effect as it spreads away from the source causing the ant to walk 'up hill' towards the source further helping convergence. Subsequently, *if multiple paths lead towards the source, wind and dissipation (if in the correct direction) averages the multiple paths into a single path.*

With respect to the a more complex setup with multiple obstacles introduced, even though the obstacles have had a largely negative impact by obstructing the flow of

air currents and subsequently, muting the role of wind to an extent, the effect of wind could still be seen whereby it has prevented the ant agents from losing track of the foraging range and for greater dissipation values, it has started favoring the convergence of paths with similar distances.

The last conclusion is regarding the role played by the dissipation: When seen in the context of simple obstacle setup, it has played a negative role in increasing the time taken for path reinforcement process whereas in case of a complex obstacle setup, where the path reinforcement formation in itself was not found to happen all the time, it has played a positive role in helping the ant agents find pheromone deposits. As regards evaporation, though we have not obtained the results that we expected, this can be seen as starting point and further research can certainly be focused on this area since we limited ourselves to select parameters for calculation of evaporation here.

## **6.2 Shortcomings**

The main limitation here is that the solver that we have considered for wind simulation by Jos Stam is not efficient in the sense that it was not designed keeping accuracy in mind. As well, it was meant to be a prototype model only. Therefore, future efforts could focus on improving the solver efficiency or even try a new solver that is more efficient. The second limitation is that the platform created here is a sequential model and therefore there's a lot of scope here for improvement with respect to achieving faster running time and concurrency.

### 6.3 Future Work

There are different possibilities for work to be done based on the platform laid. It depends on the direction that one proposes to take and what is being aimed. The ones discussed here are aimed towards creating an entirely functional ant colony mechanism thriving in a dynamic environment.

From a conceptual point of view, what we have presented is a basic simulation with default conditions. An effort could be made to make the simulation more usable in the sense that traits that are unique to a certain species of ants could be incorporated as separate modules. Therefore, by having set a base, the simulator can serve as a tool for scientists to analyze the behavior of different ant species. From a model point of view, there are many options available to consider and is reliant on the computational needs of building a colony model. Since the goal of the Prometheus project is to realize a fully functional ant colony with multiple agents using the global information available to them, it would be worthwhile to consider some of the options. Based on the work done here, the future work could be focused on the following areas:

**U-turns:** Beckers et al. [4] proved that in *Lasius niger* colonies the U-turn behavior of the ant species leads to almost always choosing the shorter path and play a larger role than plain bi-directional trail laying behavior. This U-turn behavior can be described as the tendency of the ants to turn back midway on the chosen path and then proceeding to take an alternative path. If such U-turns are made on longer paths and shorter paths are chosen as an alternative path subsequently, then this could be seen as factor hastening the selection of the best path. Therefore, this can

be added as a separate module to the algorithm that we have and further tests can be done to verify the claims. If proven, this can be seen as a parameter which can be used to force faster convergence with optimal solution.

**Multiple colonies:** The experimental setup that we have considered and modeled corresponds to a single colony of ants going in search of food and returning to the colony once a food source is found. An extension of this approach would be to consider multiple colonies living in the same neighborhood and each one working on its own task. This would give rise to complex situations where inter colony communication might have to be handled using colony specific olfactory cues. Similar strategies have been tried in optimization based applications where colonies could be working on the same objective [42] or different objectives [30].

**Other pheromone based behaviors:** Ants use pheromones not only for food foraging but also for other activities relating to sustenance in a colony that includes construction of nests, alarming fellow workers of intruders, conveying vital information like the quality of food source found, and cemetery construction. The approach required here is very similar to the mechanism that we have established here and could be seen as a direct extension of this research.

**Ant movement:** As mentioned before, here the ants are assumed to be always forward looking and therefore in a way, is restricted with respect to its olfactory boundaries. It would be interesting to observe what kind of impact will adding additional non-forward looking directional capabilities [37] will have on the foraging experiment.



**Obstacle navigation:** The technique included here for navigation through obstacles is based on a simple implementation of bug's algorithm where when an ant encounters an obstacle, it moves around the obstacle until it has a clear space to move ahead. The drawback here is that this approach may be highly inefficient for complex shaped or bounded obstacles. An extensive survey of different bug based algorithms is provided in [35] and it remains a priority to improve the obstacle navigation technique as it could play a lead role in achieving efficient solutions in a dynamic environment. Also, as mentioned before, the position, size and angle in which the obstacles are placed with respect to the foraging path need to be analyzed.

**Evaporation / Rate of pheromone decay:** As discussed, the experimental results show that the evaporation rate is too low to have an effect on the path formation process. Here, attention must be paid to the fact that we considered only the select parameters for evaporation and further research needs to be done in this field to have a more convincing say on this effect.

**Optimal Solution and parameter dependencies:** It could be noted that the algorithm's convergence rate, though a healthy one, could be increased in order to make it comparable to other well known Ant colony algorithms that we had discussed. The main culprit here was premature convergence with the agents finding and settling with suboptimal paths when a better solution could have been established and reinforced. It has been proven that the parameters play a major role in achieving an optimal path and avoiding stagnation problem [23].

**Parallel Computation:** One of the major obstacles faced while conducting simulations was the inability to perform the simulation on a larger scale due to the restriction imposed by the sequential implementation. This can be seen as the most important task for this research with respect to further enhancing its capabilities. Moreover, parallel and distributed ant colony algorithms is a burgeoning field [40, 32, 9] with exciting prospects and this is one of the immediate areas that we would like to focus on.

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