

Parallel Formation of Differently Sized Groups in a Robotic Swarm

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1. Introduction

Swarm robotics is a branch of collective robotics focused on the study of relatively large groups of robots with limited sensing and communication capabilities. One of the main benefits of such systems is their potential for parallelism. To achieve parallelism in real-world scenarios, it is important to be able to split the swarm into appropriately sized groups for different concurrent tasks.

Imagine a swarm of robots that must be deployed to monitor the spread of an environmental hazard. Different hazard areas of various sizes will need correspondingly sized groups of robots, and the hazard sites may be spread far apart. As in any such real-world scenario, it is likely that there will not be enough robots to allocate the ideal number to each hazard site. In this paper, we propose a distributed mechanism to solve this type of group formation problem, whereby large numbers of robots must be divided into multiple groups in parallel. When the number of available robots is sufficient, our system is capable of forming groups of different, pre-defined sizes. When the available robots are less than the sum of the desired sizes, our system distributes robots fairly across groups, ensuring that each group grows at the same rate.

Existing approaches to parallel group formation in multi-robot systems have limitations that render them inappropriate for this type of scenario. Decentralised task allocation and task partitioning approaches scale well, but they only work when the tasks are located close to each other and the density of robots is sufficiently high⁷⁾. Centralised approaches, on the other hand, can efficiently divide a population of robots into specific group sizes matching different tasks, but do not

scale to large swarms of robots due to high communication overheads⁴⁾. The only decentralised approaches that have tackled the formation of specific group sizes in swarms of robots have restricted themselves to forming or counting a single group of robots at a time^{3), 11)}.

Our work is inspired by the aggregation behaviour of cockroaches under shelters. The dynamics of this behaviour are well understood, and predict different aggregated group sizes in an environment with different sized shelters. Amé *et al.*¹⁾ modelled cockroaches as simple agents that walk randomly in an environment, and have a certain probability of stopping that increases with the presence of a shelter and with proximity to other stopped cockroaches. This model is a good fit for the parallel group size selection problem in robotics, as there is no communication required between agents. Our approach does not, therefore, suffer from the scalability limits of centralised approaches. We use 'active shelters', that can affect the probability of robots stopping underneath them within a certain communication range. By varying the stopping probabilities associated with different shelters, we reproduce the effect of different shelter sizes and create robotic groups of different required sizes.

2. Related Work

In swarm robotics, existing approaches to the problem of splitting up a swarm of robots into groups revolve around distributed forms of task allocation⁷⁾ — scalable, decentralised approaches with low or no communication overheads. In these approaches, individual robots have a mechanism for testing the task and allocating themselves to different tasks or sub-tasks. Testing by robots can, for example, take the form of determining whether an object is moving in a group

transport scenario¹³⁾, or testing the time taken to perform a task or sub-task¹⁵⁾. The performance (and/or convergence time) of these methods typically depends on the number of interactions among robots per time unit, which, in turn, depends on the density of robots in the environment. An ideal density range exists, in which these methods perform best. Below a certain density threshold, the robots interact too rarely for these methods to be practically applicable. Above a certain threshold, the robots spend significant time avoiding each other rather than performing their assigned tasks. In real-world scenarios, the available robots are often scarce, tasks may be located far apart from one another, and explicit group sizes may need to be allocated based on some external (human) assessment of the problem. Under these circumstances, task-allocation-based approaches may not be feasible.

Explicit group size formation has been demonstrated as feasible in the swarm robotics context, but only for a single group at a time. Melhuish *et al.*¹¹⁾ controlled group sizes in a swarm of abstract agents using a firefly-like synchronisation mechanism. However, only one group was formed at a time and the physics of the agents was not taken into account. Brambilla *et al.*³⁾ used physically embodied robots, but their system could only passively count the number of robots in a single existing group (rather than generating a group of a priori determined target size). Hsieh *et al.*⁹⁾ have studied an abstraction of the problem we study, whereby robots must distribute across multiple sites in predefined ratios. Hsieh *et al.*'s work is based on statistical models of the house hunting behaviour of the ant *Temnothorax albipennis*.

In multi-robot systems formed by a low number of individuals, market-based approaches provide a good solution to the problem of parallel group formation of explicit group sizes⁴⁾. Market-based approaches, however, have intrinsic scalability problems that render them less applicable to swarm robotics systems. In market-based approaches, all robots participate in an auction, and market forces determine the most appropriate allocation of robots to groups corresponding to particular tasks. However, the fact that every robot must participate in the auction process means that bandwidth and computation requirements increase quickly with the number of robots.

