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From Ants To Robots: A Decentralised Task Allocation Model For A Swarm of Robots

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Abstract. This paper presents a task allocation and task switching model for a decentralised group of mobile robots. The model is strongly inspired by the behaviour of social insects, typically ants, which exhibit remarkable techniques for allocating tasks and adapting to the changing environment. The agents in the model allocate tasks based on the local cues they perceive and without the need of any centralised controller. The paper compares two communication techniques inspired by the ant colony behaviour. The objective of this paper is fourfold: **(1)** to design and **(2)** implement a task allocation model for a swarm of mobile agents, **(3)** to develop two communication techniques (one in which agents communicate directly along with indirect communication and in the other they only communicate indirectly), and **(4)** empirically investigate the impact of the two techniques on the performance of the system. The agents are assumed to have limited perception and to only be able to interact locally. Experimental results reveal that the model is highly adaptive and efficient whichever communication technique is used. Furthermore, the results also show that the incorporation of explicit communication improves the performance of the system significantly over that of indirect communication. The model offers benefits to heterogeneous mobile robot systems to dynamically allocate tasks among themselves without the need of any centralised controller in such a way so as to improve the performance of the overall system.

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 attempting to attract the female ones or even the pods of dolphins dancing up and down in unison are some of the spectacular examples of collective behaviours [1,2] that animals display. Their behaviours are not only enthralling to watch (figure 1) but are also some of the finest examples of how individuals form groups which enable the group as a whole to carry out tasks that could not be accomplished by a single individual with the same efficiency. It is now well established that animals self organise [2] by repeatedly interacting with the neighbouring individuals and the environment in the vicinity resulting in the emergence of such collective behaviours. Individual agents neither have any global templates of the environment nor follow any particular leader. Instead, they behave as purely reactive individuals trying to synchronise with the immediate neighbours through some simple local interactions. Such local cohesion among the agents facilitate the tendency to become a part of a group which consequently benefits them in numerous ways including the possibility of minimizing danger of an individual from a potential predator [3], accomplishing tasks that are otherwise difficult to carry out and also in transferring vital information within the group quickly [4]. Each individual does not have enough intelligence to carry out its job optimally rather as a group such intelligence emerges (through local interactions) which is often referred to as swarm intelligence (SI). Intriguingly, such group behaviour and self organised systems are not limited to nature, but are also extremely prevalent within the very society we live in: pedestrians travelling [5] like that of the flocking of birds, spreading of rumour [6], rhythmic applause after a good concert [7, 8], traffic flow [9] in a busy road and even the evolution of a new sign language that emerged from mere interactions between the school children in Nicaragua [10] are just some of the examples of such self organized systems within our society.

Recent time has witnessed huge interest in the field of swarm intelligence and swarm robotics (SR) [14; for a brief history, see 11 – 13] among researchers in areas as different as biology and engineering. The concept of *swarm robotics* is strongly inspired from biology and especially from the behaviour of eusocial insects [15] like that of ants, bees, termites and wasps that show some remarkable examples of how a large number of simple individuals can use extremely simple rules and local communication to result in a collectively intelligent system. For engineers and roboticists, the field provides a number of key advantages (including robustness, flexibility and scalability) over the traditional deliberative based system for a wide number of practical applications whereas for the biologists, it provides a novel platform to analyse the mechanism underlying the principles of collective behaviour within animal groups.

Our work is strongly inspired by the behaviour of eusocial insects especially from that of the ants which provide us with a number of keen techniques for dividing tasks among the individuals. The individuals not only carry out a single task but also have the ability to switch between tasks in response to the changing demand or any other external perturbation. The decision to switch task does not arise from any global knowledge of the environment whatsoever but is rather taken autonomously based on the local interactions between the individuals and the stimuli received.

