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THE UNIVERSITY OF SHEFFIELD

DESIGN AND MODELLING OF DECENTRALISED TASK ALLOCATION MECHANISMS IN GROUPS OF MOBILE AGENTS

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Department of Computer Science

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Declaration

I declare that this report is composed by myself and the work contained herein is my own except where explicitly stated otherwise in the text. This work has not been submitted for any other degree or professional qualification except as specified.

Sifat Momen

Dedicated to my parents,

Professor A.M. Mominul Huq (Abbu) and

Mrs Rehana Nazneen (Ammu)

for their endless support and motivation

Abstract

Division of labour is a fundamental field of research within the context of multi-agent (particularly swarm based systems) and multi-robot systems. Eusocial insects, for instance ants and bees, are known to display remarkable capabilities of allocating tasks to nest mates when the colony gets perturbed by any internal and/or external factors. Proper understanding of the underlying mechanisms of division of labour among these social insects would enable more effective designing and developing of artificial swarm based systems which in turn can be used in tackling various real world problems. At the same time, a properly built model can be used to serve as a platform for the biologists to test their research hypotheses. These key benefits have been the prime motivations of this thesis. The thesis is based on the behaviour of ant colonies and especially on how they allocate tasks in different situations. The objectives of the thesis are twofold: (1) to develop an artificial simulated system that is ant-like and (2) to explore, identify, develop and analyse task allocation strategies within the realms of colony performance.

The first objective of the thesis is approached by investigating the behaviour of ant colonies from the existing literature and modelling their behaviours using an agent based modelling approach. To determine whether the model has met the first objective, three questions are posed: (A) Is the emergent system scalable? (B) Is the emergent system flexible? and (C) Is the system robust? For a system to be ant-like, the system has to not only give the appearance of ant-like behaviour but also has to meet these three criteria. As a part of the second objective of the thesis, three task allocation strategies based on ant colony behaviour are proposed. Furthermore, the

strategies are critically analysed to investigate the benefits of each of the strategies and also to discover under what circumstances which strategies would perform better. The research reported in this thesis is intended to provide a better understanding of the design issues of task allocation strategies thus enabling researchers to use this as a guide to design effective task allocation strategies within the concerned multi-agent systems.

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List of Publications

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Momen, S. and Sharkey, A.J.C. (2008), An ant-like task allocation model for heterogeneous groups of robots, IUSSI 2008: *4th European Meeting for the International Study of the Social Insects*, 117.

Momen, S. and Sharkey, A.J.C. (2009), An ant-like task allocation model for a swarm of heterogeneous robots, *The 2nd Swarm Intelligence Algorithms and Applications Symposium*, 31 – 38.

Momen, S. and Sharkey, A.J.C. (2009), Strategies of division of labour for improving task efficiency in multi-robot systems, *IEEE World Congress on Nature and Biologically Inspired Computing (NABIC'09)*, 672 – 677.

Momen, S. and Sharkey, A.J.C. (2010), From ants to robots: a decentralised task allocation model for a swarm of robots, *The 3rd Swarm Intelligence Algorithms and Applications Symposium*, 3 – 11.

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Chapter 1

Introduction

Flocks of birds meandering in the evening light, armies of ants marching for foraging, herds of buffalos congregating to avoid predators, synchronised flashes from male fireflies tempting to attract the female ones or even pods of dolphins dancing up and down in unison are some of the spectacular examples of collective behaviours [Camazine et al., 2001; Garnier et al., 2007; Momen and Sharkey, 2010; Sumpter 2010, 2006] that animals display. Their behaviours are not only enthralling to watch (figure 1.1) but are also some of the finest examples of how individuals form groups which allow them to work as a whole [Sumpter and Brännström, 2008] to carry out tasks that would otherwise not be accomplished by a single individual with the same efficiency. Individuals in a swarm system neither possess any global template of the environment nor follow any particular leader. Instead, they behave as reactive individuals trying to synchronise with the immediate neighbours through some simple local interactions. Such local cohesion among the agents facilitates the tendency to become a part of a group which consequently benefits the animal societies in numerous ways including (1) the possibility of minimizing danger from a potential predator, (2) accomplishing tasks that are otherwise difficult to carry out, (3) improving the chances of finding a mate and also (4) transferring vital information within the group quickly [Alcock, 2001; Hamilton, 1971, Krause and Ruxton, 2002].

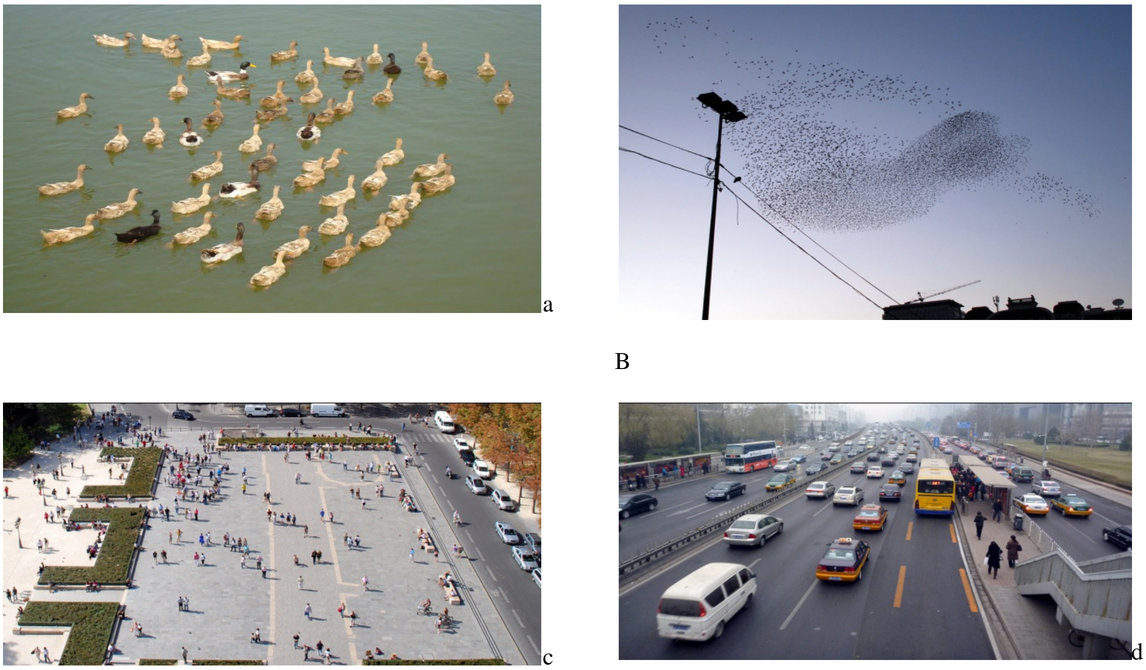


Fig 1.1: Examples of self-organised collective behaviour. a) a team of ducks (provided by Nafi Ahmed), b) a flock of birds in Milan, c) a crowd of people in front of Notre Dame Cathedral, Paris, d) traffic flow in busy Beijing. Photos (b) – (d) are provided by Lei Ye. All photos used with permission.

Research studies pertaining to animal behaviour provide many key strategies and techniques for various engineering problems and applications and thus have inspired many engineering and applied disciplines for many years. Use of similar biological principles in various research fields resulted in many interdisciplinary researches across those disciplines. *Swarm intelligence* (SI) [Bonabeau et al., 1999] and *swarm robotics* (SR) [Beni, 2005a; Sharkey, 2007, 2006], the robotics application of SI, are one such field of science that emerged, in recent times, as a result of these interdisciplinary studies. The concept of SI is strongly inspired by the collective behaviour of animals and especially by that of the eusocial insects [Wilson, 1971] and studies how a large number of relatively simple agents use repeated local interactions between the neighbouring individuals and with the environment in the vicinity to create a collectively intelligent system.

A swarm system can be regarded as a subset of multi agent systems (MAS) having the following features [Şahin, 2005]:

Autonomous agents: The agents are fully autonomous i.e. they operate without others having any direct control over their actions and internal state.

Large number of agents: There should ideally be a large number of homogeneous agents in a swarm system. A system can be heterogeneous but each heterogeneous group should ideally have large number of redundant agents.

Simple agents: The abilities of individual agents are extremely limited in the sense that they either cannot carry out a particular task on their own and even if they can, the deployments of swarms of agents dramatically improve the performance of the system.

Local interactions: Ideally, no agents should have a global view of the environment. They can only communicate with each other and with the environment within a short radius compared to the size of the environment and that there should not be any single agent that controls the execution of other agents. This ensures that 1) the behaviour that emerges is not a product of a single individual rather a cumulative effect of many local interactions between individuals and 2) there is no dependency on any particular agent i.e. there is no single point of failure (and hence the system is robust to individual failure).

Emergent Behaviour: This property is the hallmark of any swarm system [Gilbert and Troitzsech, 2005]. By the process of multiple interactions and the behavioural rules individuals follow, a collective behaviour is produced. Individual agents behave as "dumb" agents unaware of the global environment but the behaviour that emerges out through this process is an intelligent one that enables the agents to adjust themselves to the changing environment.

1.1 Inspiration from biological behaviour

Natural systems (in our case, the collective behaviour of animals), by the process of natural selection [Darwin, 1859], have been evolving for over hundreds of millions of years and by now it is expected that they have built strategies that would allow them to develop systems that are extremely stable and adaptive to the changing environment. Systems developed by mimicking these biological behaviours within an artificial environment provide engineers and scientists with some inherent benefits including:

Robustness: Robustness refers to the ability of a system to continue to operate despite failures by the individuals or any perturbations in the environment [Şahin, 2005]. A large number of redundant identical agents coupled with decentralised coordination allows a swarm system to be robust.

Flexibility: Individuals in the environment are not fixed to any particular task but are flexible. This allows the system as a whole to adapt and hence react to any perturbations caused during the course of its operation.

Scalability: Since the system is completely decentralised, it is easy to either add or remove agents without affecting the overall operation of the system.

On the other hand, the swarm systems developed by engineers can provide a unique platform that allows the biologists to formulate theoretical concepts underlying the principles of collective behaviour within animal groups [Webb, 2008; Webb, 2000].

1.2 Thesis

This thesis looks into the area of task allocation (TA) in a multi-agent system. Task allocation refers to the way tasks are chosen, assigned, subdivided and coordinated within a colony and are often referred to as a salient feature underlying the organisation and the success of a society [Anderson and McShea, 2001; Bourke and Franks, 1995; Jeanson et al., 2007; Momen and Sharkey, 2009a; Smith, 1776; Wilson and Hölldobler, 2008]. It is known to be an extremely important and fundamental area of research within the context of multi-agent and multi-robot systems. Eusocial insects (such as ants and bees) are known to display remarkable capabilities of allocating tasks to nest mates within a changing environment [see for example Gordon, 1999; Schmickl and Crailsheim, 2008a, b, c; Wilson and Hölldobler, 2008]. A proper understanding of the underlying mechanisms of task allocation within social insects would lead to effective design and development of task allocation in multi-agent systems (more specifically swarm based systems) which in turn could be used in many real world problems. At the same time, such effective designs are envisioned to provide a new platform for biologists to theoretically test their research hypotheses. These advantages that a properly designed task allocation system can possibly bring have motivated us to undertake research in this direction. Social insects and typically ant colonies are known to display a wide range of task allocation strategies under different circumstances. This thesis, therefore, is strongly inspired by the mechanisms by which ant colonies distribute and re-distribute work forces within a stochastic environment. The objectives of this thesis are twofold: (1) To develop an ant-like system which is flexible, scalable, robust and decentralised, and (2) to explore, identify, develop and analyse task allocation strategies within the realms of colony efficiency. The first objective of the thesis is approached by investigating the behaviour of ant colonies in the existing literatures and modelling their behaviours using agent based modelling approach. Agent based modelling approach enables us to visualise how the colony as a whole behaves with the given set of rules. To establish whether the model has met the first objective, three questions are considered: (A) Is the emergent system scalable? (B) Is the emergent system flexible? and (C) Is the system robust? For a system to be ant-like, the system not only has to give the appearance of ant-like behaviour, but also has to meet these three criteria. As a part of the second objective of the thesis, three task allocation strategies developed in the light of ant colony behaviour, have been proposed. Furthermore, the strategies are also empirically investigated in order to establish the circumstances under which they work better.

This research could help engineers select appropriate strategies for the particular task allocation problem they are encountering as well as helping biologists to understand the underlying mechanisms of social insect behaviour and the benefits that different task allocation strategies can bring.

Although it is common to find that engineers (and especially the roboticists) model the behaviours of social insects on swarms of simple robots in order to analyse and understand the animal behaviour as well as to solve engineering problems, the purpose of this thesis is not such. The models developed on robots tend to be fairly simple due to various limitations of the current technologies in robotics and electronics. This, however, becomes a limitation for understanding more complex behaviours that are available in nature. Hence we have chosen not to explore the mechanisms using real robots. However, in future, we intend to translate the models developed in this thesis within the realms of robotics for practical applications. It should also be noted that the models developed in this thesis are not specific to any particular ant specie. Rather, it is in line with one of the main objectives of the thesis i.e. to identify and incorporate ant-like behaviour exhibited by different species of ants and design a flexible, scalable, robust and decentralised system.

The three task allocation strategies can be briefly outlined as follows. Ant colonies exhibit various strategies and mechanisms to divide labour (on the fly) depending on the task demand. Three mechanisms have been derived from the observations of the social insects which are then evaluated in terms of the performance yielded:

Strategy 1 (Indirect communication): Within the first strategy, the agents interact with each other locally but only via the environment. Such sort of indirect communication (i.e. communication via the environment; also called stigmergic interaction) is a very common mechanism in social insects [Grassé, 1959].

Strategy 2 (Explicit communication): In this strategy, the agents not only communicate with each other indirectly but also communicate explicitly when some sort of crisis is experienced. Such behaviour has been reported in many social insects including *Leptothorax albipennis* while house hunting and red harvester ants, *Pogonomyrmex barbatus*. Direct communication comes in many forms [Jackson, 2006] including tactile, visual, acoustic, waving antennae and also touching antennae. However, one of the common forms of direct communication is that of the antennae to antennae communication in order to access a nest mate's cuticular hydrocarbon profile to know what task the other agent is carrying out. For the second strategy, the mechanism of antennae- antennae interaction has been adopted in the model for direct communication.

Strategy 3 (Hybrid System): In this strategy, a heterogeneous system has been developed within a particular caste. Two types of brood carers (i.e. two different control architectures) have been developed. In one case, the brood carers are not affected by the need for switching to foraging task (type A brood carers). These brood carers are dedicated to their own principal tasks (i.e. feeding brood members when required). The second type of brood carers, type B brood carers, is flexible and can switch tasks whenever required. The hybrid system contains both the kinds of brood carers. A detailed description of the control structures of the two types can be found in Chapter 6.

These three strategies have been developed within a 2D artificial world. Once the models are developed, it allows us to explore the models and critically investigate the advantages of the different strategies in different circumstances.

1.3 Contributions

The following list highlights the main contributions of the thesis:

(1) A simulation environment has been developed that permits the exploration of several questions about the way task allocation can be accomplished in a multi-agent system and their effect on the performance of the colony. Furthermore, a set of behavioural rules for the agents have been established by taking inspirations from the behaviour of social insects (particularly ants). The experimental results are then analysed and were found that the emergent behaviour that arises from these simple behavioural rules share similar features to that of the real ant colonies (scalability, flexibility and robustness).

(2) Three task allocation strategies have been identified, implemented and afterwards analysed to investigate the effect of each of the strategies on the performance of the colony.

(3) The performance of the colony is critically analysed to understand and investigate the strengths of different task allocation strategies.

The investigation that has been made in this thesis would help researchers in two main ways: (1) it would enable researchers to easily change many parameters as well as the strategies of task allocation to see how would these effect the colony and (2) it would also shed light to understand the advantages of different task allocation strategies under various conditions – allowing researchers to effectively choose task allocation strategy within their domain.

1.4 Organisation of the thesis

The thesis has been subdivided into eight chapters: the first one of which is the introduction. Chapter 2 introduces the background concepts of swarm intelligence and self organisation. It discusses the key ingredients of self organisation and provides a set of examples of self organised behaviour exhibited in nature. Following chapter 2, in chapter 3 a detailed discussion related to division of labour in social insects and swarm robotics has been made. Chapter 4 introduces the model and analyses the behaviour that emerges out of it. Chapter 4 discusses the behaviours of the agents in detail, and provides an account of the behavioural rules that lead to a self-organised adaptive system. In chapter 5, the model presented in chapter 4 is extended by incorporating direct communication between agents (which can be found in many ant species). Furthermore, a detailed comparison between the two models (the one in which agents exhibit indirect communication only and the other in which agents exhibit explicit communication) is undertaken in order to understand the benefits of each strategy. Chapter 6 discusses the development of the third strategy where some agents within a particular caste are made less flexible. The chapter also empirically investigates if the total degree of flexibility in agents always leads to a better performance within the colony than that of a heterogeneous system where some agents have limited degree of flexibility. Chapter 7 reviews and reflects on the results obtained in chapters 4 – 6. Furthermore, it compares the results obtained in our model with that found in the literature. Finally, chapter 8 concludes the thesis with discussions about possible future directions.

Chapter 2

Swarm Intelligence and Self-Organisation in Multi-Agent Systems

The research presented in this thesis is strongly inspired by the self-organising behaviour of social insects in which individual agents follow some specific rules to create a collectively intelligent system. Before a description of our models and the experimental results are given, an understanding of the key ideas regarding self-organisation is deemed necessary. This chapter along with Chapter 3 serves that purpose. In this chapter, the concepts of swarm intelligence and self-organisation are explained. The remainder of the chapter is organised as follows: Section 2.1 introduces the concept of swarm intelligence followed by the principles of self-organisation. Section 2.3 looks into a wide range of self-organising behaviour noticeable in nature followed by some specific examples of self-organising behaviour exhibited by social insects (section 2.4). Recently, there has been enormous interest among researchers within the robotics community in incorporating the self-organising behaviour observed in the natural world into robotics research. This is due to the fact that natural swarms suggest some key solutions to various design issues. On the other hand, swarm robotics (robotics application of swarm intelligence) research provides biologists with a unique platform to rigorously test their hypotheses. In section 2.5, we turn our attention to see how some of the biological behaviours have been incorporated into swarm robotics research. Finally, a summary and conclusion of the chapter is drawn in section 2.6.

2.1 Swarm Intelligence

Swarm intelligence has been defined as "*a paradigm for designing 'intelligent' systems as a result of cooperation among a relatively small number of simple, identical, autonomous units, interacting without common clock, typically at short range and without centralised control*"[Beni 2005b]. Although Beni's definition describes the number of autonomous units involved as small (he described units in the range of 10^2 and $10^{<<23}$ as small since he compared the number of units involved with respect to Avogadro Constant), it is generally considered to be large by many other researchers [Camazine et al., 2001; Şahin, 2005]. Furthermore, Beni considers the units involved to be identical (i.e. homogeneous in nature), but heterogeneous mixtures of agents are prevalent in natural systems and fit well within the swarm intelligence paradigm. Şahin suggests that a heterogeneous mixture in a swarm system does not violate swarm intelligence paradigm given that there are relatively large number of agents in each group [Şahin, 2005]. Beni pointed out that the word '*intelligence*', in context of swarm intelligence, is actually to be used in a limited sense [Beni, 2005a]. He suggested restricting "intelligence" to two of the qualities of intelligence while describing swarm intelligence: (1) the ability to produce something ordered from the unordered and (2) the unpredictability of the outcome. There are numerous examples of swarm intelligent systems in nature [some of them are discussed below]. The process by which these individual units (agents), with limited capabilities, create an emergent behaviour is referred to as *self-organisation* and is at the heart of any swarm intelligent system.

2.2 Self Organisation

The term “self-organisation” was first coined by Ross Ashby [Ashby, 1947] in the context of contemporary science and has been widely adopted by many researchers and scientists in order to understand the aggregate behaviour in animal societies. Self-organization can be seen as a pattern formation process in both physical and chemical and also biological systems. Examples of physical and chemical pattern formation include the circular pattern formation by the iron filings around a straight current carrying conductor, size segregation of granular mixture of particles when shaken [Rosato et al., 1987], the formation of Bénard convection cells (Fig. 2.1) when heat is applied evenly to the bottom of the tray filled with a thin sheet of viscous oil transforms and the spiral pattern formation by the Belousov-Zhabotinsky reaction (Fig. 2.2). Biological pattern formation, on the other hand, is widely found in nature and includes the v-shaped structure created by migrating geese, the pulsating wave created by slime molds while aggregating and synchronous rhythmic flashes created by fireflies.

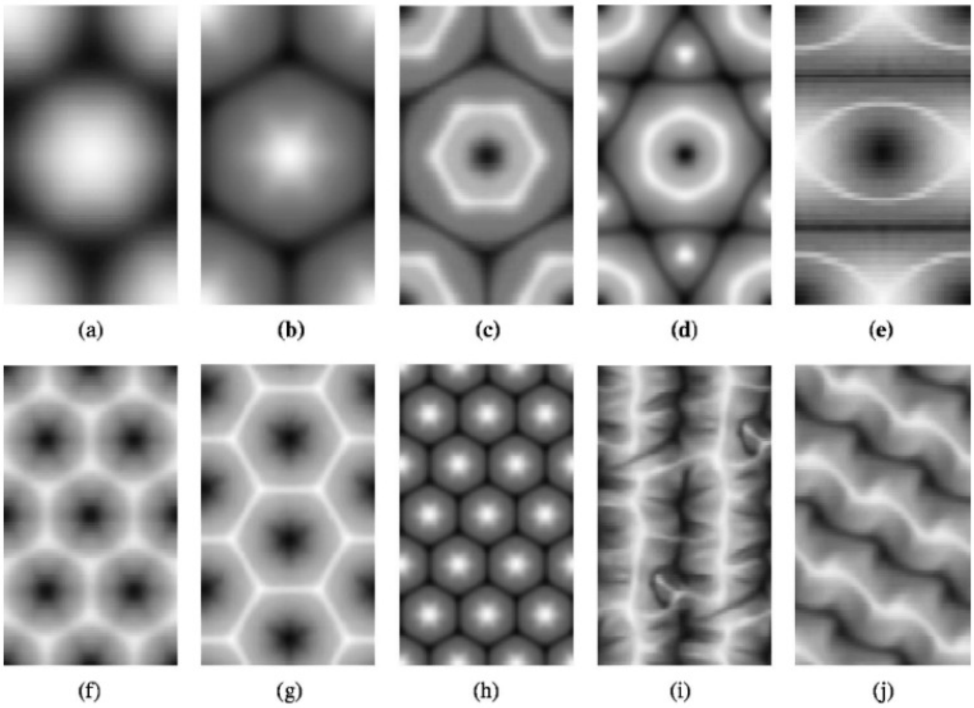


Fig 2.1: Formation of Bénard convection cells. Reprinted from [Getling and Brausch, 2003].

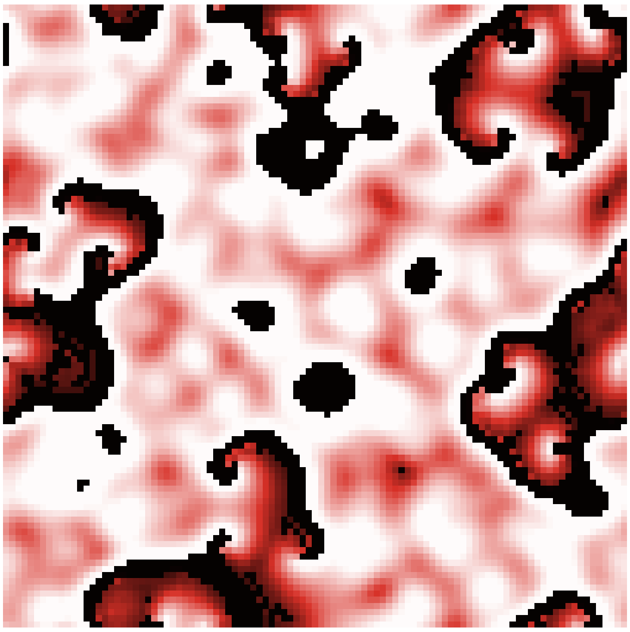


Fig 2.2: Pattern formation in the B-Z reaction

Camazine et al. [Camazine et al., 2001] define self-organization in the context of biological systems as *"a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower-level components of the* *system. Moreover, the rules specifying interactions among the system's components are executed using only local information, without reference to the global pattern."* This means that each agent (lower-level component) follows some simple rules and can interact only with the neighbouring agents and the environment in its vicinity. The agents neither have any particular leader nor any prior knowledge of the global template of the system. Following numerous interactions among the agents and the environment in the vicinity, a pattern seems to emerge at the global level of the system.

2.2.1 Basic ingredients of self-organisation

Various researchers [e.g. Bonabeau et al., 1997 and Camazine et al., 2001] have pinpointed four constituents of self-organisation:

1. **Positive feedback** (amplification): It is a simple behavioural rule of thumb that promotes the creation of a structure/pattern. Examples of positive feedback include the recruitment and reinforcement process in social insects. Simple positive feedback like "I go where you go" in birds, "I signal when you signal" in fireflies and even "I do what you do" in humans play a major role in building group patterns [Camazine et al., 2001]. In each of the cases, the behaviour of an agent is affected by its surrounding neighbours. An early investigation of whether such positive feedback mechanism is applicable in humans or not was carried out by [Milgram and Toch, 1969]. In this experiment, a stimulus group of people was planted to look up at a supposed point of interest on a busy street and observed how many passers-by also look up at the point to find out the interesting thing. Milgram and Toch found

that the proportion of passers by who looked up (P) is a function of the size of the stimulus group (C) (equation 2.1) (Fig. 2.3).

$$P = \frac{0.92 \times C^{1.04}}{1.22^{1.04} + C^{1.04}} \tag{2.1}$$

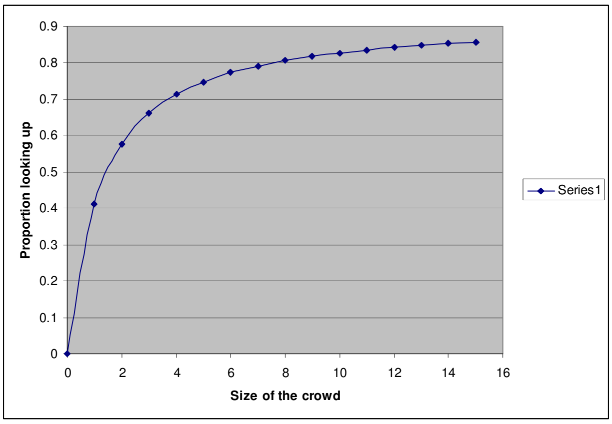


Fig 2.3: Proportion of passers-by looking up as a function

Of the size of the stimulus group

2. **Negative feedback:** While positive feedback helps building up the pattern, negative feedback helps stabilizing the pattern. Clearly if too many agents move in one direction, it would soon result in an overcrowding of agents and might even be a reason for the system to collapse. Such disaster is prevented by negative feedback. Clearly, it is the mechanism by which a system is regulated. For example, in slime mold aggregation, when too many slime molds aggregate, they prevent themselves from further aggregation by inhibiting the cAMP (cyclic adenosine 3’ 5’ monophosphate) receptors (discussed later).
3. **Multiple interactions:** All cases of self-organisation rely on multiple interactions as it enables to stabilize a pattern over time.

4. **Amplification of fluctuations:** Self-organization relies on the amplification of fluctuations as well. For self-organization, randomness is crucial since *it enables the discovery of new solutions, and fluctuations can act as seed from which structures nucleate and grow* [Bonabeau et al., 1997].

2.2.2 Direct and indirect communication

In a swarm system, agents communicate either directly or indirectly. Direct communication by an agent/individual involves simple signalling mechanisms to other agents without the need of any intermediary medium. Such signalling mechanisms (in animal societies) come in various forms including that of chirping, touching, visual pointing and even dancing. Indirect communication (also commonly referred to as stigmergic interactions [Grassé, 1959]), on the contrary, involves communication between agents via the environment. In stigmergic communication, the signs left in the environment by an action (of an agent) stimulate the performance of the next action by the same and/or different agents. Such interactions include the use of chemicals to guide other agents or even simple bumping into some objects triggering some behaviour.

2.3 Examples of self-organisation in natural systems

2.3.1 Flocking of Birds

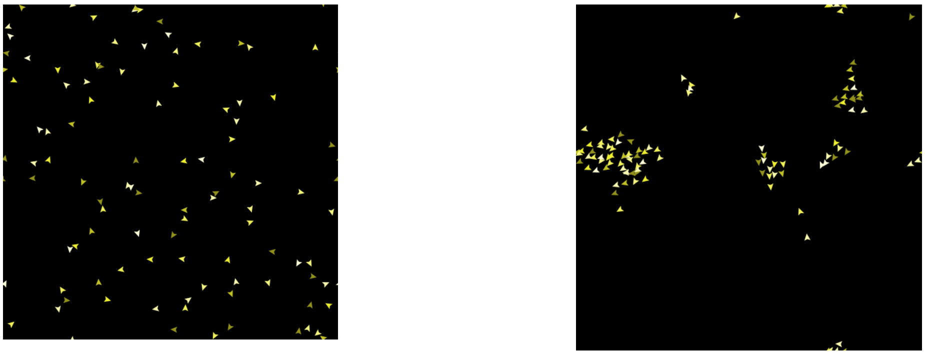
Reynolds, in 1987, first developed a simulation model to mimic the flocking of birds [Reynolds, 1987]. In his model, the boids (Reynolds called the generic simulated flocking creatures "boids") exhibit three simple steering behaviours:

1) *Separation*: steering to avoid crowding of local flock mates

2) *Alignment*: steering towards the average heading of local flock mates

3) *Cohesion*: steering to move towards the average position of the local flock mates

Using these three simple steering behaviours, boids are able to mimic the flocking of birds. In the model, each boid behaves like an autonomous agent. Whenever it finds agents within its range (flock mates), it adjusts its heading towards the average heading of the flock mates (alignment) and then coheres towards the average position (centre of mass) of the flock mates (cohesion). However, each agent maintains a minimum separation distance. Therefore, if any agent comes too close and the distance between the two agents becomes less than the minimum separation distance needed to be maintained by the agents, they steer away from each other (separation). In this way the agents maintain flying close to each other but not so close that they collide with each other. Figure 2.4 shows the snapshots of the flocking behaviour produced by boids using the netlogo simulator [Wilensky, 1998a].



a b

Fig 2.4: Flock of simulated boids. a) the initial random position of the boids, b) the flocking behaviour produced after some repeated interaction between the agents

Couzin and his colleagues [Couzin et al., 2002] proposed a model in which the agents maintain three zones (zone of repulsion, zone of attraction and zone of orientation) and mapped the corresponding behaviour depending on the zone the agent is in. By varying the radii of the three zones, they were able to show different patterns.

Momen and colleagues [Momen et al., 2007] extended the Reynold's model and developed a model within the realms of heterogeneous groups of robots by taking inspiration from mixed species flocking commonly observed among forest birds. Other interesting flocking model include that by Ke Cheng and colleagues [Cheng et al., 2009], Gokce and Şahin [Gokce and Şahin, 2009], Möslinger and colleagues [Möslinger et al., 2010] and Celikkanat and Şahin [Celikkanat and Şahin, 2010].

2.3.2 Slime Mold aggregation

Slime mold is a unicellular organism that is popularly known for exhibiting a remarkable interplay between unicellular and multicellular behaviour [Bonner, 1967, 1983; Camazine et al., 2001; Goldbeter, 1996; Schmickl and Crailsheim, 2007]. In nature, the amoebas of the slime mold *Dictyostelium discoideum* feed on bacteria and move randomly [Resnick, 1997]. However, if there is a scarcity of food and they are starved, they change their behaviour dramatically and start to aggregate towards each other, forming complex spatial patterns. It has been found that when slime molds are starved, they generate a chemical substance called cyclic adenosine 3', 5' – monophospate (cAMP) which they release to their outside environment. The amoebas then use the cAMP gradient to navigate towards each other forming a multicellular organism called a slug. The cAMP produces a positive feedback and helps in aggregating towards each other. It has also been found that higher cAMP concentration leads to higher cAMP production. However if they continue aggregating this way, they soon will collapse down to a single point. Therefore, in order to have stabilisation in the pattern, there must be a mechanism for negative feedback. Although there is some disagreement among researchers, a popular belief about the negative feedback is based on the assumption that high concentrations of cAMP desensitize the cAMP receptor i.e. when the concentration of cAMP increases above a threshold value, it seizes from aggregating further. Figure 2.5 shows the snapshots of the resulting slime mold aggregation behaviour [Wilensky, 1998b] formed by the positive feedback of the CAMP.

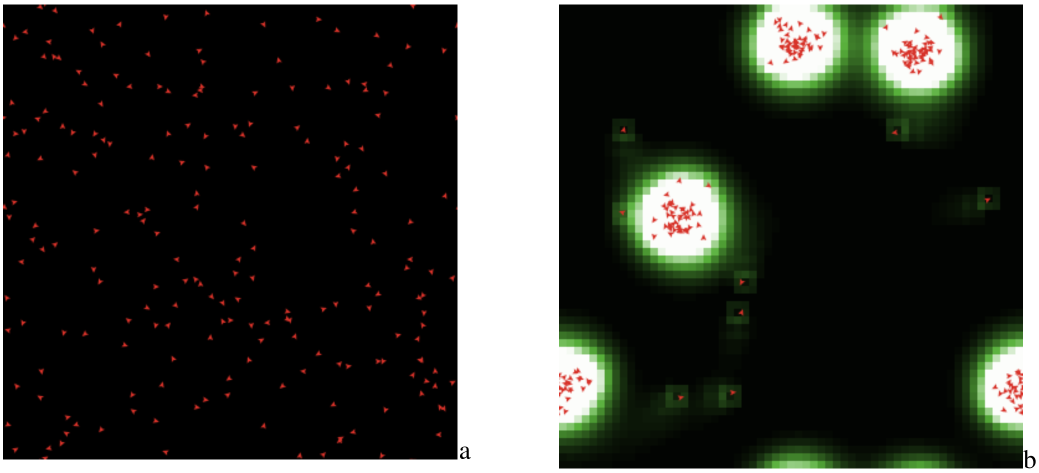


Fig 2.5: Slime mold aggregation. a) Slime molds moving on their own when there is plenty of food b) Slime molds aggregating into clusters when starved

2.3.3 Spreading of Rumours

Rumours are a form of social communication and their spreading often has severe consequences on the perception of celebrities, financial markets and even a society [Nekovee et al., 2007]. They can cause panic during wars and can create disaster in stock markets. They can also be manipulated intentionally to disrupt competitor organizations. In recent times, economists have started looking at rumour from a theoretical and an empirical point of view [Kosfeld, 2005].

Interestingly, the propagation of rumours exhibits self-organisation behaviour. This was first suggested by Daley and Kendal [Daley and Kendal, 1965] at the University of Cambridge and is now popularly known as the Daley –Kendal model (in short, the DK model).

The DK model considers a closed homogeneously mixed population of size $N+1$ where the members can fall into one of the three categories:

1. Ignorants (X): These are the members of the population who are currently not aware of the rumour. Initially i.e. at time $t=0$, $X=N$ i.e. the model assumes that initially there is only one rumour spreader and the rest are ignorant of the rumour.

2. Spreaders (Y): These are the members of the population who are currently actively involved in spreading the rumour to its neighbours. At $t=0, Y=1$.

3. Stiflers (Z): These are the members of the population who have heard the rumour but have stopped spreading it. (Initially, Z = 0).

Also, the model assumes that the population size is fixed i.e. at any time $t \geq 0, X+Y+Z=N+1$.

The rules of the model are as follows:

1. A spreader spreads rumour to one of its neighbours (who is an ignorant) at each time step (positive feedback).

2. An ignorant who hears the rumour becomes a spreader.
3. A spreader becomes a stifler whenever the spreader encounters another active spreader or a stifler.
4. A stifler knows the rumour but refrains from spreading it (negative feedback).

Positive and negative feedback on the course of the propagation of the rumours is what creates an emergent pattern.

A similar model shows how the rumour is spread in a population (Wilensky, 1998c) (Fig 2.6):

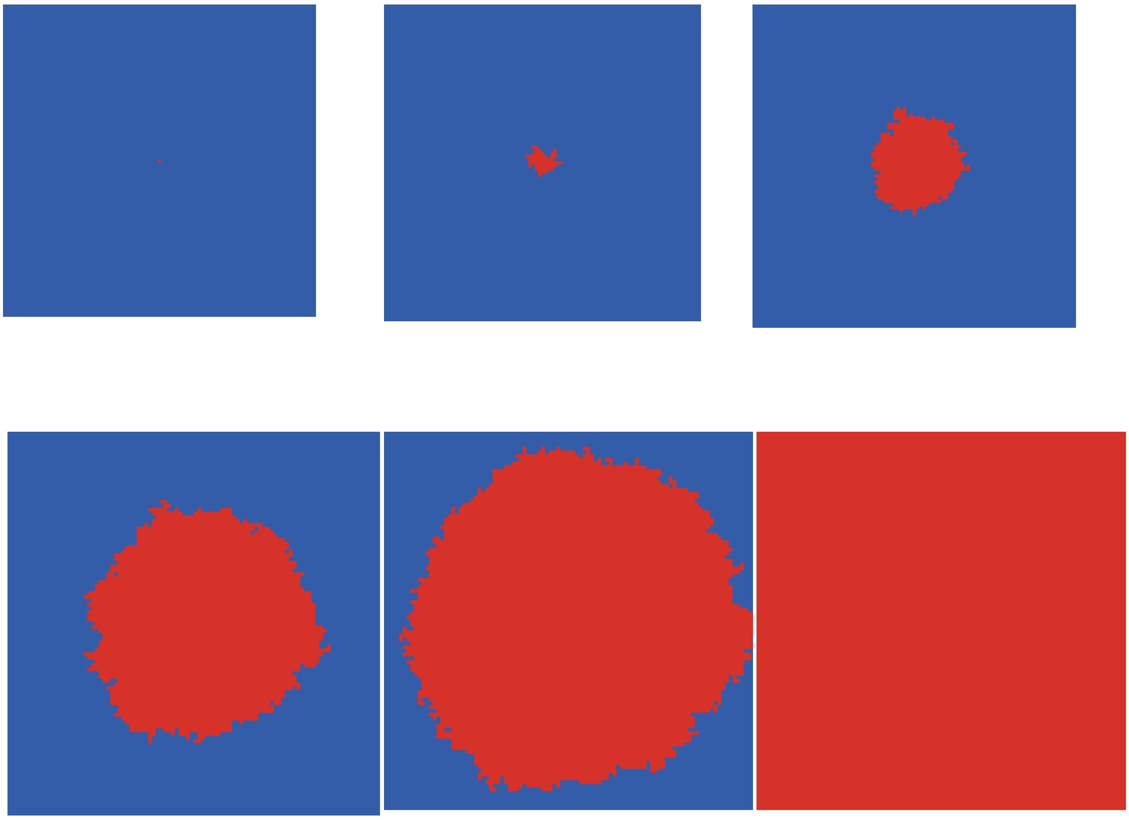


Fig 2.6: Propagation of rumours

The graph below shows a fast spreading rate is followed by a slow spreading rate over time. This is because as the rumour spreads in about half the population, the number of ignorants becomes relatively less and hence the slow spreading rate.

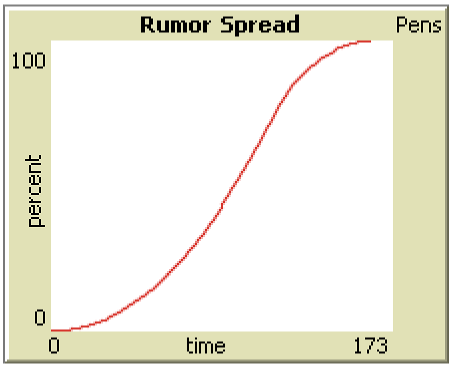


Fig 2.7: Spreading of rumour as a function of time

2.3.4 Flashing of fireflies

The flashing of fireflies has been one of the most hypnotic and wonderful experiences for explorers and naturalists over hundreds of years. It is also one of the classic examples of self-organization in biological systems. For North American rover fireflies, the synchronous flashing is a result of the courtship that involves a Morse-like code of alternating signals between the male and its mate [Camazine et al., 2001].

In another specie (*Pteroptyx malaccae*), a Thai specie firefly, the synchronized flashing is performed entirely by males and unlike the roving fireflies does not involve any Morse-like communication. In fact, all the males appear to flash simultaneously producing a stunning collective behaviour. The male *P. malaccae* resides on individual leaves causing the tree to glow at one instant and then go dark in the next instant.

