A Case Study on Self-Sufficiency of Individual Robotic Modules in an Arena With Limited Energy Resources

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***Abstract*—From self-sufficiency perspective, in an artificial robotic swarm, the critical parameter that influences the collective and individual's behavior is not the time required to locate and successfully dock to a recharge station in the arena, rather it is the time a robot occupies a recharge station to fully recharge its on-board batteries. It becomes critical because during recharging of a robot, the recharge station is no longer available for the rest of the modules in the arena. In a bigger swarm, it becomes impractical due to several reasons to deploy an equivalent number of recharge stations in the arena. Therefore, it is of great interest for the system designers to know the appropriate ratio between the number of recharge stations and the number of robotic modules. To test the behavior of an autonomous robotic swarm we have employed traditional bio-inspired techniques with a simple threshold based mechanism that uses the on-board state of charge of a robot to govern and adapt a robot's behavior in different scenarios. The paper concludes with the validation of initial work in Player/Stage simulator and a future work plan.**

***Keywords*-Autonomous robotic systems; trophallaxis; power management; self-sufficiency; charger to robot ratio; CRR.**

I. INTRODUCTION

Long term survivability and autonomy of an autonomous system (living and artificial) are governed by energy resources available in the environment and its ability to adapt itself to changing conditions. From the energy autonomy perspective, foraging as in nature, provides an ability to a mobile robotic system to be aware of its dynamically changing energy requirements in order to autonomously search and regain its replenished energy from the environment. Where as, the adaptiveness empowers a system to tune its behavior/operations with the internal and external system dynamics. The foraging principle has been applied in a variety of ways, to develop the control and behavior of a robotic swarm – both individually and collectively, e.g., collection of objects scattered around the arena and to assemble them in some random or a predefined location [1], [2], [3], and to investigate the collective behavior of a multi-robotic system [4], [5].

According to McFarland, to be energetically autonomous, the *self-sufficiency* is an ability of an autonomous system to maintain itself in a viable state for a longer period of time [6]. A self-sufficient robot therefore has the ability to perform the "basic cycle of work", i.e., find fuel and refuel itself [7].

In literature, to prolong the operational time and improve the energy autonomy of individual autonomous modules in a robotic swarm different techniques have been applied that use either, threshold mechanisms which are based on the battery voltage level [8], activation variables [9], [10], or time [11] to determine an appropriate action for a robot. Another approach that has been applied to prolong the activity time of autonomous robotic systems in a constraint environment includes "charge station sharing", as in [11], [12]. In the said approach, Michaud and Robichaud highlighted the potential issues that arise in an arena with limited energy resources, e.g., "*when is it appropriate for a robot to recharge*", "*how long should the robot recharge itself*", "*what can be done to preserve energy*". In their approach, the operational time estimated from the battery voltage is used to determine the appropriate "time" to recharge a robot.

This paper is organized as follows: Section II briefly presents the related work. Section III describes the addressed problem. Section IV then describes the proposed finite state machine that controls the behavior of a robot in different scenarios. Section V presents the strategies used to measure the overall system performance by varying swarm population and number of recharge stations. Section VI describes the experimental setup, and later presents and discusses the simulation results. At the end, Section VII draws a conclusion and presents future work plans.

II. RELATED WORK

In an approach of collective energy distribution to achieve long term survivability, Kubo and Melhuish [13] explored the idea of robot trophallaxis. Trophallaxis, which is a food sharing phenomenon found in nature, enables a robot to donate an amount of its internal energy reserve to its weaker (having less energy) fellow robots in the swarm. In their model, the robots that are engaged in a cleaning task share their energy between each other using a simple collision

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based mechanism in which after a simple arbitration mechanism, one becomes energy "donor" and the other becomes the energy "recipient". The system performance was then measured using three energy transfer rules and by varying the number of robots with a static recharge station in the arena.

