Group Performance in a Swarm of Simulated Mobile Robots

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Abstract— Division of labour (or task allocation) is considered to be one of the most fundamental fields of research within the context of swarm intelligence and swarm robotics. In this paper, we look at how swarms of simulated mobile robots (i.e. mobile agents) carry out the decision of doing a particular task in an artificial world. In this paper, we present an agent based model wherein groups of mobile agents make decisions based on some simple rules. We, furthermore present an in-depth analysis on the efficiency of the swarm – typically how factors such as the number of robots and the amount of tasks affect the average energy of the swarm (energy efficiency) and how well they are utilized (robot utilization). Our simulation results reveal a number of interesting findings including: (1) the robot utilization decreases with the increase in the number of robots and vice versa, (2) the robot utilization increases with the increase in the amount of task and vice versa, and (3) there exists a swarm size, *S*, which results in an optimal energy for the swarm.

Keywords— Agent based model, division of labor, energy efficiency, mobile agents, robot utilization.

Manuscript received on 25 October 2015and accepted for publication on 11 November 2015.

1 INTRODUCTION

Division of labor (or task allocation) is often referred to as one of the most salient features for the organization and success of a team [1, 2]. Many multi-agent systems, such as that of the swarm systems (both biological and artificial), comprise of agents that carry out tasks. Typically there are more than one task in the environment and therefore there needs to be a mechanism through which the tasks to be done are to be assigned to agents for execution. This ability to allocate tasks among the agents is referred to as task allocation or division of labor. Often, the demand for the completion of a particular task may change (i.e. increase / decrease) due to perturbations caused by internal or external factors. Consequently, agents may require to re-assign tasks on the fly to meet the changing environment.

This paper addresses the issues of division of labor within the context of a group of mobile agents that are assumed to be simple (i.e. they have simple behavioral rules) and adaptive (i.e. they can switch tasks as required). Agent based modeling (ABM) approach has been chosen to model the behavior of agents since this approach can handle more complex behavior of agents (as opposed to that of the mathematical modeling). A simple stimulus response algorithm has been developed to provide the ability for the agents to re-assign tasks on the fly without the need of any centralized controller. The paper carefully analyzes how the collective behavior of agents affect the efficiency of the system at the macro-level. We introduced and defined robot utilization and energy efficiency to understand how the efficiency at the macro-level is affected by the number of robots in the environment.

The rest of the paper is organized as follows: In section II, a background of task allocation and swarm systems is given followed by our proposed model in section III. Experimental details and their results are discussed in section IV. Finally the paper concludes in section V with a summary of our findings and potential implications in our future research endeavors.

2 BACKGROUND

Division of labor is highly noticeable in biological swarm systems such as ants, bees, termites etc. where individual agents respond to changing environment to serve the colonial demand. Division of labor in ants, in particular, are well-studied behavior within the context of social insects.

2.1 Division of labor in ants

There are more than 12000 species of ants and they show different kinds of division of labor [2, 3, 13]. The most fundamental form of division of labor in ants is the reproductive division of labor where a few individuals (often limited to one – called the queen) is solely responsible for the reproductive tasks while the other females of the colony (called workers) work as nonreproductive agents. Apart from the basic division of labor, there are three prominent kinds of division of labor (not necessarily mutually exclusive of each other) found within different species of worker ants [3]: (1) Worker polymorphism, (2) Age polyethism and (3) Individual variability.

The ants that exhibit worker polymorphism tend to specialize in particular tasks due to their morphological advantages. For example, in case of the Pheidole ants [3], there exists two kinds of workers: major workers and minor workers. Major workers have disproportionately large heads and strong mandibles. Therefore, they tend to specialize in tasks that are laborious such as guarding a nest from intruders and/or transporting heavy objects from one place to another. Minor workers, on the flip side, tend to be smaller in size and therefore they tend to specialize in softer tasks i.e. tasks that do not require much expense of energy (such as cleaning the nests or feeding the young brood members)

Some species of ants (such as the Pogonomyrmex barbatus and Catalyphis bicolor) [4] are found to display age polyethism in which the task preferred by workers tend to change with their age. The young workers tend to be closer to the queen specializing in tasks such as feeding brood members and cleaning nests while the older workers tend to specialize in foraging and carrying food items to the nest.