Our approach is inspired by the aggregation behaviour of cockroaches¹⁸⁾. Cockroach behaviour is ac-

curately mimicked by Jeanson's *et al.* model¹⁰⁾ in which cockroaches stochastically switch from stopping to performing a random walk and back. The probability of stopping rather than random walking increases with the number of other nearby stopped cockroaches. A positive feedback mechanism then results in aggregation into groups. When multiple shelters of different sizes are available in the environment, cockroaches may form groups of different sizes that correspond to the sizes of shelter available¹⁾.

Previous robotics studies have shown how cockroach behaviour can be faithfully mimicked by a group of robots. Existing robotic implementations share key features of the cockroach model. In particular, the equilibrium distribution of agents depends passively on the initial configuration of the environment and on the static mapping of environmental conditions to stop/go probabilities⁶⁾. None of the existing studies, however, have used the model to generate a priori desired group sizes, or explored how many such groups could be formed in parallel.

3. Methodology

Our approach is inspired by the aggregation behaviour of cockroaches under shelters. This behaviour has been modelled using decentralised agent-based models, whereby each cockroach agent is attracted to the shelters and to other cockroaches^{1), 10)}. In these models, cockroaches wander randomly in the environment, and decide probabilistically when to stop under a given shelter, and when to leave a shelter based on the stopping probability parameters of the model. Amé *et al.*'s cockroach model¹⁾ predicts different aggregated group sizes in an environment with different sized shelters.

We mimic some of the basic dynamics of these cockroach models to achieve parallel group formation. In our system, mobile ground-based robots play the role of cockroaches, and simple ceiling-based devices play the role of shelters. Instead of using shelters of different sizes, however, we make our shelters *active*, in the sense that they can calculate the robots' stop/go probabilities and communicate them to the mobile robots. In practise, each active shelter continuously transmits stop/go probabilities to mobile robots in a limited radius. We refer to this local communication radius as the *communication range* of an active shelter.

Analogously to cockroaches, robots wander randomly

in the environment. Occasionally, a robot encounters a shelter and decides probabilistically whether to stop underneath it or not. The decision is based on the stop/go probabilities transmitted by that particular shelter. If a robot decides to stop, it becomes part of the group associated with that shelter. Robots under a shelter may also probabilistically decide to leave the shelter (thereby leaving the associated group). By assigning different probabilities to different shelters, we can form groups of different a priori determined sizes in parallel.

Our system has a stochastic nature. The two main sources of randomness are robot motion, and the probabilistic decisions on joining/leaving a group. Robot motion influences the discovery of shelters by robots, as well as the formation and disbandment of the groups. The probabilistic group joining/leaving mechanism impacts the stability of the groups over time. To say meaningfully that we have formed groups of a particular size, therefore, the system must settle at some point into a state in which the size of individual groups can be recognised as stable. We refer to this property as *convergence*. We give a formal definition of convergence in Sec. 5.2.1.

For our system to display parallelism, the group formation mechanism must ensure that all shelters receive a fair share of robots. We refer to this property as *fair spreading*. In our approach, fair spreading occurs when the rate of growth of all group sizes is proportional to the desired sizes. In a system that displays fair spreading, convergence time does not depend on the number of groups to form. In addition, with fair spreading, a system offers equal treatment for all shelters when the number of robots available for group formation is lower than the number of robots desired in total.

We introduced and analysed a first implementation of this system in a previous work¹²⁾. The results indicate that the join and leave probabilities impact differently the dynamics of the system. The join probability mainly accounts for the rate of addition of robots into groups. The leaving probability accounts for the rate of robot loss of a group, and has dramatic effects on the dynamics of the system. Experimental results showed that setting the leave probability to a high value greatly improves spreading at the expense of group stability, thus making convergence detection by the active shelters difficult or impossible. A low value for the leave probability, on the other hand, results in high stability and unfair or non-existent spreading. Our system, pre-

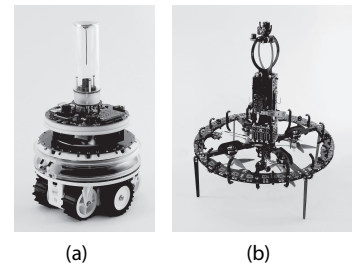


Fig. 1 The robot platforms we simulated for the experiments in this study. (a) The foot-bot; (b) the eye-bot.

sented in Sec. 5, offers a solution to this trade-off, so as to ensure both easy convergence detection and fair spreading.

4. Hardware

We first discuss the minimum capabilities necessary for a hardware platform to use active shelters as a means of group formation. We then describe the actual devices employed in this work.

4.1 Minimum Generic Requirements

An active shelter is capable of monitoring the number of grouped robots over time, with coarse periodicity. In addition, it must be capable of broadcasting the join/leave probabilities to the robots in range. Finally, active shelters must be able to broadcast a 1-bit signal to nearby shelters.