This paper addresses the issue of division of labour (DOL), inspired from the ant colony behaviour, within the realms of heterogeneous groups of robots (agents). The aim of this paper is to present an agent based model (ABM) (an extended version of that presented in [16, 17]) that would enable us to explore the dynamics of making decisions within groups of agents/robots. The model embraces threshold based approach [34] and presents two techniques (one in which agents use explicit and another

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Figure 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.

in which agents use indirect communication), inspired by the ant colony behaviour for autonomous division of labour based on the environmental and social cues they receive. Furthermore, we show that such techniques give rise to an extremely adaptive and efficient system. The system is inherently scalable owing to its decentralised nature. Here we pose and empirically investigate two relevant questions: (1) whether the behavioural rules incorporated in this model are sufficient to produce an adaptive system and (2) whether the additional use of explicit communication has any advantage over the indirect communication for the performance of the system? Answers to these questions would provide us with a better understanding of the impact of different types of interactions between the agents on the performance on the system. The rest of the paper is organised as follows: Section 2 discusses the mechanisms of DOL in social insects such as ants. Our model is proposed and described in Section 3 followed by the experiments and results in Section 4. Finally, Section 5 concludes the paper with a remark on our future work.

2 DIVISION OF LABOUR IN EUSOCIAL INSECTS

Ants are referred to as eusocial insects (insects exhibiting social behaviours including that of cooperative brood care, overlapping between generations and division of labour), a term first coined by E.O. Wilson in 1971 [15; also see 18] while classifying insects in terms of the social behaviours they exhibit, belonging to the family of *Formicidae* of the order *Hymenoptera*. There are currently over 12,000 known species of ants having colony size ranging from a few individuals to over millions. Ants are known to use simple yet extremely sophisticated communication mechanisms ranging from recruitment techniques via pheromones, tandem learning, antennal contact, and even stridulation [19]. They are extremely small in size (individuals weigh as little as 5 mg); however their social behaviours allow them to live at large.

So, what makes these tiny creatures so successful in effectively running and maintaining colonies some of which are as big as that of London city (by population)? What strategies have they embraced that led them to be socially so successful? Recent researchers [20, 21, 22, 23, 24] have pointed out that it is their embracement of effective DOL that has allowed them to be socially so successful.

A. Division of Labour in Ants

Ants are perhaps best known for their ability to effectively divide a wide range of tasks among the workers. This phenomenon of dividing tasks among workers is what is termed as *division of labour*; a term first introduced by Adam Smith, the father of modern economics, in his influential book "The Wealth of Nations" [25]. However, ants are known to have been using more effective mechanisms of dividing labour for millions of years. Not only can they divide tasks among groups, they can rearrange the distribution of workers depending on the need of the colony or any perturbation caused.

Ants exhibit a wide range of techniques for dividing labour. These mechanisms can be broadly categorised in three groups [26]: worker polymorphism, age polyethism and individual variability.

Worker polymorphism (also called physical castes) arises in ant colonies (e.g. *Atta colombica*) that have distinguishable subcastes within the worker ants [27]. One subcaste differs from the other one in terms of the size/morphology of the worker ants, which in turn influence the type of task chosen. For instance in many ant species major workers, with large head and sharp mandibles, specialise in tasks that require physical strengths like guarding nests and transporting food items whereas minor

workers tend to specialise in lighter tasks such as cleaning the nest and brood caring.

Some ant species such as *Pogonomyrmex barbatus, Cataglyphis bicolour* and *Oecophylla smaragdina* [24, 28, 29] tend to carry out tasks depending on their age (age polyethism). They tend to follow some kind of centrifugal tendency in selecting the task they carry out with the younger ones working closer to the centre of the nest and the older ones working more distant from the nest.

However most of the ant genera carry out tasks depending on the local cues they receive. Local communications between the ants influence individuals of which task to be selected.

B. Models of Division of Labour in Ants and Robots

The last two decades have witnessed the development of a number of models trying to establish the mechanism 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 the learning parameters [30].

Out of these models, one of the most important is the response threshold model, where agents have different threshold for different tasks. The agents can also update the values of the threshold/stimulus to respond to changing demand. Various versions of response threshold model has been embraced and developed by the researchers [for further details see 31, 32, 33, 34, 35].