Experimental studies on the CNS of the male fireflies revealed that the rhythmic flashing of the male fireflies is controlled by neural timing mechanisms in the brain that oscillates at a constant frequency [Bagnoli et al., 1976, Case and Buck, 1963, Case and Strause, 1978, Hanson et al., 1971]. Two techniques (Phase Advanced Synchronization and Phase Delay Synchronization) have been found to be adopted by these fireflies that result in synchronous flashing. Details of these two techniques are available in [Camazine, et al. 2001] and [Buck, 1988].

Wilensky uses the concept of the neural timing mechanism to explain the synchronous flashing of fireflies. In his model, each firefly maintains a clock of a specific cycle length (species specific). Flashing occurs at the beginning of each cycle and the clock is reset to zero once it has reached the maximum [Wilensky, 1998d]. At the start of the simulation, the fireflies were at a different point of their cycle-length thus creating an irregular flashing throughout. But as the simulation runs a more coherent flashing is observed. Each firefly looks at its neighbours to see when they are flashing. When it perceives flashes from other fireflies, it resets its clock to try to synchronize with the neighbouring fireflies. Over the time, fireflies become more synchronized in flashing creating such hypnotic experience. Fig 2.8 depicts this behaviour.

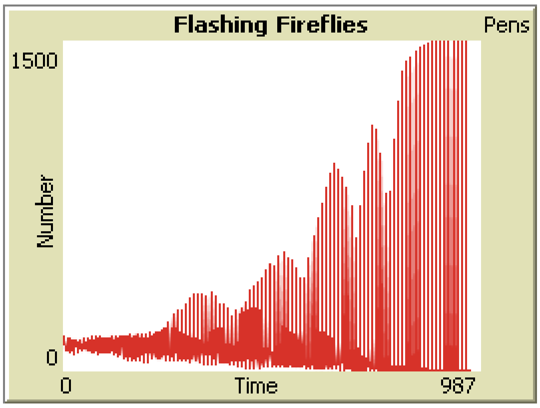


Fig 2.8: Synchronous flashing of fireflies building up over night

2.3.5 Nicaraguan sign language

Nicaraguan sign language [Senghas and Coppola, 2001] is perhaps one of the most fascinating examples of self organization in linguistics. Before the 1970s, there were no deaf communities in Nicaragua. The deaf people were largely isolated and used simple home signs to communicate with the family members. After the Sandinista revolution, the government decided to form a community for deaf people in a place called Managua. Although initially the Spanish sign language was introduced, the project failed miserably. The participants were unable to understand the Spanish sign language. However, as they started living in there, the school children started communicating with each other through different gestures and over time that has evolved into a new language.

2.3.6 Crowd Dynamics

Crowd dynamics have been studied for over three decades [Helbing et al., 2005; Moussaïd et al., 2010; Pelechano et al., 2008] and it is only recently that the self-organization effects occurring in pedestrian crowd have been appreciated. Helbing and colleagues [Helbing et al., 2001] used the self-organization mechanism to explain the principle of lane formation in oppositely moving pedestrians. In his model, he described how pedestrians moving against the stream encounter frequent and strong interactions. In each interaction, the encountering pedestrians move a little aside in order to pass each other. A pedestrian also has strong affinity to other pedestrians moving towards the same goal. These positive and negative forces form lanes in a crowd of oppositely moving pedestrians. Similar lane formation techniques were found to be displayed in the army ants [Couzin and Franks, 2002].

2.4 Self Organisation in Social Insects

So far, the concept of self-organization and how self-organization promotes structure of pattern in biological systems have been explored. Now we turn our attention towards the collective behaviour of social insects i.e. how social insects like ants, bees and termites self-organise and participate in a decision making process. The discussion begins by classifying insects in terms of their social behaviour and is followed by a discussion of the collective behaviour of some of these insects. It might be noted that there is an enormous number of examples of self organising behaviour in social insects – however, only a few popular ones have been chosen to depict the collective behaviours they exhibit.

2.4.1 Social behaviour in insects

Edward O. Wilson, in 1971, proposed to classify insect societies into four broad categories based on the following social behaviours they exhibit:

1. **Cooperative brood care:** In this case, adults cooperate in caring for the young brood.
2. **Reproductive castes:** In this case, the sterile individuals work on behalf of the fecund individuals. Reproductive caste is the most basic form of division of labour in social insects. However, with the increase in the complexity of the colony, sophistication among non-reproductive workers increases [Anderson and McShea, 2001; Bourke, 1999].
3. **Overlap between generations:** That is parents and offspring live together during some period of life.

Based on these displays, Wilson classified insects into four distinct groups (Wilson, 1971):

Solitary: This group of insects do not show any of the three behaviours i.e. the degree of social behaviour in this category of insects is minimal.

Quasisocial: Insects in this category participate in cooperative brood caring but neither have any workers available to assist the fecund workers nor does any overlapping between generations exist.

Semisocial: Semisocial insects participate in caring for the brood and also have reproductive castes (i.e. a worker caste cares for the young of the reproductive castes).

Eusocial: Eusocial insects exhibit all the three social behaviours as outlined by E.O. Wilson (Wilson, 1971) and therefore are regarded as having the highest degree of social behaviour.

Degrees of Sociality	Cooperative Brood Care	Reproductive Castes	Overlap between generations
Solitary	N/A	N/A	N/A
Quasisocial	Y	N/A	N/A
Semisocial	Y	Y	N/A
Eusocial	Y	Y	Y

Table 2.1: Classification of Insect Societies

The four categories of insects have been outlined in Table 2.1. Following in this section are some of the examples of collective behaviours that eusocial insects display.

2.4.2 Foraging behaviour in Ants

Ants are eusocial insects of the family *formicidae* of the order *Hymenoptera*. They are extremely small in size and weigh very little.

One of the most fascinating behaviour found in many species of ants is the ability of mass recruitment of nest-mates for foraging (by the trail laying mechanism).

Although the foraging behaviour differs between species of ants, the mechanism of trail laying as a guide for the nestmates towards the food source is considered to be a unique trait. Ants do not possess any global knowledge of the environment – they only follow a set of simple behavioural rules to communicate with each other. Each ant behaves like an autonomous agent and moves randomly at their initial stage of their journey. When a food source is found, she picks up a piece of food from the food source and moves towards the nest. As they move towards the nest they keep on dropping chemicals called pheromones. The pheromone can diffuse in the environment (positive feedback) as well as evaporate (negative feedback). When other ants searching for food sense the pheromones, they sniff the chemicals of highest concentration and move up the pheromone gradient (stigmergic communication). As they reach the food source, they pick up a piece of food and go back to the nest. On their way back to the nest, they continue dropping pheromones as well thus reinforcing and hence establishing the pheromone trails between the food source and the nest (positive feedback). Such means of directing a mass amount of nest-mates towards a global objective (food) is often called the recruitment process.

The combination of multiple interactions along with positive and negative feedback mechanism establishes a pheromone trail between the food source and the nest enabling them to carry the food to the nest effectively. Figure 2.9 depicts this mechanism [Wilensky, 1998e].

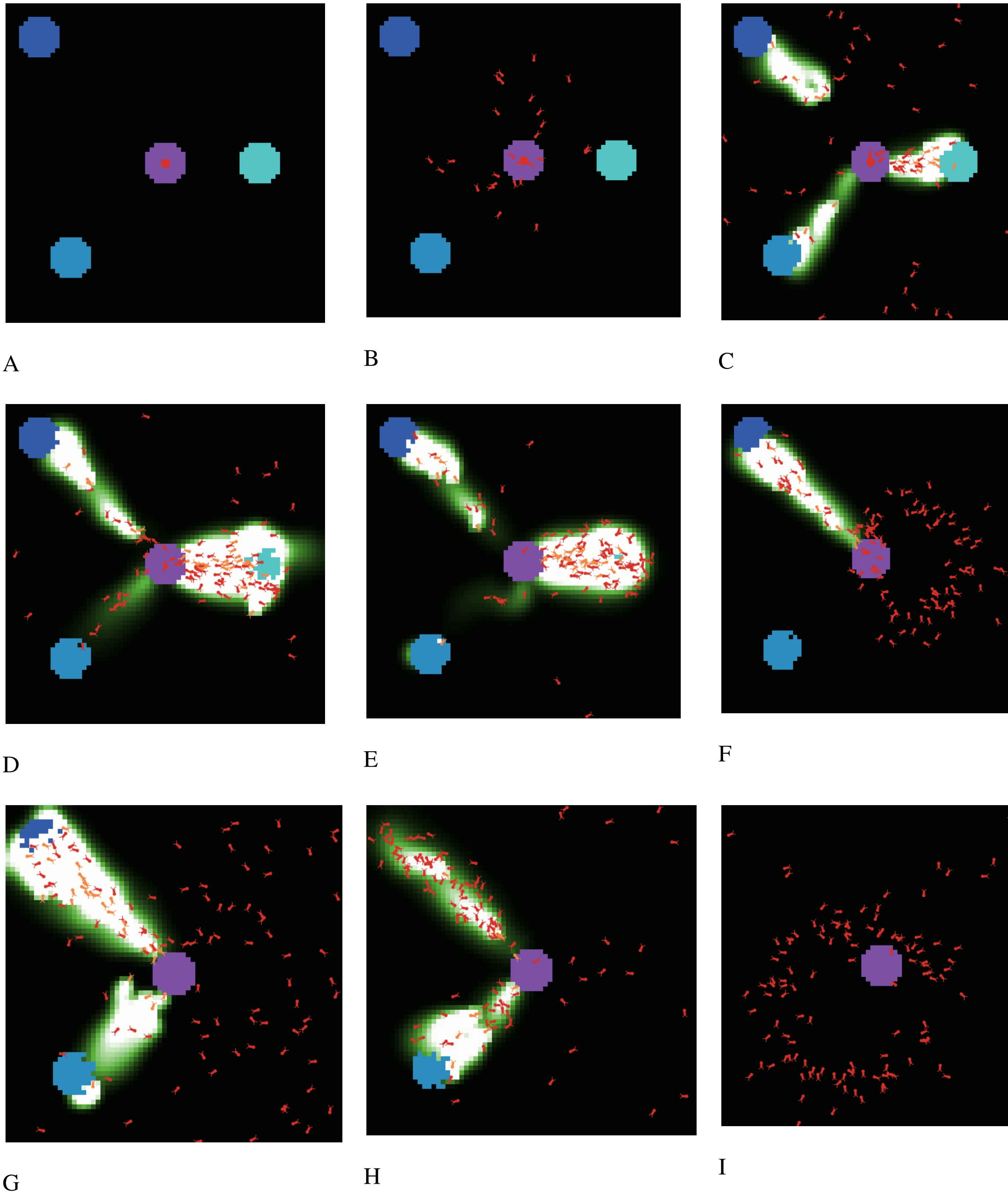


Fig 2.9: Ant foraging Mechanism

2.4.3 Nest Construction in ants

Lepthothorax albipennis (formerly known as *Leptothorax tuberointerruptus*) are one of the species of ants that exhibit impressive collective behaviour in constructing nests around them. These species dwell in flat cavities (In England, their nests are found on the Southern part on the rocky hillsides), in a colony comprising a single queen, about 500 workers and a similar number of brood [Camazine et al., 2001, Franks and Deneubourg, 1997], and use the roof and the floor of the cavities for their dwelling place [Franks and Deneubourg, 1997].

Building efficient nests is very important for *Leptothorax albipennis* as they are extremely vulnerable to intra-specific enemies and also to socially parasitic ants such as *Chalypoxenus* and *Epimyrma* [Buschinger, 1986, 1989]. They have also been found to be targeted by certain species of ants that attack *L. albipennis* with the intention of capturing the working pupae to raise up as useful slaves. Apart from biological enemies, these ants are also vulnerable to physical factors including flooding of water that can drown the inhabitants. Therefore, *L. albipennis* ants need to create an efficient defensive structure in order to survive. They have been found to use extremely simple rules to construct nests to surround the queen and the brood. The nests usually have single narrow entrance whose size is proportional to the size of the colony [Camazine et al., 2001]. This makes sure that the nest is neither too large to be subjected from external attack nor too small so that the members of the colony find difficulty residing in the nest.

The species divide the workers into two types: internal workers and external workers. External workers typically collect the building materials (e.g. stones) from outside while the internal workers regulate the nest size. The ants have been found to use the following behavioural rules to construct a nest around the queen and the brood members [Camazine et al., 2001]:

1. The external workers collect building materials (which can be as large as their entire head) and return with it to the nest.
2. The ants carrying the stones (building material) tend to release the stone after they make direct contact with a cluster of their internal worker nest-mates or other stones that have been previously deposited.
3. The external workers rarely pick up a stone that they have dropped inside the nest.
4. The internal workers pick up the stones and bulldoze them outwards if the stones are too close to the brood or the queen.

2.4.3.1 A mathematical model for the wall construction of *L. albipennis*

A mathematical model for the formation of the wall by *L. albipennis* has been described by Camazine and colleagues [Camazine et al., 2001]. In their model, an unladen ant can pick up a stone and become a laden ant. The probability of picking up a stone depends on the distance from the centre of the stone i.e. $P(r)$. The probability of a laden ant to drop a stone is given by $D(r)Q$ where $Q = 0$ when there is no free space to drop a stone at that node and $Q = 1$ when all the space in the area is free. The function for dropping a stone is maximal at $r = r_0$ whereas r_0 is the desired radius of the nest while minimum at the centre of the nest. The following equation describes such behaviour:

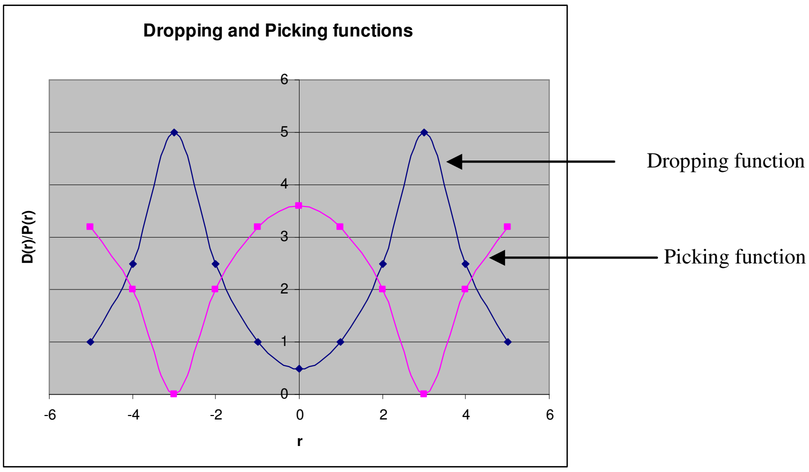
$$D(r)=\frac{D_M}{1+\tau(r-r_0)^2} \tag{2.4}$$

where D_M is the maximum value of the dropping function and τ represents the thickness of the wall.

The function for picking up a stone is minimum at $r = r_0$ while maximum at the centre of the nest i.e. if there is any stone close to the brood members and the queen, the internal workers pick them up. For $r > r_0$, the function for picking up a stone increases with the value of r. The following equation depicts this behaviour.

$$P(r) = P_M\left(1 - \frac{1}{1+\tau(r-r_o)^2}\right) \tag{2.5}$$

Figure 2.10 shows how the dropping function, $D(r)$, and the picking function, $P(r)$, varies with r, the distance from the centre of the nest.



Dropping function

Picking function

Fig 2.10: Dropping/picking function with respect to *r*

When D_M=5, $P_M = 4$, $r_0 = 3$ and $\tau = 1$

2.4.4 Honeybees

The choice of food source by a swarm of honeybees is another striking example of how insects participate in group decision making. The study of such astonishing and quick group decision making in honeybees was first investigated by an Austrian zoologist called Karl Von Frisch. In 1917, while studying the bees' sense of colour, Frisch discovered that they continue to visit a recently emptied food dish, as if they were monitoring the contents of the dish [Munz, 2005]. When he replenished the dish's supply, it was found that a lot of bees quickly appeared at the dish. He pursued this observation for a couple of years and in the early 1920's observed that after locating the food source, the bees return to the beehive and make one of the two kinds of dances – a round dance or a waggle dance. He mistakenly conjectured that the two kinds of dances represent the types of food the bees visited (round dance for the nectar and the waggle dance for the pollen) [Frisch, 1923]. However, in the early 1950's, he carried out an experiment with the same setup as in [Frisch, 1923] but this time he varied the distance between the food source and the hive. In this experiment it was found that when the food source is at a closer proximity to the beehive, the bees round dance but as the distance between the hive and the source is increased, the returning bees start waggle dancing [Frisch, 1953] thus the dancing indicates the distance between the source and the hive and not the type of food which he assumed previously.

He later also found that the honeybee uses the sun to indicate the direction of the food source. Furthermore the returning bee allows other bees in the hive to taste portions of the food collected thus giving them an idea of the quality of the food. For his discovery of honey bee dancing and recruitment process, Karl von Frisch was awarded the Nobel Prize in Physiology/Medicine in 1973 along with his colleagues Konrad Lorenz and Nikolaas Tinbergen.

The information conveyed by the forager bees (quality of the food, distance and direction to the food source) then influences the nectar-receiving bees to choose a particular food source and fly in that direction.

2.4.5 Mound building by termites

Termites are another excellent example of decentralized and self-organized systems available in nature. They belong to the group of social insects usually classified at the taxonomic rank of order *Isoptera*. They are famously known for their architectural artefacts in building mounds of as high as 9 metres (Britannica) in the savannas.

More amazingly, these termites act as autonomous agents, are assumed to follow simple behavioural rules and use only local interaction to build such fascinating structures.

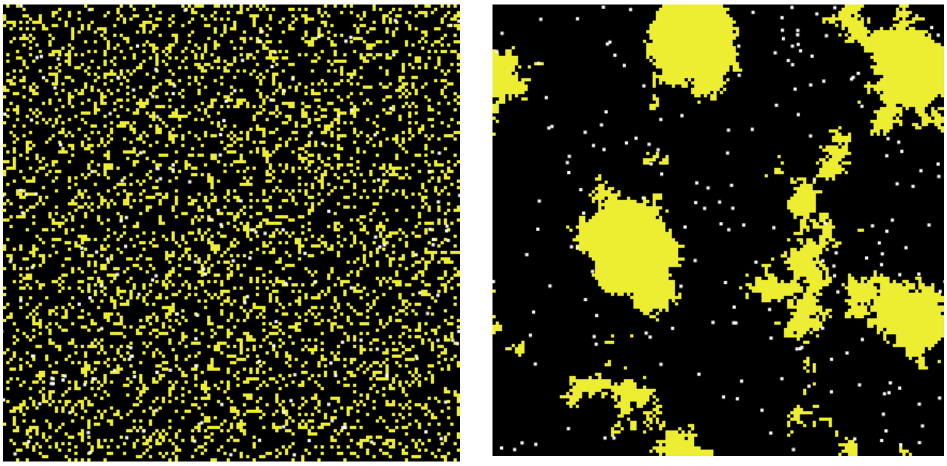
Resnick [Resnick, 1997] proposed a model for the mound building of termites. In his model, each agent follows extremely simple rules to collect wood chips from a randomly scattered environment and build a single pile from there. The rules of the model are as follows:

1. If a termite does not carry any wood chip, it continues moving randomly.

2. If it bumps into any wood chip, it picks the chip up and continues to wander randomly.

3. If it is already carrying a wood chip and bumps into another wood chip, it finds a nearest empty space and drops the wood chip off there.

Figure 2.11 shows the snapshots of the termites [Wilensky, 1998f] following the above local rules resulting in the creation of 2D termite mounds from randomly spread wood chips.



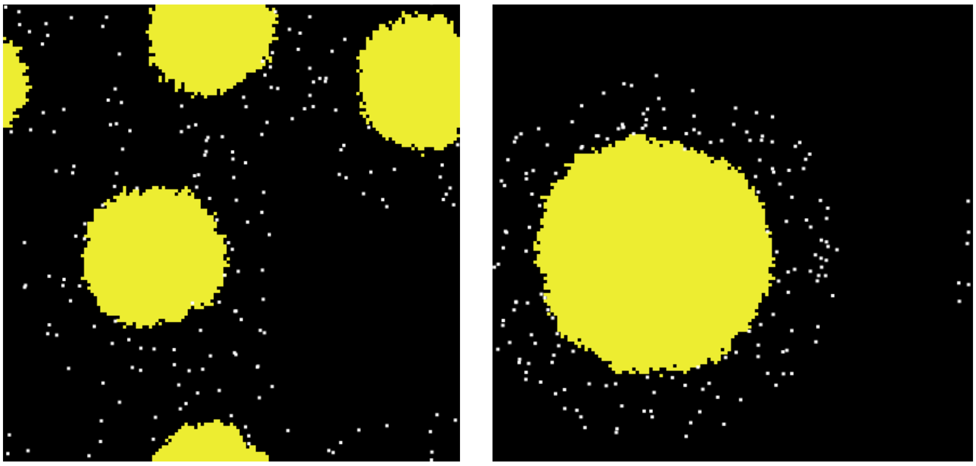


Fig 2.11: Snapshots of the building of termite mounds

It can be well observed that although the wood chips were initially randomly scattered, the termites manage to put the chips in a single pile using the simple behavioural rules.

2.5 Swarm Robotics

The term *swarm robotics* (SR) was first coined by Gerardo Beni and Jing Wang in 1989 while describing a class of cellular robots [see [Beni, 2005a] for a brief history]. SR is closely related to swarm intelligence (SI) [Beni and Wang, 1989] in the sense that they both were predominantly inspired by the studies of social insects [Sharkey, 2006]. Currently, this field of robotics has seen a great deal of popularity among researchers in the areas of robotics, artificial intelligence (AI) and psychology. As a discipline, it has attracted a significant number of research groups contributing to this field [Beni, 2005a].

The reasons for the popularity in this area can be seen as threefold:

1. The field offers the benefits of solving a number of applications which are otherwise difficult /hard to solve.
2. Because of its biological inspiration, the field is equally important to ethologists interested in the investigation of animal behaviour as to roboticists interested in developing multi-robot systems. Robots provide new platforms for the biologists to experimentally investigate their hypotheses.
3. Swarm systems have potential applications in various disciplines (for instance biology, engineering, computation etc...). Because of its interdisciplinary nature, there has been enormous interest between different disciplines in exchanging ideas to solve a common engineering problem.

SR can be formally defined as [Şahin, 2005]:

The study of how large number of relatively simple physically embodied agents can be designed such that a desired collective behaviour emerges from the local interactions among agents and between the agents and the environment.

The definition points out that in a swarm robotic system, a large number of robots (agents) are involved with each robot interacting with other neighbouring robots and the environment in its vicinity. No single robot has global knowledge of the environment and numerous interactions among the robots and between the robots and the environment set a collective pattern in their behaviour.

Swarm robotics draws its inspiration from biological swarms and hence is an area of interest to both biologists and engineers (especially roboticists). For the biologists, the modelling of biological behaviour in real and/or simulated robots often provides better understandings of the decision making process within the animal societies. Furthermore, it gives a unique platform to investigate the effect of different conditions on the decision making process. On the other hand, for the roboticists it provides good designing architectures to solve real world complex problems and also exploit some key benefits (e.g. building a decentralised system which is scalable, flexible as well as robust) of the natural swarms.

2.5.1 Features of Swarm-Robotics System

In this section, some of the features of swarm robotic systems, as highlighted by several researchers [Beni, 2005a; Şahin, 2005; Sharkey, 2007] are highlighted:

Autonomous Robots: The robots are not controlled by any central controller/ supervisor i.e. there exist no special leader robots. The robots are completely autonomous and follow some simple behavioural rules.

Large number of Robots: A large number of robots should ideally be involved in a swarm robotic system. Unfortunately, this means that the costs associated with a swarm robotic system are very high. However, as the costs of the hardware decreases, it is expected that the cost of the individual robots would also fall.

Simple Robots: The abilities of an individual robot are usually limited i.e. no single robot on its own would be able to carry out a task in an efficient manner. It should also be noted that the simplicity of the robot is in terms of its behaviour, local perception and communication. For instance, there has been some interest among researchers in using miniature helicopters to mimic the flocking motion of birds [Nardi and Holland, 2007]. Although a helicopter on its own is a complex system it could be viewed as simple in terms of its behaviour, local perception and communication. In such cases, flocks of helicopters would not violate the swarm intelligence paradigm.

Local interactions: No robot should have any prior knowledge of the environment. They can only communicate with each other and with the environment within a short radius compared to the size of the environment. This facilitates a lot of agents to operate with low bandwidth. The means of communication can be direct (e.g. simple signalling) and/or indirect (stigmergic).

Emergent Behaviour: By the process of multiple interaction, positive feedback and negative feedback, a collective behaviour is expected to emerge.

2.5.2 Approaches to swarm robotics research

Experiments involved in swarm robotics are currently approached in one of the following two ways:

- Simulation Approach
- Real-Robot Approach

2.5.2.1 Simulation Approach

This is probably the most common approach towards conducting swarm robotics experiments. Some of the reasons for the popularity of this approach are as follows:

Less Expensive: The only cost involved in this approach is perhaps the license of the simulators. On one end some simulators (e.g. Webots[1]) need to be bought while

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[1] http://www.cyberbotics.com/

on the other hand simulators such as Player/Stage[2], YAKS[3] and teambots are available without any license fee.

Less Time Cost: The time cost in simulating is usually much less than building robots. Furthermore, the cost increases with the number of robots involved in the experiment.

Performance: Simulators, such as Webots, are sufficiently faithful for the controllers to be transferred to real robots without changes and for the robots' behaviour to be qualitatively similar to those of the real robots. However the same performance cannot always be guaranteed as it highly depends on the environment of the real world including the level of noise and interference.

2.5.2.2 Real Robot Approach

In this approach, real robots are used instead of only simulations (see for instance [Krieger and Billeter, 2000]). The number of robots used in this approach, however, is usually limited since it increases the cost and at the same time degrades the performance due to overcrowding effects. Compared to the behaviour of real ants, the scalability in real robots is greatly limited due to (1) the bigger size of robots compared to the environment and (2) greater interference between robots. Real ants, on the other hand, have shown impressive capabilities of coping with high density of individuals (e.g. a density of up to 2254 foraging ants per m^2 has been recorded in yellow crazy ants [Abbott, 2005] and a massive swarm raid by 200,000 workers raiding over a width of 15 m or more and sweeping over 1500 m^2 per day has been

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[2] http://playerstage.sourceforge.net/

[3] http://www.his.se/templates/vanligwebbsida2.aspx?id=18551

observed in army ants *Eciton burchelli* [Camazine et al., 2001]). However, the use of real robots shows realistic capabilities of the swarm within the context of robotics. Also, with progression of technology, as the size of the robot shrinks, we expect to greatly increase the ratio of the size of the environment to that of the robot. This would subsequently make it possible to accommodate more robots in a given environment with little interference.

2.5.3 Collective and cooperative behaviour in swarms of robots

In this section, some examples of the use of real robots to make collective and cooperative behaviour are presented. Collective behaviours include the cases where the robots need to work together as a group in order to carry out some tasks whereas cooperative behaviours include the cases where two or more robots need to cooperate with each other in order to do a particular task.

2.5.3.1 Self Organised task allocation / Collective foraging

Self organized task allocation is currently a very active research area within swarm robotics. The problem of task allocation can be described as follows: If there are n-robots and m-tasks present in the environment, how would the m-tasks be distributed among the n-robots in order to carry out the operations effectively. Further details of self organised task allocation can be found in chapter 3.

In 2000, Krieger and Billeter devised a means of self organized task allocation to control when a robot should come out of the nest and forage [Krieger and Billeter, 2000; Krieger et al., 2000]. Figure 2.12 shows the experimental set up.

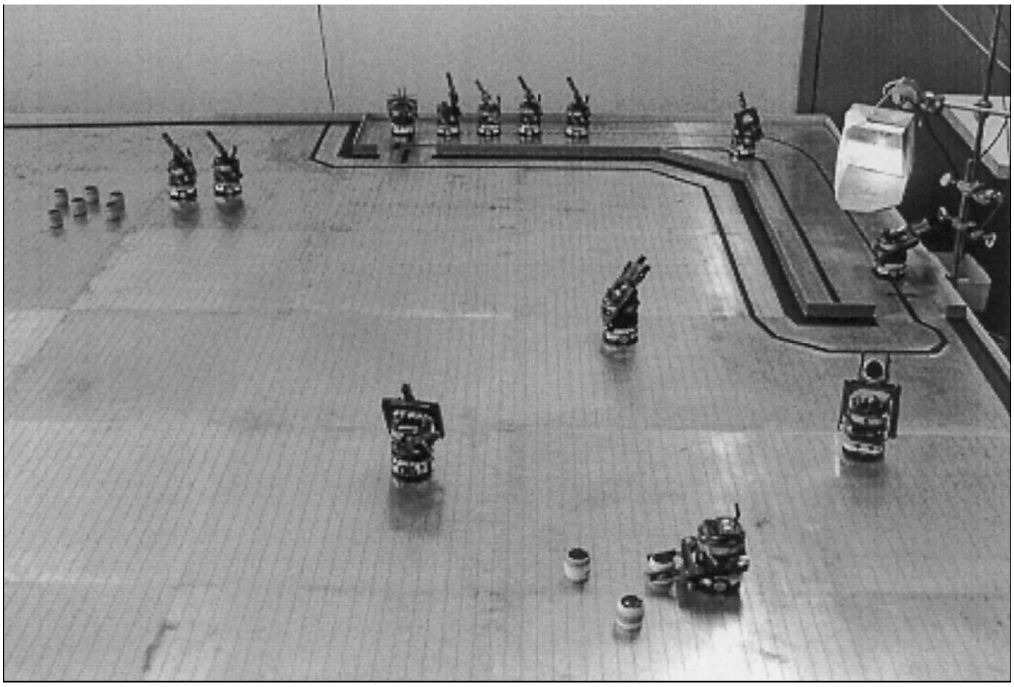


Fig 2.12: Experimental Setup [Krieger and Billeter, 2000]. Reprinted with permission.

In this experiment, the robots equipped with gripper turrets reside in the nest. They come out of the nest only when the nest energy level (broadcasted inside the nest) is low enough that it stimulates the robots to go for foraging. Figure 2.13 shows the basic mission cycle of a particular robot:

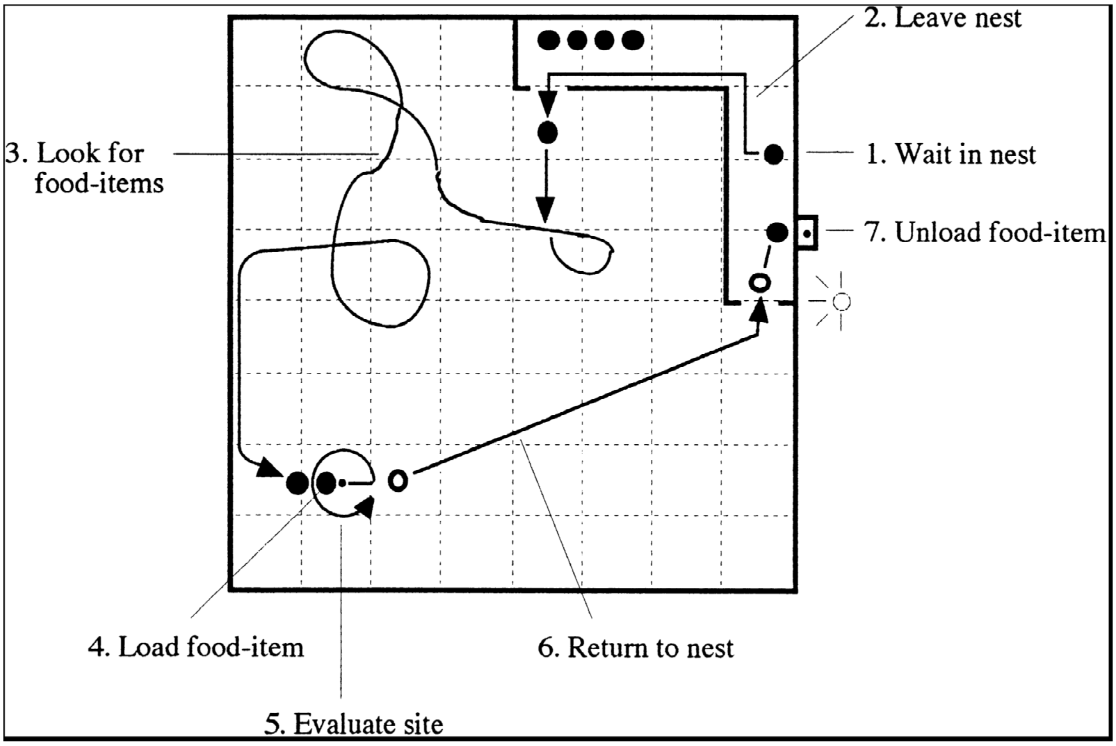


Fig 2.13: Basic Mission Cycle of a robot [Krieger and Billeter, 2000]. Reprinted with permission.

The robots initially reside in the nest and keep listening to the control station's radio message that periodically updates the nest-energy level. Each robot has some fixed threshold (randomised) for foraging. When the nest-energy level falls below the threshold of the robot, the robot is stimulated to leave the nest and go to the exit lane, to come out of the nest and start random search for the food. Once it finds the food, it loads the food, goes to the nest entrance and then unloads the food in a bucket. Krieger and Billeter carried out experiments with up to 12 mobile robots in environment where (1) food is distributed evenly and robots do not participate in recruiting other robots for foraging, (2) food is clustered around the environment and robots do not recruit other robots for foraging or (3) food is clustered and robots recruit other robots for foraging. In all the three cases, they observed that the relative colony energy (i.e. mean energy per robot) to be low at small and large number of robots. The relative colony energy is high with intermediary number of robots.

Furthermore, they also found that recruitment of other robots improve the foraging efficiency significantly.

In other studies, the robots change their tasks dynamically from resting stage to foraging stage and vice versa by updating their thresholds which might depend on a number of environmental factors like the overcrowding of robots in the search space and the successful searching of food item [for further details, refer to Labella, 2007; Liu, 2008; Liu et al., 2007a; Liu et al., 2007b]. One of the problems with Krieger and Billeter's approach is that the system is not fully decentralised but rather depends on the centralised control station's radio message which fits less well with the swarm intelligence paradigm in this respect.

2.5.3.2 Nest Construction

In this case study, a discussion is presented on the creation of sites using swarms of robots. NASA has predicted that teams of multiple robots would be required in distant planets such as Mars for tasks such as site preparation which would be essential for later mission objectives like constructing solar arrays [Parker et al., 2003]. This would require swarms of robots to create the equivalent of a nest site out of the gravels.

Construction in teams of multiple robots can be viewed in either of the following ways:

1. **Accumulation of materials:** In this approach, individual robots wander about the environment, collect building materials, carry it to the construction site and add it in

an orderly fashion. Such approaches are inspired by the behaviour of insects like that of wasps [Theraulaz and Bonabeau, 1995].

2. **Removal of materials:** In this alternative strategy, robots would be required to remove the materials from the nest preparation site. Such approaches are often observed in ants such as in the ant species *Leptothorax albipennis* described previously.

Parker and his colleagues [Parker et al., 2003] embrace the second strategy for nest site preparation using robots. The robots need only two sensors to carry out this task: one would be required to measure the force exerted on the robots by the rocks (e.g. using a bump sensor) that it is ploughing and the other would be required to detect collisions with other robots in the nest. The controller of the robot, which they call the blind bulldozer controller, can be shown as a three state finite state machine (Fig. 2.14).

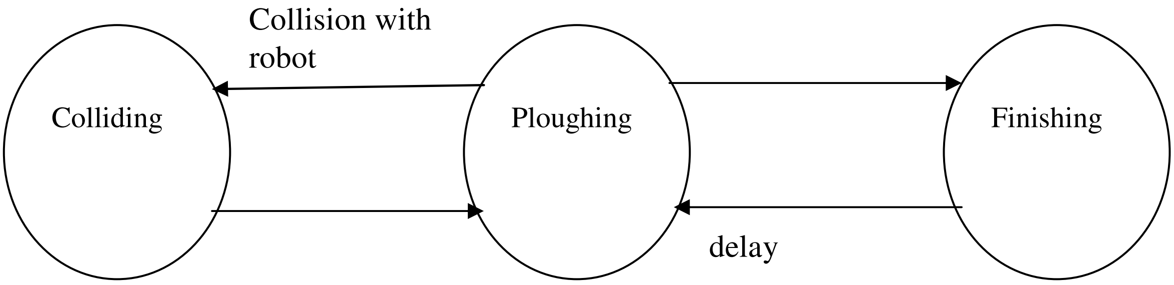


Fig 2.14: Finite state machine for the blind bulldozer controller [Parker et al., 2003].

Robots are initially in the *ploughing* state. In this state, robots move in a straight line and simply plough up any material (gravel) on its way. If the force of the gravel on the robot reaches a threshold, the robot switches to the *finishing* state. When the robot is in the finishing state, it simply turns through a random amount and reverts to the *ploughing* state. Upon detecting collisions with other robots, the robot switches to the *collision* state. Just like the *finishing* state, robots in the *collision* state, also turn through a random angle and revert to the *ploughing* state. Using such simple rules, robots are capable of creating a simple nest site. Experiments with real and simulated robots reveal that nest size grows quickly at the initial stage followed by slow growth of the nest size (since over time, thickness of the wall of the nest starts increasing resulting slow growth rate at the latter stage) and also the initial shape of the nest is preserved over time since every time the robot ploughs, it pushes gravel only by a small amount.

2.5.3.3 Stick Pulling Experiment

The stick pulling experiment [Ijspeert et al., 2001] was carried out in a circular arena delimited by a white wall. In this experiment, groups of 2 to 6 khepera robots equipped with gripper turrets are used to pull sticks out of the ground. Because of the length of the stick, it is not possible for one single robot to pull out a stick completely off the ground (Fig. 2.16). Instead, two robots were needed to work together to complete the task. The experiment is carried out both in real khepera robots and Webots, a 3D simulator.

A. Algorithm

Initially the robots start moving randomly in search of the stick. When a robot finds a stick and there is no other robot holding the stick, it grips the stick, pulls out half of the stick from the ground, starts a timer and waits for the second robot to come. If no other robot comes to help within some defined time period, it releases the grip, moves randomly and starts looking for the stick. If a second robot comes within the defined time period, it makes a second grip, pulls out the stick completely and makes a success dance to indicate successful task completion (see figures 2.15 and 2.16).

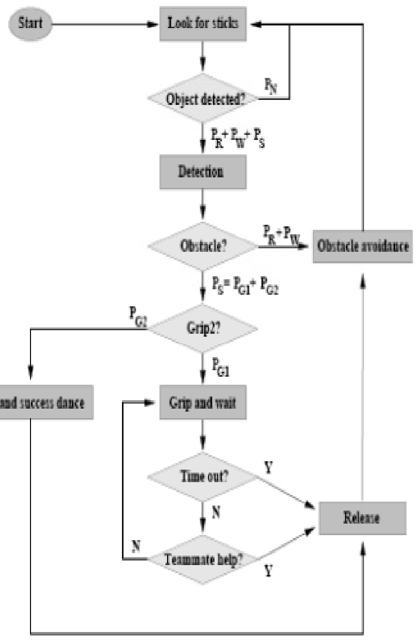
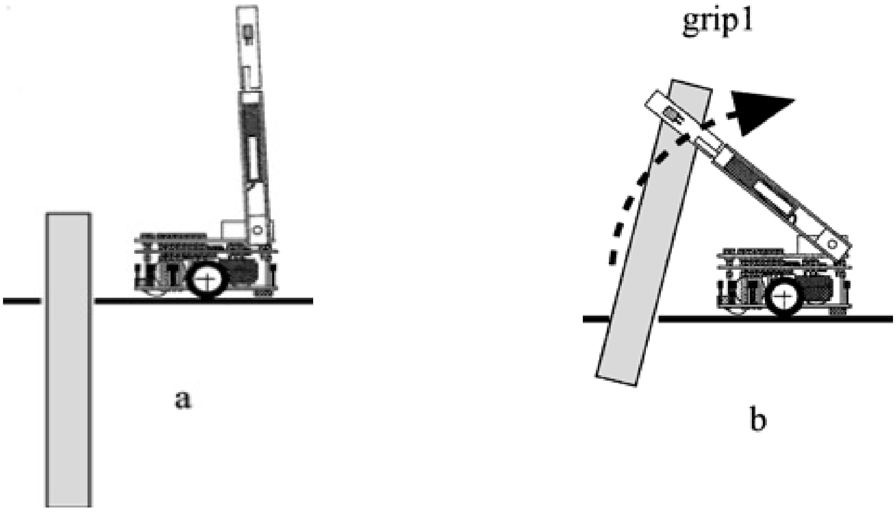


Fig. 2.15: Flowchart of the algorithm. Reprinted with permission.