A mobile robot must be capable of navigating the environment avoiding other robots. To coordinate the motion of robots joining/leaving a group as described in Sec. 5.2.1, each robot must convey 2-bit state information (joined-group/leaving-group/free) to nearby robots and shelters. A robot must detect the state of nearby robots and receive the join/leave probabilities from the closest shelter. Finally, a robot must be able to perceive nearby robots.

4.2 Devices Used in This Study

In our experiments, we employed the foot-bot²⁾ as mobile robot (**Fig. 1** (a)). The foot-bot navigates the environment through a set of wheels and tracks called *treels*. It can convey its state (joined-group/leaving-group/free) through a coloured LED ring that surrounds its body, and detect other robots' state and relative location through an omnidirectional camera.

To realise active shelters we used the eye-bot robot (**Fig. 1** (b)). The eye-bot¹⁶⁾ is a quad-rotor robot able to attach to the ceiling. To detect mobile robots, the eye-bot is equipped with a pan-and-tilt camera.

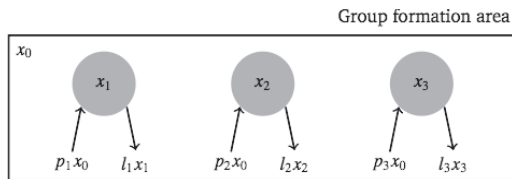


Fig. 2 A schematic representation of the mathematical model described in Sec. 5.1 with three active shelters.

Eye-bot-to-foot-bot and eye-bot-to-eye-bot communication occurs through the range-and-bearing communication system¹⁷⁾ present on all robots. This device allows the eye-bot to broadcast a message containing a 8-byte payload. The message can be received by nearby eye-bots and by foot-bots on the floor in a limited range.

The robots, as well as the range-and-bearing communication system, were developed in the Swarmanoid project⁵⁾.

5. Active Shelters

In this section, we present our system to achieve group formation control through active shelters. We analyse its properties and identify its limitations. In Sec. 5.1, we present a mathematical model that captures the most important aspects of the system. In Sec. 5.2, we present the complete implementation of the system and analyse it through targeted physics-based simulations.

5.1 Mathematical Model

The model. In **Fig. 2**, we illustrate the abstraction of the system upon which we base our mathematical model. The shelters are distributed in a rectangular area. The communication range of the shelters is displayed as a circular grey area. We assume that the communication ranges of a shelter do not overlap with those of the other shelters.

For the purposes of this model, we neglect the actual motion of the robots across the environment. We assume that the robots perform a suitable diffusion algorithm⁸⁾, so as to uniformly distribute in the environment. Thus, the probability c for a robot to be located within the communication range of a shelter is given by

$$c = \frac{\text{Area}(\text{shelter})}{\text{Area}(\text{group formation area})}.$$

A robot joins the group of shelter i with probability j_i . This probability is set by the active shelter depending on the desired group size. The probability p_i for a robot to discover that shelter and join its group is given by $p_i = cj_i$. The probabilities p_i are assumed constant

throughout the duration of a run.

A robot that is part of group i has a probability to leave it, denoted by l_i . As discussed in Sec. 3, setting l_i to a fixed value causes a trade-off between fair spreading with difficult convergence on one side, and stable convergence with unfair spreading on the other¹²⁾. Thus, to reconcile convergence and spreading, the leave probability l_i must vary between a value that promotes fair spreading (hereinafter denoted by l^{hi}), and a value that ensures convergence (hereinafter denoted by l^{low}). At the beginning of our experiments, each shelter i is configured with a probability $l_i = l^{\text{hi}} = 10^{-2}$. We thus ensure a good spread of robots early on in the group formation process. Over a period of time, each shelter exponentially decreases the value of its l_i , until it reaches $l^{\text{low}} = 10^{-5}$, thus allowing the system to gradually settle into a stable state. More specifically, the values of the l_i 's are set as follows:

$$l_i(t) = (l^{\text{hi}} - l^{\text{low}})e^{-\gamma t} + l^{\text{low}}, \quad (1)$$

in which γ is the decay constant. We define γ as a function of a parameter δ that represents the number of time steps required by the exponential to drop by 90%:

$$\gamma = \frac{\ln 10}{\delta} \quad \Rightarrow \quad e^{-\gamma \delta} = 0.1.$$