Other promising models in DOL include that of the foraging for work model (FFW) [36, 37] and that of the learning models [38, 39, 40] in deciding what task to execute. Recently there has been enormous interest in using swarms of robots to model and carry out different tasks. Using SR for such purposes not only facilitates solving various practical solutions for engineering problems, it also provides a novel platform for the biologists to understand animal behaviour better. Biologist Robert Full, professor at UC Berkeley, describes this association between biology and another discipline as biomutualism [41].

One of the earliest works in this field was carried out by Krieger and Billeter in 2000 [42]. They used up to twelve mobile robots to make autonomous decisions of whether to forage (collect items from the environment) or rest depending on the nest energy level which was periodically echoed to the robots. Wenguo Liu and his colleagues [43, 44] used a threshold based approach in simulated robots to develop an adaptive threshold based mechanism to divide the number of foragers and resters so as to optimise the net energy level of the system. Momen and Sharkey [17] used ABM to simulate ant colony behaviour within the realms of heterogeneous groups of robots. They further investigated the advantages of task switching mechanisms, exhibited in various colonies of ants, in terms of the net energy gained by the swarm.

3 Proposed Model

The model proposed in this paper places three types of agents (mobile foragers, mobile brood carers, and static brood members) within a 71 × 51 grid in a 2D environment. The model contains a nest consisting of four separate chambers with brood surrounded by brood carers whereas foragers mostly reside outside in the environment (figure 2). Each of the chambers has its own odour that is spread over the environment.

The nest chamber odours are modelled as falling linearly from its respective centre of the chamber; thus each of the four types of smells creates a potential gradient uphill towards the centre of the chamber. The use of such artificial potential field technique for navigation has been an extremely popular approach [45 – 47] in mobile robotics typically in the case of avoiding obstacles or moving towards a target.

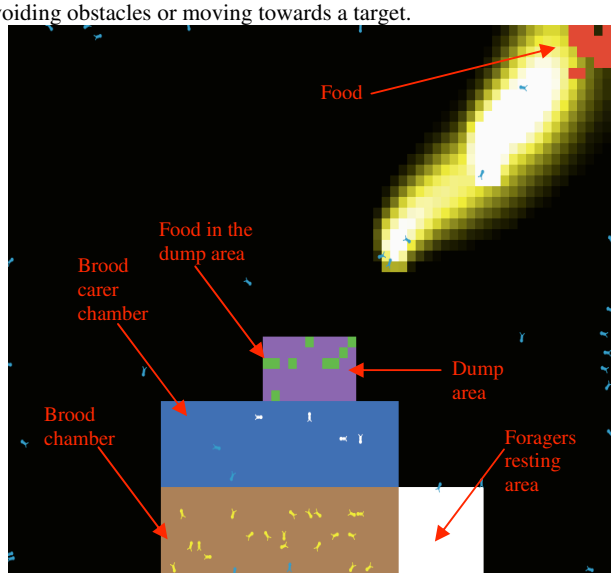

Figure 2. Snapshot of the simulation

In this model, brood reside at the lowest chamber of the nest. There is a dump area (DA) located at the entrance of the nest for the foragers to drop off food and leave it for the brood carers to pick them up for feeding the hungry brood. Similar spatial distribution is observed in various ant species [48, 24].

3.1 Behavioural Rules

Different types of agents follow different rules to accomplish their tasks. There are principally three types of tasks present in this scenario; foraging, resting and brood caring. Foraging involves foragers exploring the environment in order to find a food source, followed by picking up a piece of food, finding its path back to the dump area of the nest and finally dropping the food item there. Brood caring involves brood carers picking up a piece of food from the dump area, locating a hungry brood member, and feeding it. The resting task involves the agents (foragers and brood carers) resting within their respective chambers.