Recently, Kernbach et. al. in [14] presented a kinetic model of swarm foraging to maintain energy homeostasis in an arena with fixed recharge stations. As defined, energy homeostasis is a means of keeping the energy flow balance/equivalent among the individuals in a robotic swarm. Their model uses the time spent by the robots during *working*, *searching*, *waiting*, and *recharging*, to measure the energetic efficiency of the swarm. The model then assumes the charging and discharging time of the robotic modules to be approx. equal to the same charging and discharging currents of the *Jasmine* robot [15]. This means, while operating in the environment, one half of the swarm population keeps itself busy in performing the assigned task and the other half is docked to the recharge stations. The assumption in other words, sets the number of recharge stations to half the number of robots in the arena. To increase the energetic efficiency of the swarm in their work, they mainly focused on the time spent by the robots during "searching" and "waiting" for a recharge station rather than the "charging" and "discharging"(working) time periods.

III. Problem Statement

In an artificial robotic swarm, the parameters that control or effect the self-sufficiency of robotic modules include the energy availability in the environment, energy required to regain replenished energy, and the recharging time especially in case the energy resources are fewer than the number of robotic modules in the arena. From the system design perspective, the recharging time of an on-board battery pack, which is a critical parameter, usually depends on the battery chemistry. For example, the lead-acid battery requires roughly between 12–16 hours [16], whereas, the lithium-ion polymer cells require about 1–2 hours to fully recharge. Other parameters that depend on the battery chemistry and are relevant to the robot electronic and mechanical design include, charge/energy density, supply voltage and the size of the cells.

In an autonomous robotic swarm, the foremost objective is the long term survival of a maximum number of modules in a swarm, as in the case of the SYMBRION/REPLICATOR[1] project, which sets a grand challenge, namely 100 robots surviving 100 days. The fundamental questions that we have found unanswered in the literature includes: what type and what level of cooperation is beneficial for the group that maximizes the number of active modules in the arena? What is the effect of longer recharging time on the behavior and SOC of competing robots? In a real environment with a large number of robotic individuals, e.g. > 50 robotic modules, it is quite impractical to deploy a recharge station for every single robot in the arena, mainly, due to the cost factor involved in the production of the large number of recharge stations and the space requirement in the arena. Therefore, it is important to know how many recharge stations are minimally required to keep a sufficient number of robots alive for a longer period of time in a given environment. In other words, what should be a sensible charger to robot ratio (CRR), i.e.,

$$CRR = \frac{\text{Number of recharge stations}}{\text{Total number of robots}}. \tag{1}$$

As already mentioned, Kernbach et. al. in [14] have proposed the ratio CRR to be 0.5 – the number of recharge stations equals half the number of robotic modules, to optimize the number of active modules in the arena. But with the assumption that the charging and discharging time of the robots are equal. Whereas, we want to find out the CRR value in a scenario where the recharging time is less than the average discharging/operational time of a robot – roughly half.

IV. Finite State Machine for Collective Foraging

To survive in an arena with fewer energy resources for a longer period of time, we have developed a finite state machine to control an individual's behavior in the swarm. Figure 1 shows the finite state machine (FSM) of an autonomous foraging robot. A robot in its life cycle goes through the following states: *"nesting", "trophallaxis", "searching", "approach and dock to a recharge station", "recharging", "avoidance", "waiting", "faint"*, and finally, *"dead"*. The transition between the states is triggered either on external stimuli (from sensor values), e.g. obstacles, or on internal stimuli, i.e. state of charge (SOC) of a robot. The state transitions that are triggered on internal stimuli use two variables: "current state of charge" (SOC_{curr}) and the "state of charge reserved" (SOC_{res}), which is considered to be the maximum amount of charge a robotic module can reserve in order to search and successfully dock to a recharge station in the arena. The current state of charge of a robot's battery pack in percentage is obtained as,

$$SOC_{curr} = \frac{\text{remaining charge}}{\text{maximum charge capacity}} \times 100. \tag{2}$$

A. Nesting

It is the healthiest state of a robot in its life cycle. A robot in nesting state has enough energy to explore the environment, perform the assigned task and if required can donate its excess charge to any other distressed robot in the arena. A robot remains in nesting state until it has just