We denote the fraction of robots engaged in group $i > 0$ at time t as $x_i(t)$, and the free robots (i.e., not part of any group) as $x_0(t)$. If we consider the probabilities p_i and l_i as rates of group joining and leaving, respectively, and we denote with n the number of shelters in the group formation area, we obtain the following model:

$$\begin{cases} x_0(t+1) = x_0(t) - \left(\sum_{i=1}^n p_i \right) x_0(t) + \sum_{i=1}^n l_i(t) x_i(t) \\ x_i(t+1) = x_i(t) + p_i x_0(t) - l_i(t) x_i(t) \end{cases} \quad (\text{with } i \in [1, n])$$

Model behaviour. To study the behaviour of the model with respect to convergence and spreading, we set up a three-phase experiment. Initially, two shelters form groups of different sizes for a certain period T_1 . At time $t = T_1$, a third shelter is activated and it starts recruiting robots. Subsequently, at time $t = T_2$, shelter 2 is disabled, thus freeing all the robots within its group. The simulation ends at time $t = T_3$.

The length of these three phases is not fixed, but depends on the dynamics of the system. To study convergence at each phase, we record the times T_1 , T_2 ,

and T_3 at which the system reaches convergence in each phase. Convergence is reached when all fractions (grouped and free robots) change by a sufficiently little quantity. More precisely, we declare convergence at time t^* if $\forall k \in [0, n] |x_k(t^*) - x_k(t^* - 1)| < 10^{-6}$.

Whenever a new shelter is activated or deactivated spreading is important to ensure fair resource distribution. The newly activated or de-activated shelter thus

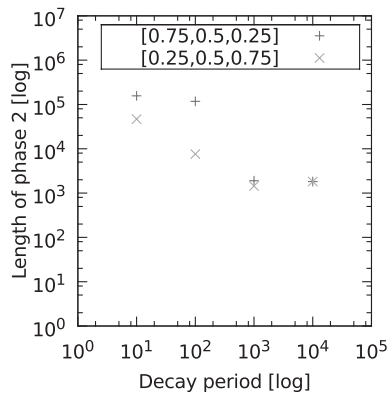
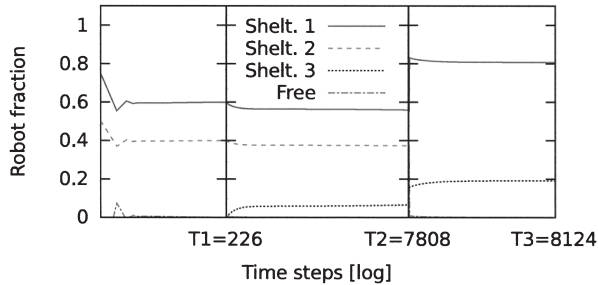
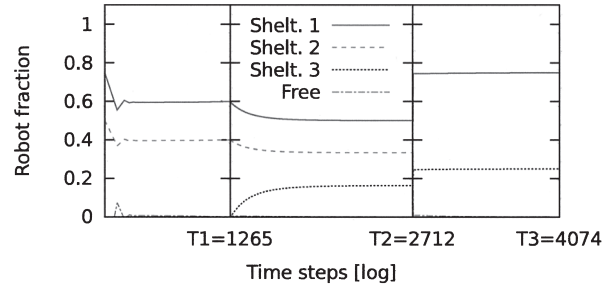


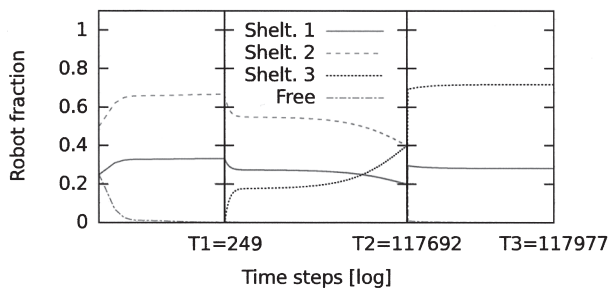
Fig. 3 Length of phase 2 in the simulations of the mathematical model for different values of the decay period δ .



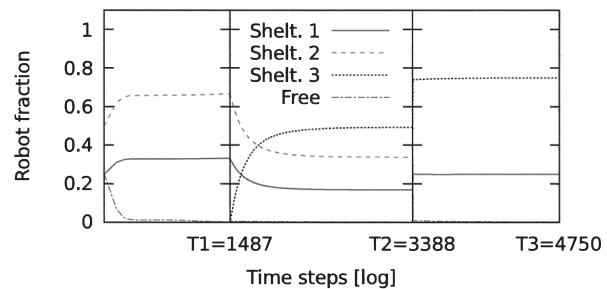
(a) $\mathcal{P}_1 = \{0.75, 0.5, 0.25\}$; $\delta^{\text{short}} = 10^2$