The behavioural rules of the agents are described below:

A. Brood

Each brood member can be in one of the two states: *hungry* or *non-hungry*. Initially all the brood 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. 1) which is selected randomly (Fig. 3). 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 (called shouting chemical here). The strength of the shouting chemical is modelled to fall linearly with the distance from the hungry brood member in such a way that it is at maximum at the location of the hungry brood member and minimum at the shouting-radius. The strength of the chemical is zero if the distance from the hungry brood member is more than the shouting-radius (eq. 3). However, if a hungry brood member is fed by a brood carer, the hunger level of the brood decreases by some constant value. If the hunger level at any time, t, is below the threshold parameter, the brood member switches its state back to the non-hungry state (eq. 2) (Fig. 4).

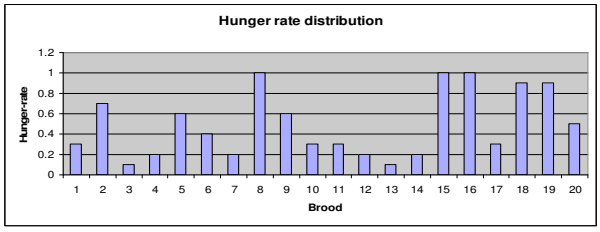

Figure 3. Hunger rate distribution across brood members of the brood in one of the runs

$$HL_{new} = HL_{old} + HR \quad (1)$$

where $0 \le HR \le 1$

$$HS = \begin{cases} 1, & HL_t \ge th_h \\ 0, & HL_t < th_h \end{cases} \quad (2)$$

Where,

HL_{new} is the new hunger level of the brood member,

HL_{old} is the previous hunger level of the brood,

HR is the hunger rate of the brood,

HS is the hunger state of the brood; 1 = hungry state and 0 = non-hungry state,

HL_t is the hunger level of the brood at time step t, and

th_h is the threshold parameter of the hunger level.

$$C_{SC} = \begin{cases} A - Bx, & x \le sr \\ 0, & x > sr \end{cases} \quad (3)$$

where,

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

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

sr is the shouting radius.

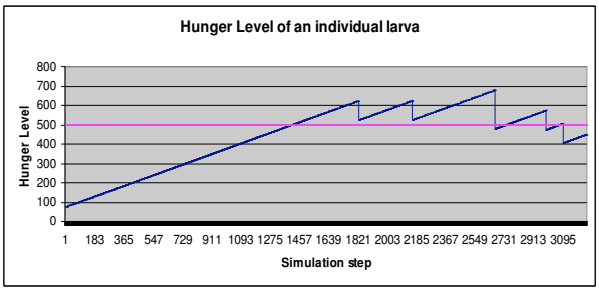

Figure 4. Hunger level of a brood member as a function of time (the reduction of the hunger level is due to being fed by brood carers)

B. Brood Carers

Brood carers respond to the need of the brood by adjusting their threshold values depending on stimuli (in this case, the shouting chemical) they receive (See section 3.2 for detailed description). Once a brood carer makes the decision to feed a hungry brood member, 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. Then the brood carer compares the relative strength of the scents in the three directions and moves in the direction of the strongest scent. This simple local interaction with the environment allows the brood carer to easily locate the DA. Once it reaches the dump area, it moves randomly within the DA to find a piece of food and as it finds a piece of food, it picks up the food item and travels towards the brood chamber in search of a hungry brood member.

The brood carer finds the brood chamber using the same technique as that of finding the dump area of the nest. Once a 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. Once the brood carer successfully locates a hungry brood member, it feeds it which causes the brood member's hunger level to be reduced by the energy provided by the food item (the simulations presented in this paper assumes that all the food items provide the same energy).

C. Foragers

Foragers can either forage or rest depending on what is required. A forager starts its journey by exiting the nest and travelling in a random direction in search of food. If it finds a food item in the environment, the forager picks the piece of food up, becomes laden and goes back to the DA of the nest by following the potential gradient of the scent of the DA. As it travels back to the nest, the forager leaves a simulated trail of chemical markers called pheromones in the environment. Once the forager reaches the DA, it leaves the food item there, decides if it needs to forage further or not and if so turns 180^0 and starts foraging again. The decision of whether to further forage or switch to a different task is explained in Section 3.2.

