Volume 14, June 2013

Performance Analysis of Task Allocation Strategies in Groups of Mobile Agents

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***Abstract*-This paper addresses the issue of allocation of tasks in groups of mobile agents. The paper presents task allocation strategies based on the behavior of real ant colonies. Agent based modeling approach is used to simulate the behavior of the ant colonies. The strategies used are evaluated in order to shed lights on the circumstances when a particular strategy works better. Experimental results indicate that the results are consistent with the biological equivalents.**

***Keywords:* agent based modelling, task allocation, swarm robotics and swarm intelligence.**

I. INTRODUCTION

Dividing labor and allocating tasks on the fly is often considered to be an important problem in the field of multi-agent and multi-robot systems where more than one agent (or robot) work together collectively in order to carry out a range of tasks. Dynamic task allocation has found a number of application areas in the field of swarm robotics (SR) – a field that has recently gained enormous interests among scientists and researchers from disciplines as different as biology, engineering and social science. Swarm robotics (the robotics application of swarm intelligence, SI) [1, 2] studies how a large number of relatively simple agents interact with neighboring agents and the environment in vicinity to create some collective behavior. One of the major inspirations of swarm robotics lies in the use of swarms of robots (or agents) to manage and carry out more than one task efficiently.

Most of the work related to SR and SI uses relatively small number of agents. In this paper, we describe a simulated system comprising of complex environment and more than one agent interacting locally. Agent based modeling (ABM) techniques have been used to simulate the system as it helps in detailing the local interactions and behavioral rules of the agents. Two strategies of task allocation (one in which the agents use only stigmergic interaction and the second in which the agents use explicit communication) are introduced in this paper and their performances are then evaluated. The strategies employed are inspired by the ant colony behavior. The novelty of this paper is threefold: (1) a more complex realistic system has been developed and described than described elsewhere, (2) two strategies of task allocations were developed in the light of ant colony behavior, and (3) their performance is evaluated and compared with that of real ant colony.

The remaining of this paper is organized as follows: Section II provides the background of the paper. Section III describes the model proposed while in section IV the results obtained are described. Finally in section V, the paper is concluded with remarks on our future work.

II. BACKGROUND

Division of labor, within the context of multi-agent systems and eusocial insects, is often referred to as one of the most conspicuous features for the organization and success of the colony [3, 4]. Social insects such as ants display sophisticated mechanisms for dividing labor. Demand for different tasks of the colony varies frequently depending on various internal and external factors and the colony has to react to the demand by rearranging part of its workforce in a way so as to function efficiently. Individual ants do not have the global information of the environment and hence cannot react immediately to the changes. However, ants interact with the neighboring ants (either via the environment or directly) allowing the information to pass over the colony.

The basic form of division of labor exhibited by ants is the reproductive divisions of labor 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 labor, there exists further division of labors among workers. Bonabeau and his colleagues, in 1999 [5], proposed that the division of labor among workers can take three (not necessarily mutually exclusive) basic forms: 1) worker polymorphism, 2) age polyethism and 3) individual variability.

In worker polymorphism, 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.

Age polyethism embraces the ideology that the task carried out by ants is not fixed over its lifetime rather a function of their age. Many species of ants exhibit age polyethism including *Pogonomyrmex barbatus*, *Cataglyphis bicolor* and *Oecophylla smaragdina* [3, 6].

Individual differences towards task preferences also exist. The differences in individuals in the preference for task selection is a result of many factors including that of past experience [e.g. 7], variation in the genes [8, 9] and physiology [10]. Grouping the individuals with respect to their task preference generate what are called behavioral castes. For further information about castes and division of labor, please refer to [4, 5].

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, motivational state of the worker, spatial arrangements of the workers in the nest and also the learning parameters. For further details, please refer to [11, 12]. Out of these models, fixed response threshold and adaptive response threshold models are found to be biologically more plausible and are embraced by entomologists wholeheartedly.

In a fixed response threshold model, each agent has some fixed threshold 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. When an agent performs a task, it lowers the stimulus for that particular task. Thus, if an agent *A* has a 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 task – thus it can so happen that the stimulus of the task *T* never reaches the threshold of agent *B* and therefore *B* never performs that task. Thus, small variation of response threshold can result in the difference in the frequency of task performance and give rise to the behavioral castes.

Fixed response threshold model assumes that the response threshold of a worker is fixed and does not change over time. However, this is not entirely true for many species of ants including ponerine ants *Ectatomma ruidum* [7] and harvester ants *Pogonomyrmex barbatus*[13]. In the adaptive response threshold model, when a worker performs a task successfully, the threshold for the particular task is reduced by a learning factor $\varepsilon\Delta t$. Similarly if the worker is unsuccessful in accomplishing a task or not receiving stimuli for a long time, the worker reduces the probability of carrying out the task by increasing the threshold by a factor $\phi\Delta t$ called the forgetting parameter. The constant learning and forgetting of tasks eventually result in the specialization of workers within the colony.