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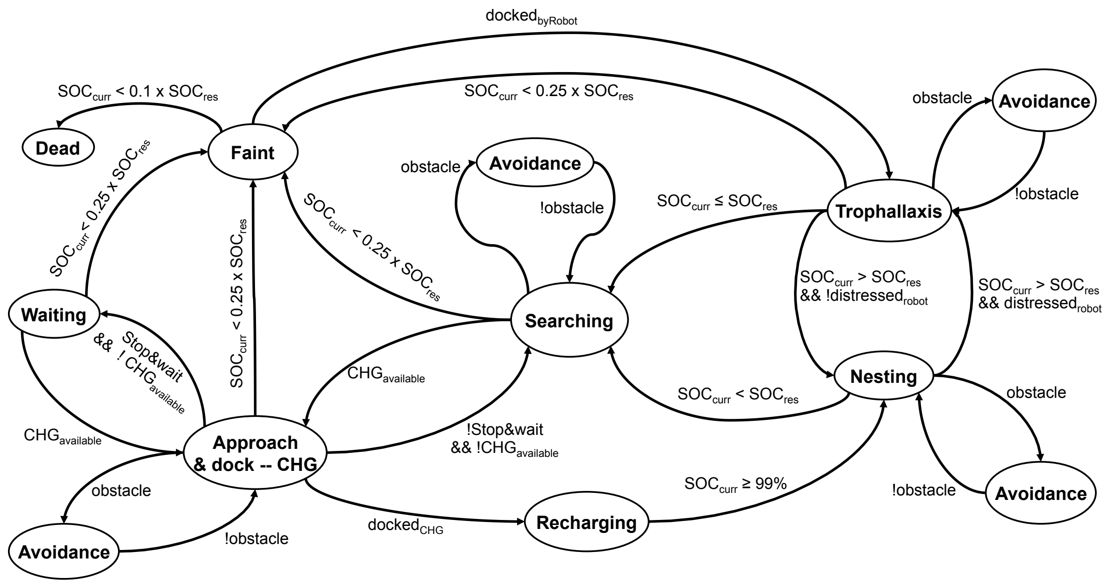

Figure 1: Finite state machine that controls the behavior of an autonomous robot

enough energy left to autonomously reach and dock to a recharge station without any external assistance, i.e.,

$$SOC_{curr} > SOC_{res}.$$

B. Searching

It is the state in which the highest priority task for a robot is to search/locate a recharge station in the arena to regain its replenished energy before it completely runs out of energy. A robot enters "searching" mode either from the "nesting" or "trophallaxis" state, when SOC_{curr} becomes less than or equals SOC_{res}. This means, when the condition

$$SOC_{curr} \leq SOC_{res}$$

becomes true, a robot spends its remaining energy for its survival. For further clarity, the variable SOC_{res} is just a threshold that assigns the foraging task as the highest priority task for a robot, when the above condition becomes true.

C. Avoidance

An obstacle can either be a robot, a recharge station or a boundary wall in the arena, within the detection range of a robot, which forces it to enter the "avoidance" state for the period of time the obstacle remains in its detection range.

D. Trophallaxis

This is a bio-inspired phenomenon employed here to increase the survival time of individual modules in a robotic swarm. Upon receiving distress messages from a faint robot a healthy, "nesting" robot in the vicinity automatically aligns and docks itself to it for the purpose of energy donation. After successfully docking, the "healthy/donor" robot donates its excess energy, i.e., $SOC_{curr} - SOC_{res}$, to the faint robot. After energy exchange, the robot in "faint" state remains in this state if its SOC_{curr} remains insufficient to start searching the recharge station in the arena again, i.e.,

$$SOC_{curr} < 0.25 \times SOC_{res}.$$

E. Approach and Dock

Upon detecting either a recharge station or a distressed robot in the arena, a robot "searching" or "nesting" automatically aligns itself towards its target for the purpose of docking. In case multiple robots approach the same target, a recharge station or a distressed robot, those that succumb return back to their previous state. On successfully docking with the recharge station, a robot enters "recharging" state.

F. Recharging

As mentioned earlier, in an arena with limited energy resources the recharging time of a robot becomes critical as the recharge station becomes unavailable to the rest of the competing robots in the arena. In case of a REPLICATOR robotic module, that uses a 6 cells lithium polymer battery pack, the recharging time is roughly between 1–1.5 hours at a continuous current corresponding to 1C, i.e., 1400 mA.