The simulated pheromone both diffuses and evaporates at constant rates. When unladen foragers looking for food encounter pheromones, they use the pheromone trails to go uphill towards the food source (See figure 2). The concentration level of pheromone at any of the patches of the environment can be modelled as in equation 4.

$$\frac{dC}{dt} = \alpha n_L + \frac{1}{8}\beta C' - (\varepsilon + \phi)C \qquad (4)$$

where,

C is the concentration level of the pheromone at the patch concerned,

n_L is the number of laden ants passing the patch concerned,

C' is the cumulative concentration level of the pheromones of the nearby eight patches,

C is the concentration of the chemical at the patch concerned,

ε is the evaporation rate of the chemical,

ϕ is the diffusion rate of the chemical, and

α and β are some constants such that $\alpha > 0, \beta > 0$.

Each of the foragers also maintains two types of clocks: a searching-clock and a resting-clock to track how long it has been searching for food and resting within its chamber. Every time a forager switches its task it resets all these clock values so that the clock values in the previous state do not affect the present state.

D. Obstacle Avoidance by Foragers

Foragers when foraging also actively prevent collision between each other by turning away from their nearest neighbour when required. The dynamic obstacle avoidance algorithm is inspired from the Craig Reynold's model of the flocking of birds [49; also see 50]. When an agent gets too close to another agent, it uses the headings of its nearest neighbour and its own heading to calculate the angle and the direction to turn in order to prevent any collision.

3.2 Task Allocation and Task Switching Algorithm

In this model, the brood create a task demand by emitting the shouting chemical whereas brood carers and foragers carry out their tasks, or sometimes switch task, in response to the changing demand. The environment is extremely dynamic and therefore the agents need to be flexible enough to meet the changing demand. For instance if there is no food available in the environment, the foragers would need to abandon their foraging task and rest in their designated area to save their energy [17]. Similarly, if the amount of hungry brood increases, some foragers might need to switch their task and become brood carers to meet the changing demand. The need for switching in the other direction might also arise if there is not enough food in the DA when the brood carers need to feed the brood. In that case, some brood carers might decide to change their task to foraging to assist the existing foragers. However, it is also important that the agents are not too flexible. Otherwise a slight change in the demand might cause all the agents to switch to the same task which would not be a desirable outcome. In order to prevent this, there is a need for some sort of "natural queue" that would allow appropriate task switching, and avoid the problem of all the foragers and brood carers switching to the same task. A threshold based mechanism [34] facilitates such a "natural queue", and provides the key motivation for embracing this technique.

Foragers and brood carers between them carry out three tasks namely **(1)** foraging, **(2)** brood caring and **(3)** resting as well as deciding which task to carry out next (Figure 5).