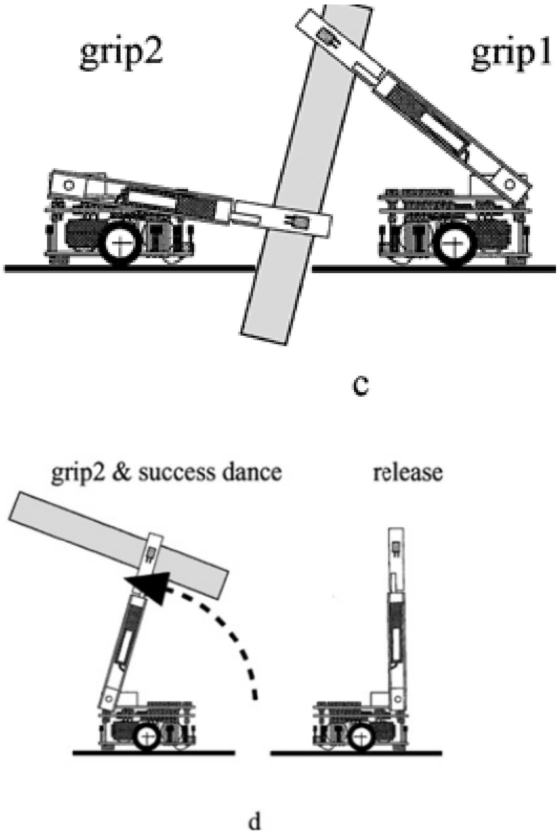


Fig. 2.16: Schematic diagram of the stick pulling experiment. Reprinted with permission.

B. Communication

Initially very little or almost no communication between the robots was used. It was however appreciated that a simple signalling scheme would improve the performance. To investigate this, a simple signalling scheme has been implemented as follows:

1. When the first robot grips the stick, it sends a continuous signal in a 60^0 cone through its frontal emitter

2. Robots which are in this arena and are looking for sticks respond to this signal by performing phototaxis towards it until they detect an object.

It was found that a simple signalling scheme improves the rate of collaboration between the robots.

2.5.3.4 Cooperative Box Pushing

Kube and Bonabeau [Kube and Bonabeau, 2000] devised a simple mechanism to push a brightly lit box from one place to another. The box is too heavy for one robot to be able to push it. However, collectively the robots would be able to push the box. Simple Braitenberg mechanisms [Braitenberg, 1986] were used to avoid robots from colliding with each other and at the same time to keep them moving towards the brightly lit box to push it. The result demonstrated a simple cooperation between the robots without the necessity for any direct communication. The work of Kube and Bonabeau [Kube and Bonabeau, 2000] and also Kube and Zhang [Kube and Zhang, 1994] employed simple stagnation recovery strategies that many ant species use to effectively transport box. Sometimes during group transportation of an object, the object's motion fail to progress any further owe to a number of factors including (1) that the force applied to the object has cancelled each other out, (2) the group has encountered an obstacle or (3) due to significant heterogeneity on the substrate [Bonabeau et al., 1999]. Many ant species are known to exhibit realigning and repositioning behaviours [Sudd, 1965, 1960] upon encountering such deadlock situation. Inspired by this behaviour that many ant species display, Kube and Bonabeau employed four strategies while transporting the box: (1) transportation without stagnation recovery, (2) employing realignment of the pushing angle, (3) employing repositioning the pushing force and (4) employing both realignment of the pushing angle and repositioning the pushing force. Kube and Bonabeau found that the reliability (success percentage) and the efficiency (measured in terms of the time required to transport the item) of transportation of the box depends on the number of robots involved. They found that the controller reliability improved with the incorporation of stagnation recovery strategies. For controller reliability, strategy (2) works out to be the best for small group size while strategy (3) works out to be the best for large group size. Strategies 1 and 4 were found to be the fastest for small and large group size respectively.

2.5.3.5 Animal-Robots Collective Intelligence

Collective Intelligence (CI) is at the core of the swarm systems. It emerges from the collaboration of many individuals. For instance, in ants, it would be very difficult for a single individual to forage for the entire colony. But through collaborations (reinforcement of pheromone trails), ants of many species are able to establish a path between the nest and the food source enabling other foragers to find food quickly and more efficiently.

Collaborations are also noticeable in robots (e.g. in the pulling of stick from a hole [Ijspeert et al., 2001], in the cooperative transport of objects [Kube and Bonabeau, 2000] and in collaborative foraging (for instance [Krieger and Billeter, 2000; Liu et al., 2007a])).

Recently, researchers and scientists have investigated whether it is possible for a collective intelligence to emerge between completely two distinct social groups: for instance between animals and robots i.e. whether it would be possible for robots to interact with animals and also vice versa. This would certainly bring a number of benefits (mentioned below) in the field of ethology and artificial intelligence [Schutter et al., 2001]:

1. Experimental Ethology: If robots and animals can interact with each other, then it would provide an elegant way for ethologists to investigate how animal societies function.

2. Pest Management: Animal pests like rats, locusts, starlings etc. are highly social species. A controlled interaction with these social groups would make it possible to control the spatial distributions of these animals and thus to manage them more efficiently.

3. Managing Endangered and Invasive Species: A greater degree of management means that species can be better controlled in terms of their behaviour and spatial distributions. Endangered species are one of the greatest threats to biological diversity. Most of these endangered species are highly social and therefore they might be also managed more efficiently through controlled interactions with the robots.

4. Development of robots: Continuous interaction with animals would contribute in developing behaviour algorithms in robots which might help them to be better by the course of time.

Although we see a number of benefits in the areas of ethology and artificial intelligence, the key questions remain unanswered. Is such integration of different social groups possible? Can animals really interact with robots?

Niko Tinbergen, in the early 1950's, was the first to show that animals and machines can interact with each other [Tinbergen, 1951]. In the 1950's, Tinbergen observed a very strange behaviour in one of his aquarium fishes; a male stickleback. Every day at the same hour, the stickleback exhibited a specified sequence of territorial displays; just as if his territory was challenged by some other male stickleback. This behaviour puzzled Tinbergen for some time. Later he realised that the other male stickleback was not a stickleback but a post truck which passes every day at the same hour in front of the lab window. But how was it that the stickleback confused a post truck with a male stickleback? Tinbergen proposed that during the courtship period, the male stickleback displays its red belly to differentiate itself from the female ones. It happens that the post truck was red in colour which was the source of the confusion.

In 2007, Halloy et al. [Halloy et al., 2007; also see Garnier et al., 2005] showed that groups of robots can interact with groups of cockroaches and can also participate in collective decision making process.

The experimental setup consists of a circular arena endowed with two shelters. Each of the shelters is large enough to host the entire group. When the shelters are identical, it has been found that all the cockroaches tend to rest under one shelter rather than splitting into two groups and resting in both shelters. When one of the shelters is made darker relative to the other, it has been observed that cockroaches prefer to rest under the darker shelter.

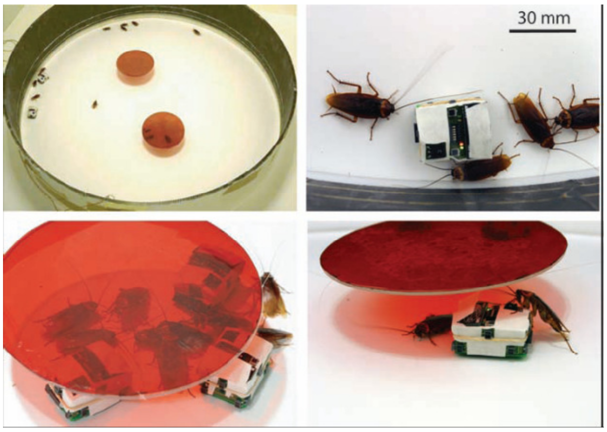


Fig 2.17: The Experimental Setup [Halloy et al., 2007]. Reprinted with permission.

It was then decided to use robots to interact with the cockroaches and investigate whether they could take part in the collective decision making process. The acceptance of robots within a cockroach society depends on the ability of robots to bear the correct chemical signal and to behave appropriately. Chemical analyses and behavioural tests were then performed to identify the main molecules constituting the odour that carries the cockroach identity. This odour was then selected from male cockroaches and was applied to robots in such a way that each robot carries equal concentration of odour as that on one individual cockroach. Initially the robots were programmed to prefer darker shelter compared to lighter one and behave similarly to the cockroaches.

Similar behaviour in the robots and the cockroaches allowed the robots to be accepted within the cockroach society. As robots become members of their groups, it is expected that they could possibly take part in and influence dynamically the collective decision making process. To verify this, the robots are programmed to prefer the lighter shelter as opposed to that of the cockroaches. It was found that the shelter previously less preferred by cockroaches was selected by mixed groups in 61% of the trials versus only 27% of the trials done without robots confirming that robots could actually participate in collective decision making process.

Other projects that involve interaction of robots with animals include the Robot Sheepdog Project (RSP) in which robots are used to control the spatial distribution of ducks [Vaughan et al., 2000].

2.6 Summary and Conclusion

This chapter provides the first part of the literature review. Although the thesis is focussed on task allocation behaviour, a general understanding of swarm intelligence and the mechanism through which agents self organise is deemed necessary before looking and critically analysing the task allocation mechanisms. This chapter serves that purpose. This chapter begins with the concept of swarm intelligence followed by the mechanisms through which simple agents can create such collective intelligent systems. A number of examples from different fields have been selected to analyse the underlying mechanism of the collective behaviour. Following this, attention was then turned towards social insects since they (more appropriately "ants") have been our prime source of inspiration. Degrees of sociality in insect societies have been discussed in terms of the social behaviours the insects exhibit. A number of examples regarding the self organising behaviour of social insects are then described and analysed. Finally some examples of self organising behaviour in the context of swarm robotics have been discussed. In totality this chapter looks into the concept and examples of self organisation in biology and in robotics.

Chapter 3

Task Allocation in Multi-Agent Systems

The previous chapter demonstrated many examples of how agents (both natural and artificial agents) can use simple rules and limited perceptions and capabilities to interact with each other numerously resulting in the creation of a self-organised complex system. One of the interesting features that are noticeable in many self organised systems (especially in eusocial insects) is that there exist many systems where agents can adapt to the environmental changes leading to an effective division of labour without the need of any centralised controller. This capability is extremely interesting within the biological field (e.g. in understanding the underlying mechanisms of animal behaviour and evolution) and has many applications within the engineering field. This chapter, therefore, is dedicated in understanding the concept of division of labour within the realms of multi-agent systems.

Division of labour (DOL) (or task allocation), within multi agent systems and especially within social insects, is often referred to as one of the most conspicuous features of the organisation and the success of a colony. Two main types of task allocation techniques are prominent in the literature [Bonabeau et al., 1999]: (1) self-organised task allocation (prevalent in social insects) and the (2) intentional task allocation approaches. Both the approaches have their own merits and drawbacks in terms of robustness, efficiency and scalability. Self organised task allocation approaches are widely exhibited in eusocial insects where agents via multiple interactions collectively decide how to effectively divide the labour. On the other hand, intentional task allocation approaches are mainly inspired by the auctioning concepts in market economy. This chapter describes the two task allocation approaches and looks into various recent work carried out by the researchers in these fields.

The rest of the chapter is organised as follows: Self organised task allocation approaches are described first. Ant colonies are well known for demonstrating self organised task allocation behaviour and thus have been used as examples to describe this approach. After describing the division of labour in ants, several models pertaining to their behaviour are discussed. Following this, task partitioning in social insects (a phenomenon related to division of labour in social insects) is analysed and described. Allocations of tasks in social insects (especially ants) have been a strong inspiration in the field of robotics. Many models have been developed to dynamically allocate tasks within the realms of robotics. Detailed discussions of some of the key models in robotics are then presented. Following this, intentional task allocation approaches are discussed and analysed. Comparisons between the two approaches are then presented and finally the chapter is concluded with a brief summary.

3.1 Division of labour in Social insects

Ants are classified as eusocial insects belonging to the family of *Formicidae* of the order *Hymenoptera*. They are perhaps the most successful living beings that have made their mark on the earth. They are extremely small in size and weigh very little yet live at large and weigh (total weight) as much as all human beings on the earth [Hölldobler and Wilson, 1994]. Ants are extremely diverse in terms of their colony size, organization of tasks and also cooperation among the nest mates for the benefit of the colony. There are currently over 12,000 known species of ants, each maintaining highly organized colonies and nests with colony size ranging from a few individuals to 20,000,000 individuals [Beckers et al., 1989]. Why are these tiny insects so successful at maintaining colonies of different sizes? What techniques have they embraced that enable them to be socially so successful? Various researchers have argued that of all the behaviour of eusocial insects, the feature of dividing labour is significantly responsible for the massive organisational success [Bourke and Franks, 1995; Gordon, 1999; Franks, 2003; Hölldobler and Wilson, 1990; Hölldobler and Wilson, 2008; Momen and Sharkey, 2009a,b; Robinson et al., 2009; Oster and Wilson, 1978] they achieve.

3.1.1 Sociality in Insect Societies

Eusocial insects, of all insects, show the highest degree of social behaviour and therefore stand out as some of the best examples of collectively intelligent systems. They are well known for their behaviour of cooperating with each other to accomplish tasks that are beyond the capabilities of a single individual (e.g. as reviewed in Chapter 2, termites building large and complex mounds, bees performing waggle dances to recruit hive mates and army ants undertaking massive raids to collect prey). Of the three social behaviours that eusocial insects display (see Chapter 2), division of labour is the most conspicuous feature responsible for the organization and the success of the colony. It is also the underlying framework for the incredible ecological success they accrue [Bourke and Franks, 1995; Hölldobler and Wilson, 1990; Hölldobler and Wilson, 1994; Hölldobler and Wilson, 2008; Wilson, 1971]. Social insects like ants display efficient ways of dividing their task and improving the task efficiency for the overall benefit of the colony they belong to. Sophistication of allocating tasks (i.e. evolution of specialised castes), in ants, is found to increase as a function of the size of the colony [Anderson and McShea, 2001; Jeanson et al., 2007]. Ant colonies are sometimes referred to as “factories within fortresses” [Bourke and Franks, 1995; Hölldobler and Wilson, 1990] to capture the notion of the existence of the specialised castes.

3.1.2 Division of labour in ants

Ants display the feature of dividing tasks within the colony members and carrying them out in parallel. This phenomenon is what is termed as *division of labour*. Although the term was first coined by the economist Adam Smith in 1776 in his influential book “Wealth of Nations” within the context of specialised skills and industrial productivity [Smith, 1776], ants seem to have been using more sophisticated and yet simple mechanisms to organise, specialise and carry out tasks for over millions of years. The basic form of division of labour exhibited by ants is the reproductive division of labour where a few individuals (often limited to only one individual – the queen) are responsible for reproductive tasks while the remaining are classed as workers. Beyond this basic form of division of labour, there exists further division of labours among workers. Bonabeau and his colleagues, in 1999 [Bonabeau et al., 1999], proposed that the division of labour among worker ants can take three (not necessary mutually exclusive) basic forms:

1) Worker Polymorphism (also called physical castes),

2) Age Polyethism, and

3) Individual Variability

3.1.2.1 Worker Polymorphism (Physical Castes)

Physical castes evolve due to the existence of anatomically distinct ants within the same colony. They are also found to be biased towards some sets of tasks depending on their morphology. For instance queens (♀) in a colony are usually the largest in size having a generalized hymenopterous thorax and deciduous wings [Hölldobler and Wilson, 1990] and work principally as the only reproductive female of the colony. The other females, called “workers”, tend to adhere to the tasks depending on their sizes. In most of the ant species, the workers are categorised as either majors or minors - however there are some species where an intermediary caste is also found (often called media workers). Major workers are characterised by disproportionately large heads and often have sharp mandibles. They tend to specialise in carrying out tasks that require physical strengths like guarding nests against foreign intruders (in *Pheidole* ants [Hölldobler and Wilson, 1990; Wilson, 1984] for instance) and transporting items back to the nest. Minor workers, on the contrary, are characterised by being smaller in size and are responsible for carrying out tasks (e.g. nest cleaning, foraging, brood caring etc…) that are not very labour intensive.

3.1.2.2 Age Polyethism

Age polyethism embraces the ideology that the task carried out by ants is not fixed over its lifetime but a function of their age i.e. the workers in a colony tend to change the tasks they carry out depending on their age. Many species of ants exhibit age polyethism including *Pogonomyrmex barbatus*, *Cataglyphis bicolor* and *Oecophylla smaragdina* [Bourke and Franks, 1995; Gordon and Hölldobler, 1987; Ingram et al., 2005]. The orders in which these ants switch tasks tend to follow some centrifugal direction away from the nest. For instance, the callow workers (newly emerged workers) tend to work in close proximity to the queen and the brood and work as brood carers, slightly older workers tend to work closer to the nest entrance and prefer to work as nest cleaners whereas the oldest workers work outside the nest and act as foragers.

3.1.2.3 Individual Variability

Even within age or morphological castes, individual differences towards task preferences exist. The difference in individuals in the preference for task selection is a result of many factors including that of past experience [Deneubourg et al., 1987; Plowright and Plowright, 1988; Theraulaz et al., 1998], variation in the genes [Oldroyd and Fewell, 2007; Myerscough and Oldroyd, 2004; Page and Robinson, 1991; Robinson and Page, 1989] and physiology [Robinson et al., 2009]. Grouping the individuals with respect to their task preferences generate what are called behavioural castes.

3.2 Models of division of labour in ants

The last three decades have witnessed the development of a number of models trying to establish the mechanisms of the selection of tasks in social insects such as ants. These models differ from each other in many aspects including worker-worker interactions, genetic basis of task selection, motivational state of the worker, spatial arrangement of the workers in the nest and also learning parameters [Beshers and Fewell, 2001]. Beshers and Fewell, in 2001, grouped the factors that play integral roles in choosing the task to be carried out under two major umbrellas - internal factors and external factors based on whether they are generated as a result of the internal state of the individual or via interactions with the colony environment. Internal factors include the genetic, hormonal and neural factors and also the effect of experience whereas the external factors include the worker-worker interactions and the stimuli that affect task performance. Both these internal and external factors affect the performance of task and effective division of labour.

The remaining part of this section describes some of the popular models of division of labour in social insects (typically that of ants).

3.2.1 Fixed response threshold model

The model assumes that each agent has some fixed thresholds for every task. If the stimulus of a particular task exceeds the corresponding threshold of the agent, the agent reacts by selecting the task and performing it. Execution of the task lowers the stimulus for that particular task. Thus, if an agent *A* has lower threshold for a particular task *T* than another agent *B*, then *A* not only responds sooner to the task *T* but also reduces the stimulus of the task – thus it can so happen that the stimulus of task *T* never exceeds the threshold of agent *B* and therefore *B* never performs that task. Thus, small variations of response threshold can result in the difference in the frequency of task performance and give rise to the behavioural castes. Page, in 1997, discusses one such behaviour seen in honeybees [Page, 1997] where the stimulus of the task results in task performance. In honeybees, when the nestmates die within the nest, the corpses result in increasing the stimulus of the task which attracts “undertaker” honeybees to drag the corpses of their nestmates, fly away with them and leave them at some distance from the nest. Similarly, the removal of the corpses causes the stimulus of the task to fall and hence attracting fewer honeybees to undertake this behaviour. Eventually when there are no more corpses left, the number of honeybees attracted to carry out this task falls to zero. Seeley [Seeley, 1992] showed that if a honey bee takes too long to unload her nectar to a storer bee, then she gives up foraging and instead starts tremble dancing to recruit storer bees. On the other hand, if her search time is within an acceptable bound, then she recruits foragers through waggle dancing. Similar examples can be found in the ant species *Novomessor albisetosus and Novomessor cockerelli* while transporting large prey items [Hölldobler et al., 1978]. When a scout discovers a large prey item, she releases a poison gland secretion to attract nestmates in close proximity. However, if this does not attract enough nestmates to carry the prey item, the scout abandons short range recruitment and instead starts travelling back to the nest dropping pheromones on its way in order to recruit more ants. Other examples include the rise and fall of the number of brood carers with the associated stimulus of the larval demand [Bonabeau et al., 1999]. Theraulaz and colleagues, in 2002, shows how a fixed threshold based mechanism can be used to explain the behaviour of ponerine ants [Theraulaz et al., 2002]. Neotropical ponerine ants, *Ectatomma ruidum*, hunt by stinging fruitflies and transporting them back to the nest. Two types of behaviours are associated with the foraging mechanism of this ant specie: (1) stinging [Lachaud, 1990; Schatz et al., 1997] the fruitflies and (2) transportation of the dead flies. The live prey increases the stimulus for the stinging behaviour to be carried out attracting the ponerine ants to attack the prey. Once the prey becomes motionless and falls to the ground, the dead corpses now increase the stimulus of the transportation behaviour resulting increasing number of transporters to come and pick them up.

Bonabeau and his colleagues [Bonabeau et al., 1996; Bonabeau et al., 1998; also see Bonabeau et al., 1999] developed an analytical model of the response threshold mechanisms based on assumptions made by Page and Mitchell [Page and Mitchell, 1991]. In their model, every individual *i* has a response threshold θ_{ij} for a particular task *j*. The probability, $T_{\theta_{ij}}$,of carrying out task *j* depends on the stimulus of the task as well as the response threshold of the individual for carrying out the task and is given by

$$T_{\theta_{ij}} = \frac{s_j^{\,n}}{s_j^{\,n} + \theta_{ij}^{\,n}} \tag{3.1}$$

where n > 1 and determines the steepness of the curve. From equation (3.1), if the stimulus $s_j >> \theta_{ij}$, then the probability approaches to 1. Similarly if $s_j << \theta_{ij}$, the probability approaches to 0. Another suitable response threshold function [Bonabeau et al., 1999] is given by:

$$T_{\theta_{ij}} = 1 - e^{-s_j/\theta_{ij}} \tag{3.2}$$

Figure 3.1 shows the curves for the threshold function with n = 2 for equation (3.1) and $\theta_{ij} = 7$ for both equation (3.1) and (3.2).

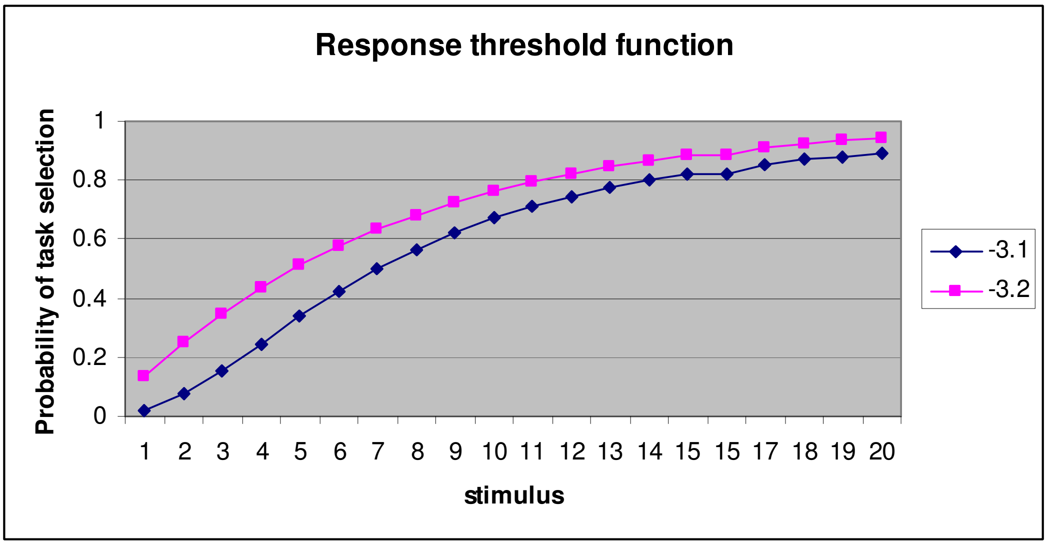


Fig. 3.1: Variation of the response threshold function with respect to the stimulus

Figure 3.2 shows how the response threshold function varies with different values of the threshold for equation 3.1.

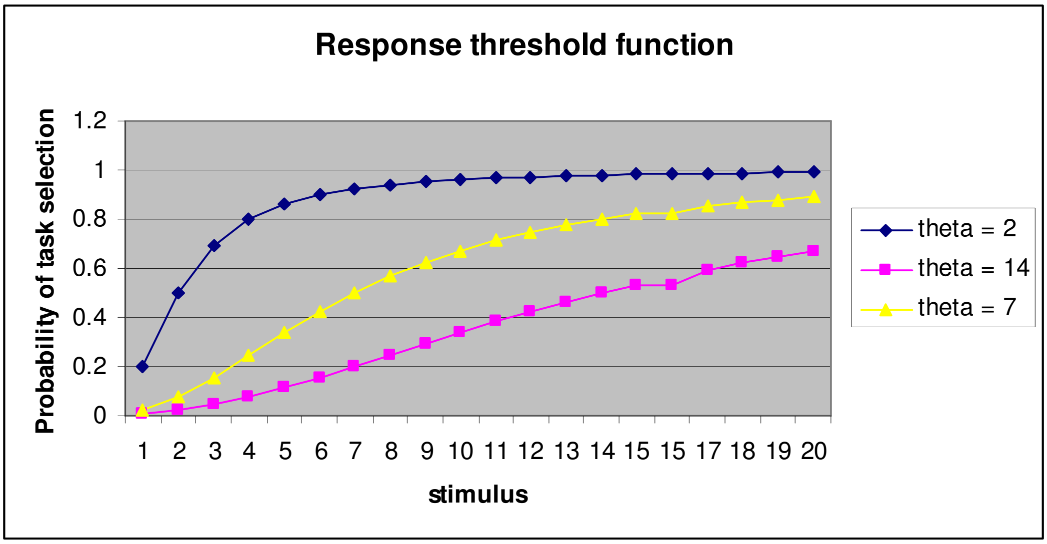


Fig. 3.2: Response threshold function as a function of stimulus and threshold

Arcaute and colleagues [Arcaute et al., 2009] described the division of labour in ant colonies in terms of attractive fields created by tasks. In their model, they used the distance between the ant *i* and task *j* as a metric to evaluate the probability of a particular ant to engage in the task. The mathematical model proposed by them is:

$$S^i_j = \tanh\left(\frac{k^i_j(t)}{\left|\underline{r}^i(t) - \underline{r}^j(t)\right| + \delta} \left(\phi_j + \psi^i_j\right) \right) \Theta_j \qquad (3.3)$$

Where S^i_j is the probability of an ant *i* located at the position vector $\underline{r}^i$ at time *t* to engage in performing task *j* located at the position vector $\underline{r}^j$ at time *t*. The model allows certain number of ants to be engaged with the same task at the same time. This is encoded in $(\varphi_j + \psi^i_j)$. For further details, please refer to [Arcaute et al., 2009].

3.2.2 Specialisation

The fixed response threshold model assumes that the response threshold of a worker is fixed and does not change over time. However, many studies show that this is not entirely true. It can be true over short time scales where the response threshold is fairly constant. However, in many ant species, over the duration of the workers lifetime this couldn’t be holding true. Division of labour in social insects is known to be affected by a number of factors including age polyethism [Bonabeau et al., 1999; Calderone and Page, 1996; Robinson et al., 1994], learning [Brutschy et al., 2011; Chittka and Muller, 2009; Franks et al., 2007; Ravary et al., 2007; Spencer et al, 1998] as well as physiology [Robinson et al., 2009]. Many ant species are known to change their task preference over their lifetime [e.g. Ingram et al., 2005] which would mean that the response threshold for the task is also changing over time. It is highly evident in many ant species that the probability of carrying out a task increases upon successful completion of the task and/or frequent interactions with other ants engaged in a particular task [Greene and Gordon, 2007] indicating that the thresholds might not be just fixed but are rather adaptive. Theraulaz and colleagues [Theraulaz et al., 1998] extended the concept of fixed response threshold model to accommodate this flexibility. In their model, when a worker performs a task successfully, the threshold for the particular task is reduced by the learning factor $\xi \Delta t$. Similarly if the worker is unsuccessful in accomplishing a task or not receiving stimuli for a long time, the worker would reduce the probability of carrying out the particular task for the next time. This is implemented by increasing the threshold for the task by the factor $\varphi \Delta t$ often called the forgetting parameter. The constant learning and forgetting of task eventually results in the specialisation of workers within the colony.

3.2.3 Physiological specialisation

Recently, Robinson and colleagues [Robinson et al., 2009] used *Temnothorax albipennis* ants to test if there is any effect of the ant's physiology on deciding what task to carry out. They argue that the physiological state of an ant can be more important than age for determining task thresholds. Corpulence or the amount of fat stored in an ant's body has been correlated to one's physiological state. Experiments with *T. albipennis* shows that leaner ants most often take the task of foraging supporting the hypothesis that there exist some physiological thresholds which determine what tasks should be carried out.

3.2.4 Foraging for work model

In the foraging for work model [Tofts, 1992; Tofts and Franks, 1993], tasks are connected functionally in a production line and arranged spatially in series of zones

– a simplification of the radial arrangement of the nest structures. The input task for the upstream zone comes from the output from the downstream one. An ant performs tasks in the zone she resides in. Once the task is completed, she tends to perform another task within the same zone. However, if there are no more tasks available in the current zone, she moves to the adjacent zone depending on the relative number of ants in the adjacent zone and the amount of task available to be carried out. Foraging for work can theoretically generate temporal polyethism. However, the model has been highly controversial [e.g. see Robinson et al., 1994; Robson and Beshers, 1997; Traniello and Rosengaus, 1997] owing to the fact that the model assumes no intrinsic effect of task performance. Despite much controversy, the foraging for work algorithm remains a very important model for dynamic allocation of tasks.

3.3 Task Partitioning and division of labour

Both *division of labour* and *task partitioning (TP)* characterize the organization of work in insect societies. Traditionally the concept of division of labour was adopted [Jeanne, 1986] and focussed on individuals and the task they perform over a period ranging from hours to the whole working life of the worker [Jeanne, 1986; Oster and Wilson, 1978; Ratnieks and Anderson, 1999; Robinson, 1992]. On the other hand the concept of task partitioning, a term first coined by Jeanne in 1986, is focussed on situations in which two or more individuals contribute sequentially to a particular task [Anderson and Ratnieks, 1999; Jeanne, 1986; Robinson, 1992].

A simple example of task partitioning can be seen in nectar collection in honey bees [Ratnieks and Anderson, 1999] where honey bee foragers bring nectar to the beehive and transfer the nectar to the bees working in the nest (known as storers or receivers) which in turn bring nectar to the respective cells. Another example of task partitioning that is highly noticeable is in the ponerine ants, *Ectatomma ruidum*, which are abundant in coffee or cocoa plantations where they prey on a wide variety of anthropods [Lachaud, 1990]. These species of ants divide the foraging tasks into two phases. In the first phase, a group of this specie (called stingers) kills prey (e.g. fruit flies) by stinging them which causes the flies to become motionless and fall onto the ground. Once the flies are dead, they are picked up by a second group of workers, often called transporters [Theraulaz et al., 2002].

With very few exceptions, almost all the examples of task partitioning in social insects are related to foraging perhaps due to the deficiencies in the survey of the literature in other areas or due to the literature itself being biased towards the studies of foraging.

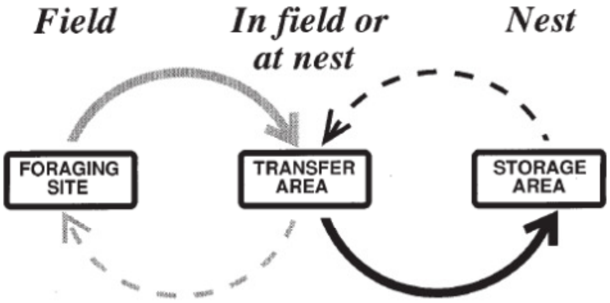


Fig 3.3: A schematic diagram of a two-stage partitioned task. The solid lines represent the flow of materials while the dotted lines represent the flow of collectors and users [Ratnieks and Anderson, 1999]. Reprinted with permission.

3.3.1 Categories of tasks

Anderson and Franks [Anderson and Franks, 2001] classified tasks into four broad categories:

1. *Individual task*, where a single individual carries out a task without any cooperation from other individuals.

2. *Partitioned task*, where a task is divided sequentially among two or more subtasks. Examples include the collection and storage of nectar by the honey bee. Figure 3.3 shows such a schematic diagram.

3. *Group task*, where a group of workers cooperate in a concurrent fashion to carry out a task successfully. There is no division of labour within the group i.e. each individual carries out the same task.

4. *Team task*, in which a group of workers not only work concurrently but also coordinate their different contributions. The key difference between group tasks and team tasks is that in group tasks, several workers cooperate by carrying out the same action concurrently whereas in team tasks, the workers need to cooperate with different actions to complete the task. Consequently, a team task needs to be divided into two or more distinct sub-tasks in order to successfully complete the task. A good example of a team task is the construction of nests by *Oecophylla smaragdina* ants. These ants build nests by gluing leaves together. The construction of the nest is divided into three

sub-tasks. One group of individuals pull leaves together and hold them in place, another group produce glue (silk produced by larvae) while a third group of individuals hold the larvae and use them as a tube of glue to bond the leaves together [Anderson and Franks, 2001]. All these three tasks are carried out concurrently in order to build the nest and hence the construction of nests by *Oecophylla smaragdina* ants is regarded as a team task.

3.3.2 Examples of Task partitioning

For the purpose of extensive discussion, some examples of task partitioning categories found in social insects are described here:

3.3.2.1 Tasks not partitioned

Foraging without task partitioning is extremely common in social insects. In this case, foragers do not transfer food to any transporters, but rather collect the food, carry it all the way to the nest and deposit there. Bumble bees collecting nectars from foraging areas, have often been reported to behave in this manner [Anderson and Ratnieks, 1999, Michener, 1974].

3.3.2.2 Tasks sometimes partitioned

In some social insects, tasks are not always partitioned; rather partitioning is a function of the size of the colony. For instance, *E. ruidum* ants do not partition tasks when the colony size is less than 16 workers. With colony size less than 16 workers, the ants hunt the food and transport it back to the nest by themselves. However when the colony size exceeds 20 workers, the task becomes partitioned between hunting by “stingers” and transferring the prey back to the nest by transporters.

3.3.2.3 Transfer at the foraging area

It has been found that some species of eusocial insects transfer food in the foraging area. For instance, the minor workers of *Oecophylla longinoda*, African weaver ant, transfer honeydew at the foraging area directly to the major workers for transporting it back to the nest. Another example is the foraging mechanism of leaf cutter ants *Atta* [Hart et al., 2002]. Some individuals climb up a tree, cut leaves and drop to the ground whereas the transporters gathers beneath the tree, collect the leaves and transport them all the way back to the nest.

3.3.2.4 Transfer at the nest

Many ant species carry food back to the nest and place it at a dump area inside the nest. Other ants working inside the nests are then responsible for carrying the food from the dump area back to the brood members. The transfer of food between foragers and the transporters can either be direct or indirect depending on what kind of food is being transferred.

3.3.3 Direct and indirect transfer of food between transporters and foragers

Direct transfer of the food (e.g. liquids) means that the transporter ant takes the food regurgitated from the mouth of the forager. In case of the indirect transfer, the forager puts the food in a designated place (often called a “dump” or a “cache”) and the transporter collects the food from the cache and takes it back to the nest. Direct transfer often results in a queuing delay [Anderson and Ratnieks, 1999] as the forager may have to wait for a transporter.

If the food is solid, the transfer of food can either be direct or indirect. However, if the food is liquid e.g. water, the transfer of food must be direct.

3.3.3.1 Costs and benefits in task partitioning

Task partitioning in foraging has both costs and benefits. Potential benefits include an increase in the task efficiency. Potential costs are shown in Table 3.1.

For Direct Transfer	For Indirect Transfer
Time is wasted between the transfer of food items between the individuals	Energy is wasted to load/unload the food at the dump site
Material is lost while regurgitation is taking place	Time is taken to locate the dump site
May incur queuing delays i.e. the forager needs to wait for a receiver to be free at the transferring area	

Table 3.1: Costs of direct transfer and indirect transfer of food

3.3.4 Bucket brigading in social insects

In almost every case, transfer of food takes place at some predetermined locations such as at the foraging area (as in *Oecophylla longinoda*), at a trail junction or at the nest entrance.

However some ants (e.g. seed-harvesting ant, *Messor barbatus*, African stink ant, *Pachycondyla tarsata*, and the grass cutting ant *Atta vollenweideri*) transfer food in an opportunistic fashion i.e. at non-predetermined locations. These ants grab the food from the foraging sites and go towards the nest until they find unladen ants. They then transfer the food to the unladen ants by direct means. The unladen ant which has just received the food (now laden) in turn takes the food and starts moving towards the nest until it finds another unladen ant. When the ant becomes unladen, it starts following the pheromone trails and moving towards the foraging site. This multi-stage transportation technique is what is called bucket brigading [Anderson, et al., 2002].

Figure 3.4 shows some of the foraging retrieval techniques and the corresponding task partitioning produced in transferring the food items from the source to the nest.

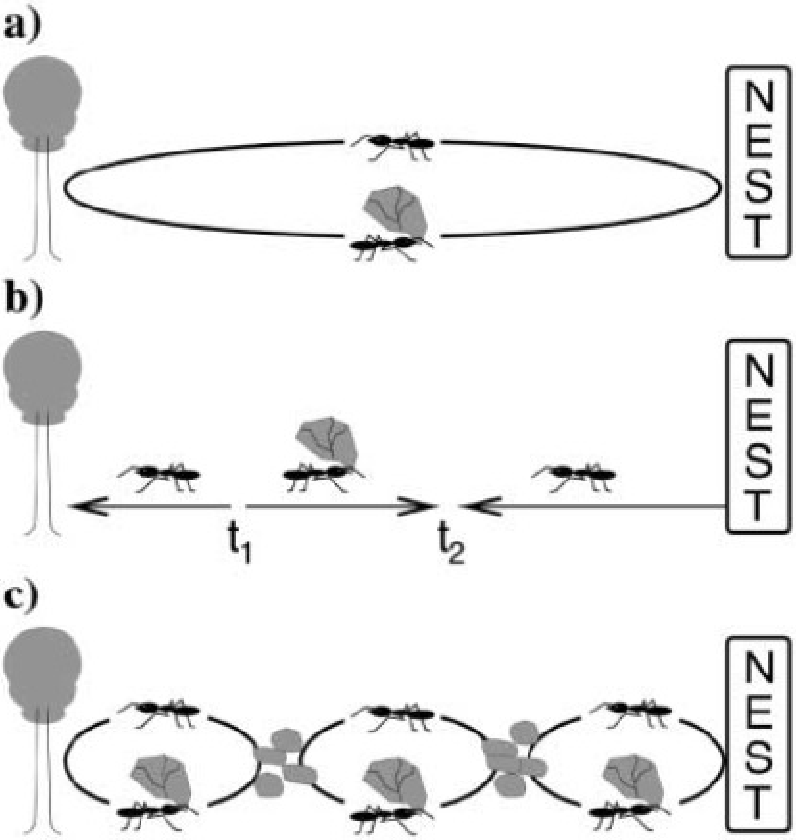


Fig 3.4: Various form of foraging retrieval. a) In this case individual ants carry piece of food from the source to the nest without transferring the food item in any intermediate places which means there is no task partitioning, b) in this case ants transfer food items at no predefined locations and therefore it represents bucket brigading, c) A multi-staged partitioned task with indirect transfer of food items [Anderson et al., 2002]. Reprinted with permission.