Likewise, in simulation, ignoring the time required for cell balancing, a robot in the state of "recharging" occupies the recharge station no longer than for a duration of approximately 1 hour, depending on its battery SOC_{curr}.

G. Waiting

A robot enters the "waiting" state, if it stops receiving beacon signals from the recharge station while in the "approach and dock" state. This happens in two scenarios: either when a competing robot in the arena successfully docks to

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the recharge station prior to it, or the robot itself moves away from the recharge station, so that it misses the line of sight. A robot remains in waiting state until it starts receiving charger signals again, or on the expiry of a waiting timer – T_w. The length of T_w is in fact the amount of time required to fully recharge a depleted battery pack at 1C. In our implementation, we set it to 10 minutes to compensate the frequent/erroneous triggering into "waiting" state, e.g., moving away form the line of sight.

H. Fainting

It is the state in which the robot's remaining SOC is considered as not enough to search and successfully dock to a recharge station in the arena. A robot in this state therefore stops moving and starts broadcasting "distress messages" on its IR communication channels. In the current framework, a robot remains in faint state until

$$0.1 \times SOC_{res} < SOC_{curr} < 0.25 \times SOC_{res}.$$

I. Dead

It is considered to be the end of the life cycle of an autonomous robot. It is reached from the "faint" state in case the distressed robot does not receive any aid from the fellow robots in the arena. It is reached when the condition

$$SOC_{curr} \leq 0.1 \times SOC_{res}$$

becomes true.

V. Foraging Strategies

To estimate a tradeoff between the number of recharge stations and robotic modules, we have devised some simple strategies to measure and compare the performance of a robotic swarm in different scenarios.

A. Simple

This scenario was in fact devised to compare and evaluate the results obtained from other techniques. In the simple scenario, the individual autonomous robots lack the ability of dynamic collaboration, i.e., trophallaxis. In fact, they are selfish in the respect that each module is concerned with its own survival in the arena. In this approach, 70% of the max. SOC is considered as SOC_{res}.

B. Trophallaxis

Trophallaxis provides an individual the ability to sense and dynamically cooperate with fellow robots in the arena. With this ability, a healthy, "nesting" robot becomes a donor by sharing its excess energy as soon as it docks to a distressed robot that resides in the "faint" state. Upon a successful docking it starts donating its excess charge to it, where the excess amount of charge "E" is calculated as the difference between SOC_{curr} and SOC_{res}, i.e.

$$E = SOC_{curr} - SOC_{res}. \tag{3}$$

C. Learn and Adapt with Trophallaxis

In the above two foraging strategies, i.e., "simple" and "trophallaxis", the variable SOC_{res} uses a fixed value, i.e. 70% of max. SOC, for the transition between the FSM states. In the case described here, with the ability to learn and adapt, each robot in the swarm learns from the environment an appropriate value of SOC_{res} each time it successfully docks to a recharge station from the time it started its search, to update its previous estimate. Let $SOC_{res}(n-1)$ be the value learned at docking instance $(n-1)$ with a recharge station, and $SOC_{res}(n)$ be the reserved SOC learned at current docking instance (n), i.e. the new value. Where, $n = 0, 1, 2, ...$ The SOC_{res} for the next run was then updated by taking the average of the two estimates, as,

$$SOC_{res}(n) = \frac{SOC_{res}(n-1) + SOC_{res}(n)}{2}, \tag{4}$$

and, by scaling it,

$$SOC_{res}(n) = SOC_{res}(n) \times 1.5, \tag{5}$$

with a factor of "1.5". The scaling was done to reduce the effect of the low value of SOC_{res} learned in the two estimates. Otherwise, an abrupt decrease in the SOC_{res} that reflects the energy abundance in the environment, may lead to a false prediction.

D. Stop and Wait

It's a simple technique that is based on the idea of energy conservation. With the "stop and wait" ability, if a robot stops receiving "charger" signals when in the "approach and dock" state, instead of switching back to "searching" state again, it enters the "waiting" state with the assumption that the charger is occupied by some other robot. A robot remains in "waiting" state until it starts receiving "charger" signals again or the waiting timer (T_w) expires. During waiting state, a robot stops its locomotion to save its energy while the rest of the on-board electronics remain active. Further, in the "stop and wait" topology, a robot disables its trophallaxis ability and strives only for its own survival.