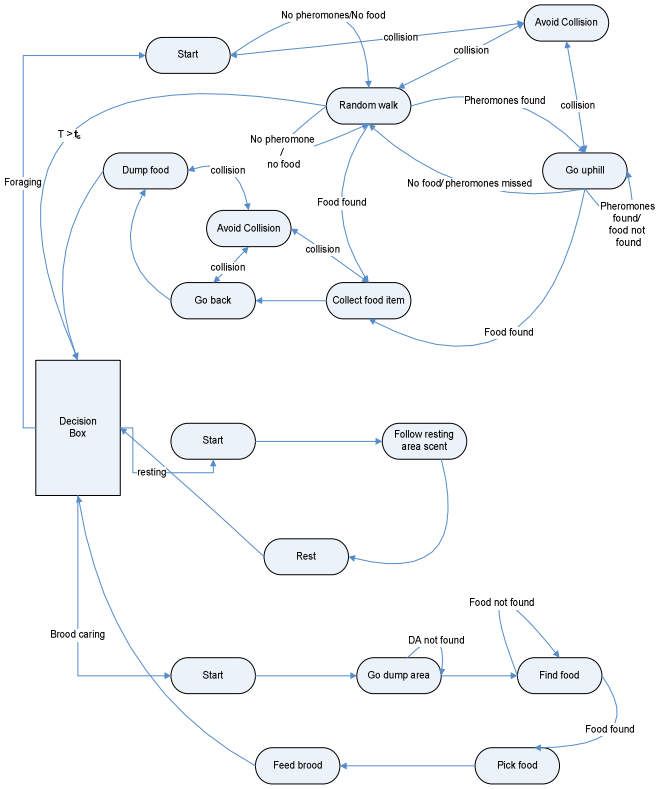

Figure 5. Schematic Diagram of the task allocation model of an agent

Every mobile agent maintains three types of thresholds: threshold for foraging (t_f), threshold for resting (t_r) and threshold for brood caring (t_{bc}) and updates them on the basis of events encountered. In a threshold based mechanism, the threshold value for a particular task of an agent is decreased when the agent encounters a stimulus for the task. Thus, over the course of time the threshold value for a task decreases significantly if exposed to greater stimuli for the task. The probability of an agent carrying out a particular task is modelled to vary inversely with the threshold value of the task and the threshold values are updated based on the events encountered; thus enabling agents to adapt to the changing demand.

We use a simple but effective principle for updating the thresholds. The threshold value for a particular task is decreased if the agent has either successfully completed the task or has received a stimulus for that task. On the other hand, the threshold value for the task is increased if either it has been unsuccessful in carrying out the task or hasn't experienced a stimulus for a long time (equation 5). This allows an agent to adapt to the dynamic system and react accordingly. Table 1 illustrates the adaptation rules for the agents.

$$t_{f,r,bc} = t_{f,r,bc} \pm \Delta \qquad (5)$$

where Δ is the adaptation rate i.e. the rate at which the agents update their threshold values.

The threshold values are bound between two threshold bounds: an upper threshold bound and a lower threshold bound. If the threshold value becomes more than the upper threshold bound, it resets the threshold value of the task equal to the upper threshold bound.

Event	Which Agent?	Action	Remarks
Shouting chemical perceived	ALL except brood	t_{bc} decreases	There is a demand for feeding the brood
Food at DA < lower threshold of food in DA	ALL except brood	t_f decreases, t_r increases	There is less food in DA. Therefore more food is Required
Food at DA > upper threshold of food in DA	ALL except brood	t_f increases, t_r decreases, t_{bc} decreases	There is sufficient food in DA.
Brood carers looking for food in DA too long	Brood carers	t_f decreases, t_{bc} increases	There is insufficient food in DA
Foragers searching too long for food	Foragers	t_f increases, t_r decreases	There might not be enough food in the environment
Resting too long inside The chamber	Foragers	t_f decreases, t_r increases	There might be a need for foraging instead
Resting too long inside the chamber	Brood Carers	t_r increases	Should look out for other tasks
Successful retrieval of food	Foragers	t_f decreases	There might be some more food out in the environment

Table 1. Adaptation Rules for the agents

Similarly, if the threshold value falls below the lower threshold bound, the threshold for the task is reset to be equal to the lower threshold bound. The task with lowest threshold is selected with some probability.

3.3 Indirect versus Explicit Communication

The effect of two different forms of communication, (i) indirect, and (ii) explicit, are compared here. In the indirect case, the agents carry out tasks and update their thresholds as outlined in Table 1. They do not explicitly communicate among themselves. Such communication techniques are what we call indirect communication. In explicit communication, ants briefly communicate about their status when they are close (either the distance between the agents is less than one body length or they are present at the DA to sense how much food is available there). This is inspired by the observation that in many ant species (e.g. the red harvester ants *Pogonomyrmex barbatus*) where when two ants are extremely close, they communicate with each other using their antennae to determine what task the other ant is carrying out by accessing their cuticular hydrocarbon profile [51].