(b) $\mathcal{P}_1 = \{0.75, 0.5, 0.25\}$; $\delta^{\text{long}} = 10^3$



(c) $\mathcal{P}_2 = \{0.25, 0.5, 0.75\}$; $\delta^{\text{short}} = 10^2$



(d) $\mathcal{P}_2 = \{0.25, 0.5, 0.75\}$; $\delta^{\text{long}} = 10^3$

Fig. 4 Results with the mathematical model presented in Sec. 5.1. The experiments are composed of three phases. In phase 1, two shelters are active. In phase 2 (starting at time T_1), a third shelter is activated. In phase 3 (starting at time T_3), shelter 2 is deactivated. The experiment ends at time T_3 . The length of each phase depends on the dynamics of the system. \mathcal{P}_1 and \mathcal{P}_2 account for the desired group size of each shelter. Parameter δ corresponds to the decay period for the probability to leave a shelter.

we tested $\delta = \delta^{\text{short}} = 10^2$ and $\delta = \delta^{\text{long}} = 10^3$ time steps. As the plots show, the length of the decay period of the leave probability has a strong impact on the behaviour of the system and the values of T_1 , T_2 and T_3 . If the decay period is short ($\delta = \delta^{\text{short}}$), the value of the leaving probability drops quickly and the system behaviour results in unfair spreading and very long convergence times. A long decay period ($\delta = \delta^{\text{long}}$), on the other hand, has a positive effect on both properties, because the robots have sufficient time to spread across the shelters.

5.2 Physically Simulated Robot

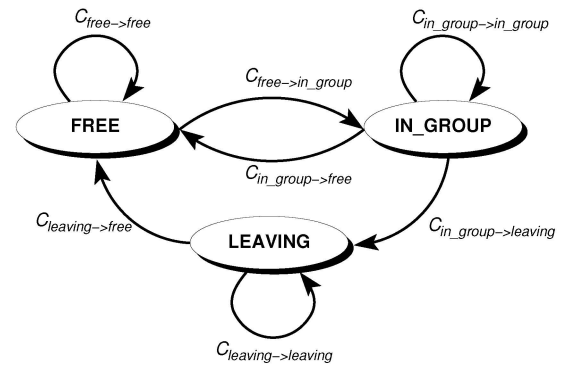
5.2.1 Implementation

We performed experiments in detailed physics-based simulations using the ARGoS robot simulator¹⁴⁾ to validate the predictions of the model in a physically realistic robotic system. A prominent aspect that affects the system performance is interference among mobile robots. In our system, interference occurs mainly under the active shelters. The mobile robots must organise in tight aggregates under the shelters, while permitting the flow of leaving and joining robots.

In our physics-based simulations, we assume that the robots are randomly distributed in a group formation area in which shelters are distributed. At any moment, a robot performing random walk across the environment can either be under a specific shelter or in a shelter-free area. The robot behaviour is described by the simple state machine reported in **Fig. 5**. The meaning of the states are as follows:

- state FREE: A robot does not belong to any group. The robot performs random walk with obstacle avoidance. This state is conveyed with LEDs lit up in green.
- state IN_GROUP: A robot is part of a group. This state is conveyed with LEDs lit up in red.
- state LEAVING: A robot is leaving a group to which it previously belonged. This state is conveyed with LEDs lit up in blue.

Join probability. When a robot in state FREE enters the communication range of shelter i , it transitions to state IN_GROUP with probability j_i . This probability is related to the target group size q_i associated to the shelter. We aim to find a simple relationship between j_i and q_i . The communication range of a shelter is limited in size and, thus, can house a maximum number of robots, which we denote with f . We assume that all the shelters have identical communication ranges, so f



State transition conditions	
$C_{\text{free} \rightarrow \text{in_group}}$	$\text{JustInRange}() = \text{true}$ and $\text{Rand}() \leq j_i$
$C_{\text{free} \rightarrow \text{free}}$	$\text{InRange}() = \text{false}$ or $(\text{JustInRange}() = \text{true}$ and $\text{Rand}() > j_i)$
$C_{\text{in_group} \rightarrow \text{free}}$	$\text{InRange}() = \text{false}$
$C_{\text{in_group} \rightarrow \text{leaving}}$	$\text{InRange}() = \text{true}$ and $\text{Rand}() \leq l_i$
$C_{\text{in_group} \rightarrow \text{in_group}}$	$\text{InRange}() = \text{true}$ and $\text{Rand}() > l_i$
$C_{\text{leaving} \rightarrow \text{free}}$	$\text{InRange}() = \text{false}$
$C_{\text{leaving} \rightarrow \text{leaving}}$	$\text{InRange}() = \text{true}$