3.4 Task preference in relation to caste

Many ant species show high degree of correlation between tasks chosen by individual worker and the caste the worker belongs to. *P. barbatus* ants, for instance, show some degree of task preferences in the range of tasks they are involved in. *P. barbatus* ants are known to have four behavioural castes (patrollers, foragers, nest maintenance workers and midden workers), each having their corresponding primary jobs. The ants of this specie use cuticular hydrocarbon profiles to communicate with nest-mates. It is believed that hydrocarbon profiles dissipated on the exoskeleton of the insect (cuticle) gives rise to the existence of the castes in the specie. Hydrocarbons are by far found to be the most abundant class of chemicals to coat the cuticle of insects [Jackson and Blomquist, 1976; Nelson and Blomquist, 1995; Provost et al., 2008]. They provide various benefits to insects including (1) providing barrier against water loss preventing lethal dessication (alkanes are mostly responsible for this function [Gibbs, 2002]), (2) protection against infection and (3) facilitating chemical communication (alkenes are found to be mostly responsible for this function). Hydrocarbons play important roles in various contexts of insect biology including that of the regulation of reproduction, nest-mate recognition, task allocation and many more. Researchers have found that in many species of ants the difference in the composition or concentration of cuticular compounds give rise to the castes within a specie. For instance in *Camponotus floridanus* ants, the foragers and the callow workers are found to have different hydrocarbon profile [Lavine et al., 1990]. Howard and colleagues [Howard et al., 1982] experimented on termite specie *Reticulitermes verginicus* found that the specie has four distinct castes (worker, soldier, nymph and neotenic) each having the same hydrorbon profile but of different concentration. Wagner and colleagues [Wagner et al., 1998, Wagner et al., 2001] found that foragers and patrollers of *Pogonomyrmex barbatus* ants have same hydrocarbon composition but both categories have higher proportion of straight-chain alkanes and alkenes than nest maintenance workers. Different composition and concentration of hydrocarbon compounds can arise due to several factors including temperature and the humidity of the environment, genes as well as interaction between workers which consequently can give rise to a different behaviour in a group of ants from its nestmates thus resulting a caste formation. Such caste formations normally are classed under the category of behavioural castes.

The following is a summary of the functionality of the four castes of *Pogonomyrmex barbatus*.

1. Patrollers: These ants are one of the first groups of ants to emerge out of the nest. They come out very early in the morning moving around the nest and evaluating whether it will be safe to forage or not. The successful return of the patrollers triggers foragers to come out of the nest and forage.

2. Foragers: The successful return of the patrollers triggers the foragers to emerge out of the nest in search of food. Foragers use the direction chosen by patrollers by following the pheromone trails laid by the patrollers and sometimes even completely ignoring the food sources that are not explored by the patrollers. Once they find food (seed), they pick it up and head towards the nest. The successful return of the foragers trigger further foraging activity in the colony.

3. Nest Maintenance Workers: The castes reside in different chambers of the nest and it is the job of the nest maintenance workers to constantly repair, clean and maintain the chambers inside the nest. During untoward situations e.g. the damage of the nest by flood or wind, the activity of the nest maintenance workers are found to increase.

4. Midden Workers: They usually sort and pile the refuse pile or midden. The actual behaviours of midden workers are not well known [Gordon, 1999] but they are found to move midden from one side of the mound to another.

Although the different castes of the *P. barbatus* have different tasks to do, they show a remarkable ability to adapt to the situations as required [Gordon et al., 2008]. When there is a need for one task, some of the ants from other castes are found to switch from their original task to meet the changing demand. However, every task switching transition is not evident indicating that the probability of task selection by an individual worker depends on the caste she belongs to. For instance if there is a need for foraging, nest maintenance workers, midden workers and patrollers can switch their task to foraging task however if there is a need for more patrollers, only the nest maintenance workers are found to switch their task to patrolling (refer to figure 3.5 for details).

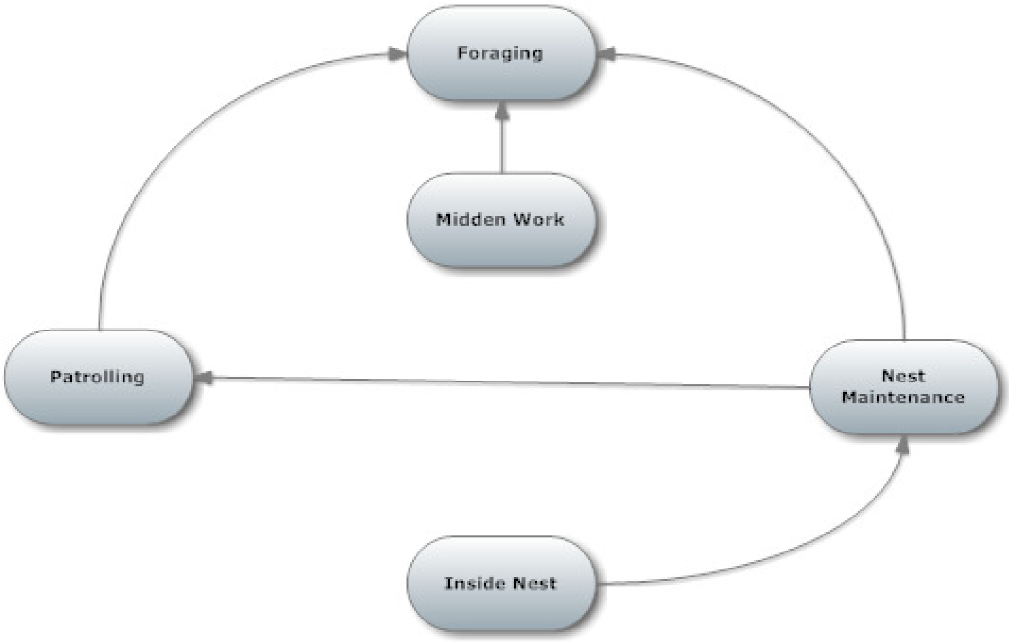


Fig 3.5: Possible task switching transitions for red harvester ants

It is possible that this variation in task preferences is a result of the setting of the individual's threshold values. Deneubourg explains this using the fixed response threshold model (personal comm.). Deneubourg argues that it has quite often been observed that an individual ant which is found to often perform a particular task always gets triggered when the stimulus of that task is found. He says that it is possible that the particular ant has a very low threshold for that particular task. This results in the ant being more sensitive to that particular task. Whenever there is a stimulus for the task and the stimulus exceeds the threshold value, the ant gets activated. It is then not difficult to imagine result when an ant is exposed to two tasks (T_A and T_B). If a particular ant has low threshold for T_A and high threshold for T_B, it is more likely that the ant will almost all the time perform T_A and very little of T_B and therefore a difference in the threshold creates a bias in its task preferences. In some extreme cases, it is possible to find that a particular ant is so biased towards a particular task (extreme specialisation) that it seldom switches task even when there would be a benefit to the colony for it to switch tasks. Such examples of task preferences among the castes within the same species can be found in many other ant species including that of *Ectatomma ruidum* [Theraulaz et al., 2002] and *Pheidole pallidula* [Detrain and Pasteels, 1992; Hölldobler and Wilson, 1990].

3.5 Task allocation in robotics

Task allocation is a fundamental area in the field of swarm robotics [Ducatelle et al., 2009; Groß et al., 2008; Jones and Matarić, 2003; Momen et al., 2009a, Yongming et al., 2009, Zhang et al., 2007]. Much of the work pertaining to the dynamic allocation of labour in response to the change in the environment or demand of a particular task is strongly inspired by the behaviour of the social insects. An early example of the work carried out in this area is that by Krieger and colleagues [Krieger and Billeter, 2000; Krieger et al., 2000]. Although their work was mentioned in chapter 2, we feel the necessity of mentioning it briefly again for the completion of this chapter. Their work was strongly inspired by the fixed threshold response model of the social insects. The robots (kheperas) were assigned some fixed thresholds for foraging from uniform distribution between ¾ and full initial nest energy. The robots in the nest periodically communicate with the control station and update the nest energy level. When the radioed nest energy level is below the activation threshold (or threshold for foraging), the robot leaves the nest and starts foraging. It is a simple mechanism of using a fixed threshold response to dynamically allocate tasks. However, one deficiency of this approach was the use of a centralised control station to communicate the nest energy level to the robots. Such a mechanism does not provide a fully decentralised system. Subsequent studies by Labella [Labella, 2007] and Wenguo Liu and colleagues [Liu et al., 2007a, b] worked towards building a fully decentralised system for allocating tasks. Furthermore, their studies were strongly inspired by the way social insects specialise.

Labella [Labella, 2007] proposes variable delta learning algorithm for automatically adjusting the ratio of the number of foragers to resters for foraging robots. His model was inspired by Deneubourg's learning model [Deneubourg et al., 1987] which has been developed to explain the foraging patterns observed in the *Pachycondyla apicalis* ants.

In the original model, Deneubourg et al. (1987) assume that each ant has a probability (say P_1) of leaving the nest. They further assume that there are N possible foraging sites and that each ant has the probability of Q_i to go to the i^{th} foraging site. Each site is assumed to have a probability, r_i, of containing a prey.

The model works in the following way:

- If a trip to the site i is successful, the ant increases both P_1 and Q_i by ΔP^+ and ΔQ^+ respectively.
- If the trip is unsuccessful, the ant decreases both P_1 and Q_i by ΔP^- and ΔQ^- respectively.

Labella modified the model by keeping track of consecutive success and failures of the robots. The range of P_1 has been limited to $[P_{min}, P_{max}]$ to ensure that the value of P_1 becomes neither too high nor too low. Labella calls this algorithm "variable delta algorithm" since the algorithm does not increment or decrement the value of P_1 by any fixed value (unlike Deneubourg's model).

```
Variable Delta Algorithm:

Initialization: $succ \leftarrow 0; fail \leftarrow 0, P_1 \leftarrow P_{init}$

If success then                              if failure then
  $succ \leftarrow succ + 1$                   $succ \leftarrow 0$
  $fail \leftarrow 0$                          $fail \leftarrow fail + 1$
  $P_1 \leftarrow min\{P_{max}, P_1 + succ \times \Delta\}$    $P_1 \leftarrow max\{P_{min}, P_1 - fail \times \Delta\}$
fi                                           fi
```

Liu and colleagues [Liu et al., 2007a,b] used similar mechanisms but updated the searching time and resting time thresholds depending on three different cues (internal cues, environmental cues and social cues). They then introduced four different strategies of foraging by using different combinations of the cues outlined in Table 3.2.

Strategies	With internal cues	With environmental cues	With social cues
S1	×	×	×
S2	√	×	×
S3	√	×	√
S4	√	√	√

Table 3.2: Different strategies of foraging

The internal cue allows the robot to reward itself when it is successful in foraging. For instance, if a robot is successful in bringing a food item back to the nest, the robot reduces it's threshold of resting thus increasing the time spent for foraging. The environmental cue takes the case of collision with other robots into consideration. When a robot is outside the nest and collides with other robots, it reduces its threshold of searching and increases its threshold of resting thus increasing the time of resting within the nest and decreasing the time of searching. This is because when a robot collides, it assumes that there are more robots out in the environment foraging and hence it does not need to contribute towards foraging. For social cues, a successful robot sends a broadcast message to other robots inside the nest and they consequently increase their thresholds of searching and reduce their thresholds of resting. In their works the greater the threshold for searching is the longer is the time of searching and vice versa (unlike the way the biologists and other roboticists use thresholds). For further details, please refer to [Liu et al., 2007a, b; Liu and Winfield, 2010].

Yongming and colleagues [Yongming et al., 2010] used a fixed response threshold model to develop a system where simulated robots can autonomously decide whether to leave the nest and forage or not. Their model assumes that there are N_I items of food in the home (nest) initially which get consumed at a particular rate leaving n_t items of food after time t. All robots have the same fixed threshold (θ) and a random value of n (bounded within a fixed range) for making robots to respond differently to the stimulus. Each robot can then determine whether to switch to a foraging state or not depending on the amount of food available in the home. The lower the amount of food available in the nest is, the greater is the propensity for the robot to leave the nest and start foraging. Equation (3.4) shows the probability that of a robot to undertake the foraging task(P_f).

$$P_f = \begin{cases} 0, & n_t \geq N_I \\ \dfrac{(N_I - n_t)^n}{(N_I - n_t)^n + \theta^n}, & n_t < N_I \end{cases} \tag{3.4}$$

Zhuang and Yin [Zhuang and Yin, 2008] used a similar technique (taking inspiration from the behaviour of honeybees) to allocate tasks in a simulated stochastic environment.

Jones and Matarić [Jones and Matarić, 2003] used a simple adaptation rule to vary the propensity for foraging for two types of pucks (red puck and green puck) depending on the ratio of their availability. The pucks are scattered in the arena. The robots at any time, t, can either be a $Robot_{red}$ or $Robot_{green}$. If it is $Robot_{red}$, it forages for the red pucks and vice versa. At any time, t, a robot can either continue foraging for a particular type of puck or decide to switch its state and forage for the other type of puck. The underlying algorithm is expressed by the following equations:

$$P(Green \rightarrow Red) = \begin{cases} (GR - GP) * (1 - GP) & \text{if } GR > GP \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

$$P(Red \rightarrow Green) = \begin{cases} (RR - RP) * (1 - RP) & \text{if } RR > RP \\ 0 & \text{otherwise} \end{cases} \tag{3.6}$$

Where *P(Green → Red)* and *P(Red → Green)* are the probabilities of robots foraging green and red pucks deciding to change their foraging states to red and green pucks respectively. All robots use two history windows (limited and constant sized) to store the state information. One of the history windows contain recent observed pucks in the arena while the other history window observes the neighbouring robot's foraging state from the colour of the beacon the robot is emitting (if the foraging state of a robot is to forage red pucks, then it emits beacon coloured red and vice versa). *RR* and *RP* are the proportion of $\text{Robot}_{\text{red}}$ entries and Puck_{red} entries in the Robot History and Puck History respectively. Similarly *GR* and *GP* are the proportion of $\text{Robot}_{\text{green}}$ entries and $\text{Puck}_{\text{green}}$ entries in the Robot History and Puck History respectively. The robots then use the two history windows to determine their chances of switching their foraging state. Jones and Matarić showed that the simple algorithm proves to be adaptive to the stimulus demand. To test the flexibility of the algorithm, they changed the distribution of the pucks in the middle of the simulation and found the robots to adjust their thresholds accordingly. Galstyan and Lerman, in 2004, analysed the algorithms presented by Jones and Matarić analytically using an approximation of the stochastic Master equation and found the results to be in agreement with the simulation results [Galstyan and Lerman, 2004].

Ducatelle and colleagues [Ducatelle et al., 2011, Ducatelle et al., 2009] presented two task allocation methods (*light based task allocation* method and *gossip based task allocation* method) for two types of heterogeneous robots working together to complete a task. The types of robots involved are *Footbots* (which are the wheeled robots) and *Eyebots* (the flying robots). The *Eyebots* execute high level search to find targets in a bounded environment. Once the target is found, Eyebots visit the targeted site and attract the *Footbots* to come to the area to carry out the tasks. In the *light based task allocation* method, the robots use multi-coloured LEDs placed around their bodies to influence others' behaviour. For instance, once the *Eyebot* visits the target area, it changes the colour of the LEDs to yellow. *Footbots* are programmed to be attracted to the yellow light and repelled by green light. So, once the *Footbots* detect yellow light in their vicinity using their omnidirectional camera, they start travelling towards the yellow light (in this case, the target). Using green and yellow lights, *Eyebot* can control the number of *Footbots* travelling to the targeted region. Also, as the *Footbot* perceives yellow and green light simultaneously, it increases the frustration level of the *Footbot*. When the frustration level exceeds some threshold, the *Footbot* performs an escape movement. In the *gossip based task allocation* strategy, *Eyebot* sends the announcement of the task to the nearby *Footbots* and corresponding *Footbots each* transmit messages to the *Footbots* near it. In this way, the announcement of the task is propagated throughout. Each message contains information about all tasks a robot knows about which include:

- *Robot ID:* the ID of the transmitting robot.
- *Number of tasks:* Number of tasks the sending robot has information about.
- *For each task:*
    - *Task ID:* ID of the task

    - *Required Workers:* the number of workers required for the task
    - *Hops:* the number of hops to the task.
    - *Route length:* the distance to the task following the hops.
    - *Age:* the age of the information about the task.

Each receiving robot then recalculates most of the messages before forwarding the message to any other robots [See Ducatelle et al., 2009 for further details]. The robot uses the number of hops and the route length as the first two criteria to decide if it is going to commit to the task. If the age exceeds some threshold, the robot assumes that the information is stale and decides to drop the message.

Experiments with different experimental setups reveal that the *gossip based task allocation* method almost always works better than the *light based task allocation* method. However, if the numbers of robots present are enough, the two task allocation methods yield almost the same performance.

Hoeing and colleagues [Hoeing et al., 2007] developed a prototype system called COMSTAR (Co-operative Multi-Agent Systems for TArget Recognition) where a swarm of simulated unmanned aerial vehicles (UAV) can identify a task (target) and cooperatively carry out the task. In their model, each UAV initially roams around the environment in search of any target. Upon recognising a target the UAV emits a certain amount of synthetic pheromones (where concentration of the pheromone is related to the urgency of the task) to mark the location and the priority of the task. This facilitates other UAVs that are roaming around in search of a target to come to the target place. Once the desired numbers of UAVs reach the target place, they carry out the task. The authors also developed a corresponding intentional task allocation model for this problem. Within the intentional task allocation model, once the simulated UAV finds the target, it starts auctioning. The other UAVs which can take up the task participate in the bidding process. The bidding mechanism is explained in further details in Section 3.5. Once the auctioning is over, the UAV that started the bidding process selects the top n bidders (where n = number of UAVs required to accomplish the task) to carry out the task.

Zecca and colleagues [Zecca et al., 2009] proposed a model in which the environment is populated with robots and RFID tags. RFID tags include instructions for the robots and their next destination. Thus distributing the RFID tags within the environment enables the robots to distribute themselves and allocate tasks. However, such a mechanism does not take changes in the environment into consideration and hence is not flexible to changing demands.

All the studies presented above look into developing systems that allocate tasks in a dynamic fashion. However, in most cases the complexity of the environment is fairly simple. Some even used a centralised control station [Krieger and Billeter, 2000, Krieger et al., 2000] for communication purposes. The natural world, on the other hand, provides much more complex strategies that facilitate effective task allocation using threshold based approaches in a more stochastic environment. This thesis looks into possibilities of understanding and using some of the strategies that nature provides to develop systems which would allow the agents to effectively allocate tasks in a much more stochastic environment. The thesis also looks into empirical evaluation of the strategies to understand when and in what conditions does a particular technique benefit the multi-agent system.

3.6 Intentional task allocation approach

In contrast to the self-organised task allocation approaches, in intentional task allocation approaches, agents tend to be more complex and to coordinate with each other with the explicit intent of achieving the team goal [Kalra and Martinoli, 2006]. Market based approaches are one class of popular intentional task allocation approaches in which the agents act as self interested agents participating in a virtual market economy with the intention of winning a bid. Unlike the self-organised task allocation approaches, the allocations of tasks in market based approaches are carried out by some centralised supervisor agents (called auctioneers). Matarić and colleagues [Matarić et al., 2003] devised a simple task domain in the simulation to study task allocation approaches for multi-robot system. The model environment is comprised of 10 X 10 grid inhabited by 10 robots (agents) and some events (tasks) scattered within the environment. When an event needs to be allocated to one of the robots, the auctioneer advertises the task to all the robots present. The robots that are free and can take up the task participate in the bidding process by conveying their position to the auctioneer. The auctioneer evaluates the bids by determining which robot is closest to the event. Once evaluated, the auctioneer declares the winner by broadcasting the id of the winner. Gerkey and Matarić [Gerkey and Matarić, 2000] introduced a novel mechanism (MURDOCH) to dynamically allocate tasks to a group of heterogeneous robots. MURDOCH implements a publish/subscribe messaging technique which in turn depends on subject based addressing. In subject based addressing, when robots having some facilities need to be addressed, the auctioneer tags a message with a subject or sets of subjects as necessary and publishes it to the network. For instance, for a particular event to be handled, if the robot needs some facilities, say gripper and camera, then the auctioneer tags a message with the subject (gripper camera) and publishes it to the network. The robots /agents on the other hand subscribe to only those messages which they can serve. For instance, when the message with the subject (gripper camera) is published in the network, the robots that do not have these features simply discard the messages. The others which are free and have a pair of grippers and camera respond to the auctioneer by giving some fitness value. The auctioneer then evaluates all the fitness values it has received from the candidate robots. After the evaluation process, the auctioneer sends a message to declare the winning robot. Parker [Parker, 1998] introduced the ALLIANCE architecture which enables robots to allocate tasks through two motivation states: impatience and acquiescence. Each robot communicates its progress to all other robots. The robot's impatience increases when it finds another robot trying to carry out a particular task is failing to execute it properly. On the other hand, if the robot is failing to execute its task properly, its level of acquiescence increases. If the robot's level of impatience exceeds some threshold, it starts carrying out that particular task. On the other hand, if its level of acquiescence exceeds some threshold, the robot becomes frustrated with the task it is carrying out and leaves the task it was currently executing.

Kalra and Martinoli [Kalra and Martinoli, 2006] performed a comparative study between the two approaches of allocating tasks. Both the approaches have some benefits. For instance, the self-organised approaches do not need the explicit communication of the intentional task allocation approaches and consequently suffer from low communication and computational complexity. On the other hand, market based approaches tend to allocate tasks more efficiently and are consequently found to be able to be able to handle more tasks than the threshold-based counterparts. However, if the amount of noise is more and the task estimation is imperfect, the performance of market based approaches starts to fall. Another problem with the intentional task allocation approaches (for instance in the ALLIANCE architecture) is that the approach might not be scalable in the order of thousands of robots due to the fact that the robots need to constantly communicate their progress to all other robots and also to keep track of the progress of all other robots. On contrary, self organised task allocation approaches theoretically tend to be more robust owe to the fact that they are completely decentralised and need less communication among themselves.

3.7 Summary and Conclusion

This chapter discusses the task allocation approaches adopted by many researchers. Self organised task allocation approaches are strongly inspired by the behaviour of eusocial insects and in many cases tend to allocate tasks by means of threshold based mechanisms. The agents in self organised task allocation approaches use only local sensing and communication to decide what task to accomplish. On the contrary, intentional task allocation approaches are strongly inspired by market economy where each agent participates in bidding for a particular task. Communication either tends to be between all agents or there exists a need for a centralised controller to allocate tasks. In general, intentional task allocation approaches are found to allocate tasks more efficiently than the self-organised counterparts but also suffer from high computational and communication complexity. Furthermore, the performance of intentional task allocation approaches is strongly affected by the amount of noise and interferences.

This thesis is strongly motivated by threshold based mechanisms exhibited by social insects to design a multi-agent system that can allocate tasks dynamically in response to the changing demand. A number of multi-agent systems have been designed and developed by researchers in the past. Howerver, we find a number of limiting factors in the existing literatures: for instance 1) the models developed by previous researchers usually tend to be simple in terms of the number of agents involved, stochasticity, stigmergic interactions as well as in terms of the number of tasks involved, 2) many models, although inspired by eusocial insects, have failed to capture all the necessary features that eusocial insects display, 3) some models (e.g. Krieger et al., 2000; Krieger and Billeter, 2000) even used centralised system for transmitting messages and others such as Liu et al., 2007a,b relied on broadcasting signals rather than local interactions in certain cases, 4) many simulation lack the issue of embodiment while modelling the interaction between the agents and the environment, and 5) in many models the task allocation was not driven by the need of the colony. For example Liu and colleagues [Liu et al., 2007a,b] used a number of simulated robots that collect food items from the outside environment. The motivation of foraging is influenced by the internal, environmental and social cues and is not driven by the need of the colony. In reality such need for adaptation is a result of the demand created from the inner core of the colony. This thesis intends to fill these gaps while designing the multi-agent system.

In this chapter, the literature in the field of Entomology has been explored to understand how social insects and in particular ants behave and allocate tasks. Detailed understanding of their mechanism then led to the design and development of three models of allocation of tasks. In all the models, the worker agents use three thresholds and a competition between the thresholds decides what task they are going to perform. A stochastic environment (in terms of the number of agents involved, interactions among the agents and between the agents and the environment and the behavioural rules followed by the agents) has been presented in the models to analyse how well agents can self-organise and allocate tasks in a changing environment.

The first model proposed (described in chapter 4) is based on simple, local and stigmergic interactions between the individuals. In chapter 5, direct local communications between the agents have been used along with the stigmergic interactions already described in chapter 4. Very little work has been done previously to analyse the impact of incorporating direct communication along with the indirect ones. However, in natural swarms, direct communications do play an important part over the performance of the swarm. Chapter 5 empirically evaluates the benefits of colony efficiency when the direct communication is incorporated under various situations. Chapter 6 extends the idea of threshold based mechanisms to the role of mixed agents (dedicated and flexible) on the performance of the swarm. To the best of our knowledge, this research is the first to explore the role of dedicated (biased) agents in the performance of the colony.

Chapter 4

A Flexible Task Allocation Model for a Swarm of Simulated Agents

Dividing labour and allocating tasks on the fly can be considered as a benchmark problem in the field of multi-agent systems where more than one agent works together collectively in order to carry out a range of tasks. Effective task allocation strategies that allow task specialisation and execution of tasks in parallel fashion are expected to yield better performance compared to those that execute tasks sequentially and do not have any provision for task specialisation [Hölldobler and Wilson, 2008; Oster and Wilson, 1978]. Social insects are known to exhibit some effective task allocation strategies that allow them to schedule and re-schedule tasks without the need of any centralised controller. Such task allocation ability is often referred to as the most prominent feature of the organisation and the success of colonies [Bourke and Franks, 1995; Hölldobler and Wilson, 2008, 1994, 1990; Momen and Sharkey, 2009a,b; Robinson et al., 2009] (also see Chapter 3) enabling many species (and ants in particular) to effectively maintain colonies of as many as 20,000,000 individuals [Beckers et al., 1989] (see Chapter 3 for further details).

Flexible task allocation strategies allow assigning tasks and redistributing part of the workforce in response to the changing demand. Such mechanisms are extremely important as they enable the agents not only to carry out their operation but also to adapt to the changing environment and allow them to re-organise themselves in such a way so as to meet the changing demand. In a perfectly stable environment, once the workers distribute tasks among themselves, it might not be necessary to re-distribute tasks at some future time. However, in most complex systems, the environments are dynamic and unpredictable which consequently requires workers to make decisions about what task to carry out next and to redistribute the workforce in proportion to the demand of the tasks.

In this chapter, a task allocation model suitable for a swarm of agents is presented. The agents are considered to be simple in terms of their behaviour, completely autonomous with limited sensing and communication capabilities and having no prior knowledge of the environment. The work is strongly inspired by the ant colony behaviour and especially the plasticity of behaviour that many ant species exhibit. The remainder of the chapter is organised as follows: first a brief discussion of the modelling approaches that have been embraced is provided, followed by a detailed description of the environment of the model. Behavioural rules for the agents are then established taking inspiration from the behaviour of the individual ants in a colony. A discussion of how the performance of the colony is evaluated is then given followed by the results that were obtained. We then compare the simulated results obtained with the behaviour that real ants display in nature. Finally, the chapter is concluded with comments on the next set of experiments.

4.1 Modelling Approaches

One of the objectives of this research is to develop and analyse a flexible, scalable and robust task allocation model for a swarm of agents. The work, as previously mentioned, is strongly inspired by ant colony behaviour since ants are known to display efficient task allocation strategies (more details can be found in Chapter 3) that work well with various colony sizes. Therefore, the approach we adopt to build the model is to mimic the behaviour of "real world" ants to establish the behaviour of individual agents and analyse whether similar colony behaviour (as observed in nature) emerges as a result or not. This leaves us with three possible ways of gaining better understanding of their behaviour:

(1) **Using real ants**: One of the possibilities is obviously to use real ants in a laboratory controlled experiments and analyse how the colony behaviour changes with different task demands. Thorough analyses of the behaviour of ant colonies then allow the researchers to model their behaviour. Although, this approach is popular among biologists, there exist a number of disadvantages with this approach: it is **(1)** time consuming, **(2)** costly and most importantly **(3)** a wide number of parameters (e.g. the pheromone diffusion rate, the rate of food availability, size of the swarm) are difficult to vary for the purpose of analysis. However, such approaches are capable of providing much deeper insights about how collective behaviour emerges within the colony under investigation.

(2) **Using robots**: The use of real robots to mimic the behaviour of individual ants [e.g. Krieger and Billeter, 2000; Kube and Bonabeau, 2000; Parker et al., 2003] and analysing how the colony behaviour emerges out of the numerous local interactions among robots has been another popular approach in recent times. Unfortunately this approach is limited due to a number of factors: (1) the size of the swarm that can be used is limited due to the cost involved, (2) the performance of the robot swarm has been reported to decrease with the increase in the swarm density largely due to the interference between robots [e.g. Krieger and Billeter, 2000; Liu et al., 2007a,b; Rybski et al., 2008] that arises mainly due to the usually limited dimension of the size of the environment compared to that of a single robot and (3) limitations in the sensor and other technologies makes it almost impossible to mimic every aspect of the real ant. For instance, the commonly occurring stigmergic interactions (i.e. communication between agents via the environment) in ants are very difficult to incorporate into real robot behaviour.

(3) **By developing computer models**: In recent times, the use of simulators to develop models has proven to be another useful technique for solving such kinds of problems. Such simulators usually can accommodate massively parallel agents carrying out sets of instructions concurrently. The benefits of using a computer model are manifold, including (1) the ease by which parameters can be varied, (2) the environmental conditions can easily be altered and (3) ease of repeating simulations several times and analyse the results obtained. The approach is also relatively less expensive when compared to the other two approaches mentioned.

Within the domain of modelling social phenomena, two kinds of modelling techniques have been embraced by researchers: (1) macroscopic modelling and (2) microscopic modelling. Macroscopic modelling involves describing the overall collective behaviour of the system and not the specific rules of the individual agents. Often macroscopic modelling is expressed in terms of rate equations derived by analysing flow in compartmental frameworks [Gold, 1977; Lerman et al., 2005] and focuses on the dynamics between large groups of entities. Rate equations are commonly used but not the only approach to modelling the collective behaviour when adopting the macroscopic modelling techniques. Schmickl and colleagues [Schmickl et al., 2009], for instance, presented two approaches (namely stock and flow model and spatial model of self propelled particles) to macroscopic modelling of robotic swarms. One of the biggest disadvantages with this type of modelling techniques is that it does not take the individual variability into account [Lehmann, 2009] and often tends to smooth out fluctuations – although under certain conditions fluctuations can be amplified [Bonabeau, 2002].

On the other hand, microscopic modelling is a bottom up approach involving detailing the behavioural rules and local interactions of the individual agents and capturing the emergent phenomenon that arises over time. Agent based modelling (ABM), otherwise known as individual based modelling (IBM), is an example of such a microscopic modelling approach. Bonabeau identifies three key benefits of agent based modelling over other modelling techniques [Bonabeau, 2002]: **(1)** ABM captures emergent phenomenon, **(2)** ABM provides a natural description of the system and **(3)** ABM is flexible in the sense that the number of agents involved and their behavioural rules can be easily programmed.

For the purposes of our research, we look into how simple individuals, with given rule sets, interact with each other and the environment in the vicinity to carry out tasks collectively and redistribute part of the workforce, as needed, in response to the task demand. Our approach is thus a bottom up, microscopic approach and involves describing and establishing behavioural rules of the agents and capturing any emergent pattern that arises. Hence, the agent based modelling technique has been taken as an approach to solving the problem.

4.1.1 Modelling Environment

Netlogo [Wilensky, 1999], a programmable modelling environment for simulating natural and social phenomena, was chosen as the platform to develop the agent based model described here. The following are some of the features of netlogo that prompted its choice as the modelling environment:

(1) Netlogo is well suited for modelling complex systems that develop over time. Many naturally occurring phenomena evolve over time i.e. the emergent property stabilises with numerous local interactions. In case of the model presented in this chapter, agents collectively decide how to divide their workforce depending on the task demand. The collective decision made by the agents is an emergent property that arises through numerous interactions between the agents.

(2) Netlogo is capable of deploying hundreds and thousands of autonomous agents all following their behavioural rules concurrently.

(3) Direct interactions between agents as well as stigmergic interactions between the agents and the environment can be easily implemented.

(4) Netlogo comes with a powerful interface builder which facilitates the parameters to be varied easily.

(5) It also has a behaviour space tool which can collect data from multiple runs of a model. This can later be used to analyse the effect of different parameters on the performance of the system.

4.2 Description of the Model

One of the main objectives of this research is to design and develop a decentralised, flexible, robust and scalable task allocation model for a swarm of agents that can self organise by following some simple behavioural rules and allocate tasks dynamically in response to the needs of the colony. Similar models, in this area have been presented by other researchers (for further description of these models see chapter 3): however in most of these models, the number of tasks involved, the level of communication and the number of agents used in the simulations were limited. In this chapter, a more complex system (in terms of the communication, number of agents and tasks) has been designed and analysed to see how agents perform in such situations. Furthermore the models presented in this thesis use a number of novel strategies to improve the efficiency of the colony. A threshold based approach has been utilised in the design of the model. The microscopic behaviours of the agents were formulated on the basis of inspiration from the behaviour of ant individuals, and their tendency to vary their propensity for carrying out a task depending on (1) how successful or unsuccessful they were in carrying out tasks, (2) the task demand (stimuli of the task) and (3) interaction with other individuals.

The model, used in chapters 4 and 5, consists of an environment (2D grid world) populated with three types of agents (dynamic foragers and brood carers and static brood members), a nest comprising four chambers (dump area, brood carer chamber, brood chamber and foragers' resting area), stimuli (chemical signals, chambers' odour) and food items initially located at the top right hand corner of the environment. The topology of the world is non-torroidal – more specifically referred to as "box" as the world is bounded in all dimensions. The space is treated in discrete patches (71×51) however the movement of the dynamic agents is modelled in continuous space so that at each time step t, each agent's floating point coordinate is mapped to an integer type coordinate of the local patch. Chemical signals (pheromones and shouting chemical) are emitted by agents (laden foragers while returning to the nest and hungry brood members) while unique odours are emitted from the different chambers of the nest. Each agent possesses orientation and follows simple local rules as described later. Brood members are immobile and can either be in the *hungry* or *non-hungry* state depending on the hunger level of the individual. Foragers and brood carers, on the other hand, are mobile and can dynamically switch their roles depending on the need of the colony.

The remaining of this section gives a more detailed description of the components of the model.

4.2.1 Nest

The model consists of a nest (located at the bottom of the environment) comprising four separate chambers: one for each type of agent (brood chamber, brood carers' chamber and foragers' resting area) and a dump area for temporary storage of food (figure 4.1). The dimensions of the four chambers are as follows:

Brood chamber and brood-carer chamber: 27 × 7

Foragers' resting area: 9 × 7, and

Dump area (DA): 10 × 6

Such nest designs (consisting of separate chambers) are evident in many species of ants including that of the red harvester ants, *Pogonomyrmex barbatus* [Gordon, 1999] and leaf cutter ants, *Atta colombica.* Each of the chambers has its own odour. The odour is spread over the environment in such a way that its intensity falls linearly from its respective centre (the intensity of local stimuli is modelled discrete). Thus each of the four types of smells/ odours creates a potential gradient uphill towards their respective centre of the chamber.

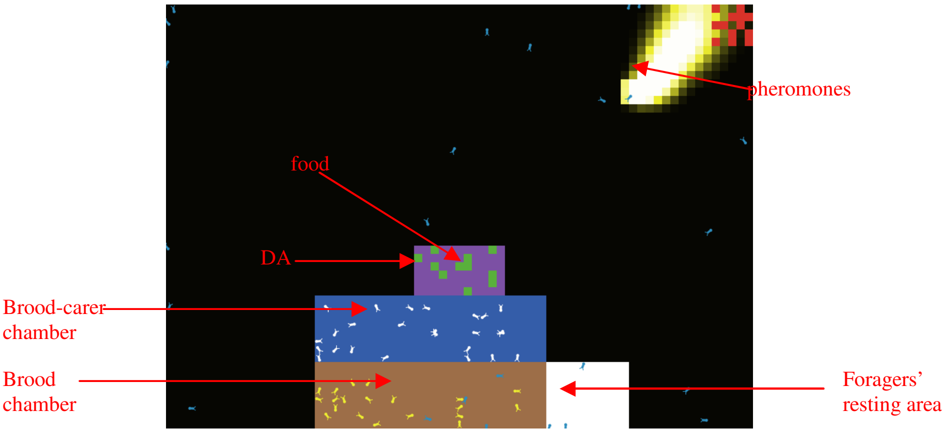


Fig 4.1: Snapshot of the model

4.2.2 Behavioural Rules

Individual agents have limited perception and communication range and follow simple local rules. This section describes the behavioural rules each agent type follows using indirect communication.

4.2.2.1 Brood

Each brood member can be in one of the two states: *hungry* or *non-hungry*. Initially all the brood members are in the non-hungry state having a randomised hunger level. At every simulation time step, the hunger level of each brood member increases by its hunger rate (eq. 4.1) which is distributed randomly between 0 and 1 across the population of brood members (Fig. 4.2). The difference in the hunger rate in individuals allows the brood members to get hungry at different instants – thus making the demand for feeding more stochastic. Furthermore, this is in line with real ants where the hunger rate of the brood members has been found to be a function of a number of factors including their appetite, the ability to communicate their hunger to the workers and also the life-stages of the brood members [Cassill and Tschinkel, 1999]. When the hunger level of a brood member exceeds some threshold (th_h), it switches its state to hungry, and seeks the attention of the brood carers by emitting a chemical signal instantaneously (termed 'shouting chemical' here) (Fig. 4.3). The strength of the shouting chemical is modelled to fall linearly with the distance from the hungry brood member so as to have its maximum strength at the location of the hungry brood member and its minimum at the periphery of the shouting-radius. The strength of the chemical is zero if the distance between a patch and the hungry brood member is more than the shouting-radius (eq. 4.3). If a hungry brood member is fed by a brood carer, the hunger level of the brood member decreases by some constant value (E_{food}; see Table 4.1) and when it falls below th_h, the brood member switches its state back to the non-hungry state (eq. 4.2) (Fig. 4.4). In the model, brood members are fed upon request i.e. the non-hungry brood members are not fed.

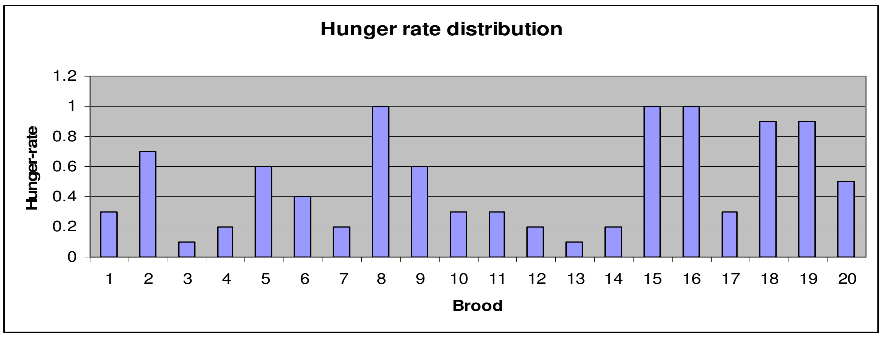


Fig 4.2: Hunger rate distribution across brood members of the brood in one of the runs

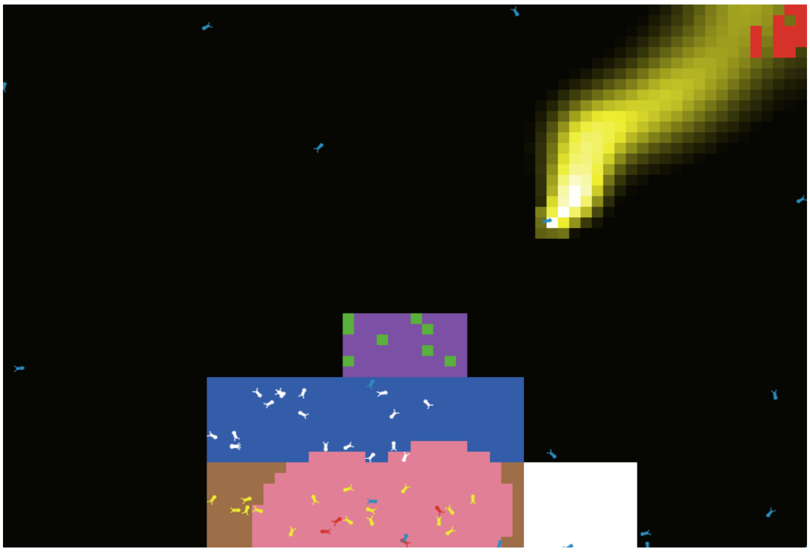


Fig 4.3: Shouting chemical emitted by hungry brood members (hungry brood member and the shouting chemical are shown in pink)

$$HL_{t+1} = HL_t + HR \qquad (4.1)$$

where $0 \leq HR \leq 1$

$$HS_t = \begin{cases} 1, & HL_t \geq th_h \\ 0, & HL_t < th_h \end{cases} \qquad (4.2)$$

Where,

HL_{t+1} is the new hunger level (i.e. at time step t + 1) of the brood member,

HL_t is the previous hunger level (i.e. at time step t) of the brood member,

HR is the hunger rate of the brood,

HS_t is the hunger state (at time step t) of the brood member;

1 = hungry state and 0 = non-hungry state, and

th_h is the threshold parameter of the hunger level.

$$C_{SC} = \begin{cases} A - Bx, \; x \leq sr \\ 0, \; x > sr \end{cases} \tag{4.3}$$

where,

C_{SC} is the concentration level of the shouting chemical,

x is the Euclidian distance from the centre of the hungry brood,

sr is the shouting radius, and

$A = sr$, B = 1.