In our model, if agents are communicating explicitly, not only do they follow the rules outlined in Table 1., they also follow two further rules: (1) If agents perceive the shouting chemical, then for a brief period of time, they explicitly pass on information about the shouting chemical to other agents they encounter with, causing those agents to reduce their t_{bc}., (2) Similarly, if the amount of food in the dump area becomes less than the lower threshold of food in DA (the agents perceive the amount of food in DA by the chemical strength of the food in DA), the agents who perceive this would pass on information (for a brief period of time) to other agents they encounter about this incident which causes the agents to reduce their t_f.

4 Experiments and Results

Each simulation runs 20 times using the behavioural rules discussed in section 3 for 5000 simulation time steps. For every run, the following readings are recorded after the 5000th simulation time step: the number of agents (1) foraging, (2) brood caring and (3) resting, (4) the number of food items left at the DA, (5) the initial hunger level i.e. the hunger level at $t=0$ and (6) the final hunger level i.e. the hunger level at $t=5000$ and their mean is evaluated after the 20 runs. The hunger level, here, is the cumulative hunger level per unit brood member, which is used to measure the performance of the system and is calculated using the equation 6.

$$hunger\,level=\frac{\sum_{\forall brood} HL}{A\times n_b} \qquad (6)$$

Where, HL is the hunger level of each brood member (as mentioned in Section 3), A is some constant (for experimental purposes $A=th_h=500$ [also refer to equation (2)]) and n_b is the number of brood. Figure 6 shows a typical curve for HL with respect to time.

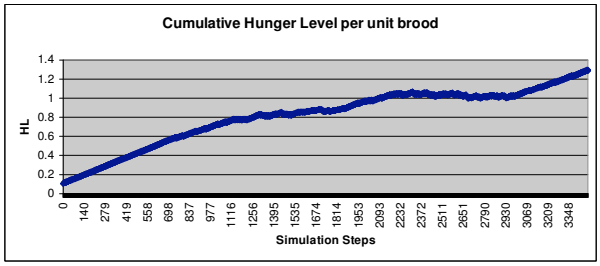

Figure 6. A typical HL curve as a function of time

The following analyses the two questions posed earlier i.e. (1) whether the behavioural rules of the agents mentioned here result in a system that can adapt to the changing demand?, and (2) whether the employment of explicit communication results in an improvement over the indirect communication with respect to the performance of the system?

A. Is the system adaptive?

One of the key motivations for taking inspiration from living swarm systems is that these systems are highly adaptive and flexible. In SR and other engineering applications of swarm intelligence, the design of such adaptive system is extremely crucial.

In this situation, it is necessary that foragers and brood carers continuously change their tasks in order to meet the changing demand[17,18]. This can be best investigated by analysing how the ratio of the two types of workers varies with the change in the demand. Figure 7 shows three curves plotted over the simulation time steps; red line at the top indicating the amount of food present in the dump area, violet line the number of hungry brood while the black line draws the ratio of the number of foragers to that of the brood carers. Initially there was no hungry brood and the amount of food in the DA was adequate; hence no demand was there. As a result, the ratio of the two types of workers did not need to be adjusted and hence remained constant. However, a demand for food by the brood instigates some foragers to switch their tasks to brood carers and assist other brood carers in feeding the brood. As the number of hungry brood members continues to increase and the amount of food in the DA continues falling it triggers more mobile agents to take up the foraging task in order to meet the demand.