Task allocation is a fundamental area in the field of swarm robotics [14 – 19]. Much of the work pertaining to dynamic allocation of labor in response to the change in the environment or demand of a particular task is strongly inspired by the behavior of social insects. An early example of the work carried out in this area is by Krieger and Billeter [20] where they used fixed response threshold mechanisms in Khepera robots to forage when the energy in the nest is low. Labella [21] and Liu and colleagues [22] used adaptive response threshold mechanisms to allow the robots to either forage or rest. Yongming and colleagues [18] 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. Jones and Matarić [16] used a simple adaptation rule to vary the propensity for foraging two types of pucks (red puck or green puck) depending on their ratio of availability. Ducatelle and colleagues [14] 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*(wheeled robots) and *Eyebots* (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-colored LEDs placed around their bodies to influence others' behavior. Momen and Sharkey used ABM to devise task allocation strategies in groups of heterogeneous agents [12, 17].

III. PROPOSED MODEL

ABM has been embraced in order to detail the behavioral rules for the agents and also to evaluate the macroscopic behavior that emerges out of the local interactions among the neighboring agents and also between the agents and the environment in the vicinity.

The model proposed in this paper consists of a 2D grid world populated with three types of agents (dynamic foragers and brood carers and static brood members), a nest comprising of four chambers (dump area, brood carer chamber, brood chamber and foragers' resting area), stimuli (chemical signals, chambers' odor) 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 modeled 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 odors 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.

Agents communicate in one of the two ways:

- Indirect Communication: In this communication technique, agents do not communicate with each other directly rather communicate passively via the environment. Such types of communication are very common in social insects and are often referred to as stigmergic communication.
- Explicit Communication: In this communication technique, agents not only communicate with each other indirectly but also communicate with each other directly (e.g. by antennal touch and sound).

Fig.1. Snapshot of the model

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

A. Nest

The model consists of a nest (located at the bottom of the world) that comprises of four separate chambers. 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 *Pogonomyrmex barbatus* 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.

B. Behavioral Rules

Individual agents have limited perception and communication range and follow simple local rules.

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 randomized hunger level. At every simulation time step, the hunger level of each brood member increases by its hunger rate (eq. 1) which is distributed randomly between 0 and 1 across the population of brood members. 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). The strength of the shouting chemical is modeled 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. 3). If a hungry brood member is fed by a brood carer, the hunger level of the brood member decreases by some constant value (100) and when it falls below th_h, the brood member switches its state back to the non-hungry state (eq. 2). In the model, brood members are fed upon request i.e. the non-hungry brood members are not fed.

$$HL_{t+1} = HL_t + HR \tag{1}$$

Where $0 \le HR \le 1$

$$HS_t = \begin{cases} 1, & HL_t \ge th_h \\ 0, & HL_t < th_h \end{cases} \tag{2}$$

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, $HR \sim U[0,1]$

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 (= 500) is the threshold parameter of the hunger level.

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

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 (= 7 patches in the simulation), and $A = sr$, B = 1.

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 paper), 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).

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.

C. Task Switching Mechanisms

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. 5, 17, 21, 22]. We use a simple but effective principle (as observed from the behavior 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 behavior that many ant species are reported to have displayed [e.g. 4, 5, 10, 11]. For a greater details of the parameters used, please refer to Table III.

The selection of which task to carry out next is modeled 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 below) 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). Using the principles adopted for updating thresholds, the following behavioral rules for foragers and brood carers are formulated when they communicate indirectly:

1. If an agent perceives the shouting chemical, it realizes 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.

For explicit communication, the only changes that have been made are the addition of four more behavioral rules (Rules 8 – 11) to the dynamic agents (i.e. the foragers and brood carers).

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 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.

IV. EXPERIMENTS AND RESULTS

The model proposed and discussed above is simulated using Netlogo (a multi-agent programmable modeling environment) simulator. Each simulation for a particular experiment is run for 5000 simulation time steps and is repeated 20 times. (5000 simulation time step is sufficient for the average hunger level to converge; see figures 3 and 4). The average reading is then calculated from 20 trials.

Performance of the algorithms is measured by the average hunger level of the brood after the 5000th time step.

$$A.H.L. = \frac{\sum_{\forall brood-member} HL}{th_h \times n_b} \tag{4}$$

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.

A. *Effect of Task Allocation Strategies on the performance of the colony*

Communication is essential for effective task allocation but this does not necessarily mean that sophisticated communication would always yield better performance. Infact, Anderson and McShea [23] pointed out that as the ant colony size increases, they tend to use more and more sophisticated communication strategies which indicate that smaller colony size do not use very sophisticated technique. A possible hypothesis for this observation is that smaller colony does not have great colony demand and as a result they do not need sophisticated communication strategies. On the contrary, larger colony size would have more demand within the colony and consequently the ant colonies need to use much more sophisticated communication strategies to meet the demand.