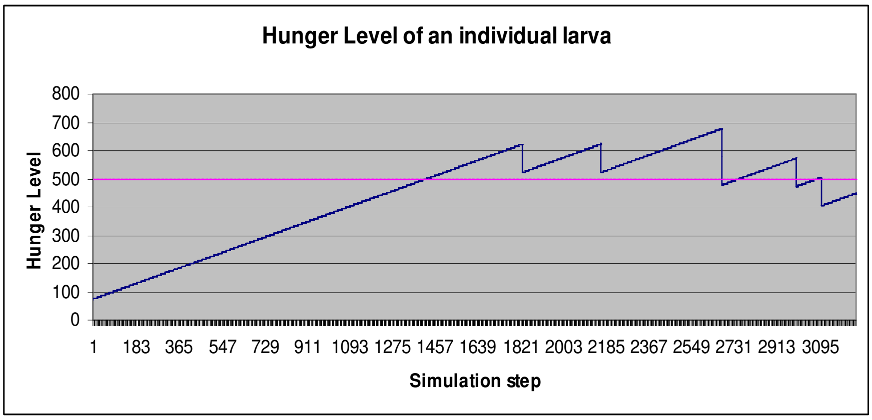


Fig 4.4: Hunger level of a brood member as a function of time (the reduction of the hunger level is due to being fed by brood carers; the pink line indicates the threshold level of the brood member to get hungry)

4.2.2.2 Brood Carers

Brood carers update their thresholds as a response to the stimuli perceived. Once a brood carer makes the decision to feed a hungry brood member (the decision making process is discussed later in this chapter), it goes to the dump area (DA) of the nest in search of food. It uses its local sensing to smell the scent of the dump area at its immediate patch ahead, patch left and ahead and patch right and ahead. The brood carer then compares the relative strength of the scents in the three directions and moves in the direction of the strongest scent. If the scents in all the three directions are equally high, the brood carer goes forward. This simple local interaction with the environment allows the brood carer to locate the DA. Once the agent reaches the dump area, it moves randomly within it to find a piece of food and when successful (i.e. when it is on the same location as that of the food item), picks the food item up and travels towards the brood chamber following the odour of the brood chamber in search of a hungry brood member.

When the brood carer reaches the brood chamber, it uses the potential gradient of the shouting chemical to go uphill in order to locate a hungry brood member. After locating a hungry brood member, the brood carer feeds it causing the brood member’s hunger level to be reduced by a constant value (in the simulation, it is assumed that all food items provide the same energy).

4.2.2.3 Foragers

The principal task of foragers is to collect food items from the environment. They start from their chamber and travel randomly in search of food items. If an agent finds a piece of food, it picks the food item up, becomes laden, rotates 180^0 and travels towards the dump area of the nest. While travelling, both foragers and brood carers wiggle (i.e. move its heading by small random angles). Wiggling allows the movement of the foragers and brood carers to be ant like. Laden foragers use local sensing to navigate around potential gradient to reach the dump area. When a forager picks up a food item, the amount of food available in the environment decreases. If the amount of food present in the environment falls below some specific value (10 units in the model), a random amount of food (between 1 and 20) is produced in the environment (in random location). Thus the amount of food available in the environment never falls to zero. As the laden agent travels towards the nest, it drops simulated chemicals called pheromones (that both diffuse and evaporate) in the environment. Once the agent reaches the DA, it leaves the food item there, evaluates what action to carry out next and starts executing the task to be carried out. When unladen agents find pheromones in the environment, they use the chemical signal to travel uphill towards the food source. If there is not enough food available in the environment it would result long searching time for the forager to find a food item. If the forager takes too long to find a food item, she abandons the foraging task, goes back to her chamber and rests for a predefined time.

4.3 Task switching mechanism

Behavioural plasticity is one of the desirable features in a multi-agent system since it enables agents to redistribute the workforce (as required) in a highly stochastic environment enabling the system to be extremely adaptive to changing environment. In this model, for instance, if there is less food (than some minimum threshold parameter) available in the dump area then task switching of some brood carers to foragers would help in coping with the changing environment. Similarly, when more brood members are hungry, switching of some foragers to brood carers and strengthening the brood carer workforce would also be a desirable behaviour. This behavioural plasticity has been implemented by means of a threshold based mechanism.

The mobile agents, at any time t, can carry out any of the three tasks: foraging, brood caring or resting. Each of the mobile agents maintains three threshold parameters: t_f (threshold for foraging), t_r (threshold for resting) and t_{bc} (threshold for brood caring). Threshold values, in the simulations, are constantly updated to meet the changing demand. Updating the thresholds updates the probability for a particular task to be chosen by an agent depending on the demand of the task and is a widely used technique for allocating tasks on the fly [e.g. Bonabeau et al., 1996; Labella et al., 2004, Liu et al., 2007a,b; Momen and Sharkey, 2008, 2009a,b, 2010]. We use a simple but effective principle (as observed from the behaviour of social insects) for updating the thresholds:

(1) The threshold value for a particular task is decreased (i.e. the probability for carrying out the particular task is increased) if either the agent has successfully completed the task (and hence is motivated to carry out the same task further) or has received a stimulus for that task.

(2) The threshold value for a particular task is increased if either an agent has been unsuccessful in carrying out the task or hasn’t experienced a stimulus for a long time.

The above two principles are built on the behaviour that many ant species are reported to have displayed [e.g. Greene and Gordon, 2007, Gordon, 2002, Theraulaz et al., 2001].

The selection of which task to carry out next is modelled in the following way:

(1) Let $T_{carryoutnext} = \arg\min\{t_f, t_r, t_{bc}\}$ where $T_{carryoutnext}$ is the next task candidate.

(2) A random number, R, is generated between 0 and 1. If $R <= 0.7$, $T_{carryoutnext}$ is selected otherwise the agent would continue carrying out the task it is currently doing.

Thresholds of mobile agents are constantly been updated in the model (described previously) over the simulation period. Whenever a threshold value needs to be changed (either increased or decreased), it is adjusted by a small value (adaptation-rate = 0.09; Table 4.1). Using the principles adopted for updating thresholds, the following behavioural rules for foragers and brood carers are formulated:

(1) If an agent perceives the shouting chemical, it realises that a brood member needs to be fed. The stimulus of feeding the brood member causes the agent to reduce its t_{bc}.

(2) When an agent is at the DA, it knows the amount of food available there from the cumulative smell of it. If the amount of food at DA is below the lower threshold of food, more food needs to be accumulated – hence it reduces its t_f and increases the t_r.

(3) Similarly, if the amount of food at DA exceeds the upper threshold of food, it does not need to do further foraging as there is already enough

food present in the DA. Rather the agent should carry out other tasks. Hence it increases the t_f and reduces the t_{bc} and t_r.

(4) When a brood carer goes to the DA of the nest to pick up a piece of food in order to feed a hungry brood member, it finds the food by walking randomly inside the DA. It also keeps track of how long it is searching for food inside the dump area. If the searching time exceeds some critical allowed time (50 time steps), it reduces its t_f and increases t_{bc} since there is not just enough food in the DA.

(5) If a forager is searching for a food item for a long time and is unsuccessful, it assumes that there is not enough food in the environment. Hence it reduces the t_r and increases its t_f.

(6) Both foragers and brood carers keep timing records of how long they have rested for inside the chamber. If the resting time exceeds some allowed time (50 time steps), they increase their t_r (for both foragers and brood carer) and reduce the t_f (if it is a forager).

(7) If a forager is successful in bringing a food item back to the environment, it gets a positive reward and reduces its t_f.

At any time the thresholds are bounded between -5 and +5. If the threshold exceeds + 5, that threshold is set to the maximum possible value for the threshold (+5). Similarly if the threshold value is below -5, it is set to the lowest possible value of the threshold which is -5.

4.4 Parameters Used

The list of parameters used is outlined in table 4.1.

Parameter	Meaning	Value(s) used
N_b	Number brood members	5 – 20, 50
S	Number of mobile agents (i.e. number of foragers [N_f] + number of brood carers [N_{bc}])	20 – 100
$R_{f\text{-}bc}$	Initial ratio of foragers to brood carers. This can be used to determine the number of foragers and brood carers as follows: $N_f = \lfloor R_{f-bc} \times S \rfloor$ $N_{bc} = S - N_f$	0.2, 0.5, 0.9
$E_{pheromones}$	Evaporation rate of pheromones	5%
$D_{pheromones}$	Diffusion rate of Pheromones	60%
Adaptation-rate	The rate at which the thresholds are adapted	0.09
Shouting-radius	The number of patches the brood member can shout when it gets hungry	7
E_{sc}	Evaporation rate of shouting chemical	50%

U_{food}	Upper threshold of food	40
L_{food}	Lower threshold of food	5
max-separate-turn	The maximum angle an agent can turn when avoiding another agent	1.25^0
E_{food}	Energy provided by the food which causes the hunger level of the brood member fed to decrease	100
Th_h	Threshold parameter of the hunger level	500

Table 4.1: Parameters used in the model

4.5 Measure of Performance

The performance of the task allocation strategy is measured by the mean hunger level of the brood at the end of the simulation. As an example, if there are 5 brood members and their corresponding hunger levels at the end of the simulation are 510, 515, 520, 500 and 500, then the mean hunger level would be

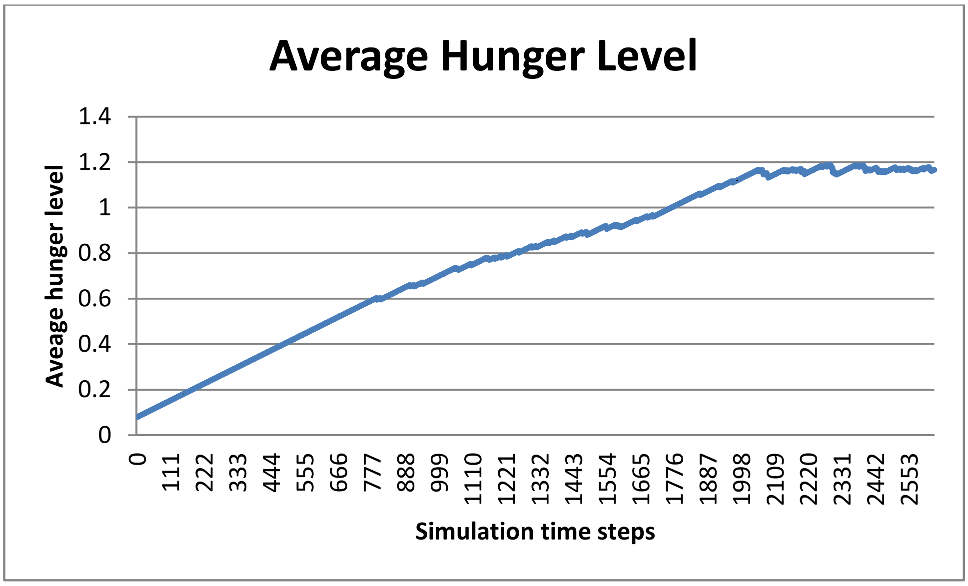
$$\frac{\sum\limits_{\forall brood-members} HL}{n_b} = \frac{2545}{5} = 509$$

For the purpose of evaluating the performance of the task allocation strategy, the following measure has been used:

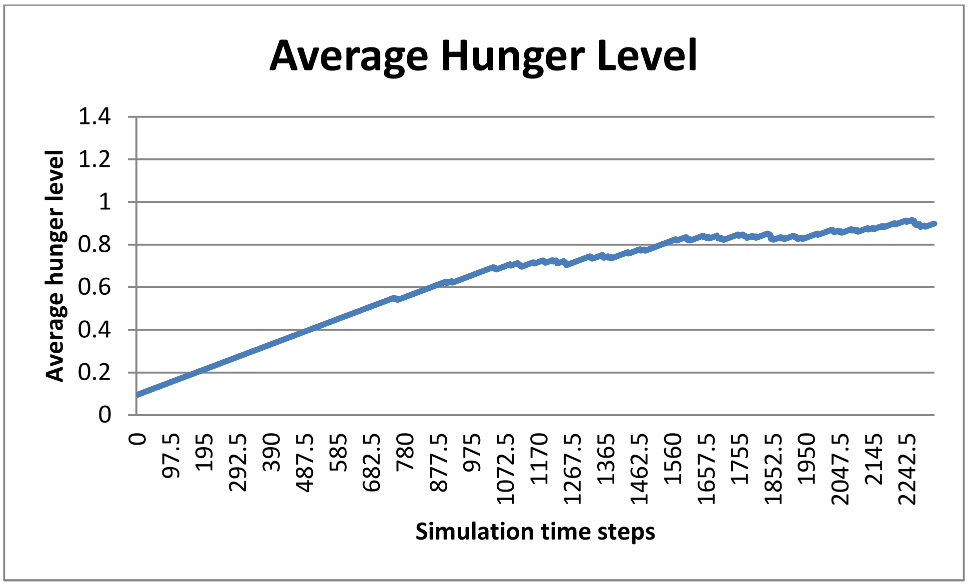
$$A.H.L. = \frac{\sum\limits_{\forall brood-member} HL}{th_h \times n_b} \tag{4.4}$$

where th_h is the threshold parameter of the hunger level and *A.H.L.* is the average hunger level of the brood. It needs to be noted here that since our objective is to regulate the hunger level of the brood, the lower the value for *A.H.L.* we obtain, the better is the performance of the strategy used.

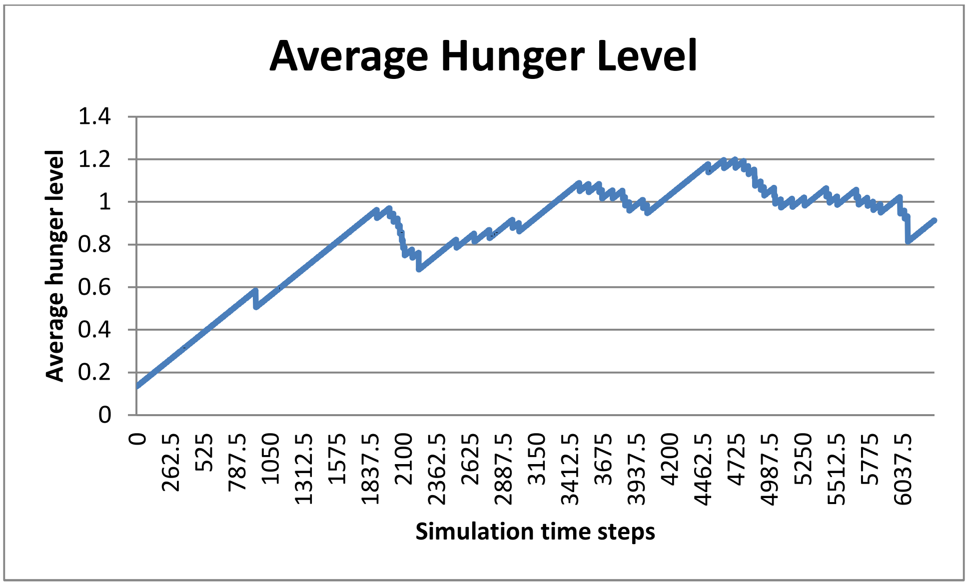
Figure 4.5 shows how the characteristic curve for *A.H.L.* varies under different sets of parameters. As evident from figure 4.5, the *A.H.L.* initially increases linearly followed by a non-linear curve indicating that the system is trying to regulate the hunger level. The initial linear increase of the *A.H.L.* is due to the linear rise of the hunger level of the brood members (below the Th_h) during the initial duration for the brood carers to start bringing food items back to the hungry brood member. When the hunger level is below Th_h, brood members do not advertise that they are hungry. However when the hunger level of the brood member exceeds Th_h, it advertises its hunger by emitting shouting chemical. As hungry brood members are being fed, the overall rate of hunger level falls resulting the nonlinear curve in figure 4.5. Finally as the agents are able to meet the requirements of the hungry brood members, the curve starts getting more and more flat. However, there is always some fluctuation due to the constant increase of the hunger level of the brood members at their corresponding hunger rate.



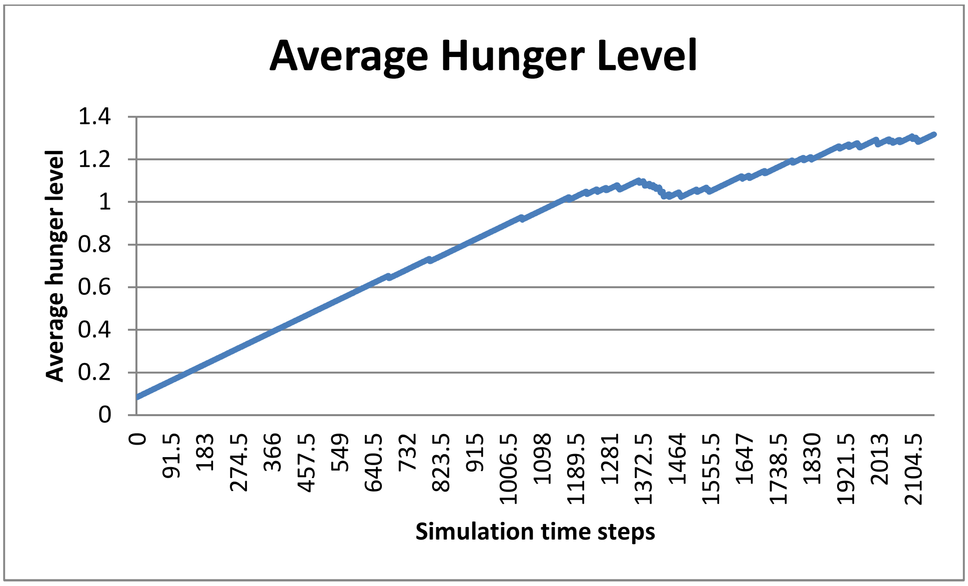
a. $N_b = 25$, $S = 60$, $R_{f\text{-}bc} = 0.2$



b. $N_b = 25$, $S = 60$, $R_{f\text{-}bc} = 0.9$



c. $N_b = 5$, $S = 30$, $R_{f\text{-}bc} = 0.2$



d. $N_b = 15$, $S = 40$, $R_{f\text{-}bc} = 0.2$

Fig 4.5: Average hunger level of the brood (N_b = number of brood members, s = number of foragers and brood carers and $R_{f\text{-}bc}$ = initial ratio of foragers to brood carers)

4.6 Results Obtained

The model is designed by taking inspirations from the behaviour of ant colonies and is expected to build a system that would be scalable, flexible as well as robust. In order to test if the behavioural rules designed (discussed in Section 4.2 and 4.3) lead to such a system, a series of experiments have been conducted. Each simulation, for a particular experiment, is run 20 times for 5000 simulation time steps. The mean readings from the 20 simulations runs are then calculated from which the performance of the task allocation mechanism is evaluated. Experiments were conducted to obtain the answers to the following questions: Is the system that emerges (1) scalable?, (2) flexible? and (3) robust?

A. Is the system scalable?

A system is said to be scalable if it can operate under wide range of group sizes [Şahin, 2005]. The performance of the swarm can vary with the number of agents involved – however increases or decreases should not prevent the system from operating. Swarm intelligence systems are highly decentralised systems which ensure the scalability of the swarm. To test if the system is scalable, experiments have been carried out with various swarm and brood sizes. The results are presented in figure 4.6.

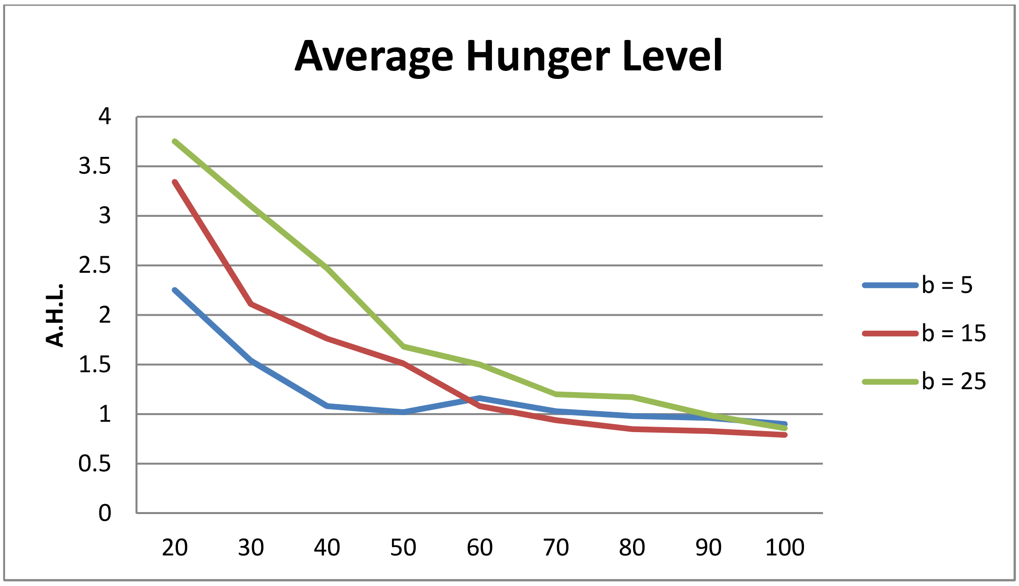


Fig 4.6: Average hunger level of the brood as a function of the swarm size (where x-axis represents the total number of foragers and brood carers and A.H.L. = average hunger level at the end of the simulation run)

From figure 4.6, it is evident that an increase in the size of the swarm reduces the average hunger level of the brood members and hence improves the performance of the system. It can also be seen from figure 4.6 that with greater number of brood members the average hunger level increases and vice versa. However, with the increase in the number of foragers and brood carers, the average hunger level decreases and hence the system performs better. Furthermore, it should be noted that the operation of an individual agent is not dependent on any other agent(s) – hence the system functions fully with different group sizes – however the performance of the system depends on a number of factors including swarm size, availability of food and the hunger level of the brood members. For the purpose of scalability tests, the number of dynamic agents is varied between 20 and 100 (for other tests, the number is limited between 20 and 60) to check if the average hunger level unexpectedly increase with the number of dynamic agents or not.

Since (1) the agents are completely decentralised and (2) the performance improves with the increase in the number of worker agents, the swarm exhibit scalability.

B. Is the system flexible?

A system can be called flexible if it has the ability to distribute agents dynamically in response to the changing demand. The system might start with some initial configuration (for instance with some particular ratio of the agents allocated to the tasks) but it should be able to adapt the number of agents in response to the task demand.

In order to test the flexibility of the system, experiments were conducted with the same value of S (number of foragers + number of brood carers) but different $R_{f\text{-}bc}$ (initial ratio of foragers to brood carers)[0.2, 0.5, 0.9]. Each experiment was repeated 20 times for 5000 simulation steps and the average hunger level for every run was recorded. The experiment is then repeated in this fashion but with different values of S (ranging between 20 and 60) and brood sizes (5, 15, 25).

Now, if the system is flexible, it should be expected that a similar *A.H.L.* should be obtained for the same brood and swarm sizes even if there is a difference in the initial ratio of the foragers to brood carers. The system modelled is highly stochastic and hence statistical measures have to be taken into account in order to scrutinise the differences. The mean values of the *A.H.L.* of the brood with different values of S and $R_{f\text{-}bc}$ (“r” is used for simplicity) are shown in Table 4.2 and Table 4.3.

	S=20, r=0.2	S=20, r=0.5	S=20, r=0.9	S=30, r=0.2	S=30, r=0.5	S=30, r=0.9	S=40, r=0.2	S=40, r=0.5	S=40, r=0.9
$N_b = 5$	2.21	2.59	2.25	1.43	1.47	1.54	0.97	1.07	1.08
$N_b = 15$	3.37	2.78	3.34	2.11	2.51	2.11	1.85	1.82	1.76
$N_b = 25$	3.73	3.55	3.75	2.74	2.93	3.10	2.24	2.40	2.47

Table 4.2: Mean Hunger Level

	S= 50, r = 0.2	S= 50, R = 0.5	S= 50, r = 0.9	S= 60, r = 0.2	S= 60, r = 0.5	S= 60, r = 0.9
$N_b = 5$	0.91	1.03	1.02	0.94	1.05	1.16
$N_b = 15$	1.19	1.40	1.51	0.94	0.82	1.08
$N_b = 25$	1.43	1.90	1.68	1.26	1.40	1.50

Table 4.3: Mean Hunger Level

Each of the mean values shown in Table 4.2 and 4.3 are the results of average of 20 trials. If the system is flexible, it is expected that the initial ratio of the agents (i.e. r) should not influence the *A.H.L.* rather the agents would constantly switch tasks to serve the demand of the system. To test the flexibility, therefore, a significance test needs to be carried out.

There are two types of statistical tests (namely parametric and non-parametric tests) that can be conducted on the data sets to check if they significantly differ from each other or not. One of the differences between the two tests is that the parametric test assumes that the data sets are normally distributed whereas on the other hand, non-parametric tests do not make any assumption on the distribution of the data. Therefore, in order to decide which test to carry out, the data sets need to go through normality tests.

To check for normality, one can either conduct Kolmogorov-Smirnov test (also called KS test) or Shaprio-Wilk test. KS test is usually preferred for large sample size whereas Shapiro-Wilk test is preferred for sample size < 50 although it can be applied to large sample sizes. In our case, the sample size is less than 50 and therefore the Shapiro-Wilk test is preferred to check for normality.

SPSS (statistical package for social science) is used to carry out all statistical analyses. Table 4.4 indicates the results for the normality tests carried out on the data sets with brood size = 5.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	Df	Sig.
B=5 s =20 r = 0.2	.148	20	.200*	.932	20	.172
B=5 s=20 r=0.5	.207	20	.025	.850	20	.005
B=5 s=20 r=0.9	.118	20	.200*	.967	20	.699
B=5 s=30 r=0.2	.179	20	.091	.921	20	.104
B=5 s=30 r=0.5	.212	20	.019	.755	20	.000
B=5 s=30 r=0.9	.223	20	.011	.734	20	.000
B=5 s=40 r=0.2	.213	20	.017	.853	20	.006
B=5 s=40 r=0.5	.396	20	.000	.666	20	.000
B=5 s=40 r=0.9	.273	20	.000	.797	20	.001

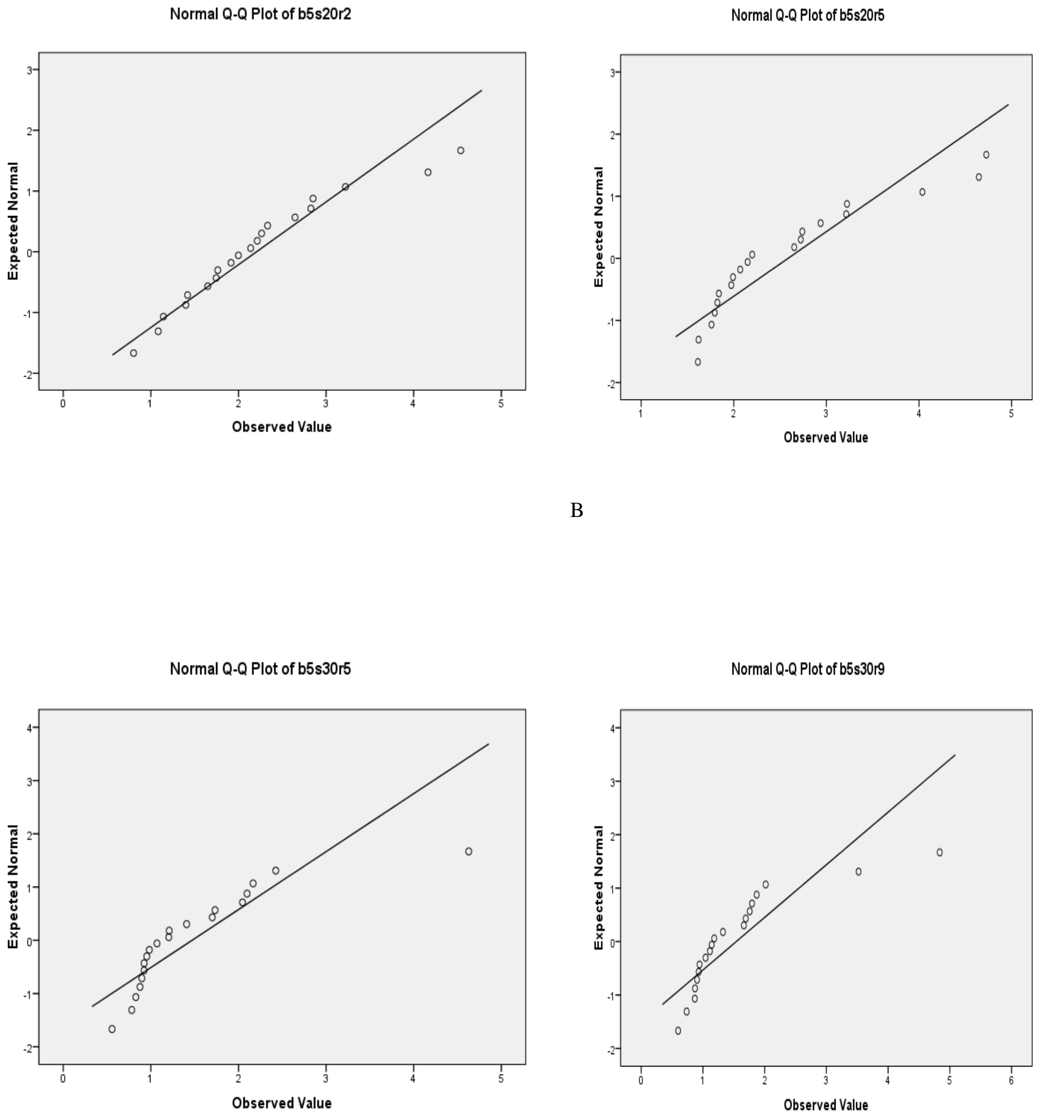
B=5 s=50 r=0.2	.260	20	.001	.808	20	.001
B=5 s=50 r=0.5	.321	20	.000	.688	20	.000
B=5 s=50 r=0.9	.283	20	.000	.790	20	.001
B=5 s=60 r=0.2	.337	20	.000	.744	20	.000
B=5 s=60 r=0.5	.334	20	.000	.560	20	.000
B=5 s=60 r=0.9	.312	20	.000	.644	20	.000

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

Table 4.4: Normality tests on data sets with brood size = 5

Shapiro-Wilk test assumes that if the significant value (the last column of table 4.4) is greater than 0.05, then the data is normally distributed otherwise the data significantly deviates from normal distribution. From table 4.4, it is evident that although for some data sets the significance value is greater than 0.05 (i.e. the data set is normally distributed), there are also some data sets where Shapiro-Wilk's significance value is less than 0.05 and hence the data sets deviate significantly from the normal distribution. Since some data sets deviate significantly from normal distribution, it is preferred to refrain from assuming any distribution of the data. Hence, non-parametric tests are preferred to that of the parametric tests. Figure 4.7 shows quantile-quantile (Q-Q) plots of some of the data sets that were tested for normality.



A

B

C

D

Fig 4.7: QQ plot for brood size = 5 and (a) S = 20, r = 0.2, (b) S = 20, r = 0.5, (c) S = 30, r = 0.5, (d) S = 30, r = 0.9

QQ plots also show how closely the data sets resemble normal distribution. If the data sets on the QQ plot are close to the diagonal line, the data set can be considered to be normally distributed. The data sets in figure 4.7 (A) & (B) are close to the diagonal line and hence can be said to conform normal distribution. However, the data sets in figure 4.7 (C) & (D) are clearly distant from the diagonal line and therefore the data sets in figure 4.7(C) and (D) do not follow normal distribution. This graphical interpretation is in agreement with the results shown in Table 4.4. Now, that it has been confirmed that some data sets deviate significantly from normal distribution, the use of non-parametric tests compared to that of the parametric tests is strongly justified.

From this onwards, in matters of using statistical tests, the following principles are adopted. The principles adopted are in line of standard statistical practices [Greene and D'Oliviera, 2006; Sokal and Rohlf, 1981].

1. Non parametric tests are used since no assumption is made regarding the nature of the distribution of data. Use of parametric tests could have been well justified if the distributions of the datasets follow normal distribution. However, the results presented above shows that many of the data for average hunger level significantly deviate from normal distribution and hence the use of non-parametric tests is preferred.
2. If there exists more than two experimental conditions, a Kruskal Wallis test using Bonferroni correction is performed to check if the data sets across the experimental conditions significantly differ from each other or not. However, if the experimental conditions tested are limited to only two, a planned comparison using Mann Whitney tests is performed.
3. If the Kruskal Wallis test (using Bonferroni correction) reveals significant difference in the data sets across the experimental conditions, planned comparison Mann Whitney tests are performed to analyse if two chosen data sets significantly vary from each other or not.

4. For data sets that reject the null hypothesis on Mann Whitney tests, a Bonferroni correction is furthermore used to find which data sets reject null hypothesis under a very stringent test.

If the system is flexible, the average hunger level (*A.H.L.*) should not significantly differ as long as the brood size and the number of agents stay the same (whatever the initial ratio of the foragers to brood carers be). A Kruskal-Wallis test was chosen to check if such is the case or not. Table 4.5 summarises the results obtained using the Kruskal-Wallis test.

Test Statistics[a,b]

	Data
Chi-Square	1.517
Df	2
Asymp. Sig.	.468

a. Kruskal Wallis Test

b. Grouping Variable: r

I.

Test Statistics[a,b]

	Data
Chi-Square	.035
Df	2
Asymp. Sig.	.982

a. Kruskal Wallis Test

b. Grouping Variable: r

II

Test Statistics[a,b]

	Data
Chi-Square	.260
Df	2
Asymp. Sig.	.878

a. Kruskal Wallis Test

b. Grouping Variable: r

III

Test Statistics[a,b]

	Data
Chi-Square	.744
Df	2
Asymp. Sig.	.689

a. Kruskal Wallis Test

b. Grouping Variable: r

IV

Test Statistics[a,b]

	Data
Chi-Square	2.908
Df	2
Asymp. Sig.	.234

a. Kruskal Wallis Test

b. Grouping Variable: r

V

Table 4.5: Kruskal-Wallis tests for brood size = 5 and (I) S = 20, r = 0.2, 0.5, 0.9, (II) S = 30, r = 0.2, 0.5, 0.9, (III) S = 40, r = 0.2, 0.5, 0.9, (IV) S = 50, r = 0.2, 0.5, 0.9, (V) S = 60, r = 0.2, 0.5, 0.9.

Kruskal-Wallis test assumes:

H_0 (null hypothesis): $M_1 = M_2 = M_3$ i.e. the medians do not significantly vary

H_1 (alternative hypothesis): the median of the three data sets significantly deviate from each other.

If the p-value of the Kruskal-Wallis test < 0.05, then H_0 is rejected. The significant value is always found to be greater than 0.05 (table 4.5). Therefore the null hypothesis is accepted and it is concluded that data sets do not significantly vary from each other for the same swarm size but different initial ratio of the foragers to the brood carers. Consequently, it means that the ratio (r) is irrespective with the mean hunger level i.e. whatever the initial configuration is, the agents self organise depending on the task demand (which means the system is highly flexible). Tests with brood size = 15 and 25 also reveals that initial ratio (r) does not affect the average hunger level of the brood.

Figure 4.8 (a and b) depicts two situations in which agents constantly switch their states in order to respond to the changes in the hungry broods' demands.

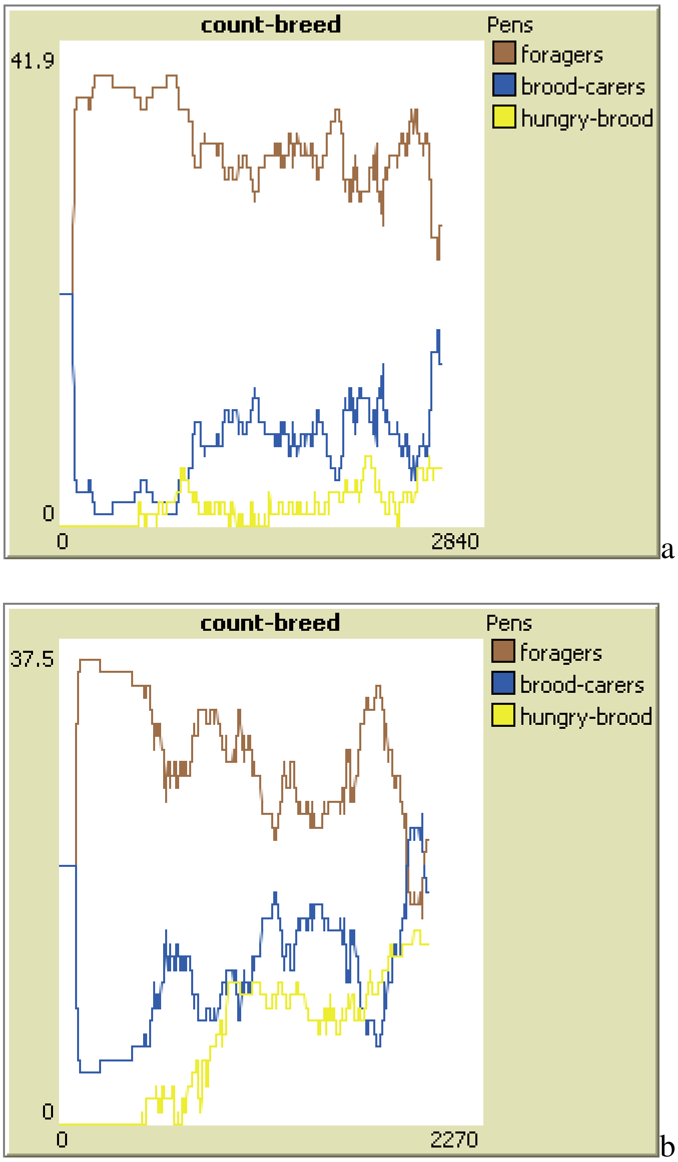


Fig 4.8: Variation of foragers and brood carers in order to respond to the changing demand by the brood: a) brood size = 10, total number of foragers and brood carers = 40; b) brood size = 20, total number of foragers and brood carers = 40.

The agents constantly switch their states in order to meet the changing demand. Initially, there are low numbers of brood carers since brood members are initially not hungry. But as the number of hungry brood increases, more agents start switching from the foraging task to the brood caring task resulting in an increase in the number of brood carers. When the demand for brood caring is high, as in Fig 4.8 (b) compared to that of Fig 4.8 (a), the number of agents switching to foraging task is also high – thus trying to regulate the demands. The reader is advised to refer to Chapter 5 (Section 5.4) for a further explanation of this behaviour.

Since it has been found that there is no statistical difference between the average hunger level of the colony despite different initial ratio of foragers to brood carers, it implies that the agents can switch comfortably to meet the demand of the colony i.e. the swarm exhibits flexibility.

C. Is the system robust?

Robustness refers to the ability of the system to continue to operate (although at lower performance) despite failures of the individuals or perturbations in the environment [Şahin, 2005]. Self-organised systems are, in general, robust due to a number of factors including (1) decentralised coordination, which ensures that the system does not depend on any particular agent and hence does not suffer from any bottlenecks, (2) redundant homogeneous agents, which ensures that even if some agents do not function properly, there would be other agents to take up the job and (3) numerous local interaction between the individuals, which allows the stimulus of any task to propagate within the swarm even if some agents do not function properly. The model presented in this chapter has these three attributes (i.e. decentralised coordination, redundant homogeneous agents and numerous local interactions between the agents) and therefore can be expected to operate in a robust manner.

To establish whether the model is robust or not, the model presented initially has been altered in the following ways:

1. The agents operate normally in the way described in the original model.

2. Except that at the 500th simulation time step, 10 random agents (foragers or brood carers or a mixture of both) are removed.

3. Experiments were carried out with brood size = 15 in the same manner as previous experiments (i.e. each experiment was repeated 20 times and the average hunger level has been recorded). Experiments were repeated with S = {20, 30, 40, 50} each repeated 20 times.

Figure 4.9 shows the comparisons of the results obtained when 10 agents malfunction in the middle of the operation to the results obtained from the original model where all the agents continue to function fully.