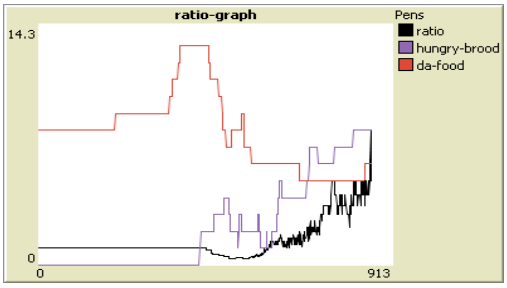

Figure 7: Switching of tasks between foragers and brood carers

B. Explicit Communication versus Indirect Communication

To compare and investigate the impact of using explicit communication and that of the indirect communication on the performance of the system and also to investigate whether explicit communication has any significant improvement in terms of the performance of the system over that of the indirect communication, the number of brood members is varied between 5 and 20 and for each of these cases, the experiment is repeated 20 times. The mean hunger level is then calculated. The experiment is repeated for both the conditions (i.e. with explicit and indirect communication). Table 2 and figure 8 depict the results obtained.

Number of brood	Mean Hunger Level (with Explicit comm.)	Mean Hunger Level (with Indirect comm.)
5	1.031596	1.155916
10	1.245766	1.680475
15	1.470009	2.128418
20	1.796184	2.305359

Table 2. Mean Hunger level

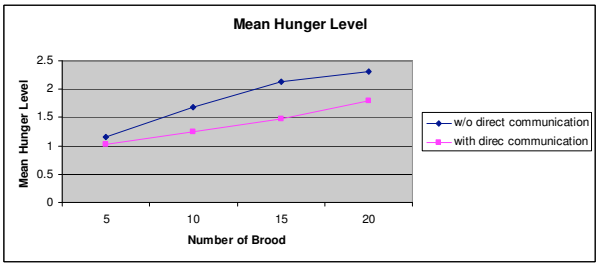

Figure 8. Variation of mean hunger level with the number of brood

Figure 8 shows that as the size of the brood increases, the mean hunger level also increases. More intriguingly, the mean hunger level in the explicit communication in general tends to be lower than the one where indirect communication has been used indicating that the system performance is improved by the inclusion of explicit communication. Regression analysis reveals that the slope of the graph (i.e. the rate of the mean hunger level with respect to the size of the brood) in indirect communication is 1.4 times greater than that in the explicit communication indicating that the performance keeps on improving with explicit communication with the size of the brood. Furthermore, a statistical t test with 95% confidence reveals that the dataset with explicit communication is significantly different from that with indirect communication except when the number of brood = 5 where the mean hunger levels for the two sets of experiment are not significantly different.

C. Performance of the System

Performance is measured in terms of the mean hunger level of the brood members. The higher the mean hunger level is, the lower is the performance of the system and vice versa. If the simulation is run for considerable time, the mean hunger level stays greater than 1. The performance of the system in percentage (%) is calculated using equation (7) [Also see equation (6)].

$$P = \frac{100}{hunger\,level} = \frac{100 \times A \times n_b}{\sum_{\forall brood-members} HL} \quad (7)$$

Figure 9 shows the performance of the system for both explicit and indirect communication and indicates that the performance of the system is always better with the explicit communication than that of indirect communication.

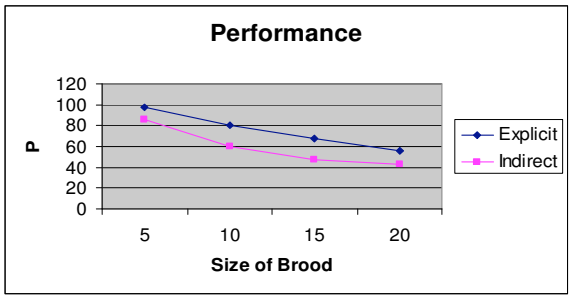

Figure 9: Performance of the system

5. Conclusions and Future Work

We have presented a task allocation and task switching model for a simulated swarm of autonomous mobile robots. 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. Furthermore two communication techniques (indirect and explicit communications) have been presented and compared. Both the techniques work well in terms of responding to the changing demand; however empirical investigation shows that agents engaged in explicit communication work better than that of the ones engaged with indirect communication. Future work will be based on carrying out experiments to see the impact of the food availability and the swarm size on the performance as well as the robustness of the system. We also plan to develop a hybrid system of specialised and generalised agents to see if such system has any advantage(s) over the ones presented here.

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