In order to investigate if this really happens in the simulated ant colony, we ran each experiment 20 times for 5000 simulation time steps. The mean reading for the average hunger level are shown in tables I and II.

Table I: Average hunger level of brood when using indirect communication (S = Number of foragers + Number of brood carers and N_b = Number of brood members)

S ->	20	30	40	50	60
$N_b = 5$	2.25	1.54	1.08	1.02	1.16
$N_b = 15$	3.34	2.11	1.82	1.51	1.08
$N_b = 25$	3.75	3.10	2.49	1.68	1.50

Table II: Average hunger level of brood when using explicit communication (S = Number of foragers + Number of brood carers and N_b = Number of brood members)

S ->	20	30	40	50	60
$N_b = 5$	1.88	1.14	1.03	1.05	1.08
$N_b = 15$	2.65	1.59	1.23	1.17	0.99
$N_b = 25$	3.48	2.49	1.98	1.66	1.24

Table III: List of Parameters

Parameter	Meaning	Value(s) used
N_b	Number of brood Members	5, 15, 25
S	Number of mobile agents (i.e. number of foragers [N_f] + number of brood carers [N_{bc}])	20 – 100
$r = R_{f\text{-}bc}$	Initial ratio of foragers to brood carers. This can be used to determine the number of foragers and brood carers as follows: $N_f = \lfloor R_{f-bc} \times S \rfloor$ $N_{bc} = S - N_f$	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

Figures 2 – 4 show how the performance (i.e. average hunger level at the 5000th simulation time step) vary with swarm size and the brood size for both indirect and explicit communication.

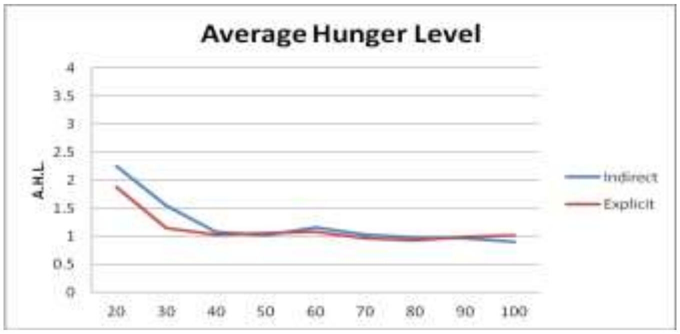

Fig. 2. Average hunger level when brood size = 5 and swarm size 20 – 100

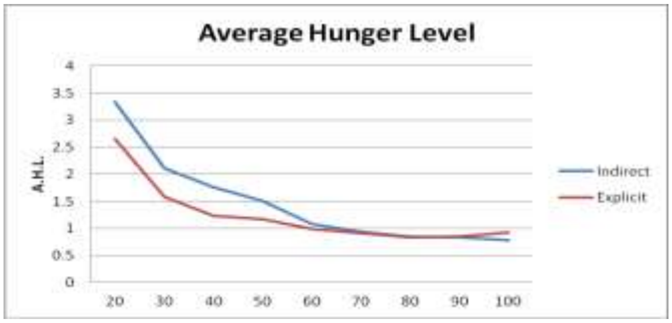

Fig.3. Average hunger level when brood size = 15 and swarm size 20 – 100

Fig.4. Average hunger level when brood size = 25 and swarm size 20 – 100

Figures 2–4 show that the increasing the swarm size (number of dynamic agents) decreases the A.H.L. and that the A.H.L. is almost always lower for explicit communication than indirect communication. So, apparently it seems that explicit communication almost always work better than indirect communication. But the graphs also indicate for some swarm size, the difference in the average hunger levels for indirect and explicit communication is very narrow. To test if explicit communication strategy always yields significantly better performance than indirect communication, statistical significance tests needed to be carried out. Series of Mann-Whitney tests with ($\alpha = 0.05$, level of significance) were carried out to investigate if explicit communication strategy always yields statistically significant result from that of the corresponding indirect communication strategy. The result is displayed in Table IV.

Table IV: Results Obtained

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

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. The statistical tests indicate that explicit communication does not always yield significantly better result than that of indirect communication. Rather when the demand of the colony is considerably great (i.e. when brood size is large and there are not sufficient foragers and brood carers to meet the demand), employment of explicit communication improves the performance of the colony. This is in line with what is observed in real ant colonies.

V. CONCLUSION

This paper looks at the effects of using explicit and indirect communication strategies in a simulated colony of ants, and at the circumstances explicit communication strategy outperforms the other. 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 nest mates. Entomologists have established that in more complex situations, ants tend to use more sophisticated communication mechanisms. The simulated colony presented in this paper shows similar result as that of the real ant colonies. Explicit communication tends to improve the performance of the colony when the colonies are more stressed (e.g. when there are large brood size creating a lot of demand or when there are less number of dynamic agents present to meet the demand). In less stress situations, indirect communication strategy tends to perform as good as explicit communication strategy. For future work, we are making a formal guideline of the design issues regarding selection of appropriate task allocation strategies in different circumstances.

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