However, most species of ants tend to demonstrate individual variability wherein they select tasks depending on their learning experience based on different factors. Consequently such colonies of ants tend to adapt to environment quickly and respond to the change in demand of the colony. For instance, in case of the red harvester ants, the worker class tends to carry out a number of tasks including foraging, patrolling, feeding younger brood members and cleaning nests. However, if the system is perturbed by external agencies, the situation changes. For instance, rain often results in the damage to the nest and this increases the demand to clean up the nests. When this happens, some of the ants doing other tasks are found to switch to nest cleaning job in response to the increased colonial demand for cleaning the messes [5]. This behavioral plasticity is the key factor behind the effective organization and the success of a colony.

2.2 Division of labor in swarm robotics

Animal behavior and in particular the behavior of social insects have strongly inspired many engineering disciplines. One such discipline that emerged over the past fifteen years is the field of swarm robotics where groups of robots (physical robots or simulated robots) or agents interact with each other to perform some tasks. These agents are autonomous in the sense that they carry out tasks without the need of any intervention of a centralized controller. The agents have simple behavioral rules and interact only locally i.e. they do not have the knowledge of the global template of the environment. One of the early papers written in this area was that by Krieger and Billeter [6] where they used up to twelve mobile robots to make the decision of whether to forage or rest. Unfortunately, the robots were not fully autonomous in the sense that periodically radio messages were sent to the robots from a control station briefing out when to forage or not. This is in violation with the swarm intelligence paradigm. However, the paper remains an important one as this was the first time, ant behavior was simulated in real robots. Subsequent studies by Labella [7] and Wenguo Liu and colleagues [8] worked towards building a fully decentralized system for allocating tasks. Yongming and colleagues [9] used a fixed response threshold model to develop a system where simulated robots can automatically decide whether to forage or rest. Ducatelle and colleagues [10], inspired from the work of Momen and colleagues [11] in mixed species flocking, presented task allocation strategies in the realms of heterogeneous groups of mobile robots. In their model, they had two kinds of simulated robots (wheeled robots and flying robots) working together to perform a common task. Zahadat and colleagues [14, 16] developed distributed adaptive partitioning algorithm for swarms of underwater robots. Their work was inspired by the age polyethism behavior demonstrated by honeybees. Brutschy and colleagues [15] on the other hand developed a method of allocating sequentially interdependent tasks to swarms of robots. In 2013, Momen [17] proposed how swarms of heterogeneous robots allocate tasks in a stochastic environment.

All the studies in the literature looks into developing systems that allocate tasks in a dynamic fashion. However, the factors affecting the efficiency of a multi-agent system is not well addressed in the literature. In this paper we present a simulated group of robots that can divide their labor to carry out complex tasks. We also carefully inspect the issue of efficiency in the context of swarm systems.

3 Proposed model

Agent based modeling approach has been taken to model a swarm system in which agents make decisions of what tasks to do at any given moment. The model is developed using Netlogo [12], a cross-platform multi-agent modeling environment.

The specification of the proposed model is given below:

3.1 Specification of the model

The model consists of an environment (which is a 2D grid world) populated with mobile robots and objects (called boxes) placed randomly in the world (see figure 1). The topology of the world is referred to as 'Box' as the world is bounded in all dimensions. The agents (robots) can carry out three major tasks. Within each major tasks, there are a number of sub-tasks. The major tasks carried out by the simulated robots in our model are outlined below:

1) Charging- In this case, the robots go to a designated charging area (in the top left hand corner of the environment) in order to charge themselves up.

2) Box searching- In this case, robots search for boxes in the environment.

3) Box transport- Once a robot finds a box, it grabs the box using its gripper, moves towards a designated dumping area (on the top right hand corner of the environment) and leaves the box there.

The space is treated in discrete patches (81x41). However, the movement of the robots is modelled in continuous space so that at each time step t, each robot's floating point coordinates is mapped to an integer type coordinate in the local patch.

3.2 Behavioral rules

Each robot possesses orientation and follows simple rules as described below (see figure 5 for further details).