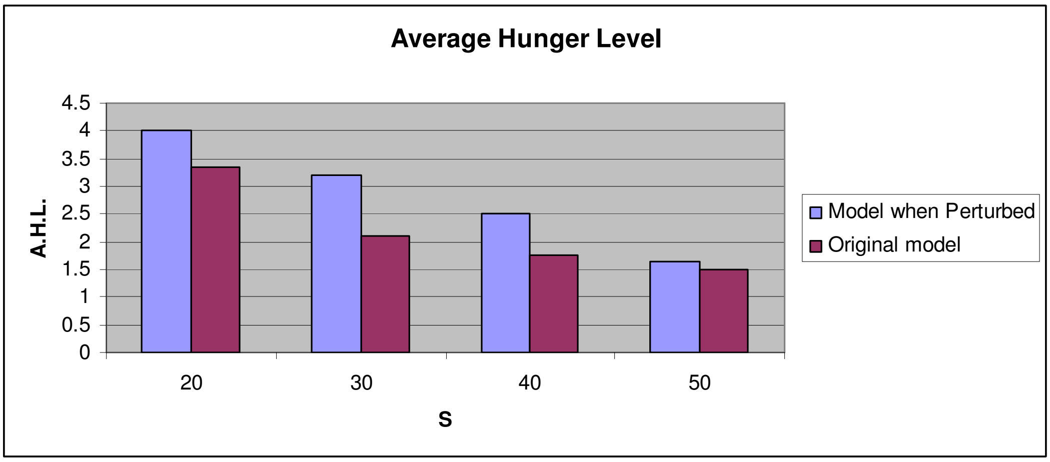


Fig 4.9: Robustness of the model (s = total number of foragers and brood carers and A.H.L. = average hunger level of the colony at the end of the simulation)

It is apparent from Figure 4.9, that the model continues to operate (although at a slightly reduced performance) even when 10 agents malfunction during the course of the experiments, indicating that the model presented is robust. Furthermore, it is evident from figure 4.9 that the robustness of the system improves with the number of the dynamic agents. This is because when there is greater number of redundant agents available, then the likelihood of another agent taking up the job of a malfunctioned agent is more.

4.7 Discussion

It is claimed that the results obtained from this model are coherent with what is observed in the real ant-world. Ant colonies are known to be extremely flexible and hence adaptive to the changing demand. For example, Greene and Gordon reported that they extracted and isolated the cuticular hydrocarbons of the patrollers of the red harvester ants [Greene and Gordon, 2007]. Patroller mimics were then created by coating a bead with one ant equivalent of hydrocarbons. The beads with coated hydrocarbon profile were then thrown in front of the nest entrance to see if the patroller mimics caused the ants in the nest to come out and forage [In red harvester ants, the return of successful patrollers trigger foraging activity]. When the rate of simulated patroller return was increased, the rate of foragers coming out of the nest was found to increase. Gordon, in another experiment, changed the condition of the environment by placing a pile of toothpicks in front of the nest entrance. This causes a barrier for the foragers and patrollers to come out of the nest and carry out the foraging task. Gordon reported that in such conditions, it was found that there was an increase in the number of nest maintenance workers i.e. workers residing deep inside the nest were found to be shifted to nest cleaning work indicating that they were flexible towards the changing environment. Theraulaz et al., in 2001, discusses flexibility observed in the ponerine ants. The workers of *E.ruidum* ant species work as either stingers or transporters depending on the circumstances. When live drosphila (fruit flies) are presented to the colony, the ants start behaving as stingers. As more drosphilas fall off, the need for transporting these increases and consequently the ants shift part of the work force from stingers to transporters in order to meet the demand for transporting the drosphilas. This shows how easily ant individuals can adapt to the changing demand.

The model shows close resemblance to the behaviour of ant colonies in many ways including the emergence of a system that is (1) scalable, (2) robust and (3) flexible. The threshold based techniques employed in this model are similar to the adaptive threshold based techniques employed in various models. However, in our models each agent uses three thresholds and the competition between the thresholds gives rise to the task the agent is going to carry out next. Furthermore, unlike many early models, the model described in this chapter captures all the basic features of eusocial insects as described by Wilson [Wilson, 1971] (i.e. division of labour, overlapping of generations (e.g. brood and workers) and cooperative brood caring for the hungry brood members).

4.8 Conclusion

A task allocation and task switching model for a simulated swarm of autonomous mobile agents has been presented here. The model contains a rich set of interactions between agents. The communication between agents, presented in this model, is stigmergic. The model employs a threshold based approach for adapting to changing demands and is strongly inspired by the behaviour of eusocial insects. Simple local rules have been developed for the agents that allow them to self organise and adapt to the changing environment as needed by the colony. With the simple behavioural rules, the modelled swarm demonstrates:

(1) An improved performance with increases in the size of the swarm (which makes it scalable)

(2) Flexibility between workers, and

(3) Robustness to the perturbations of the environment

A performance measure for the model has also been presented which will be used in later chapters (Ch-5 and Ch-6) when comparing different task allocation strategies.

Chapter 5

Performance Analysis of Explicit and Indirect Communication

Effective communication is an extremely vital element for the enormous success that insect colonies accrue. Social insects constantly face numerous challenges including environmental disruptions (e.g. nest damages by flood, wind etc…), predator attacks, pathogens and even inter-colonial disturbances. Besides external perturbations, insect societies also face constant challenges from within the colony (including the need for nurturing the young brood members, cleaning and repairing of nests, food retrieval and processing, guarding nests and so on). In order to cope with both external and internal challenges, ant colonies need to develop effective communication mechanisms. In fact insect societies are known to employ wide range of communication mechanisms depending on need and circumstances. Means and strategies of communication usually vary from one colony to another and depend on a wide number of factors (including environmental conditions, nest complexity, size of the colony and urgency of the task that is needed to be carried out).

Of various communication mechanisms, indirect communications among nest-mates stand out as being very common. In indirect communication, nest-mates usually communicate with each other via the environment (e.g. through the deposition of volatile chemicals as a means of signalling other nest-mates). Intriguingly, many ant species are also found to use explicit communication in conjunction with indirect communication. Explicit communications are exhibited within a shorter radius than that of indirect communication and involve the use of one-to-one direct communication between the individuals. Unfortunately, in contrast to indirect communication, research related to the benefits of explicit communication is very limited. In this chapter, an attempt is made to investigate the benefits of explicit and indirect communication in a simulated colony of ants. Particularly, the question that is posed in this chapter is whether the use of explicit communication along with that of indirect communication would bring any benefit to the colony in relation to circumstances in which they use indirect communication alone.

The rest of the chapter is organised as follows: Section **5.1** begins with a detailed discussion of various modalities of communication used by eusocial insects (typically ants). After the discussion of communication in social insects, an investigation of the various strategies of communication across a range of genus is highlighted. Following this, in section **5.3**, a description of the proposed model is given. The results obtained from section **5.3** are analysed in section **5.4**. Finally, in section **5.5,** the chapter is concluded with some remarks on the results obtained.

5.1 Communication in eusocial insects

Social insects demonstrate a wide range of communication modes [Billen, 2006; Jackson and Ratnieks, 2006] that include at least visual, acoustic, tactile, magnetic and chemical means. Mechanisms of communication between individuals are mostly local and are exhibited through the transmission of signals (which can be of various forms). A signal, in biological aspects, can be formally defined as *any act or structure which alters the behaviour of other organisms, which evolved because of the effect, and which is effective because the receiver's response has also evolved* [Smith and Harper, 2003]. The definition has some implications and therefore needs some explanation. When signalling occurs, the behaviour of the receiver tends to alter in a way that is favourable to the signaller. For instance, if a stag pushes another stag backwards, it cannot be considered as a signal rather can be referred to as coercion. However, if the stag roars and this causes the other stag to retreat, then it can be referred to as a signal. This is because the action of the retreating stag depended on the evolved properties of the brain and the sense organs of the receiver [Smith and Harper, 2003]. The definition also clearly separates signal from cue, a term first coined by Lorenz [Lorenz, 1939]. A widely accepted definition of cue was provided by Hasson where he defined cue as *any feature of the world, animate or inanimate, that can be used by an animal as a guide to future action* [Hasson, 1994]. Hölldobler and Wilson consider a cue to be a stimulus that can be used to convey information but has not been shaped by natural selection to serve as communication signal [Hölldobler and Wilson, 2008].

For the remaining of this section, different communication mechanisms exhibited by eusocial insects (and typically ants) are discussed.

5.1.1 Visual communication

Evidence for visual communication in ants and other social insects is weak in comparison to the rich evidence of tactile and chemical communication [Billen, 2006; Hölldobler and Wilson 2008]. However there exist some species, such as the genus *Cataglyyphis* and *Gigantiops*, with large eyes that are known to use vision to detect moving prey, although unfortunately the actual mechanism for such communication is not very well understood. Some species of ants are known to use visual cues to navigate. Desert ants, for instance, are not keen on using chemical signals to navigate due to the high rate of evaporation of the chemicals in hot desert. Instead it is believed that these species use the polarized light of the sun [Wehner, 2003] to reach their destination. It is also known that bees use visual cues (such as the sun) to find new hive during house hunting.

5.1.2 Acoustic communication

Many ant species are known to use vibrational signals in conjunction with other commonly used signals (such as the chemical signals) to communicate. Two forms of vibrational signals are often noticeable in various species: (1) body rapping against substratum and (2) stridulation (i.e. rubbing of specialised body parts to produce a "chirp") [Hölldobler and Wilson, 1990]. The vibration of sound waves through air as a means of communication is found to be the least probable. Instead, in most cases the medium of vibration happens to be via the soil, nest wall or other solid substratum. This is most likely due to the fact that most ants are nearly deaf to airborne vibrations but sensitive to vibrations through substratum [Fielde and Parker, 1904; Haskins and Enzmann, 1938]. Entomologists believe to have pinpointed at least three functions of stridulation in various species and castes of ants [Hölldobler and Wilson, 1990].

1. Leaf cutter ants, *Atta* are found to have used stridulation as an underground alarm system in conjunction with other signals such as high concentrated volatile chemicals.

2. Young queens of *Pogonomyrmex* (harvester ants) ants are often found to use stridulation during the mating process. These ants usually gather in the vegetation or ground during their nuptial flight where stridulation would be effective. During the mating process, when the spermathecae of the queens become filled, they stridulate vigorously signalling the male ants to stop the courtship procedure. To the best of our knowledge, not a single case has so far been encountered where the queens use stridulation as a means of attracting the male ants.

3. Some species of ants (for instance, *Leptogenys* and *Messor* genus) are found to employ stridulation in conjunction with pheromones to recruit nestmates for foraging.

5.1.3 Magnetic orientation

Banks and Srygley suggested the possibility for leaf cutter ants to use magnetic cues [Banks and Syrgley, 2003; also see Riveros and Srygley, 2008] to orient during foraging. In experiments with leaf cutter ants (*Atta colombica*), they tested the orientation of the ants under magnetic fields of reversed polarity. With the sun's disc unobstructed by the cloud, ants were not found to be affected by the reversed polarity of the magnetic field. However, in gloomy environments, the experimental treatment was found to have significantly shifted their mean orientation both in comparison with controls and reversed-polarity ants under the sky. Although a total reversal in orientation was not obtained, they consider that the possibility of the use of magnetic cues to navigate still remains. The ability of other ant species to perceive earth's magnetic field has also been demonstrated by many researchers [e.g. see Anderson and Meer, 1993; Avalos et al., 1999].

5.1.4 Tactile communication

Tactile communication is one of the most frequently used communication techniques in ant species. Ants (such as *Pogonomyrmex barbatus*) often use brief antennal-antennal contact to access the cuticular hydrocarbon profile of another to determine the task it is carrying out [Greene and Gordon, 2003]. Other forms of tactile communication include grooming brood members, tapping the abdomens of the leaders during tandem running [Franks and Richardson, 2006] and also during trophallaxis (exchange of liquid food from the crop of one ant to the alimentary tract of the other ant). All these forms of tactile communication are believed to be used to transmit messages. Antennae-antennae interaction, for instance, is a means to quickly propagate the information about the available tasks within a colony. Tandem running is a technique adopted by many species of ants whereby one ant leads another ant towards a particular destination. For instance, during house hunting in

Leptothorax albipennis ants, they display a range of interesting behaviours. Initially ants repeatedly explore the potential nest site to decide if the new nest site is a plausible habitat or not. They also recruit naive nest-mates via tandem running from the old nest to the new one so that they can participate in nest evaluation and subsequent recruitment. After a quorum of decision makers at the new nest is reached and they collectively decide to emigrate to the new nest, ants switch from the slow process of leading other ants via tandem running to a much faster process of carrying the nest-mates at their back. Ants are also found to exhibit brief antennal contact when visiting and assessing a candidate nest. For further information, refer to [Pratt, 2005].

Trophallaxis in ants is believed to serve two main purposes:

1. To inform the individual colony members of the nutritional state of the colony as a whole. It results in conveying messages to the foragers of what type of food is required.

2. To transmit pheromones with the liquid as it is ingested or regurgitated.

5.1.5 Chemical communication

Chemical communication is the most frequently used communication mode in social insects. Ants are the masters at using chemical signals to talk to other fellow nest mates. They use chemical signals for a wide range of activities. Some of them include recruitment of nestmates for foraging, in alerting nestmates from intruders or any possible dangers (alarm pheromones), to distinguish between friend and foe, to attack intruders by stinging venomous chemicals onto the body of the intruders (e.g. by fire ants *Solenopsis invicta*) and also in communicating the individual's hunger level.

5.1.6 Classification of communication methods

All these forms of communication can however be classified under two categories: 1) Indirect communication and 2) Explicit communication. In indirect communication, ants do not communicate with each other directly but rather make use of the environment to pass messages. This passive means of interacting with each other is extremely common in social insects and is often referred to as stigmergic interaction [Grassé, 1959]. Direct communication on the other hand includes passing a message or signalling directly to another ant without any intermediary medium. In the previous chapter (Chapter 4), a model for decentralised task allocation was proposed that is based on the behaviour of eusocial insects. The communication mechanisms employed in that model were indirect. However, in biological ant colonies, some degree of explicit communication takes place between colony members. In this chapter, the model proposed in chapter 4 is extended to include some degree of explicit communication and investigate whether, when explicit communication is used, any benefit is obtained over the commonly used indirect communication only. For explicit communication, the virtual ants use direct communication with each other along with the stigmergic interaction. In indirect communication, however, there is no direct communication between individuals.

5.2 Communication and Specialisation

Bourke, in 1999 [Bourke, 1999], used the term "simple" and "complex" to categorise ant species based on the following four criteria: (1) morphological differences between reproductive individuals and workers, (2) existence of physical castes polymorphisms among workers, (3) nest complexity and (4) communication systems. Anderson and McShea expanded the Bourke's cluster to include several aspects of colony life [Anderson and McShea, 2001] that was previously not taken into account. Table 5.1 shows the classification introduced by Anderson and McShea.

	Simple Societies	Complex Societies
I Introduction		
Colony Size	Low	High
II Polyphenism		
Worker polymorphism	Low	High
Individual specialization	None → behavioural →physiological	→ morphological
Types of specialization	Temporary	Permanent
III Totipotency		
Functionality of ovaries	High	Low
Morphological skew	Low	High
Worker policing	Absent	Present
Intracolony conflict	High	Low
Physiological constraints	Low	High
Individual complexity	High	Low
IV Organization of work		
Colony control	Centralised	Decentralised
System redundancy	Low	High
Homeostasis	Low	High

Groups and teams	Absent	Present
Task partitioning	Absent	Present
Nest complexity	Low	High
Colony-constructed nest	No	Yes
Number of chambers	One	Many
Foraging strategy	Solitary → tandem running → mass	→trunk trail → group hunting
Defence	Generalists non-sacrificial workers	Specialists sacrificial defenders
Tempo	Low("cool")	High("hot")
Individual competence	High	Low
Most complex task type	Individual → group→	Team & partitioned
Efficiency	High	Low
V Communication and Functional Integration		
Average system Connectedness	High	Low
Use of cues	Low	High
Use of modulatory Signals	Low	High
Heterogeneity of Interaction	Low	High

Table 5.1: Classification of simple and complex societies

From Anderson and McShea's classification, it is evident that the social organisation of ant species varies greatly depending on how complex the colony is. Simple societies constitute societies having lack of division of labour (and hence low degree of specialisation), small colony size and high intra-colony conflict. The colony members are mostly monomorphic and exhibit very simple communication techniques. Complex societies, on the other hand, constitute of colonies having large colony size, low intra-colony conflict, task partitioning and effective division of labour as well as the existence of polymorphism and teams in carrying out tasks. It is also evident from the classifications made by Bourke [Bourke, 1999] and Anderson and McShea [Anderson and McShea, 2001] that the communication strategies adopted by the colony are themselves the result of an evolutionary strategy and depend on a wide number of factors (including the size and the organisation of the colony). Communications among nest-mates tend to be more complex, diverse and sophisticated with the increasing complexity of the colony. Simple societies tend to use very simple communications such as signalling and reactive behaviour. However, with the increase in the complexity of the colony, many different task allocation strategies start emerging: e.g. the emergence of dividing tasks into a number of sub-tasks and also the existence of teams [Anderson and Franks, 2001; Franks, 1986] where individuals not only work concurrently but also coordinate their different contributions [see Anderson and Franks, 2001; Franks et al, 2001; Franks, 1986]. Jeanson and colleagues [Jeanson et al., 2007] used monte carlo simulation techniques to analyze how increased group size and its correlates (demand and the number of tasks) affected the intensity of the division of labour. Using a fixed response threshold model, Jeanson and colleagues showed that the division of labour, under most conditions, are strongly correlated with the group size.

The general trend that is observed in ant colonies in terms of the communication techniques employed by them is that as the complexity of the colony increases the individual insects tend to adopt more sophisticated communication strategies. They tend to use redundant signals, modulatory signals as well as more cues to keep the colony running. Heterogeneity of interaction between insects increases and in extreme situations evolution of teams are observed. It seems likely that the employment of sophisticated strategies is a necessity for running more complex colonies. This is in line with the biological observation that individual social insects tend to be more simple in simpler societies and vice versa.

In the model proposed in chapter 4 and further extended in this chapter (see section 5.3), two kinds of communication strategies have been implemented: (1) indirect communication – where the agents communicate with each other via the environment and (2) explicit communication – where the agents communicate both directly and indirectly. We argue that the employment of direct communication along with indirect communication will help to transmit task demands (e.g. a need for feeding the brood) within the colony quickly, resulting in a better performance. It is suggested here that the adoption of explicit communication would be useful in stressful situations. Situations that are already well managed would probably not benefit much from explicit communication. This means that in cases where dynamic agents are already able to quickly serve brood members without direct communication, the employment of direct communication would probably not be very helpful (particularly advantageous). However, in more stressful cases where dynamic agents are not able to quickly serve the needs of the colony, an employment of direct communication might help to propagate the demand quickly to the dynamic agents which consequently would result a better performance. In order to explore this possibility, a series of experiments have been designed.

In the model developed for this thesis, demand is created by brood members. The larger the number of brood is the more the colony becomes stressed. On the other hand, the larger the number of dynamic agents is the more the agents can satisfy the need and hence the less stressed the colony becomes. From the discussion made above, we would expect explicit communication strategies to benefit colonies in more stressful situations. In order to test the arguments, models have been implemented and tests have been conducted (over a range of number of agents: dynamic agents ranging from 20 – 60 while static brood members ranges between 5 and 25)to evaluate the effect of the communication strategies on the average hunger level of the colony.

5.3 Proposed Model

The main communication mode of ants is chemical signalling. This is perhaps one of the many reasons that led early researchers to mainly focus on stigmergic interactions. However, in recent times various researchers have started to investigate explicit communication in ants [see e.g. Franks and Richardson, 2006; Leadbeater et al., 2006; Momen and Sharkey, 2010]. In this chapter, we explore whether, and when, the use of explicit communication offers any added advantages to the performance of the system. In order to do so, the model proposed in chapter 4 has been extended to incorporate some explicit communication between the agents based on the forms of explicit communication that are found in complex ant societies.

The environment of the model (including the nest size, nest complexity, agent size and food distribution) (Figure 4.1) is kept unchanged.

The only change that has been made in order to accommodate the explicit communication between the dynamic agents is the addition of four behavioural rules

(Rule #8 – Rule #11) to the repertoire described in section 4.3. The additional four rules are as follows:

(8) If an agent perceives shouting chemical, it not only reduces its own t_{bc}, but also participates in the direct transmission of the message (for a brief period; 80 simulation time steps), “urgent brood caring needed” (U_{bc}), to other foragers and brood carers lying within twice its body size.

(9) When other agents receive the message U_{bc}, they also reduce their threshold for brood caring. However these agents refrain from further transmission of messages.

(10) Similarly, when an agent is in the dump area of the nest and perceives that the amount of food in the dump area is below some critical threshold (set to 5 throughout the experiment), it not only executes rule # 2 (see section 4.3) but also send a message U_f (urgent foraging needed) to other agents that lie within 2 patches from the transmitting agent for a brief period (80 simulation time steps).

(11) When other agents receive the message U_f, they react by reducing their own threshold for foraging. However, they refrain themselves from further transmission of the U_f messages.

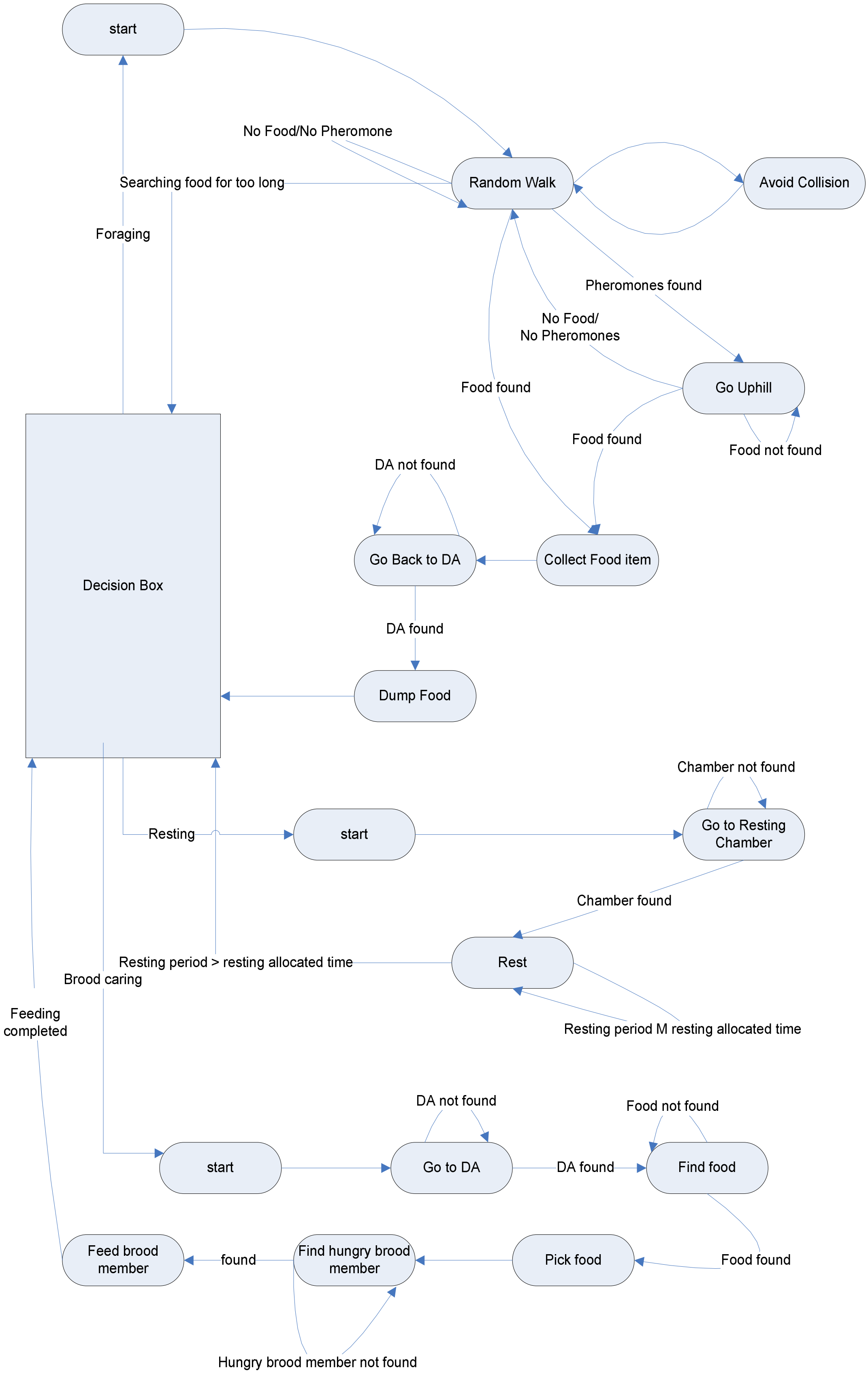


Fig 5.1: State transition for foragers and brood carers

It is well known that many species of ants make use of more than a single mode of communication in situations that need urgent attention (e.g. the use of direct transmission of messages through frequent direct interactions). For instance the leaf cutter ants *Atta colombica* are well known to use both stridulation and alarm pheromones in order to alert nest-mates about possible intruders. The use of more than one communication mechanism for signalling has a number of benefits including:

1. Quick transmission of appropriate messages within the colony, and
2. To make use of redundant signals to amplify the need and hence attracting more ants.

In this model, it can be argued that there exist two cases of urgency: (1) when the number of food items present in the dump area is too low (in which case, more foragers would be required to bring food items from outside) and (2) When the brood members get hungry. The hunger of brood members has direct consequences on the performance of the colony and hence should be one factor that the agents need to minimise. Therefore, when either of these two cases is perceived, agents use both the communication strategies (i.e. indirect as well as direct communication) to communicate. Indirect communication makes use of the environment only to convey messages to other agents whereas in the explicit communication agents not only use the environment to pass on the messages but also transmit messages directly to other agents by various means (e.g. via tactile communication, smell and even through sounds in many species). Such “indirect + direct communication” is what is referred to as explicit communication.

A finite state automaton (FSA) for dynamic agents using either indirect or explicit communication is shown in Figure 5.1. The agents use the same FSA for either types of communication.

If the agent is a forager, it starts moving randomly in search of food until it finds some. Once the forager discovers a food source, it picks the food item up, becomes laden and goes back to the nest. As it goes back to the nest, it keeps on dropping simulated chemicals (called pheromones) on its way for other unladen ants to use as a guide to navigate towards the food source. As foragers travel randomly in search of food, they also avoid collisions with other agents by moving in a random direction if the distance between two agents becomes less than the body length of a single agent. Brood carers, on the other hand, are activated when brood members get hungry. Brood carers first reach the dump area of the nest in order to collect food items. Once a brood carer reaches the dump area, it moves randomly within the area until it bumps into a food item. When it discovers a food item inside the dump area, it picks the food item up and then traverses towards the brood chamber. The brood carer then uses the shouting chemical signalled by the hungry brood member to eventually reach the hungry brood member. Once it reaches the hungry brood member, the brood carer feeds the brood member with the food it was carrying. Detailed explanation of the traversal and threshold updating mechanisms were provided in chapter 4. Both foragers and brood carers are constantly updating their thresholds by following the 11 behaviour rules (for explicit communication) and 7 behavioural rules (in case of indirect communication) described above. When the state transition of either the forager or the brood carer reaches the “decision box” state, the agent decides what role to play (i.e. whether it will act as forager or brood carer or whether will it rest) next depending on the three thresholds (t_f, t_r, t_{bc}). The procedure for the next task selection is as follows:

(1) Let $T_{carryoutnext} = \arg\min\{t_f, t_r, t_{bc}\}$ where $T_{carryoutnext}$ is a candidate of the task to carry out next.

(2) A random number, R, is generated between 0 and 1. If $R <= 0.7$, $T_{carryoutnext}$ is selected otherwise the agent continues carrying out the task it was already carrying out.

5.4 Experiments and Results

The parameters used in experiments are listed in table 5.2

Parameter	Meaning	Value(s) used
N_b	Number brood members	5, 15, 25
S	Number of mobile agents (i.e. number of foragers [N_f] + number of brood carers [N_{bc}])	20 – 60
$r = R_{f\text{-}bc}$	Initial ratio of foragers to brood carers. This can be used to determine the number of foragers and brood carers as follows:	0.2, 0.5, 0.9

	$N_f = \lfloor R_{f-bc} \times S \rfloor$ $N_{bc} = S - N_f$	
$E_{pheromones}$	Evaporation rate of Pheromones	5%
$D_{pheromones}$	Diffusion rate of Pheromones	60%
Adaptation-rate	The rate at which the thresholds are adapted	0.09
Shouting-radius	The number of patches the brood member can shout when it gets hungry	7
E_{sc}	Evaporation rate of shouting chemical	50%
U_{food}	Upper threshold of food	40
L_{food}	Lower threshold of food	5
max-separate-turn	The maximum angle an agent can turn when avoiding another agent	1.25^0
E_{food}	Energy provided by the food which causes the hunger level of the brood member fed to decrease	100
Th_h	Threshold parameter of the hunger level	500

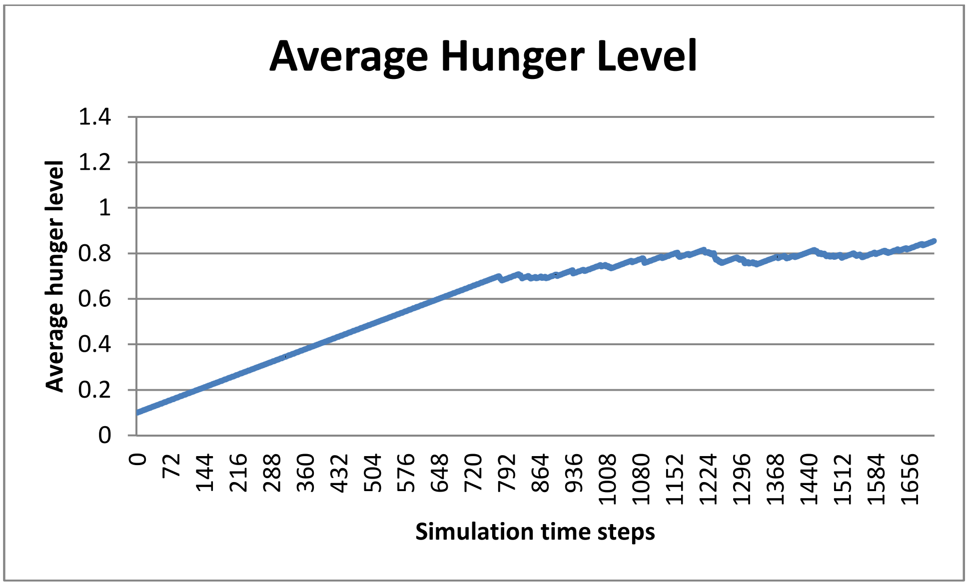
Table 5.2: Parameters used in the experiments

5.4.1 Performance Measure

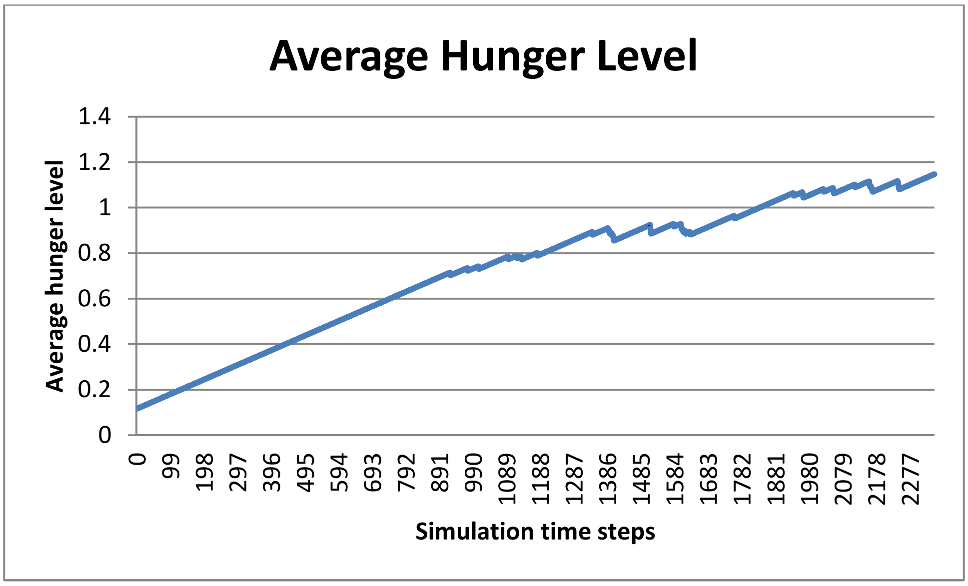
Simulations are all carried out in the Netlogo environment. Each experiment runs for 5000 simulation time steps and is repeated 20 times. The average reading is then calculated from the 20 trials.

Performance of the algorithms is measured in terms of the average hunger level (see equation 1) of the brood after the 5000th time step. Figure 5.2 shows how the average hunger level of the brood varies with simulation time steps (when using explicit communication).

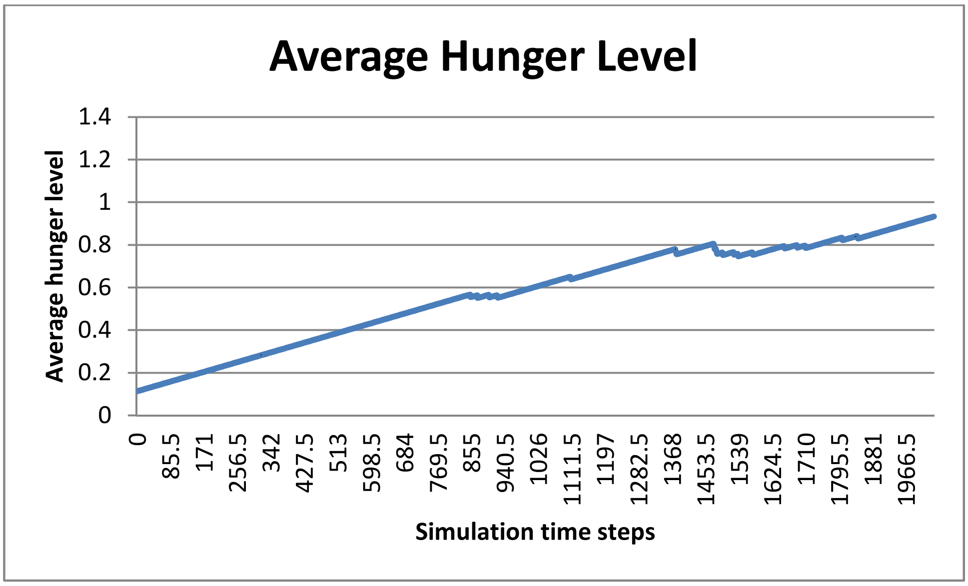
$$A.H.L. = \frac{\sum_{\forall brood-member} HL}{th_h \times n_b} \qquad (1)$$



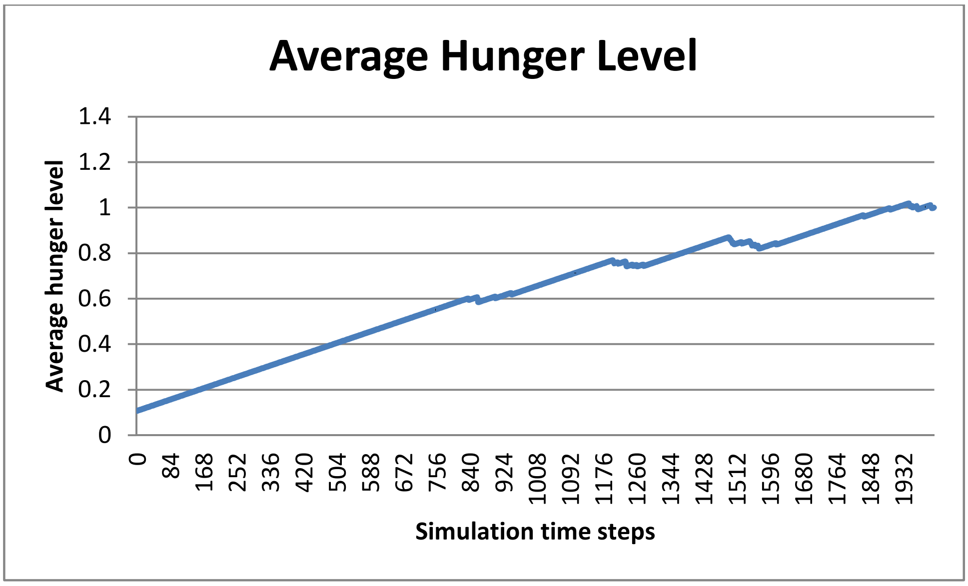
a. $N_b = 25$, $r = 0.9$, $S = 60$



b. $N_b = 15$, $r = 0.9$, $S = 30$



c. $N_b = 15$, $r = 0.2$, $S = 40$



d. $N_b = 25$, r = 0.5, S = 40

Fig. 5.2: Average hunger level of the brood (N_b = size of the brood, r = initial foragers to brood carer ration and S = number of foragers + number of brood carers)

5.4.2 Results

Tables 5.3 and 5.4 show the resulting average hunger level of brood after 5000th time step (for indirect communication).

	S=20, r=0.2	S=20, r=0.5	S=20, r=0.9	S=30, r=0.2	S=30, r=0.5	S=30, r=0.9	S=40, r=0.2	S=40, r=0.5	S=40, r=0.9
$N_b = 5$	2.21	2.59	2.25	1.43	1.47	1.54	0.97	1.07	1.08
$N_b = 15$	3.37	2.78	3.34	2.11	2.51	2.11	1.85	1.82	1.76
$N_b = 25$	3.73	3.55	3.75	2.74	2.93	3.10	2.24	2.40	2.47

Table 5.3: Mean Hunger level (indirect communication) (N_b = number of brood members, s = number of foragers + number of brood carers, r = initial ratio of the foragers to brood carers)

	S= 50, r = 0.2	S= 50, R = 0.5	S= 50, r = 0.9	S= 60, r = 0.2	S= 60, r = 0.5	S= 60, r = 0.9
$N_b = 5$	0.91	1.03	1.02	0.94	1.05	1.16
$N_b = 15$	1.19	1.40	1.51	0.94	0.82	1.08
$N_b = 25$	1.43	1.90	1.68	1.26	1.40	1.50

Table 5.4: Mean hunger level (indirect communication) (N_b = number of brood members, s = number of foragers + number of brood carers, r = initial ratio of the foragers to brood carers)

However when explicit communication is employed along with indirect communication, the following results are obtained (tables 5.5 and 5.6)

	S=20, r=0.2	S=20, r=0.5	S=20, r=0.9	S=30, r=0.2	S=30, r=0.5	S=30, r=0.9	S=40, r=0.2	S=40, r=0.5	S=40, r=0.9
$N_b = 5$	1.69	1.89	1.88	0.99	1.26	1.14	0.83	1.11	1.03
$N_b = 15$	2.51	2.96	2.65	1.84	1.77	1.59	1.18	1.28	1.23
$N_b = 25$	3.06	3.09	**3.48**	2.18	2.50	2.49	1.87	1.93	1.98

Table 5.5: Mean hunger level (explicit communication) (N_b = number of brood members, s = number of foragers + number of brood carers, r = initial ratio of the foragers to brood carers)

	S= 50, r = 0.2	S= 50, R = 0.5	S= 50, r = 0.9	S= 60, r = 0.2	S= 60, r = 0.5	S= 60, r = 0.9
$N_b = 5$	0.88	0.91	1.05	0.84	0.88	1.08
$N_b = 15$	1.14	1.14	1.17	1.01	0.98	0.99
$N_b = 25$	1.47	1.32	1.66	1.40	1.39	**1.24**

Table 5.6: Mean hunger level (explicit communication) (N_b = number of brood members, s = number of foragers + number of brood carers, r = initial ratio of the foragers to brood carers)

Both explicit and indirect communication mechanisms show a decrease in the average hunger level with the increase in the number of the dynamic agents. For instance if we consider the explicit communication mechanism for brood size = 25 and r (the initial ratio of foragers to brood carers) = 0.9, the mean hunger level varies from 3.48 to 1.24 showing a decrease in the hunger level (and hence an improvement in the performance of the system) with an increase in the number of the dynamic agents (see Table 5.5 and Table 5.6 – the two values are in bold font). In order to test if the increase in the performance with increasing number of dynamic agents (due to the reduction of the average hunger level) is statistically significant or not, a kruskal wallis test can be employed. The result for the kruskal wallis test using Bonferroni correction (obtained using SPSS) is shown in table 5.7.