Fig. 5 State transition logic for robots at each time step. $\text{InRange}()$ and $\text{JustInRange}()$ are functions returning *true* when the robot is within the communication range of a shelter, and has just entered it, respectively. $\text{Rand}()$ is a function returning a random number in $\mathcal{U}(0, 1)$. j_i is the join probability for shelter i , l_i is the leave probability. State transition conditions are represented by the symbol C and a subscript. For example, $C_{\text{in_group} \rightarrow \text{in_group}}$ represents the conditions under which an aggregated robot will stay aggregated in its group in a single time step.

is a constant across the shelters known a priori. In addition, we assume that the target group sizes q_i cannot exceed f . Each shelter constantly monitors the number of robots currently engaged in its group. If the group size exceeds the target size, the shelter must stop recruiting robots. From these considerations, we derive the following simple definition for j_i :

$$j_i = \begin{cases} q_i/f & \text{if current size of group } i < q_i, \\ 0 & \text{otherwise.} \end{cases}$$

Leave probability. A robot in state IN_GROUP beneath shelter i transitions to state FREE with probability l_i . The probability l_i decays exponentially following (1).

Robots joining and leaving a group. Physical interference among grouped robots may have severe effects on the system, especially when the density of robots under a shelter becomes high. Upon deciding to leave, a robot located in the centre of a group needs a clean path out of it. However, if the area beneath a shelter is

crowded, the formation of the exit path is likely to push some robots located at the border of the group out of the communication area, thus losing contact with the shelter. Thus, interference reduces stability, especially in large groups.

To solve these issues, we consider each robot to be immersed in two virtual potential fields¹⁹⁾. The first field attracts robots that decide to be part of a group towards the centre of such group, or repels those who decide to leave the group. The second field allows a robot that decides to leave the group to push its way out without disrupting the integrity of the group.

Convergence Detection. It is important for a shelter to be able to detect convergence. However, due to the probabilistic nature of our system, the group size displays continuous fluctuations. Thus, the notion of convergence to a target group size must be linked to these fluctuations. Intuitively, a shelter can declare convergence when the magnitude of the fluctuations remains for a certain period of time within a specific range.

In practise, each shelter monitors the fluctuations of the number of its aggregated robots over a period of time T_C . If the magnitude of the fluctuations stays within some tolerance boundaries for the entire period, the shelter considers the system to have converged. The tolerance boundary B is defined as a function of the leave probability l^{low} , the length of the monitoring period T_C and the size of the aggregate g_i at the beginning of the monitoring period:

$$B = \sqrt{T_C g_i l^{\text{low}} (1 - l^{\text{low}})}$$

B is derived by considering the changing number of aggregated robots under a shelter as a time series produced by a binomial distribution in which $p = l^{\text{low}}$. B is calculated as the standard deviation of such a time series over the monitoring period T_C .

5.2.2 Experimental Evaluation

Experimental setup. We ran experiments with a 3-phase setup analogous to what we presented for the mathematical model. The values of $T_1 = 50$ s, $T_2 = 250$ s, and $T_3 = 500$ s were chosen to give the system sufficient time to reach convergence at each stage.

We distributed 30 robots in the group formation area. In the first phase, the target sizes of shelter 1 and 2 are always set so that their sum is less than 30. This first phase therefore allows us to test whether the system is capable of converging to the correct group sizes in the simple case where there are enough robots to satisfy all

target sizes. The second phase, in which also shelter 3 is activated, tests the spreading property of the system in response to the activation of new shelters. In particular, we set shelter 3's target size to make the sum of the target sizes greater than the total number of robots in the group formation area. The third and final phase tests the spreading property of the system, this time in response to the release of robots by shelter 2. The convergence property of the system is tested in all three phases of the experiments.

For the experiments in this section, we tested two target size configurations: [15, 10, 20] and [12, 12, 12]. In the first configuration, shelter 3's target size is greater than those of shelter 1 and shelter 2, thus requiring the system to redistribute robots. This corresponds to setting \mathcal{P}_2 of the experiments with the mathematical model. The second configuration was chosen to specifically assess the spreading property. For the decay period, we selected the value $\delta = \delta^{\text{long}} = 10^3$.

Results. The results are reported in **Fig. 6**. The plots show that convergence is reached in both experimental settings, regardless of desired group sizes. The detection of convergence in phase 2, which is the most critical phase in the experiment, is achieved by all robots within slightly less than 10 simulated minutes from the beginning of the phase.