1. Each robot maintains an energy value [initialized randomly between 500 and 1000].
2. A robot moves randomly within the environment.
3. After every step, the energy value of a robot decre ments by a fixed small value.
4. Every robot has to maintain a minimum energy in order to operate.
5. If the energy of the robot falls below the minimum energy, the robot activates the charging task. (see figure 2) and moves towards the charging area.
6. Once it goes to the charging area, the energy value of the robot increases and it gets charged up.
7. If a robot finds a box within its visible range, it approaches the box, grip it using its gripper and starts moving towards the dumping area.
8. Once it reaches the dumping area, it releases the box and switch to box-searching mode for picking up new boxes.
9. The robots know the locations of the dumping area and the charging area and therefore they can simply face towards the area they need to move and starts travelling in that direction.

3.3 Parameters used in this model

The following table summarizes the parameters used in this model.

TABLE I. Parameters in the Model.

Parameter Name	Value	Remarks
Number of robots	Variable	This parameter specifies how many robots are used in a particular simulation.
Number of boxes	Variable	This parameter specifies the number of boxes placed randomly in the environment.
Minimum energy	185	This is the minimum energy a robot must have in order to operate. A robot having energy below this value needs to go to the charging area and charge itself up.
Energy decrement	0.12	This is the amount by which the energy of a robot decreases after every move.
Vision range	8.5	This is the depth of patch a robot can see.
Vision angle	440	This is the angular vision of the robot. The robot can see 220 to its left and 220 to its right.
Grab range	3.7	If a box is within its grab range, the robot can grip the box and start transporting.

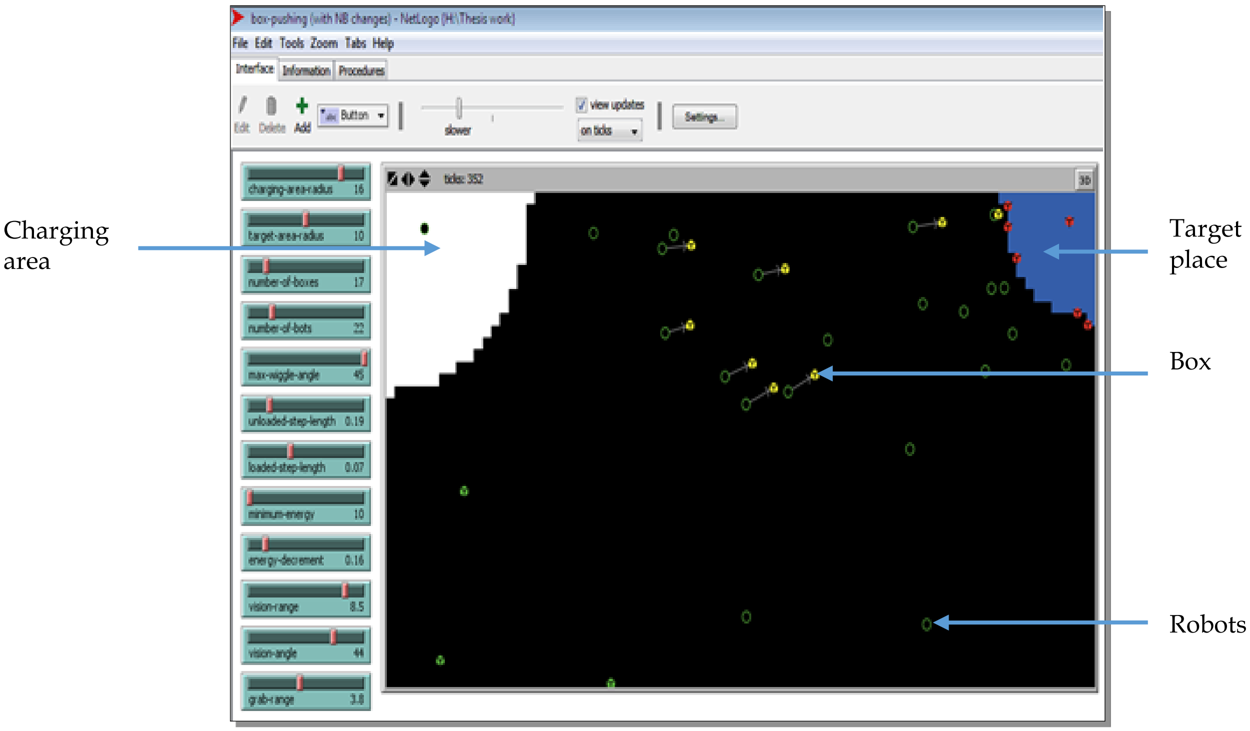

Figure 1: Snapshot of the model (robots are marked as green circles, the boxes are boxed shape and colored green if not yet being picked up, yellow if it is currently being transported by a robot and red if it is left in the target area.