Kruskal-Wallis Test

Ranks

	S	N	Mean Rank
VAR00001	20	20	86.90
	30	20	62.85
	40	20	48.60
	50	20	36.00
	60	20	18.15
	Total	100	

Test Statistics[a,b]

	VAR00001
Chi-Square	65.058
Df	4
Asymp. Sig.	.000

a. Kruskal Wallis Test

Test Statistics[a,b]

	VAR00001
Chi-Square	65.058
Df	4
Asymp. Sig.	.000

a. Kruskal Wallis Test

b. Grouping Variable: S

Table 5.7: Results for the Kruskal Wallis test

Kruskal-Wallis test assumes:

H_0 (null hypothesis): $M_1 = M_2 = M_3$ i.e. the medians of average hunger level do not significantly vary, and

H_1 (alternative hypothesis): the median of the data sets significantly deviate from each other.

Since p-value is found to be 0.000 which is less than 0.01 (0.05 / 5; here 5 is the number of tests made), the null hypothesis, H_0 is rejected using Bonferroni correction which means that the increase in the number of dynamic agents (i.e. the number of foragers + number of brood carers) significantly reduces the average hunger level of the colony.

To determine whether explicit communication has improved the performance of the colony in comparison to that of indirect communication mechanisms, a graph of average hunger level (on the y-axis) against the number of dynamic agents, s, (on the x-axis) is plotted. In most of the cases, it is found that the average hunger level, when incorporating the explicit communication, is lower than in the cases when indirect communication was only used alone indicating that the use of explicit communication improves the performance of the swarm.

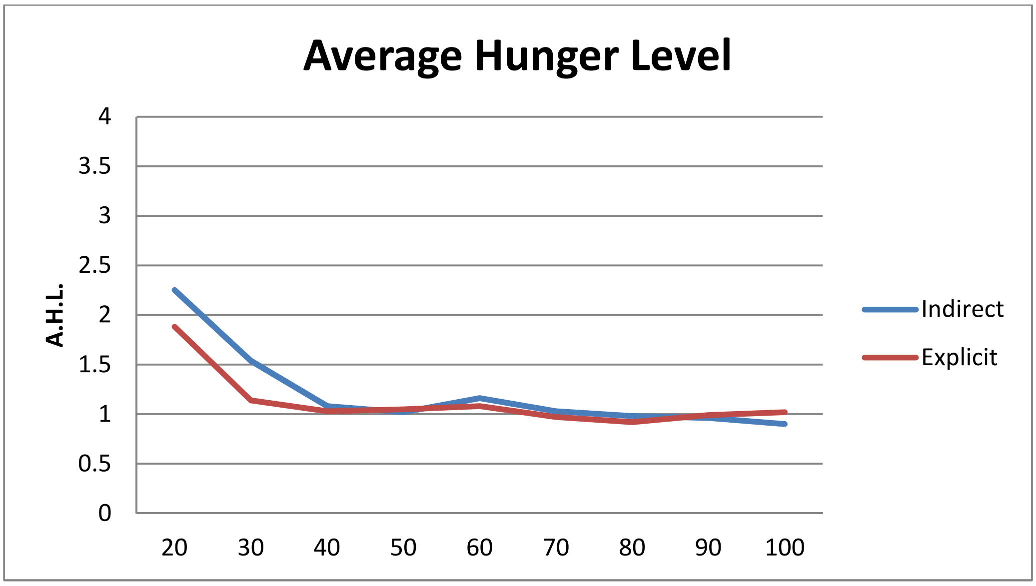


Fig 5.3: Average hunger level for both types of communication (brood size = 5, x-axis represents the number of dynamic agents and the initial ratio, r, of the foragers to brood carers = 0.9)

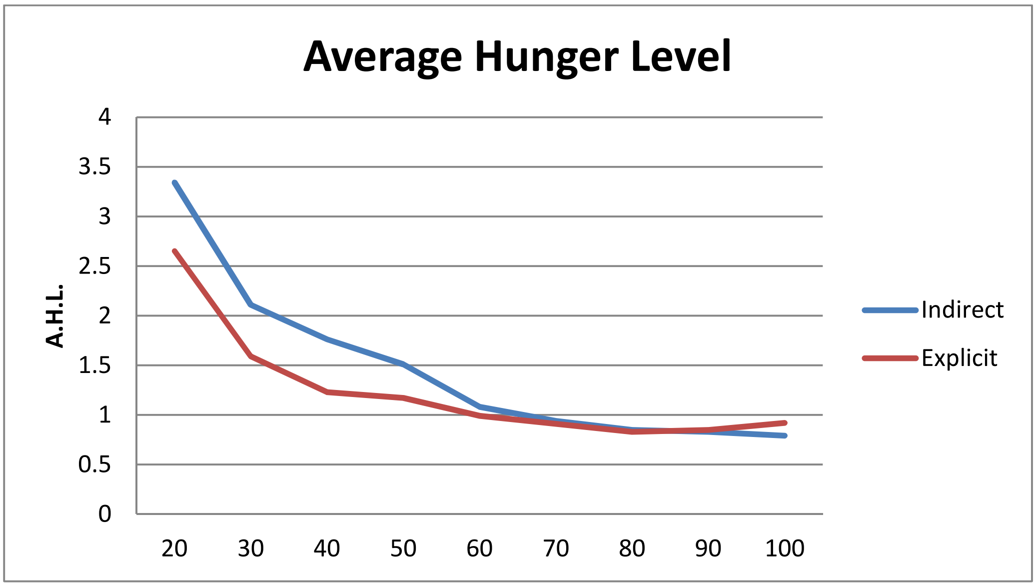


Fig 5.4: Average hunger level for both types of communication (brood size = 15, x-axis represents the number of dynamic agents and the initial ratio, r, of the foragers to brood carers = 0.9)

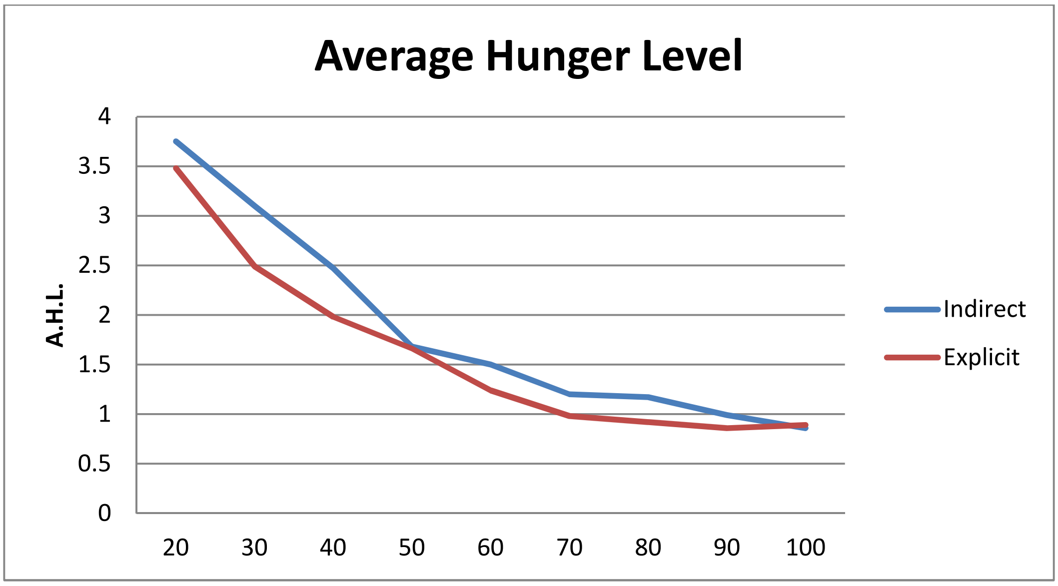


Fig 5.5: Average hunger level for both types of communication (brood size = 25, x-axis represents the number of dynamic agents and the initial ratio, r, of the foragers to brood carers = 0.9)

To test if the improvement in the performance in the case of explicit communication as compared to indirect communication alone is statistically significant, a series of planned comparisons (using Mann-Whitney U tests) between the two communication types were made.

Mann-Whitney test assumes the following hypotheses:

H_0: $\text{Median}_A = \text{Median}_B$ (i.e. the two data sets A and B are not statistically different).

H_1: $\text{Median}_A \neq \text{Median}_B$ (i.e. the two data sets are statistically different)

With brood size = 5 and the initial ratio of foragers to brood carers = 0.9, the Mann-Whitney test produces the following results:

Test Statistics[b]

	VAR00001
Mann-Whitney U	123.000
Wilcoxon W	333.000
Z	-2.083
Asymp. Sig. (2-tailed)	.037
Exact Sig. [2*(1-tailed Sig.)]	.038[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

A. $s = 20$

Test Statistics[b]

	VAR00001
Mann-Whitney U	163.000
Wilcoxon W	373.000
Z	-1.001
Asymp. Sig. (2-tailed)	.317
Exact Sig. [2*(1-tailed Sig.)]	.327[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

B. $s = 30$

Test Statistics[b]

	VAR00001
Mann-Whitney U	177.000
Wilcoxon W	387.000
Z	-.622
Asymp. Sig. (2-tailed)	.534
Exact Sig. [2*(1-tailed Sig.)]	.547[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

C. $s = 40$

Test Statistics[b]

	VAR00001
Mann-Whitney U	152.000
Wilcoxon W	362.000
Z	-1.298
Asymp. Sig. (2-tailed)	.194
Exact Sig. [2*(1-tailed Sig.)]	.201[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

D. $s = 50$

Test Statistics[b]

	VAR00001
Mann-Whitney U	167.000
Wilcoxon W	377.000
Z	-.893

Asymp. Sig. (2-tailed)	.372
Exact Sig. [2*(1-tailed Sig.)]	.383[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

E: s = 60

Table 5.8: Mann Whitney tests between indirect and explicit communication for brood size = 5

The results for brood size = 15 and 25 are shown in tables 5.9 and 5.10 respectively. For all the comparison, the initial ratio of foragers to brood carers is kept the same (0.9).

Test Statistics[b]

	VAR00001
Mann-Whitney U	69.000
Wilcoxon W	279.000
Z	-3.544
Asymp. Sig. (2-tailed)	.000
Exact Sig. [2*(1-tailed Sig.)]	.000[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

A. s = 20

Test Statistics[b]

	VAR00001
Mann-Whitney U	108.000
Wilcoxon W	318.000
Z	-2.489
Asymp. Sig. (2-tailed)	.013
Exact Sig. [2*(1-tailed Sig.)]	.012[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

B. s = 30

Test Statistics[b]

	VAR00001
Mann-Whitney U	68.000
Wilcoxon W	278.000

Test Statistics[b]

	VAR00001
Mann-Whitney U	119.000
Wilcoxon W	329.000

Z	-3.571
Asymp. Sig. (2-tailed)	.000
Exact Sig. [2*(1-tailed Sig.)]	.000[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

Z	-2.191
Asymp. Sig. (2-tailed)	.028
Exact Sig. [2*(1-tailed Sig.)]	.028[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

C. s = 40

D. s = 50

Test Statistics[b]

	VAR00001
Mann-Whitney U	153.000
Wilcoxon W	363.000
Z	-1.271
Asymp. Sig. (2-tailed)	.204
Exact Sig. [2*(1-tailed Sig.)]	.211[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

E. s = 60

Table 5.9: Mann Whitney tests between indirect and explicit communication for brood size = 15

Test Statistics[b]

	VAR00001
Mann-Whitney U	142.000
Wilcoxon W	352.000
Z	-1.569

Test Statistics[b]

	VAR00001
Mann-Whitney U	107.000
Wilcoxon W	317.000
Z	-2.516

Asymp. Sig. (2-tailed)	.117
Exact Sig. [2*(1-tailed Sig.)]	.121[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

A. s = 20

Asymp. Sig. (2-tailed)	.012
Exact Sig. [2*(1-tailed Sig.)]	.011[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

B. s = 30

Test Statistics[b]

	VAR00001
Mann-Whitney U	85.000
Wilcoxon W	295.000
Z	-3.111
Asymp. Sig. (2-tailed)	.002
Exact Sig. [2*(1-tailed Sig.)]	.001[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

C. s = 40

Test Statistics[b]

	VAR00001
Mann-Whitney U	193.000
Wilcoxon W	403.000
Z	-.189
Asymp. Sig. (2-tailed)	.850
Exact Sig. [2*(1-tailed Sig.)]	.862[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

D. s = 50

Test Statistics[b]

	VAR00001
Mann-Whitney U	129.000
Wilcoxon W	339.000
Z	-1.921
Asymp. Sig. (2-tailed)	.055
Exact Sig. [2*(1-tailed Sig.)]	.056[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

E. s = 60

Table 5.10: Mann Whitney tests between indirect and explicit communication for brood size = 25

If p-value < 0.05, ($\alpha = 0.05$, level of significance), the null hypothesis, H_0, is rejected. The results obtained from the series of Mann-Whitney tests are summarised in table 5.11.

S	20	30	40	50	60
$N_b = 5$	√	×	×	×	×
$N_b = 15$	√$^+$	√	√$^+$	√	×
$N_b = 25$	×	√	√$^+$	×	×

Table 5.11: Summary of the significance tests between the performances of the explicit and indirect communication techniques

where

× represents those cases in which the performance of the explicit and indirect communication do not vary significantly, and

√ represents those cases in which the performance of the two communication strategies vary significantly

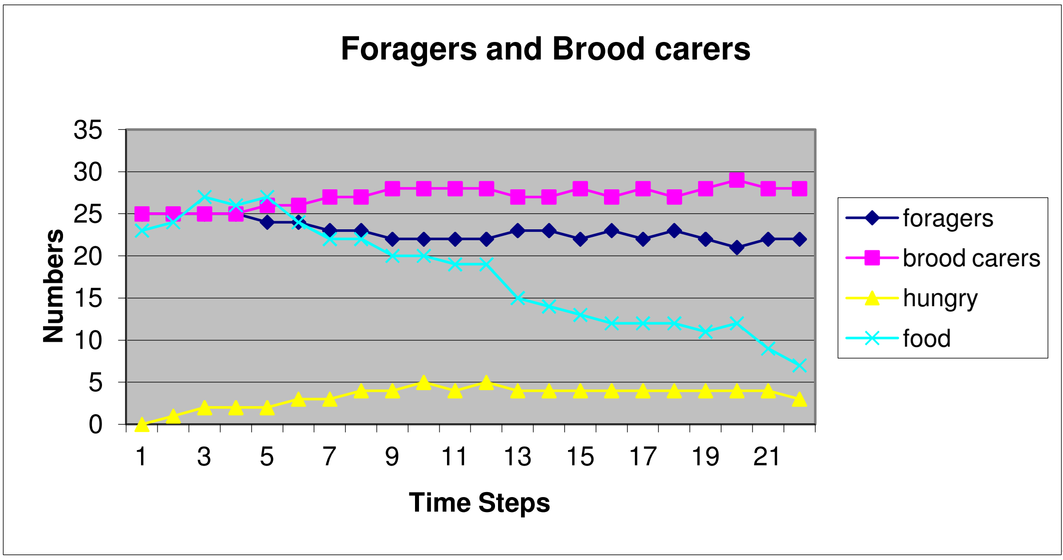
+ represents the data sets that show significant difference using the very conservative Bonferroni tests.

Since the mean hunger level for explicit communication strategy is always found to be lower than that of the indirect communication strategy, the symbol √ also represents a statistically significant improvement of the performance when explicit communication has been employed. On the other hand, × indicates that although there was an improvement in the performance it was not statistically significant.

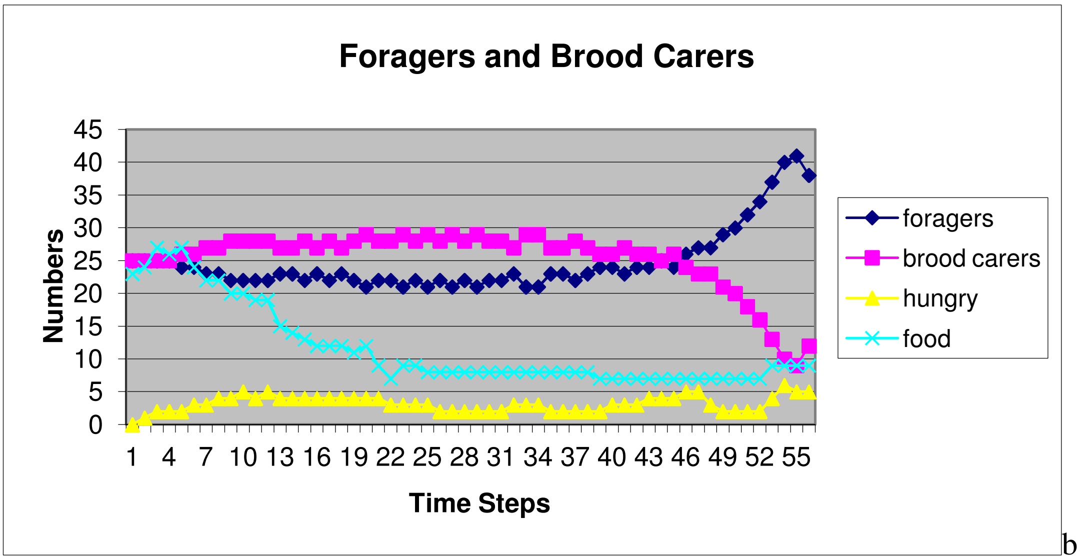
For the experiments with the number of brood = 5, the demand of brood caring is lower than when the number of brood are 15 and 25 respectively. The higher the number of brood is, the greater is the demand for brood caring and vice versa. For lower number of brood (i.e. when the demand for brood caring is low), a statistically significant improvement has been found when the number of dynamic agents is 20. For a higher number of dynamic agents, the use of explicit communication did not result in a statistically significant improvement over that of the indirect communication. This is most likely due to the fact that when the demand for brood caring is low, the increase in the number of dynamic agents is enough to meet the demand for hungry brood members. Further direct communication was not necessary and hence did not improve the results significantly. However with a greater number of brood members (for number of brood members = 15), the use of explicit communication improved the performance of the swarm significantly (for $20 \leq number of\ dynamic agents \leq 50$). The performance, however, did not improve significantly with 60 dynamic agents where there were already enough dynamic agents to meet the demand of the hungry brood. This suggests that for a moderately higher number of brood members, the use of explicit communication helps to propagate the required message (i.e. either to feed the brood members or to collect food items from outside the nest) and hence suppress the average hunger level of the colony. However for large number of dynamic agents (60 dynamic agents), explicit communication is not needful as there already is a sufficient number of agents to satisfy needs of the colony. With N_B (number of brood members) = 25, a statistically significant improvement of the performance of the colony is found (when using the explicit communication in contrast to the indirect communication) with numbers of dynamic agents ranging from 30 – 40. The use of explicit communication, on the other hand, did not significantly improve the performance of the colony with number of dynamic agents (s) = 20, 50 and 60. With brood size = 25, there is a high demand for brood feeding and consequently foraging (since the increase in the rate of feeding the brood members result in quickly diminishing the number of food items available in the dump area of the nest). When the number of dynamic agents = 20, the colony did not have enough agents to feed the hungry brood members and keep the hunger level lower. However with the increase in the number of dynamic agents, the hunger level was moderated. Furthermore, for brood size = 25 (i.e. when the demand for feeding is high), the use of explicit communication improved the performance of the colony by keeping the hunger level lower until the number of dynamic agents is enough so as to the use of explicit communication did not result in any further advantages. The results obtained are in line with the assumption that was made before carrying out the experiment – that in a stressful situation it is likely that the incorporation of explicit communication would yield better performance of the colony.

5.4.3 Variation of the state of the agents with respect to the demand of the colony

The previous sections illustrate the rules followed by the individual agents, the communication modes the agents use and also how the performance of the colony varies with the size of the swarm and the strategy the swarm uses. It is already known both from this chapter as well as the preceeding chapter that the agents dynamically change their states from foraging to brood caring and vice versa to meet the demand of the colony. This sub-section however illustrates a pictorial depiction of how the states of the agents vary throughout the simulation process. Time step is measured from the time the first brood member gets hungry. The section takes the example of one of the cases however the similar type of results can be obtained from different initial configurations illustrating that the agents dynamically change their states to meet the demand of the colony.



a



b

Fig 5.6: Variation of the numbers of foragers and brood carers

In this particular case, there are same number of foragers and brood carers (initial value). As brood members start getting hungry, the number of brood carers increases to meet the changing demand (Figures 5.6a, 5.6b). Consequently the amount of food available in the dump area of the nest decreases (Figure 5.6b) triggering brood carers to switch to the foraging task. This behaviour will keep on repeating over the rest of the simulation period but this single cycle itself explains how agents constantly change their states in order to meet the demand of the colony.

5.5 Conclusion

This chapter looks at the effects of using explicit communication in a simulated colony of ants, and at the circumstances in which it improves performance. Ants are popularly known to use indirect communication to signal other nest mates. However, in many situations, ants have been found to use explicit local communication with the nest mates. This chapter analyzes the advantages of using a combination of direct communication and indirect communication. The model for task allocation described in chapter 4 has been extended (in this chapter) in order to incorporate the explicit communication in ants. Experiments were carried out with brood size ranging from 5 – 25 and number of dynamic agents (number of foragers + number of brood carers) ranging from 20 – 60. In most of the cases it was found that the performance is improved by the use of explicit communication in comparison to indirect communication.

Before the experiment was carried out, it was predicted that the use of explicit communication would benefit the colony under stressful conditions (i.e. when the number of brood members is high). The use of explicit communication is always found to be of benefit when there is moderate level of demand (from the brood carers) and a low – medium number of dynamic agents. In case of high demand from brood members (i.e. when number of brood = 25), the use of explicit communication tends to improve performance for a moderate number of dynamic agents. This is in line with the prediction that was previously made – that the use of explicit communication would turn out to be useful in situations where the colony is under greater stress (i.e. in situations where there are less dynamic agents to feed the brood members and a greater demand for feeding). In nature, the greater the colony complexity is, the more is the demand for the colony to run and consequently the workers in complex societies use more sophisticated communication strategies compared to that of the simpler societies to effectively meet the demand of the colony. This is in line with the results obtained from our simulations (i.e. under stressful conditions, use of explicit communication improves the performance of the colony significantly compared to that of the indirect communication)

Chapter 6

Task Allocation Model for a Swarm of Hybrid Agents

This chapter presents an extension of the models presented earlier (in chapters 4 and 5 respectively). The two models in chapters 4 and 5 assume that agents are simple in nature (i.e. follow simply rules and fairly homogeneous in terms of behaviour) and react only to the stimulus (signal) that they receive. However, in many complex situations, a number of factors besides stimulus have been found to affect the propensity of task selection. Some of these include location of the individuals within the nest, genetic factors, age, morphology and also physiology. It is quite often the case that castes within a colony are more biased towards certain tasks than others. This chapter uses and extends the concept of task preference within a caste to see if such bias and heterogeneous mixture within the society serves any advantage to the colony.

Although evidence exists of task preferences among castes in many ant species (see section 3.5), little work has really been done in investigating the benefits for the colony of such preferences. In this chapter, we examine the question of whether such task preferences within a caste (i.e. by the formation of sub-castes) would have any advantage on the performance of the overall colony. To provide us with an insight into the advantage, if any, of the biasness (i.e. preference in task execution) within the castes of the colony, a heterogeneous mixture within the brood carers caste has been made. In this model, two types of brood carers exist: (1) flexible brood carers and (2) biased brood carers. The flexible brood carers can update their thresholds. They are not biased to any particular task and can take up any of the three tasks: (A) brood caring, (B) resting and (C) foraging. However biased brood carers are dedicated to the brood caring task only and refrain from undertaking any foraging or resting tasks. It should be noted here that the default state of a biased brood carer is to rest within its chamber (it only reacts to the shouting signal of the brood members) although in this case we refrain from denoting resting as a task. This is because the biased brood carers do not choose to rest by updating the threshold of resting rather they only rest because the shouting signal of the brood members is not enough to make them (the biased brood carers) react.

In order to establish whether the existence of biased brood carers has any impact on the performance of the colony, the number of brood members and the ratio of the biased brood carers to the flexible brood carers are varied and the average hunger level of the colony at the end of the simulation is recorded. Two conditions for the experiment were introduced: (1) a benign condition and (2) a harsh condition. In the benign condition, the food in the environment grows adequately so that there is no scarcity of food in the environment and consequently it is easy for the forager to find a food item. On the other hand in the harsh condition, food in the environment grows at a much slower rate causing difficulty for foragers to find a food item relative to that of the benign condition. As the number of brood members is increased the average hunger level is expected to increase. In the harsh condition, we do not expect the existence of biased brood carers will improve the performance of the colony. Moreover, we believe that as the ratio of the biased brood carers to that of the flexible brood carers is increased, the consequence would be a deterioration in the performance of the colony. This is because as more and more brood carers become dedicated to brood caring, the foraging task is under resourced (since there are less foragers and on the top of that it is relatively more difficult to foraging due to the lower growth of food in the environment). However, in case of the benign condition, a different result is expected. Since there is adequate food in the environment in the benign condition, the foraging task can be carried out relatively easily. In this case the existence of some biased brood carers might actually help them to improve the brood caring tasks and consequently the performance of the colony. However, if the ratio of the biased brood carers to that of the flexible brood carers is too high, this could create underresourcing of foraging tasks resulting in poor performance. Therefore we would speculate that in the benign condition, the performance of the colony should improve with the increase in the ratio of the biased brood carers to that of the flexible brood carers but only upto some critical ratio beyond which the performance would decrease.

The rest of the chapter is organised as follows: in section 6.1, the new model investigating this strategy is proposed. The model is described along with the behavioural rules the agents follow. Section 6.2 explains the experiments carried out along with the results that are obtained from them. Finally, in section 6.3 the chapter concludes with a brief description of likely future work.

6.1 Proposed Model

The environment of the model is similar to that as described in section 4.2 of chapter 4. One key difference in this model is that the food items in the environment grow at a particular rate (3×10^{-4} units per unit time if the condition is benign or 3×10^{-5} units per unit time if the condition is harsh; further discussion of this is made later in the chapter). Another vital difference in this model is the inclusion of two types of brood carers. The following subsection discusses this to further details.

6.1.1 Behavioural rules

The three groups of agents (static brood members and the dynamic brood carers and foragers) behave in the similar fashion as outlined in chapters 4 and 5 of the thesis. However, in the realms of this model some modification to the behaviour brood carers has been made. Therefore, in this section we provide brief description to the behaviours of brood carers only. To refer to the descriptions of the behaviours of other agents (foragers and brood) please refer to section 4.2 of chapter 4.

The brood carers in this model are heterogeneous rather than homogeneous in the sense that they do not follow the same sets of rules. Two kinds of brood carers exist in this model: (i) adaptive brood carers and (ii) biased brood carers. Adaptive brood carers switch tasks and adapt to the changing environment as required (between foraging, brood caring and resting). Biased brood carers, on the other hand, have preferences in terms of which tasks they like to execute and have a more limited degree of flexibility. In this model, such brood carers refrain from taking up the foraging task and hence are limited to either brood caring or resting. All brood carers, when triggered to feed the brood members, use the potential gradient of the scent of the dump area to reach the dump area first. Once they reach the dump area, they move randomly within the dump area for a stipulated length of time. During this time, if they find a piece of food, they pick the food items up and then move towards the brood chamber by following the scent of the brood chamber. Once the brood carer reaches the brood chamber, it uses the shouting chemical emitted by a hungry brood member to reach it and feed the hungry brood member.

Foragers and adaptive brood carers follow behavioural rules (11 sets of rules) as described in Sections 4.3 and 5.3. However, one key difference of this model is the presence of the biased brood carers which do not participate in carrying out all the tasks. Rather, these brood carers are biased towards one particular task only (i.e. brood caring). Biased brood carers reside within the brood carer’s chamber and keep on listening for the shouting of the brood members. Upon receiving the signal from the brood members for feeding them, these brood carers decide whether to activate brood caring task or not. The finite state machine (FSM) for biased brood carers is presented in figure 6.1.

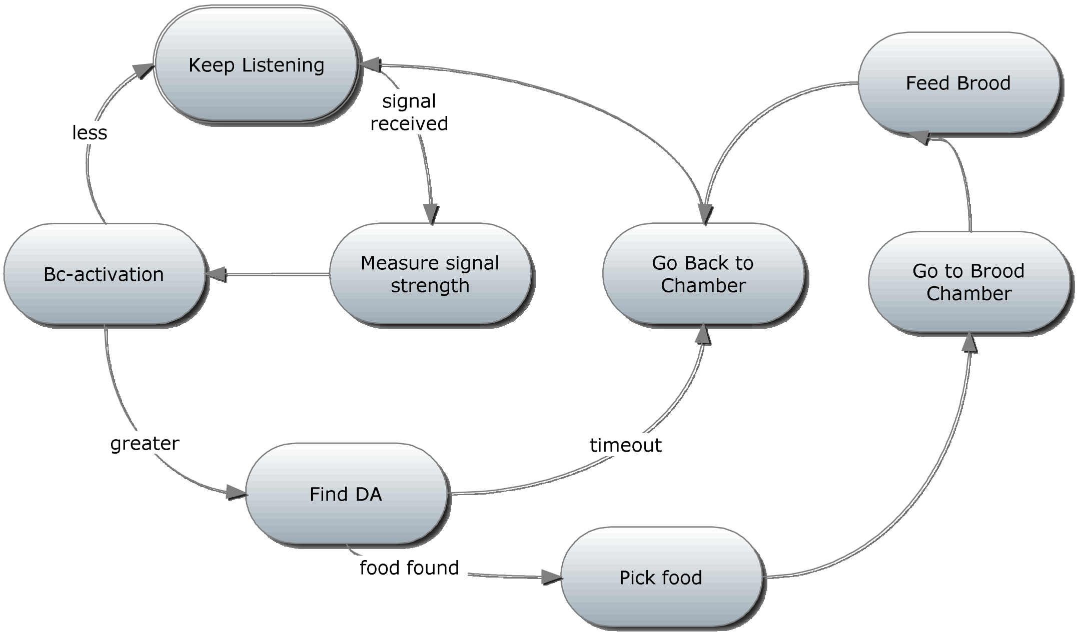


Fig 6.1: Finite state machine for biased brood carers

The agents use a set of action sequences in order to carry out their task effectively. These action sequences are explained as follows:

Keep Listening: In this phase, the brood carer stays in its chamber but keeps on listening for any indication of a need to feed the brood members.

Measure Signal Strength: Upon receiving signals from the brood members that feeding is required, it measures how much signal strength it has received.

Bc-activation: Depending on the signal strength the brood carer has received, it decides whether to activate brood caring task or not. If the signal strength received by the brood carer is less than the cumulative signals that can be sent by 3 brood members, the brood carer refrains from switching its task to brood caring and keeps on listening for further signal from brood members. This ensures that the brood carers are not too sensitive to feeding brood members and prevents one brood member's signal from activating several brood carers

Find DA: When the brood carers respond to the demands of the brood members, they need to first pick up a food item from the dump area. To do this, they use the gradient of the scent of the dump area chamber to reach the dump area of the nest. Once a brood carer reaches the dump area, it moves randomly within it in search of food.

Pick food: When a brood carer finds a piece of food, the brood carer picks it up and heads towards the brood chamber.

Go back to chamber: If there is not enough food in the dump area it might take the brood carer too long to find a piece of food. If it takes longer that the time allowed for it to search, it gives up finding food there and instead use the potential gradient of the scent of the brood carers chamber to head towards the chamber. Once it reaches its chamber, it resumes listening for any further signal from the brood members.

Go to brood chamber: If a brood carer has successfully picked up a food item from the dump area, it heads towards the brood chamber by following the potential gradient of the scent of the brood chamber.

Feed brood: Upon entering the brood chamber, the brood carer uses the shouting chemical of the hungry brood members to locate a brood member that needs feeding. Once the brood carer reaches the hungry brood member, it feeds the brood member which results a lowering of the brood member's hunger level. Once the brood member has fed the brood carer, it heads towards its chamber and resumes listening to further signals from the brood members.

6.2 Experiments and Results

The objective of this chapter is to investigate what advantages, if any, are there on the performance of the colony as a whole when some groups of agents are biased towards certain tasks: specifically, when some agents are biased towards brood caring. To investigate this, the ratio of the number of biased brood carers and the dynamic brood carers is varied in order to test how the degree of flexibility for brood caring affects the performance of the system. The experiment has been conducted within two environmental modes: (1) within benign conditions and (2) within harsh conditions. To test our speculations (as mentioned before) experiments have been carried out using agent based methodology within the Netlogo environment (refer to chapter 4 for further details). Each experiment was run for 5000 simulation time steps and was repeated 20 times. The average reading was then calculated from the 20 trials. The performance of the system is calculated in terms of the average hunger level of the colony after the end of the simulation i.e. at 5000th simulation time step.

The list of parameters used is outlined in Table 6.1.

Parameter	Meaning	Value(s) used
N_b	Number of brood members	20, 60, 80

N_f	Initial number of foragers	10
N_{tbc}	Total number of brood carers	25
$E_{pheromones}$	Evaporation rate of Pheromones	5%
$D_{pheromones}$	Diffusion rate of Pheromones	60%
Adaptation-rate	The rate at which the thresholds are adapted	0.09
Shouting-radius	The number of patches the brood member can shout when it gets hungry	7
E_{sc}	Evaporation rate of shouting chemical	50%
U_{food}	Upper threshold of food	40
L_{food}	Lower threshold of food	5
max-separate-turn	The maximum angle an agent can turn when avoiding another agent	1.25^0
E_{food}	Energy provided by the food which causes the hunger level of the brood member fed to decrease	100
Th_h	Threshold parameter of the hunger level	500

R	Ratio of the number of biased brood carer to the total number of brood carers	0, 0.12, 0.16, 0.2, 0.4, 0.8, 1
Food-growth	Probability of food growth	3×10^{-4} (benign), 3×10^{-5} (harsh)

Table 6.1: List of parameters

When the probability with which the food grows in the environment is kept at 3×10^{-4}, food remains abundant in the environment. Such a condition is referred to as a "benign" condition. However, when the probability of food growth is reduced to 3×10^{-5}, the availability of the food growth outside in the environment is reduced and hence it becomes more difficult for foragers to find food to bring back to the nest. Subsequently, this affects the hunger level of the brood members and hence the performance of the colony. Such a condition is referred to as "harsh" condition.

Table 6.2 illustrates the average hunger level of the brood (i.e. average of 20 experimental readings in the benign condition) after the 5000th time step

R	0	0.12	0.16	0.2	0.4	0.8	1.0
$N_b = 20$	1.21	0.97	0.94	0.94	1.00	2.58	3.94
$N_b = 60$	2.81	2.58	2.58	2.54	3.24	4.17	4.64
$N_b = 80$	3.40	3.01	3.02	3.17	3.55	4.36	4.77

Table 6.2: Average hunger level at the end of the simulation(here R = ratio of the number of biased brood carers to the total number of brood carers and N_b = number of brood members)

Figure 6.2 – 6.4 shows how the average hunger level of the brood members varies with the ratio of the number of biased brood carers to the total number of brood carers (R) during the benign conditions.

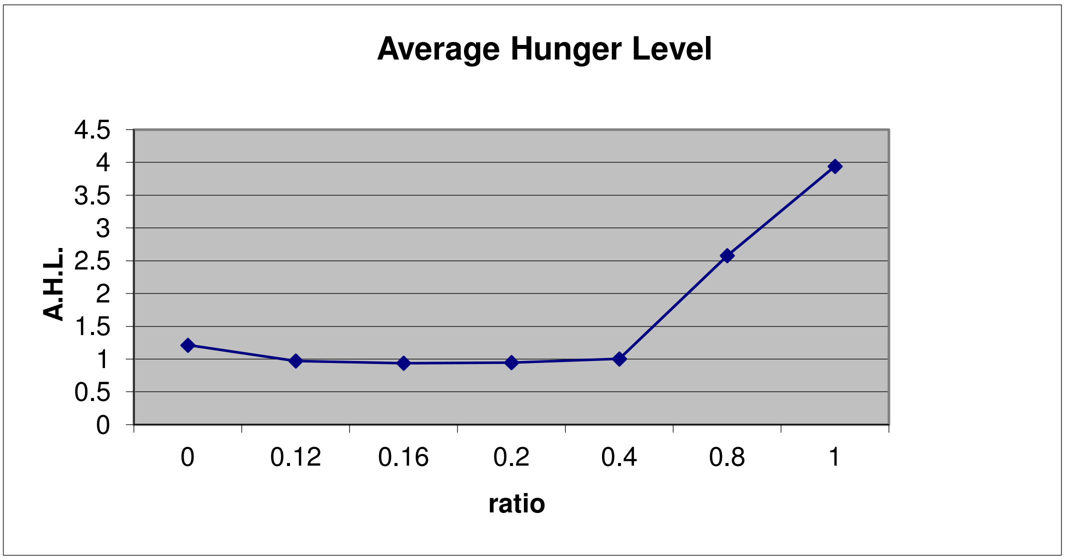


Fig 6.2: Average hunger level for $N_b = 20$ (N_b = Number of brood members)

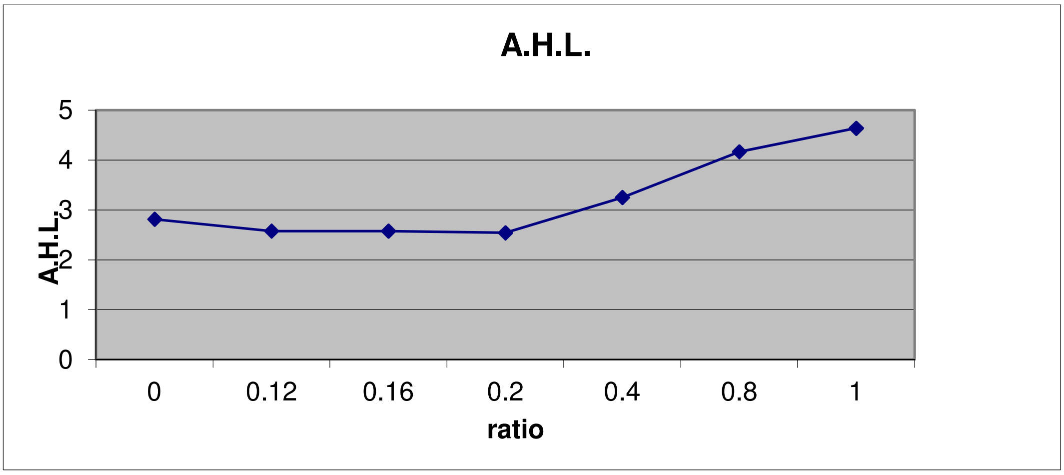


Fig 6.3: Average hunger level for $N_b = 60$(N_b = Number of brood members)

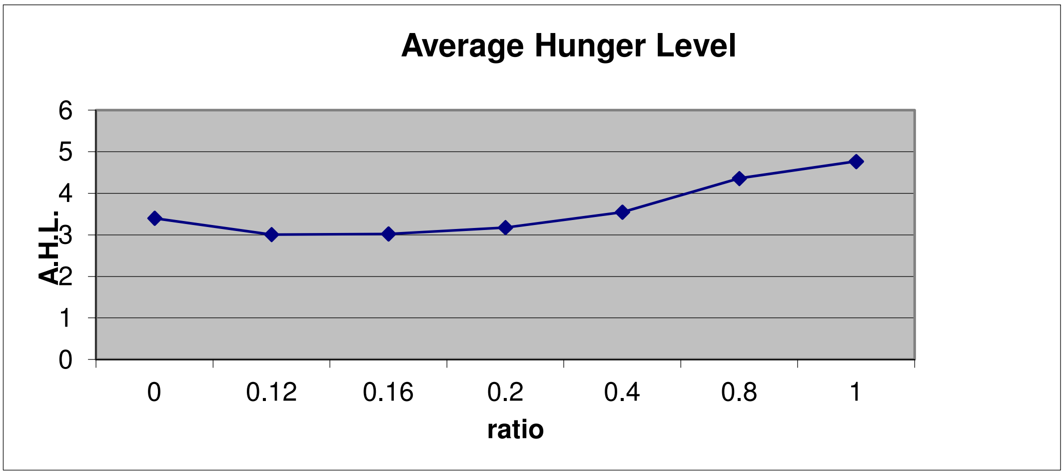


Fig 6.4: Average hunger level for N_b = 80(N_b = Number of brood members)

From figures 6.2 – 6.4 it is evident that introducing preference towards some tasks has some impact on the performance of the colony. When the ratio in the graphs is zero, there are no biased brood carers. However increasing the ratio of the number of biased brood carers to the total number of brood carers can be seen to reduce the average hunger level (i.e. improve the performance) of the colony upto some critical ratio beyond which the average hunger level starts increasing. For instance when the brood size is 20, the average hunger level reduces from 1.21 to 0.94 as the ratio increases from 0 to 0.2. When the ratio is increased further, the average hunger level also increases with it (figure 6.2). Similarly, it is evident from figure 6.3 where the brood size is 60, the average hunger level reduces from 2.81 to 2.54 as the ratio increases from 0 to 0.2 beyond which the average hunger level increases. When the brood size is 80, the average hunger level has been found to reduce from 3.40 to 3.02 as the ratio increases from 0 to 0.16 beyond which the hunger level starts increasing. To investigate if the lowest hunger level found due to the introduction of some biased brood carers is a significant improvement over when there were no biased brood carers (i.e. ratio = 0), a series of Mann-Whitney test has been conducted. Tables 6.3 - 6.5 shows the results found from the Mann-Whitney tests.