E. Stop and Wait with Trophallaxis:

It is meant to see the combined effect of two simple techniques on energy distribution in the swarm. In this topology, the robots in the swarm on one side preserve their energy by actively choosing the "wait" state and on the other side donate their excess energy to fellow robots to increase the number of active robots in the arena.

VI. Experimental Setup and results

At this stage of development, to explore the dynamic behavior of robotic modules with limited sensing abilities in the arena, we implemented a simple robot model and the test scenarios in Stage simulator [17]. For this purpose, we were provided with an abstract model of a REPLICATOR robot

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in the "Stage" simulator by Wenguo Liu from the Bristol robotic laboratory (BRL), University of the West of England, Bristol, UK.

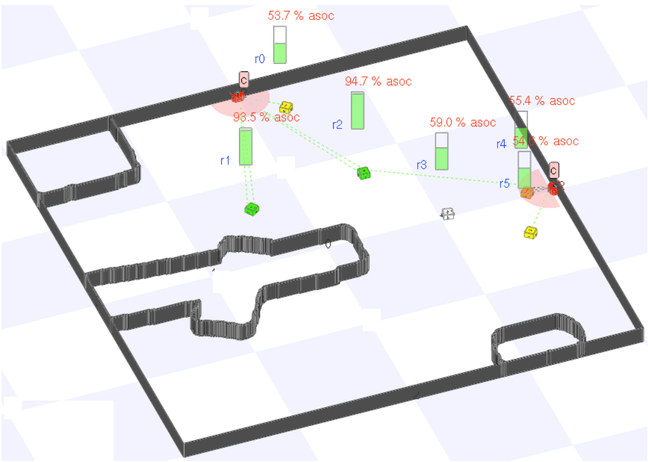


Figure 2: A screen shot of an example scenario in Stage simulator: 6 robots with 2 recharge stations in a simulation arena of dimensions 4m × 4m

A. Robot Model

The dimensions of the simulated robot model are 80 mm × 80 mm × 80 mm. It has four infra-red (IR) sensors (one on each side) for communication in the arena, four status LEDs (one on each side), eight light sensors (two on each side), four docking units (one on each side), a locomotion drive, a battery pack, and a robot controller. The IR and light sensors help the robot to perform beacon detection in order to align itself towards the target. The on-board partially simulated battery pack as in the original robot, provides the nominal voltage of 22.2 V with maximum 1400 mAh of charge capacity. Considering 75 % efficiency of the LiPo battery pack, it finally provides a max. capacity of 1050 mAh. The battery management module uses a coulombs counting approach for the estimation of battery capacity and the absolute state of charge. The simulated robot current consumption values are also taken from empirical values recorded with real robot hardware. On every time instant "*t*", the on-board electronics current consumption was taken randomly between 25 mA to 50 mA at nominal voltage. During random walk the robot's locomotion drive consumed a continuous current of 250 mA, whereas the docking unit that becomes active only during docking and undocking with a recharge station or to a robot for a period of 5 seconds as in the original system, drew a current of 55 mA per second.

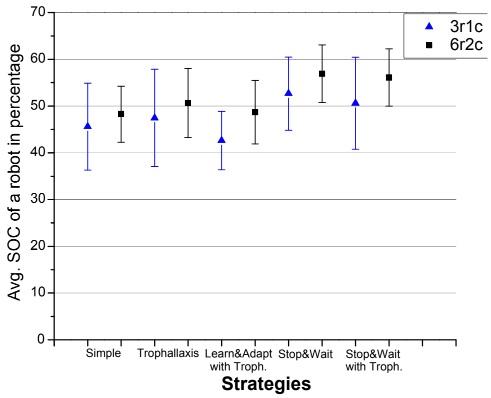
B. Simulation Results

To explore the foraging behavior of a robotic swarm, collectively and individually, with limited energy resources we have varied the number of robots with fixed number of recharge stations in a simulation arena of 4m × 4m. Figure 2 shows a screen shot of an example scenario in Stage simulator [17] with 6 robotic modules and 2 fixed recharge stations.