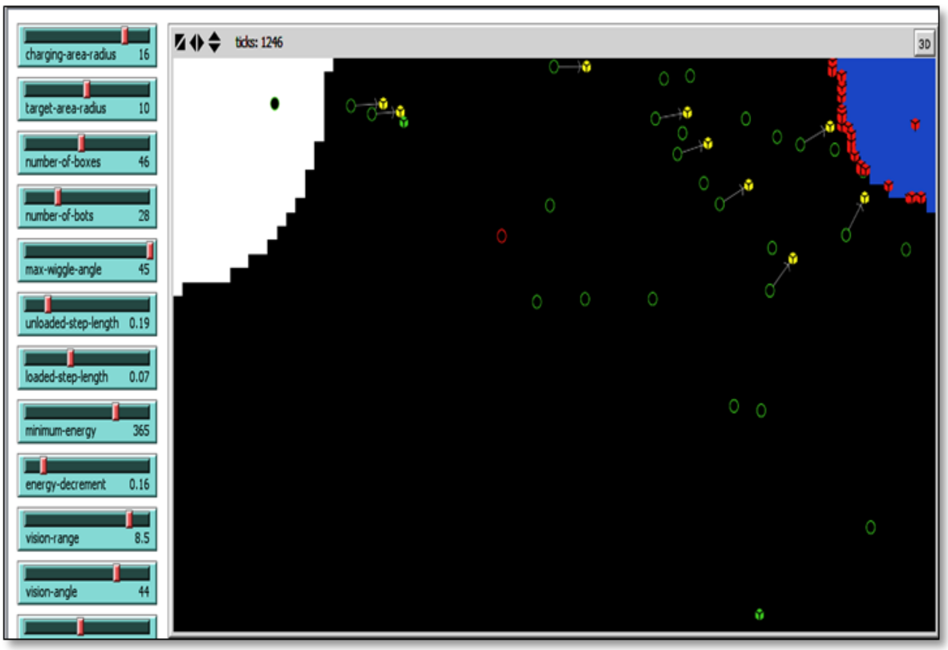

Figure 2: The robot colored red (shape circle) has low energy and has activated the charging task. Hence it is moving towards the charging area.