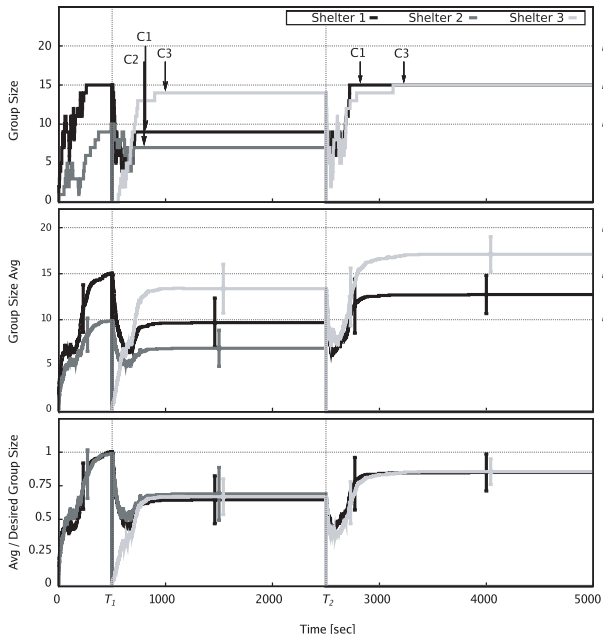
Regarding spreading, the bottom plots of **Figs. 6** (a)–(b) show the average fulfilling percentage of the groups. In both experimental settings, regardless of the desired group size, these percentages stabilise on the same value in all phases.

6. Scalability Assessment

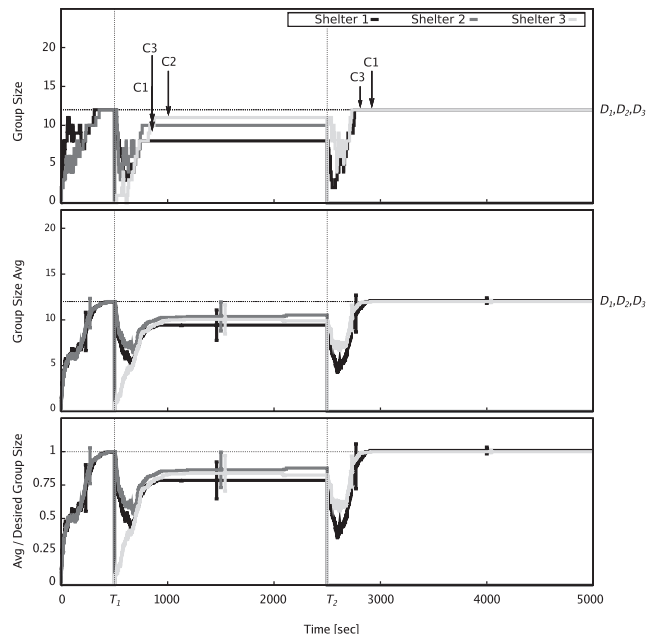
One of our key motivations to create a new group formation mechanism is to achieve scalability (see Sec. 2). This motivation is the driving force behind our choice of a decentralised cockroach-inspired model. In this section, we test the scalability properties of our approach. We conduct experiments with hundreds of mobile robots that must be divided in dozens of groups. Parallel group formation with these numbers would be difficult to achieve with existing group formation approaches.

6.1 Experimental Setup

The shelters are distributed in a $N \times N$ grid. We set the desired group size to 25 for all the shelters. The experimental setup is shown in **Fig. 7**. **Fig. 7** (a) is a snapshot of the simulated group formation area.



(a) Target sizes: [15, 10, 20]



(b) Target sizes: [12, 12, 12]

Fig. 6 Results with physically simulated robots following the behavior explained in Sec. 5.2.1. The experiments are composed of three phases. In phase 1, two shelters are active. In phase 2 (starting at time T_1), a third shelter is activated. In phase 3 (starting at time T_2), shelter 2 is deactivated. The experiment ends at time T_3 . The top plots show a representative experimental sample in the pool of the 100 repetitions we ran. The middle plot reports the average system behavior. The bottom plot shows the ratio between the current and the desired group size.

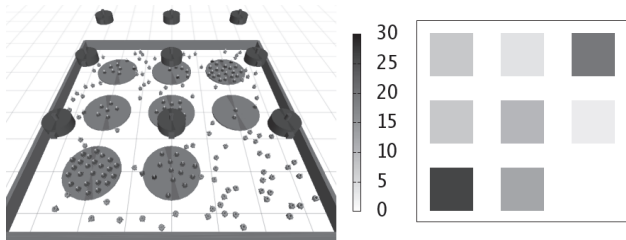


Fig. 7 Snapshot from scalability experiments with physically simulated robots. Left: Simulation snapshot. Right: Abstracted representation of this simulation snapshot—the grey intensity level of each square is proportional to the recruited group size of the correspondingly positioned shelter (i.e., to the number of robots recruited by that shelter).

Fig. 7 (b) is an abstract representation of the same group formation area in which the grey intensity of each square is proportional to the number of grouped robots. This representation allows for visual analysis of the sizes of the groups and their spatial distribution in the group formation area over time.