Test Statistics[b]

	VAR00001
Mann-Whitney U	123.000
Wilcoxon W	333.000
Z	-2.083
Asymp. Sig. (2-tailed)	.037
Exact Sig. [2*(1-tailed Sig.)]	.038[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

Table 6.3: Result of Mann Whitney tests for N_b = 20

Test Statistics[b]

	VAR00001
Mann-Whitney U	118.000
Wilcoxon W	328.000
Z	-2.218
Asymp. Sig. (2-tailed)	.027
Exact Sig. [2*(1-tailed Sig.)]	.026[a]

a. Not corrected for ties.

Test Statistics[b]

	VAR00001
Mann-Whitney U	118.000
Wilcoxon W	328.000
Z	-2.218
Asymp. Sig. (2-tailed)	.027
Exact Sig. [2*(1-tailed Sig.)]	.026[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

Table 6.4: Result of Mann Whitney tests for $N_b = 60$

Test Statistics[b]

	VAR00001
Mann-Whitney U	91.000
Wilcoxon W	301.000
Z	-2.948
Asymp. Sig. (2-tailed)	.003
Exact Sig. [2*(1-tailed Sig.)]	.003[a]

a. Not corrected for ties.

b. Grouping Variable: VAR00002

Table 6.5: Result of Mann Whitney tests for $N_b = 80$

For each of the cases the p-value is found to be less than 0.05 implying that the reduction of hunger level due to the introduction of biased brood carers is a significant improvement over the flexible brood carers. For a brood size of 80, the improvement of performance (at an alpha level of 0.1) is found to be significant even under the conservative Bonferroni test (as p-value, 0.003, is found to be less than $\frac{0.1}{21} = 0.0048$).

When the condition of the system is switched to “harsh” instead of “benign”, the average hunger level does not improve with the introduction of biased brood carers (figures 6.5 to 6.7 show the graphical output of the results for harsh conditions while table 6.6 summarises the results for the harsh condition). This can probably be explained as being due to the fact that in the harsh condition, there is a greater need for foraging than in the benign condition and limiting the foraging ability by the introduction of biased brood carers does not help in lowering the average hunger level.

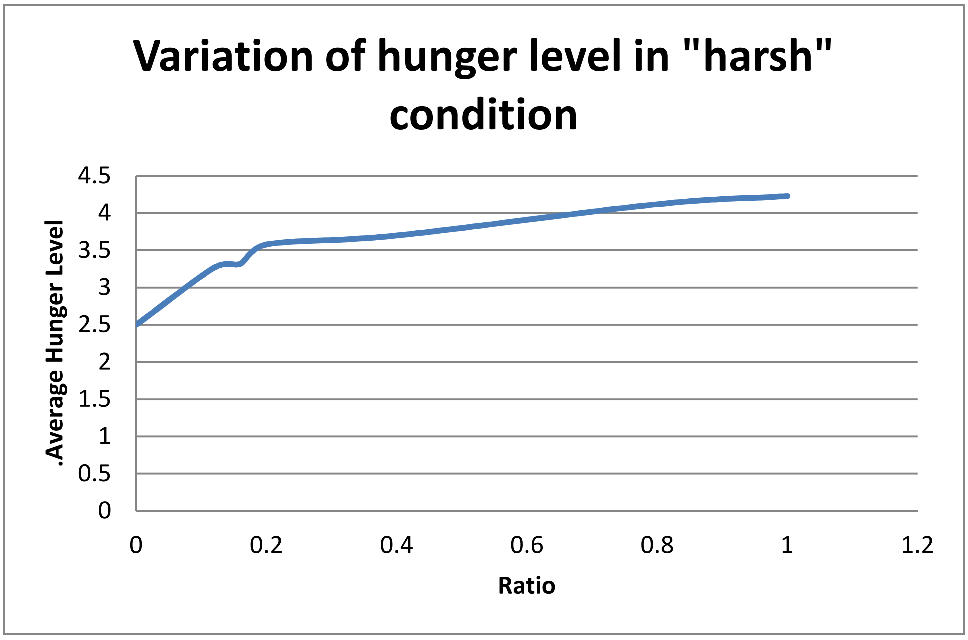


Fig 6.5: Average hunger level for $N_b = 20$ (N_b = Number of brood members)

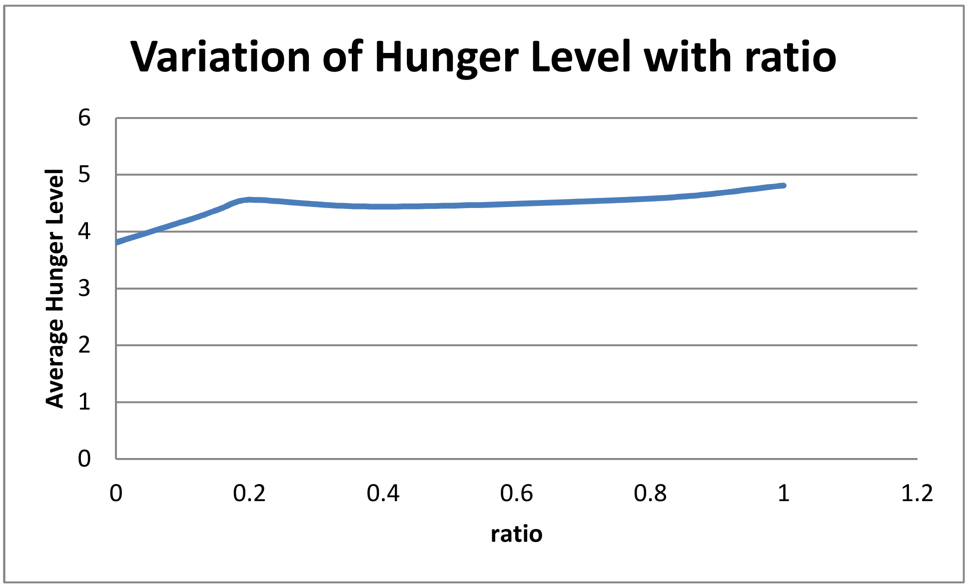


Fig 6.6: Average hunger level for $N_b = 60$ (N_b = Number of brood members)

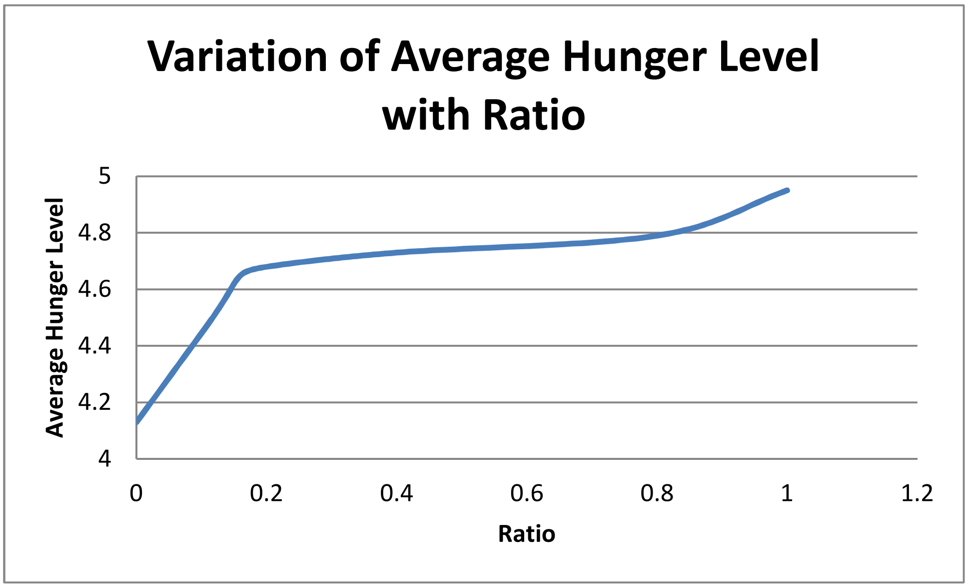


Fig 6.7: Average hunger level for $N_b = 80$ (N_b = Number of brood members)

R	0	0.12	0.16	0.2	0.4	0.8	1.0
$N_b = 20$	2.5	3.27	3.32	3.58	3.7	4.12	4.23
$N_b = 60$	3.81	4.25	4.42	4.56	4.44	4.58	4.81
$N_b = 80$	4.13	4.51	4.65	4.68	4.73	4.79	4.95

Table 6.6: Average hunger level after the 5000th simulation time step (harsh condition)

6.3. Conclusion

This chapter provides the third strategy for allocating tasks and analyses the effect of the strategy on the performance of the colony. This model is inspired by the behaviour of many ant species that show preferences in task selection. In the previous models presented in this thesis, the agents select tasks based purely on the stimuli (signals) they receive. This model, however, introduces an internal parameter (which in natural world can be due to many factors including genes, age, morphology and so on) that influences the selection of tasks in agents. Experiments were carried out in the Netlogo environment. The results obtained are then statistically evaluated to see if such task preferences have any benefit or not. It was speculated before carrying out the experiments that such strategy (i.e. the introduction of biased brood carers) in benign conditions would actually improve the performance of the colony up to some critical ratio. On the other hand, it was expected that this strategy would not provide any benefit to the performance of the colony in harsh condition but rather would be detrimental to the performance. Experimental investigation using agent based methodology shows the outcome of the result is in agreement with our initial speculation. It is concluded that the third strategy for task allocation can improve performance of the colony. Reducing the flexibility of task allocation, and having some dedicated brood carers improves the performance in benign conditions, when there is plenty of food available. It is interesting to note that such biased task allocations are found in nature in complex societies living in hospitable environment.

Chapter 7

Discussion

This chapter reflects on the results presented in chapters 4 – 6 and critically reviews the impact of different task allocation strategies (mentioned in chapters 4 – 6) on the performance of the colony. Furthermore, this chapter makes qualitative comparisons between the results produced in the models and others described in the literature. This includes a discussion of both the similarities and the differences of our models with those in related papers and of the extent to which the implications of the present findings are found consistent with other research.

The rest of the chapter is structured as follows: in section 7.1, a discussion of the results presented in chapters 4 – 6 is articulated. This includes some observations about the effects of different strategies on colony performance. Furthermore, the implications of the results are carefully reviewed. Section 7.2 compares our models (and results) with the findings of other researchers and discusses the ways the models we developed resemble and/or are different from them. Finally, the chapter is concluded in section 7.3 with a summary of its main points.

7.1 Results

Chapter 4 presents a base model for this thesis from which other strategies of task allocation presented in chapters 5 and 6 are developed. The model described in chapter 4 uses stigmergic interactions between agents to meet colony demand. For detailed information about the model, please refer to Chapter 4 of the thesis. The key questions explored in the chapter include whether the system that emerges out of the simple rules (specified in section 4.3) is (1) scalable, (2) flexible and (3) robust. To check if the system is scalable, the number of dynamic agents (i.e. number of foragers + number of brood carers) is varied between 20 and 100 for brood size = 5, 15 and 25. For each set of parameters, experiments are repeated 20 times and then the average hunger level of the brood over the 20 runs is determined. The results show increasing average hunger level with brood size. Moreover, as the number of dynamic agents is increased, the average hunger level decreases thus improving the performance of the colony. Improvement of the performance of the colony with the size of the number of dynamic agents suggests that the system is scalable.

Dynamic agents use threshold based mechanisms to adapt to the changing demand. To address the question of flexibility, the initial ratio of the number of foragers to brood carers is varied as follows: 0.2, 0.5 and 0.9. If the system is flexible, then the initial ratio of foragers to brood carers would not affect the result as long as the total number of dynamic agents and the brood size stays the same. For the number of dynamic agents varying between 20 and 60, initial ratio of foragers to brood carers varying as 0.2, 0.5 or 0.9 and the brood size varying between 5 and 25, the change in the average hunger level is found to remain statistically insignificant as long as the total number of dynamic agents and that of brood size remain the same. This illustrates that the initial ratio of foragers to brood carers has no effect on the final average hunger level of the brood indicating that the dynamic agents are flexible enough to adapt themselves over the simulated time period.

To check if the system is robust (i.e. that the system continues to operate despite the malfunction of some of the agents), experiments were carried out where 10 random agents (foragers and/or brood carers) die at the 500th simulation time steps (the simulation runs for up to 5000 simulation time steps). When the agents die, they are instantly removed from the model. Experiments with brood size = 15 and initial number of dynamic agents = {20, 30, 40, 50} reveal that the perturbed model generates a slightly greater average hunger level than that of the non-perturbed model. But the overall operation of the system does not cease. Furthermore, the difference in the average hunger level between the perturbed and the non-perturbed model decreases with increasing number of dynamic agents indicating that greater number of dynamic agents contribute to a more robust system.

Chapter 5 presents another strategy for task allocation, that is noticeable in many social insects, where agents not only interact with each other indirectly via the environment but also communicate directly when in need. This kind of communication is referred to as explicit communication in the thesis. The chapter presents a comparison between explicit and indirect communication strategies within the realms of the colony performance. Experiments reveal that for both the strategies, the increase in the number of dynamic agents reduces the average hunger level of the colony (i.e. improves the colony performance). The chapter further concludes that explicit communication almost always resulted in better colony performance than that of the indirect communication counterpart. However, the performance of the explicit communication is found to be more useful under stressful conditions.

Chapter 6 presents the third and final strategy of task allocation developed in the thesis wherein the brood carer agents can be one of the two types: (i) adaptive brood carers and (ii) biased brood carers. Adaptive brood carers behave in the same fashion as outlined in Chapter 5 whereas biased brood carers are dedicated to only one kind of work i.e. feeding hungry brood members when needed. Experimental results reveal that during benign conditions (i.e. when food items are available in abundance), having a slight proportion of biased brood carers always improves the performance of the colony.

7.1.1 Implications of the results

The results from chapters 4 – 6 imply that there is no particular task allocation strategy that works best for every situation but that the best strategy is a function of various factors including those of the environmental constraints, number of agents involved and the demand of the colony. However, the results do show some general trends for the three task allocation strategies explored. For instance, incorporation of direct communication along with that of indirect communication is found to improve the performance of the colony. But the improvement of the performance becomes more prominent when colonies are placed under much more stressful conditions. Chapter 6 of the thesis further reveals that the performance, under benign conditions, can further be improved by employing some biased agents (biased brood carers) along with the dynamic brood carers.

7.2 Comparison of our models with other relevant models/experiments in the literature

This section compares some of the relevant work found in the literature with the research reported in this thesis. The comparison includes both differences and similarities between the models and/or results presented in chapters 4 – 6 with other notable works mentioned in chapters 2 and 3.

7.2.1 Differences

The models we presented differ from many other related works in two main ways: (1) approach and (2) strategies.

A number of researchers have adopted other approaches unlike the agent based modelling used in this thesis. Mathematical modelling [e.g. see the works of Arcaute et al., 2009; Galstyan and Lerman, 2004; Halloy et al., 2007, Schmickl et al., 2009] for example, is one such approach wherein a set of identical individuals are treated as a population and the interaction between different populations are formulated using partial or ordinary differential equations. Such methods generally ignore the differences within the members of the population and consequently limit the understanding of how patterns are formed. However, these methods have proved to be a useful vehicle to systematically study complex systems. Other mathematical modelling techniques that are prominent in the literature include the use of probabilistic approaches to mathematical modelling [Lerman et al., 2005; Liu and Winfield, 2010] involving geometric means to predict transition probabilities [Liu, 2008].

Another popular approach is the use of simulated and/or real robots [e.g. see Krieger and Billeter, 2000; Labella, 2007; Liu, 2008; Liu et al., 2007a,b; Yongming et al., 2010] to understand and capture the emergent properties noticeable in biological systems. Such systems often incorporate physical properties such as sensor and actuator characteristics. However, the approach has been found to be limiting in terms of the number of agents that can be used. Furthermore, such approaches also suffer from the difficulty of properly replicating many of the behaviours that animals and in particular social insects display. Unlike such approaches, our models incorporate a greater number of agents and tasks and also contain a richer set of behavioural rules.

Another important way our models differ from those of other researchers is the development of a number of task allocation strategies (three) and the exploration of the benefits that different task allocation strategies bring.

7.2.2 Similarities

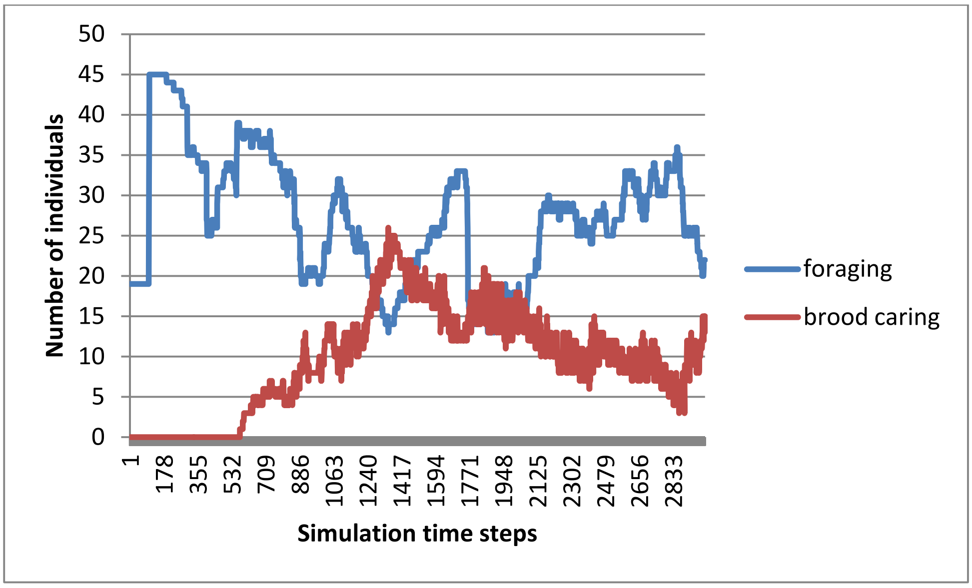
The models developed in this thesis are found to bear close resemblance (in terms of the results generated) with the behaviour of many insect societies. Gordon, for instance, carried out a number of experiments where she and her colleagues perturbed colonies of red harvester ants in various ways and found that the social insects are resilient to external perturbations [Gordon, 2002; Gordon et al. 2008; Greene and Gordon, 2003]. It is known that in red harvester ants, the return of successful patrollers lead to increase in the foraging activity. Greene and Gordon extracted the cuticular hydrocarbons of patrollers and used it to coat beads [Greene and Gordon, 2007], which in turn were placed in front of the nest – thus artificially increasing the rate of returning patrollers. This consequently increased the foraging activity indicating that insect societies are extremely responsive to the stimulus received. Experiments with ponerine ants result in similar outcomes. The workers of ponerine ants, *E. ruidum*, act either as stingers where they kill the live drosphillas (prey) by the act of stinging, or transporters where they carry dead drosphillas from the ground to the nest [Theraulaz et al., 2001]. The ratio of stingers to transporters was found to vary with the stimulus (i.e. live dropsphillas trigger stinging operation and dead drosphillas trigger transporting operation) which further shows that social insects are extremely adaptive to the changing demands. Schmickl and Crailsheim [Schmickl and Crailsheim 2008a, b, c] used an agent based modelling approach to develop task selection models for honeybees. They then carried out a number of perturbations to different castes of simulated honeybees and investigated the effect of each perturbation on the colony. The general observation that can be made is that each perturbation causes the colony to react so as to meet the extra demand created by the perturbations. For instance, a sudden increase in the brood size in the simulation results in an increase in the number of nurse bees (since more nurse bees would be required to feed the brood members). Similarly the removal of the brood members results in the decrease in the number of nurse bees.

The model developed in this thesis also shows similar resilience to the dynamic changes in the environment. Figures 5.6a and 5.6b depict this and show how the number of foragers and brood carers (initially there were an equal number of foragers and brood carers) varies with time. When the brood members get hungry, the number of brood carers increases – thus meeting the demand of the brood members. Figure 5.6b also shows that when the amount of food items present in the dump area is considerably reduced, some brood carers switch to the foraging task in order to meet the foraging demand.

To provide further insights into the way that external perturbations result in dynamic allocations of tasks (as seen in social insects) so as to meet the changing demand, the following alterations have been made to the model described in chapter 5.

1. The model (with initial brood size = 5 and number of dynamic agents = 50) is run undisturbed for the first 1000 time steps to allow the colony to reach an equilibrium state.
2. At 1000 time steps, some new brood members are added (either 10, 20 or 30) which causes an increase in the demand for brood feeding.

Each experiment is repeated 20 times and the average result is illustrated in the accompanying figure (figure 7.1). The result of the undisturbed colony is also shown in figure 7.1.


Number of individuals
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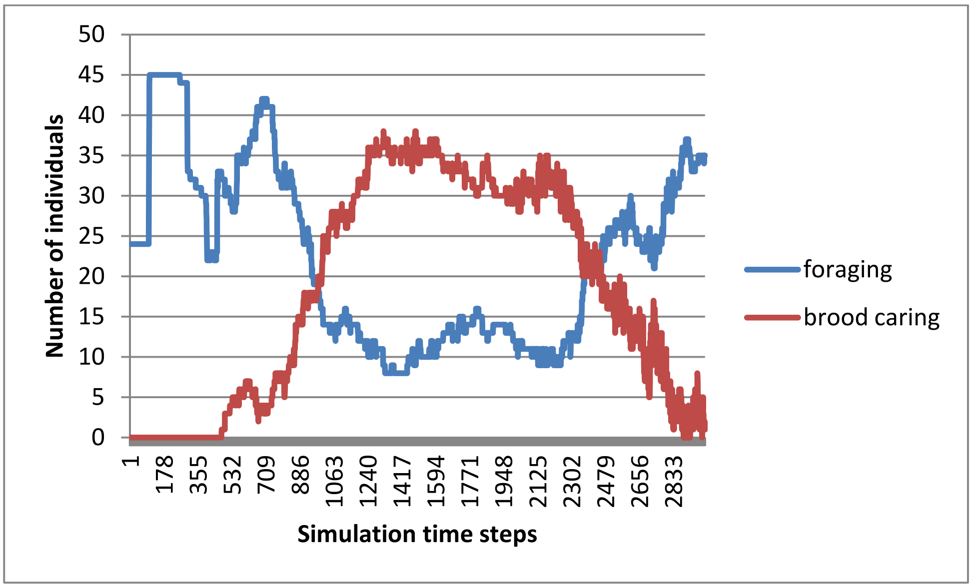
45
40
35
30
25
20
15
10
5
0
1
178
355
532
709
886
1063
1240
1417
1594
1771
1948
2125
2302
2479
2656
2833
Simulation time steps
foraging
brood caring

a


Number of individuals
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2125
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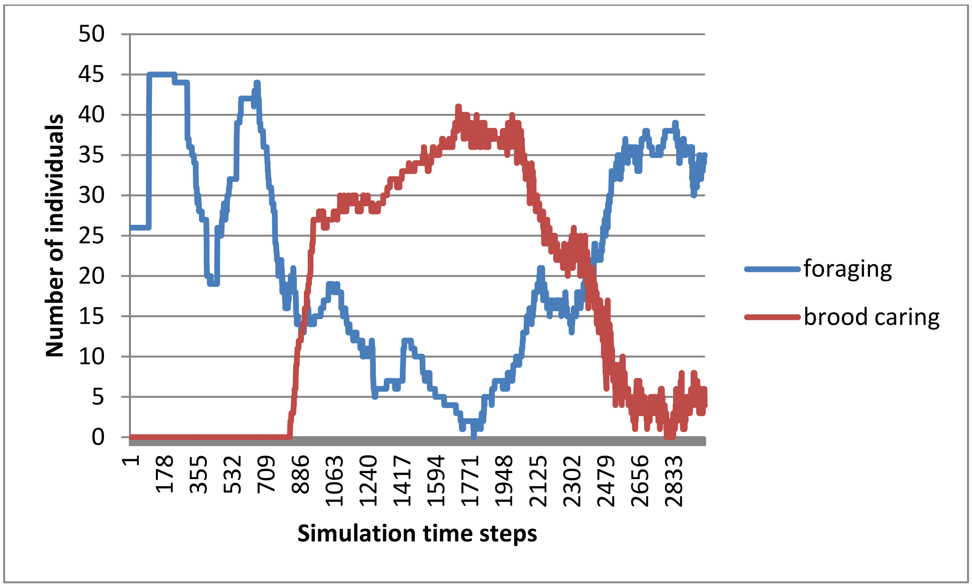
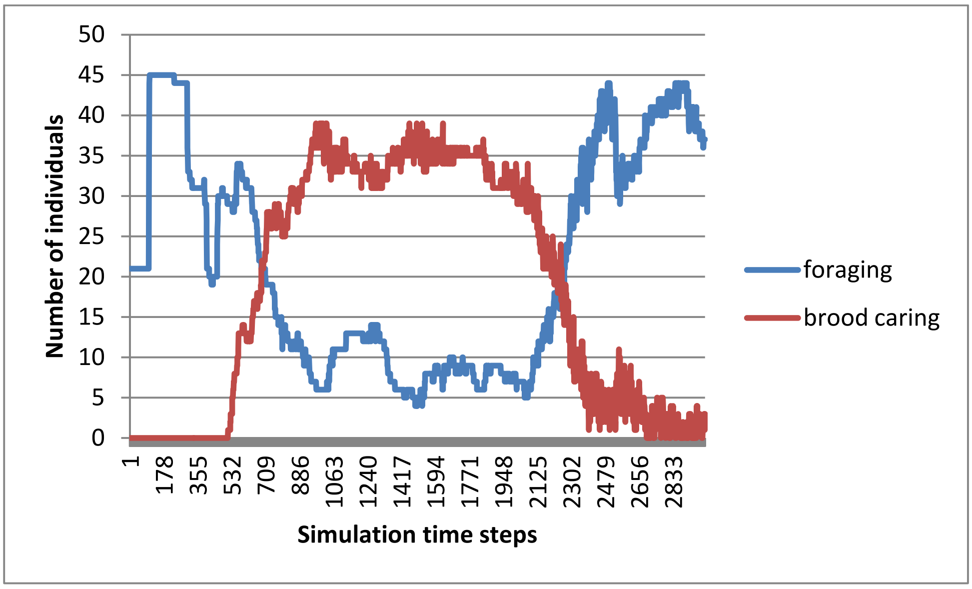
Simulation time steps
foraging
brood caring

b



c



d

Fig 7.1: Variation of foragers and brood carers: a) undisturbed colony, b) 10 new brood members are added, c) 20 new brood members are added, d) 30 new brood members are added.

Figure 7.1a shows a typical variation of foragers and brood carers when the colony is left undisturbed by any external perturbations. After the 500th time step, brood members gradually start getting hungry (as the threshold of hunger level of brood members is fixed to 500; for further details, refer to chapters 4 and 5) thus resulting in an increase in the number of brood carers after the 500th time steps. After an initial increase in the number of brood carers, the number of foragers and brood carers then fluctuates over time and constantly adapts to the changing environment. When the colony is perturbed by the insertion of additional brood members, the number of brood carers is also found to increase and exceed the number of foragers for a considerable time period (unlike the situation with undisturbed colonies) to meet the additional demand created. This is in line with the observations made in insect societies including the results obtained by Schmickl and Crailsheim where an increase in the brood size in honeybees results in an increase in the size of the nursing cohort [Schmickl and Crailsheim, 2008b].

7.3 Conclusion

This chapter presented a critical review of the results reported in the experimental chapters. The results obtained in chapters 4 – 6 were carefully examined and compared. Furthermore, the models developed in the thesis were compared to other related research work highlighting the similarities and the differences in terms of approach, results and implications. The comparisons indicated that the behaviour of the simulated agents in our models bore close resemblances with that found in many social insects.

Chapter 8

Conclusions

Division of labour (DOL), in the context of multi-agent and multi-robot systems, is considered to be one of the most important areas for managing work distributions. Multi-agent systems are usually populated with groups of homogeneous and/or heterogeneous agents that typically engage themselves in carrying out one or more tasks. Many approaches have so far been used by researchers in dealing with multi-agent systems. One of the most recent and successful approaches that has lately been embraced by many researchers is that of swarm intelligence that studies how a large number of relatively simple agents can use repeated local interactions between the neighbouring individuals and with the environment in the vicinity to create a collectively intelligent system. The field is strongly inspired by the collective behaviour of animals and especially by that of the social insects (mostly that of ants, bees, termites and wasps) that show some remarkable displays of swarm intelligence.

A crucial problem in most multi-agent systems and especially the self-organised systems is the effective allocation of tasks among the agents. In most cases, the environment within the self-organised system continuously changes and therefore the demand for tasks also continuously changes. So, in order that the agents can meet the demands, they need to continuously adapt to the changing environment. Self organised systems and particularly that exhibited by the eusocial insects are very well known to display effective allocation of tasks in response to the dynamic changes in the environment and the demands within the colony. This thesis is strongly inspired by such capabilities of eusocial insects (particularly ants) and devoted to understanding how tasks can be allocated effectively in a dynamic fashion to the agents in a self-organised multi-agent system. The author delves into the literature of entomology to investigate the different strategies ant colonies adopt under different circumstances to allocate tasks. In particular, three strategies of task allocations (by taking inspirations from the behaviour of ant colonies) are proposed and modelled in line with the behaviour of ant colonies. The strategies are then critically analysed to understand the effectiveness of the strategies in terms of colony performance under different circumstances.

8.1 Approach to the problem

The best way to model and analyse strategies for a system is perhaps by observing and understanding how other similar systems work. Since nature provides us with plenty of self organised systems, a good approach would be to understand how these systems work under various situations. Once these natural systems are well understood, they can be modelled and various strategies the natural agents use then can be simulated to see how well they perform under different circumstances. This has principally been our approach for designing and investigating task allocation models for swarm based multi-agent systems. Social insects and more particularly ants, were chosen to understand the strategies for decentralised task allocation since ants are very well known for displaying numerous examples of decentralised division of labour.

There are currently over 12,000 known species of ants, each maintaining highly organized colonies and nests with colony size ranging from a few individual to 20,000,000 individuals [Beckers et al., 1989; Momen and Sharkey, 2009b]. Different species often have different strategies for task execution – thus providing us with the possibility of developing and understanding different task allocation techniques. Furthermore ants are remarkable in managing tasks as well. Ants use simple yet sophisticated means of allocating tasks allowing them to manage colonies with such wide range of nestmates. All these points have prompted the decision to model and analyse task allocation strategies based on the behaviour of ants.

8.2 Summary of the thesis

In this thesis, we analyse and reason about how ants behave in various situations. This has led to an understanding of how ants behave, and more importantly how they allocate tasks among themselves without having a global view of template of the environment. Furthermore, three strategies for task allocation are suggested based on the understanding of their behaviour. In order to see if the suggested strategies are ant-like, it was necessary to model them and observe the dynamics involved. To realise this, agent based modelling techniques have been adopted to model their behaviour. The primary reasons for choosing agent based modelling techniques are (1) it allows us to see the dynamics of their behaviour, (2) it makes it possible to change behavioural rules quickly (if needed be) and to visually watch how it affects the collective behaviour of the agents and (3) it makes it possible to experiment with wide range of parameters.

This thesis is comprised of eight chapters. Chapter 1 provides an introduction to the thesis and sets out the goals and objective of the thesis. Chapters 2 and 3 provide a detailed literature review that acts as a base for the thesis. Chapter 2 mostly discusses the self-organising system in various systems in nature including that of ants while chapter 3 specifically discusses the task allocation strategies in self organised and market based systems.

The first model proposed was presented in Chapter 4 of the thesis. This chapter includes a detailed discussion of the behavioural rules of the agents, the topology of the environment, the communication strategies between the agents and the constituents of the environment. The chapter also discusses in good detail how the performance of the colony can be evaluated and presents a series of experiments and their results in different circumstances. The chapter, furthermore, shows that the behavioural rules that were used generate a system that is scalable, robust and decentralised. The chapter uses the concept of simple thresholds to enable agents to respond to a particular task.

Chapter 5 extends the model that was presented in chapter 4. The communication method that was used in chapter 4 was entirely stigmergic i.e. agents do not directly communicate rather only communicate indirectly via the environment. However, in real ants, it is very well established that ants use direct communication in conjunction with stigmergic communication. This concept has been adopted and used in modelling the behaviour of agents. In this version of the model, the ants use explicit communication (i.e. indirect communication + direct communication under certain condition) and we analyse whether, and when, this helps to improve the colony efficiency. A series of experiments were created with different conditions and settings to see if explicit communication at all benefits the performance of the colony. Statistical tests were carried out to analyse whether the performance for explicit communication between the agents is a significant improvement over that of the indirect communication. Our results indicate that explicit communication has an advantage over sole indirect communication but the performance of the colony that exhibits explicit communication is not necessarily always a significant improvement over that of the indirect communication. This finding is remarkable because it gives us an indication why many colonies of ants use purely stigmergic communication while there are many that exhibit explicit communication.

Chapter 6 looks into the concept of heterogeneous mixture within a particular caste. This work intends to see how the performance of the colony is affected if a caste is slightly biased towards a particular task. The ratio of bias can be varied by varying the number of biased agents within that caste. It has been interestingly found that some degree of bias within the caste significantly improves the performance of the colony. A series of experiments have again been carried out to see if the improvement of the performance of the colony due to slight biasness is always true or not. Two conditions of the environment (benign and harsh) have been developed and a detailed analysis has been made about the effect of biasness on the colony and also when the incorporation of biasness can improve the performance significantly.

All these experiments led us to conclude that there is no universal best strategy for task allocation. Rather the optimal task allocation strategy is a function of many factors including the condition of the environment (e.g. food availability), the number of agents involved and the demand of the colony (e.g. hungry brood members). The results of the experiments indicate the situations when a particular task allocation strategy can be expected to benefit the colony and hence can be employed while designing similar multi-agent systems.

Discussion and comparison of the results from three models is critically analysed and reviewed in chapter 7.

The task allocation strategy used in chapter 4 use stigmergic communication between agents. The model presented in chapter 5 uses explicit communication between the agents for allocating tasks. Use of explicit communication is always found to yield better colony performance compared to the indirect communication. However, when the results were statistically evaluated, it was found that explicit communication works better under stressed conditions. The results obtained were in line with the predictions made. The third strategy looks into a mixture of heterogeneous agents having different task preferences towards brood caring. It was found that a slight bias (preference) towards a particular task always improves the performance of the colony. This result is in line with the observation of natural ant colonies where we find different castes to emerge within the colony. The results found suggest that a slight biasness within the colony results in a greater colony performance. From the results obtained, it can be suggested that while designing a similar multi agent system, it is important to evaluate the condition of the system. For instance, if the environment is simple and less stressful, stigmergic communication between the agents could yield a good performance of the colony. However, if the system is more complex and stressful (i.e. there is a more frequent need to meet the demand), incorporating explicit communication would yield better colony performance. Finally, the performance of the colony can possibly be enhanced further by introducing the right mixture of heterogeneity among the agents.

8.3 Contributions

A number of contributions have been made in this thesis. The main contributions of the thesis include:

1. **A detailed simulation environment that facilitates a deeper understanding of task allocation mechanisms in groups of mobile agents is developed and described:** In order to capture the dynamics involved and to better understand the task allocation mechanisms, it was essential to develop a simulation environment that would make it possible to vary the parameters easily and to investigate how well the task allocation mechanisms perform under different circumstances.

   A bottom up approach (using agent based modelling techniques) was used to model the system rather than a top down approach since it allows the detailed modelling of local interactions among the neighbouring agents and also between the agents and the environment in the vicinity – thus enabling the capture of the emergent phenomena from the simple interactions of the agents. A top down approach would not have allowed the modelling of such local interactions between the individuals. Rather it would mainly involve modelling at the aggregate level i.e. looking at how the populations of agents behave as a whole. The bottom up approach adopted in this thesis provides a natural description of the system and is flexible in terms of experimentations with varying parameters [Bonabeau, 2002].

The simulation environment takes many aspects of ant colonies and ant behaviour into consideration at a level of detail usually not found in other models of ant colony behaviour. The number of agents and the range of tasks involved are larger than those usually involved in swarm robotic research.

The simulated environment also captures a high degree of eusociality. Although many researchers describe their work as being inspired by the social behaviour of insects, they often fail to take all the key aspects of social behaviours as mentioned by [Wilson, 1971] into consideration. The models presented in this thesis capture the fundamental aspects of eusocial behaviour (i.e. cooperative brood caring, overlapping of generations and division of labour) as outlined by [Wilson, 1971] and are unusual and more ant like in that respect.

2. **Three task allocation strategies in the light of ant colony behaviours are proposed:** Three task allocation strategies have been designed and developed in this thesis. The task allocation strategies are all inspired by how ant colonies behave. The first strategy, presented in Chapter 4, uses only stigmergic interactions between the agents to communicate with and also to influence other agents to take up some particular task. In Chapter 5, a second strategy of task allocation was presented. In this strategy, the agents use both direct and indirect communication to allocate tasks among themselves. Finally, in Chapter 6, a third strategy was presented where a heterogeneous mixture of agents participates in the allocation of tasks. In previous

investigations of task allocation, the strategies that have been modelled, or investigated, have mostly involved the use of indirect communication. The present thesis is unusual in its development and exploration of explicit measures of communication and their advantages under different circumstances. The exploration of the advantage of bias in the colony is a further novel contribution of this thesis. Such biases are noticeable in complex colonies but to our knowledge no work has previously been done to understand the benefit of them by means of modelling techniques such as those presented here.

3. **As a consequence of the detailed simulation environment and the modelling of different task allocation strategies, a better understanding of the strengths of different task allocation strategies under different circumstances has been achieved:** This thesis takes a systematic approach to investigating the relative strengths of the three task allocation mechanisms under different circumstances. Although it can be concluded that there is no universal best task allocation strategy, the thesis finds some general trends that indicate the circumstances under which a particular task allocation strategy would be expected to work better. For instance, chapter 5 of the thesis indicates that although agents using explicit communication almost always perform better than those using only indirect communication, their performance is significantly better under stressful condition (please refer to chapter 5 for further details). In chapter 6, the role of bias towards brood caring in the colony was investigated and it was found that a slight bias under benign conditions tends to improve the performance of the colony. Such identifications of the relative strengths of different task allocation strategies

should help researchers to design more effective task allocation mechanisms for multi-agent systems.

8.4 Future Works

This thesis has explored the design and modelling of task allocation behaviour for swarm systems. The thesis takes its inspiration from the way the eusocial insects allocate tasks in response to the changing demands. Three task allocation strategies, in the light of how ant colonies behave, have been developed and analysed. The results obtained from the analyses made could be used to guide researchers to choose effective task allocation strategies for the systems they are involved with. In future, we intend to carry out further investigations that would lead us to understand task allocation strategies and the effect of the strategies on the colony performance better. We intend to carry out further investigations into the following research areas that will improve our understanding of the effects of the task allocation strategies on the colony performance:

A. Effect of parameters on the performance of the colony:

The experiments reported in chapters 4, 5 and 6 varied some of the parameters of the model to investigate the effect of the parameters on the performance of the colony. For our future work, it would be interesting to do a complete sweep of parameter space to investigate the effect of each of the parameters on the colony performance and also to find the set of parameters that result in maximum performance. Use of genetic algorithms (GA) to determine optimal or near-optimal solution would also be an interesting approach for finding optimal solutions.

B. Stronger model validation:

The models developed have captured many aspects of the behaviour of ant colonies including cooperative brood caring, foraging techniques, task allocation techniques using threshold based mechanism and decentralised mechanism. The results obtained from the simulation experiments show similar behaviour to that of the real ant colonies (in terms of robustness, flexibility and scalability). Therefore, in one way the model is validated. But the stronger the validation of the model is the stronger would be the reliability of the model. Therefore, for our future work, we intend to move towards more rigorous validation of the model. One way of doing this would be to compare the behaviour that we obtain from experimenting with real robots with that of the simulated behaviour to give us an understanding how close the models are.

C. Extend the task allocation models:

In future, we would like to model more task allocation strategies that ants exhibit and create a library for task allocation for users. Such libraries could then be used to analyse the impact of the different task allocation strategies on the performance of the colony. This in turn would help to make it possible to quickly use different known task allocation strategy in different situations and analyse how it affects the performance of the colony.

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