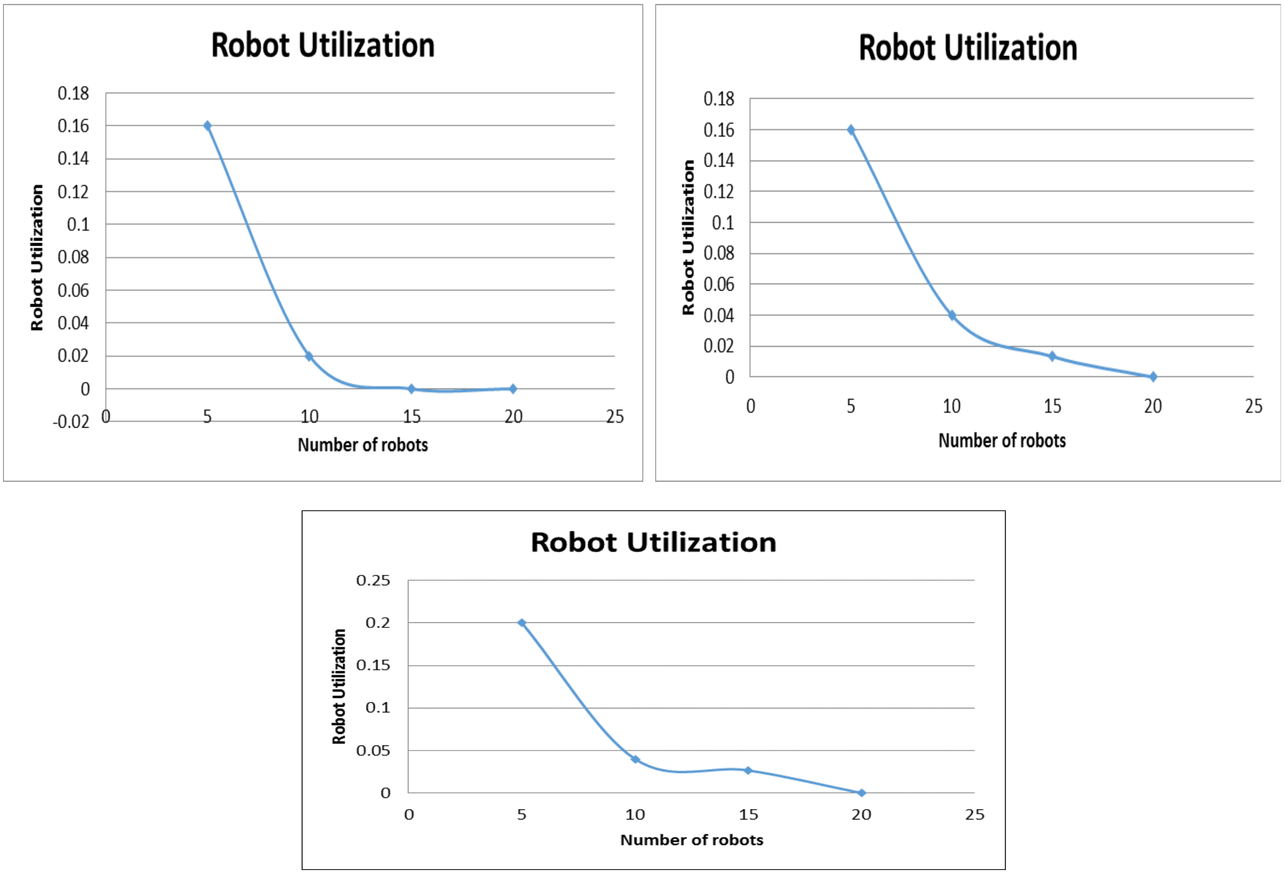

Figure 3: Robot Utilization as a function of the number of robots. In a) there are 5 boxes in the environment whereas in b) and c) there are 15 and 20 robots in the environment.