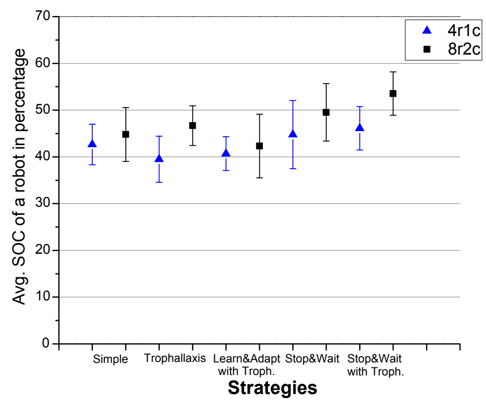
In our experiments we are focusing on the average state of charge of robotic modules as it provides a rough estimate of flow of energy and number of dead robots in the arena. The higher the energy level of the robotic individuals the longer they can survive on their own which in turn enables them to perform a variety of tasks collectively and individually in the arena. Therefore, to get a reliable estimate of average SOC of a robot and the average number of dead robots in a given condition, we ran each strategy, as mentioned in section V, 10 times with each robot having an initial SOC of 80 % of the max. battery capacity. Each time the simulation was then recorded for a period of 10 hours.

Figure 3 shows the simulation results in three cases recorded by varying the number of robots in the arena with a fixed number of recharge stations. In figure 3, the horizontal axis shows the applied "strategies", and the vertical axis shows the "average SOC of a robot" in percentage – averaged over 10 simulation runs. The error bars show the standard deviation of 10 simulation runs. Figure (3a) shows the average SOC of a robot, to compare the effect of limited energy resources in two scenarios: 3 robots with 1 recharge station (3r1c) and 6 robots with 2 recharge stations (6r2c), thus keeping the ratio CRR constant, i.e. 0.333. Figure (3b) shows the average SOC of a robot with CRR = 0.25 in two scenarios: 4 robots with 1 recharge station (4r1c) and 8 robots with 2 recharge stations (8r2c). And lastly, fig. (3c) shows the average SOC of a robot with CRR = 0.166 again in two scenarios: 6 robots with 1 recharge station (6r1c) and 12 robots with 2 recharge stations (12r2c). Before discussing the results shown in figure 3, to get an idea of the applied strategy on the swarm it is important to see the average number of dead robots at the end of simulation runs. Figure 4 shows the average number of dead robots in different scenarios with CRR = 0.333, 0.25, and 0.166. The horizontal axis shows the applied "strategies", and the vertical axis shows the "average number of dead robots". The error bars again show the standard deviation of 10 simulation runs.

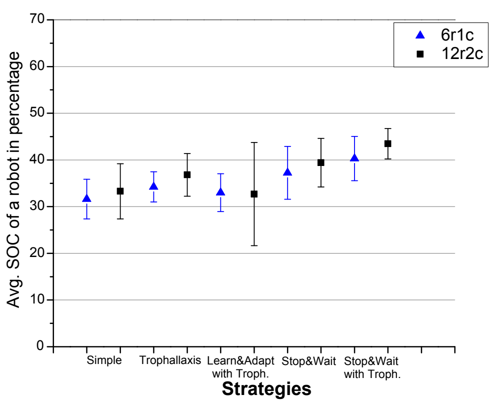
In the case CRR = 0.33, the trophallaxis feature in a smaller swarm size neither contributed in increasing the avg. SOC of robots nor in decreasing the average number of dead robots. But on the contrary, in the bigger swarm it improves the avg. SOC of robots and slightly decreases the avg. dead robots. The "learn and adapt" strategy is barely able to produce the same results as with the simple strategy. The "stop and wait" has shown its effect only in the bigger swarm. In the case CRR = 0.25, the trophallaxis feature likewise in the smaller swarm fails to show it presence on the avg. SOC of robots. But the stop and wait strategy together with trophallaxis feature in the bigger swarm decreases the avg. no. of dead robots by increasing the avg. SOC of the