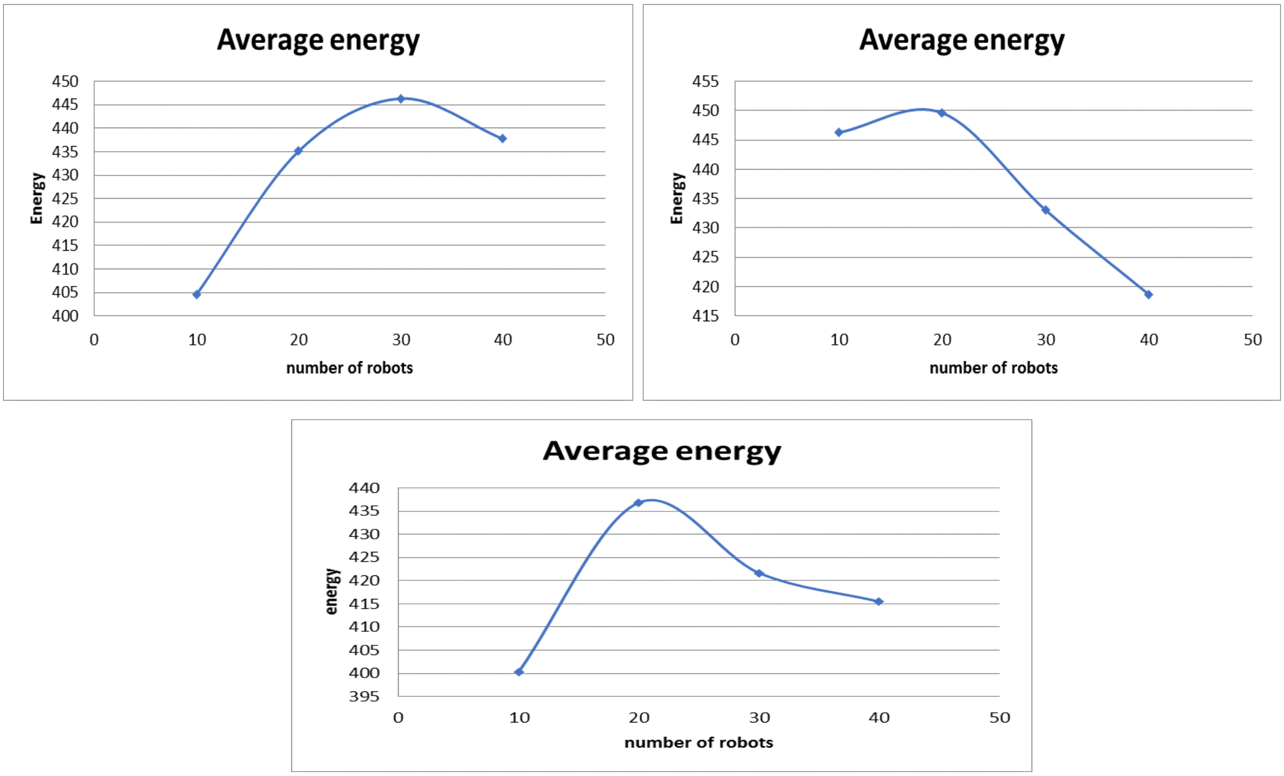

Figure 4: Average Energy of robots. There are 10 boxes in (a), 20 boxes in (b) and 30 boxes in (c).