(a) CRR = 0.33

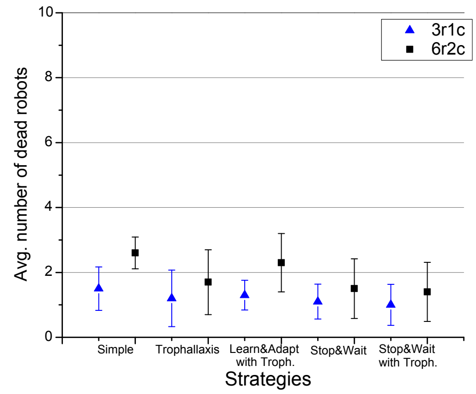


(b) CRR = 0.25

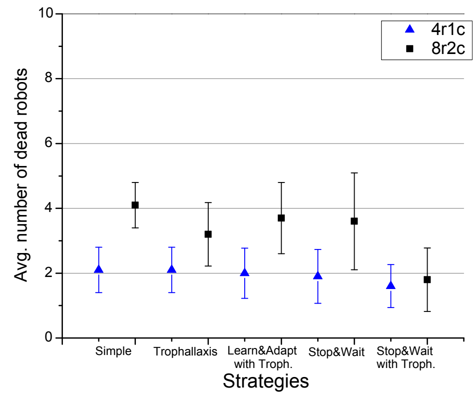


(c) CRR = 0.166

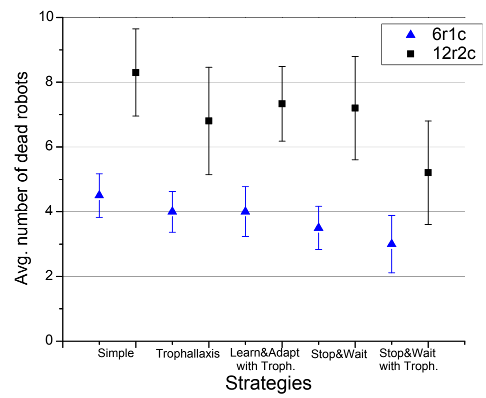
Figure 3: Average state of charge (SOC) of a robot in different scenarios with CRR = 0.33, 0.25, and 0.166. The error bars show the standard deviation of 10 simulation runs.



(a) CRR = 0.33



(b) CRR = 0.25



(c) CRR = 0.166

Figure 4: Average number of dead robots in different scenarios with CRR = 0.33, 0.25, and 0.166. The error bars show the standard deviation of 10 simulation runs.

robots in the swarm. At the end, in the case CRR = 0.166, we have seen nearly the similar trend in avg. SOC of robotic modules and the avg. number of dead robots as we have in case of CRR = 0.25.

Concerning the active number of robots, it is evident from figure 4, that the "trophallaxis" feature alone especially in the bigger swarm decreases the avg. number of dead robots in the arena and its effect is also comparable with the "stop and wait" strategy. Therefore, the combination of the two strategies showed a significant decrease in the avg. number of dead robots, especially in case of CRR = 0.25 and 0.16.

VII. CONCLUSION AND FUTURE WORKS

A. Conclusions

In this paper, we have explored the effect of few potential issues in a simulated environment that may become critical for a robot swarm operating in a real environment with limited energy resources. For this purpose in our preliminary work, we have implemented a basic robot model and the test scenarios in Player/Stage simulator. The performance of the system is then evaluated from the avg. SOC of robotic modules and the avg. number of dead robots in the arena. Considering the two measures, we have seen that the CRR = 0.25 provides us a fair trade off between the number of recharge stations and the number of robotic modules in a closed environment. As in a bigger swarm, the robotic individuals are able to achieve nearly the same avg. SOC as in case of CRR = 0.33. This in fact provides us the motivation to test the system behavior with a bigger swarm size with the ratio CRR = 0.25.

B. Future Works

In the current framework, a critical parameter that is left and requires the attention of the system designer is the system energy loss especially during energy trophallaxis. In future, along with the simulation work we plan to implement and test such simple strategies on a real robot swarm, i.e., REPLICATOR robotic modules, to compare it with simulation results. The testing on the real hardware also involves the measurement of energy losses during trophallaxis and power sharing between the robots.

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