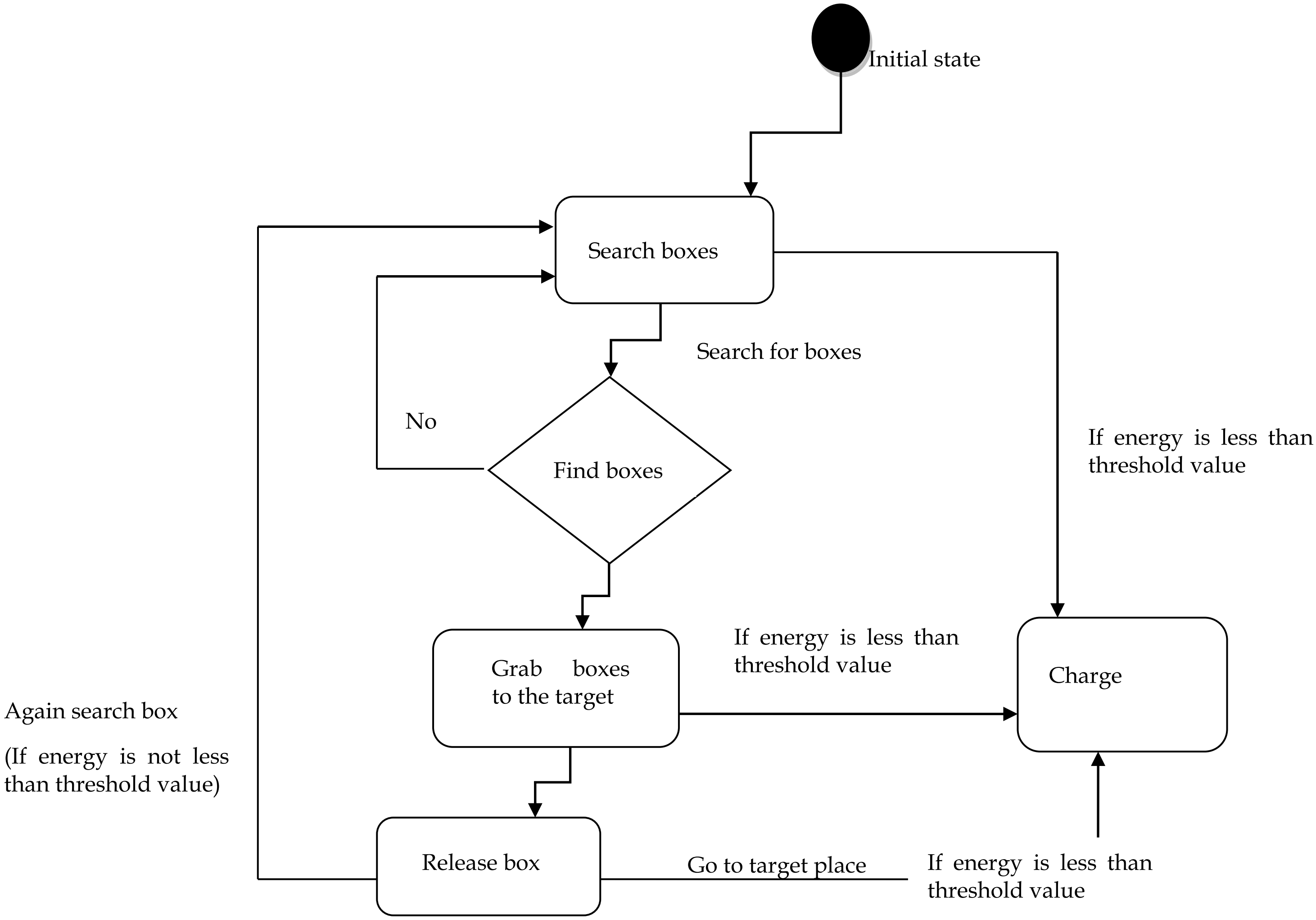

Figure 5: State Transition diagram

4 Experiments and Results

In this section, we discuss how the number of robots participating affects the efficiency of the swarm system. This is particularly important since there is a notion of understanding in the literature that the increase in number of robots will improve the overall efficiency of the system. Swarm sytems are characterized by large number of redundant agents to improve the efficiency of the swarm. However, in reality, it can be different. If there are too less robots participating compared to the number of boxes in the environment (i.e. the amount of task in the world), then it will take long time to complete tasks and hence the efficiency would be low. On the other hand, if there are too many robots compared to the number of boxes, then too few robots will be effectively used and consequently it will result in poor resource utilization. In order to therefore understand efficiency, we define and inspect robot utilization and energy efficiency. Each experiment is repeated 20 times (runs) for 4000 time steps and the average reading is taken into account.

4.1 Robot Utilization

Robot utilization refers to the average number of robots been used in transporting boxes It is the ratio of the average number of robots carrying boxes compared to the total number of robots present in the environment – thus this is the measure of the fraction of robots that are engaged in effective tasks. Figure 3 shows how the robot utilization varies with the number of robots in the environment. The graphs show some interesting trends: (1) as the number of robots increases, the robot utilization decreases. So, it is not a good idea to always use a really high number of robots. Higher number of robots in a swarm system will allow tasks to be done in a shorter time but at the same time there are many robots that do not have any effective task to do, (2) as the number of boxes in the environment increases, robot utilization increases. This indicates that with greater number of tasks (if there are more boxes in the environment, there will be more transporting activity – so the number of tasks also increases), there is an increase in robot utilization. However, if the robots are over utilized, the efficiency of the system will decline. So, when there are more tasks in the environment, the increase in the number of robots to participate is justified.

4.2 Energy Efficiency

In this section, we investigate how the average energy of a swarm at the end of experiments varies with the number of robots participating in the experiments. Figure 4 shows the results obtained. Experiments were repeated with different number of boxes in the environment. All graphs indicate that there is an optimal number of robots for which the average energy of the swarm is maximum which agrees to our hypothesis. If the number of robots is less than the optimal value, the average energy of the swarm will be less. Similarly, if the number of robots participating is more than the optimal value, the average energy of the swarm again declines. This indicates that if there are too few robots in the world, they need to carry a lot of tasks and consequently the average energy of the swarm stays low. On the other hand, if there are too many robots, many of them will roam around in the environment trying to look for a box that they can pick up. Meanwhile, they continue to lose their energy and consequently again the average energy of the swarm stays low.

5 Conclusion and Future Work

This paper presents an agent based model in which swarms of simulated mobile robots carry out more than one task. The robots make dynamic decisions of when to carry out a particular task without the need of any centralized controller. The issue of efficiency of a swarm is investigated in details and some interesting trends have been found as illustrated in Section 4. In future, we plan to explore this model further and analyze how different parameters affect robot utilization and energy efficiency in a swarm. We also plan to adopt genetic algorithm to investigate the range of parameters that result in optimal energy efficiency and robot utilization.

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