In all the experiments, we set the number of available mobile robots to $20N^2$. In this way, if fair spreading oc-

curs, at convergence, a group of 20 robots should have been formed under each shelter.

6.2 Convergence

In this section, we present a set of experiments designed to test the convergence property of the system. We ran experiments with 16 and 25 shelters (320 and 500 mobile robots, respectively). The duration of each experiment was set to 750 s.

The results are reported in **Fig. 8**. The top plots show the dynamics of a sample run taken at random from the 80 experiment repetitions. We also display three snapshots at 250 s, 500 s and 750 s. After an initial period of instability, in which the group sizes grow with large fluctuations, the system converges in both experimental settings. The length of the decay period δ in these experiments was set to 350 s, which explains the duration of the fluctuating phase, about 400 s. At convergence, for both experimental settings, the distribution of the group sizes is centred around the target value of 20. In particular, the median of the group size distribution is 21. With 16 shelters, the first quartile of group size is 14 and the third quartile is 23, while with 25 shelters the interquartile extrema are 15 and 25.

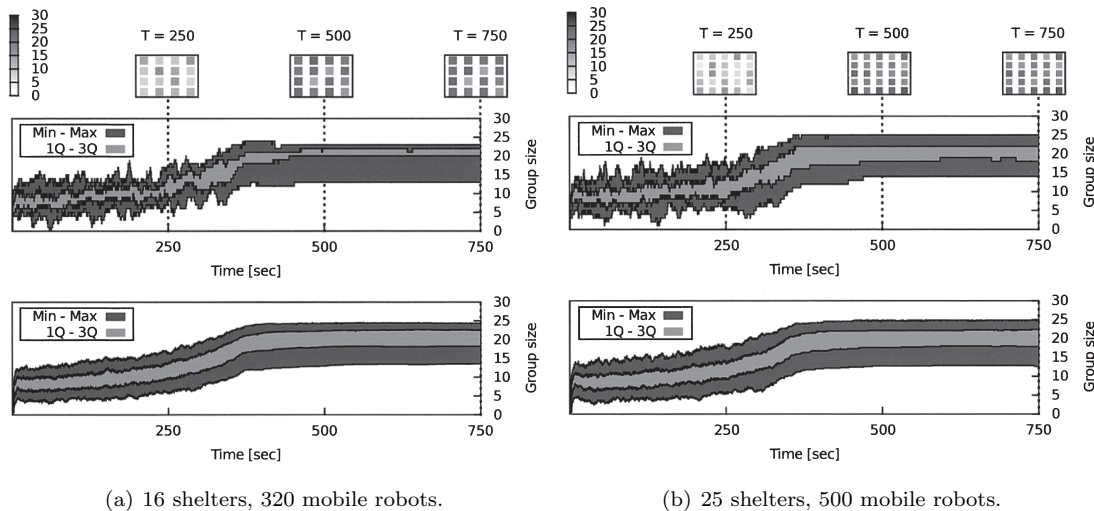


Fig. 8 Scalability experiments testing the *convergence* and *spreading* properties of the system. Results are shown for two sets of experiments with 16 shelters (a) and 25 shelters (b). 80 experimental runs per set of experiments. The top plots show the behaviour of the system in a single sample experiment that we have selected. The grids of squares represent snapshots of the state of the system at given moments in time during this sample experiment. The grey intensity of each individual square corresponds to the number of mobile robots recruited at that time by a single shelter. The min-max lines show the size of the largest recruited group of mobile robots and the size of the smallest recruited group of foot-bots at any given moment. The 1Q and 3Q lines show the inter-quartile range of the distribution of recruited group sizes among the shelters. The 1Q is the first quartile and shows the minimum recruited group size once we discard the lowest 25% of groups. The 3Q line is the third quartile, and shows the maximum recruited group size once we discard the highest 25% of the data. The bottom plot shows the same data averaged over all 80 runs.

The average behaviour of the system over 80 runs, showed by the bottom plots of **Fig. 8**, confirms these observations. The median of the formed groups grows to 22, and the extrema of the interquartile range of the final sizes we observed are 15 and 25.

The plots also show that the time to reach convergence is very similar with 16 and 25 shelters. The convergence time of the system appears to be practically independent of the number of robots, thus confirming that the proposed group formation mechanism displays the spreading property. This result is expected because our system is completely parallel and based on local interactions among mobile robots and shelters.

6.3 Spreading

To test spreading, we devised a two-phase experimental setting. In the first phase, the system is given 750 s to reach convergence. At the beginning of the second phase, we activate or deactivate a shelter. These events force the system to redistribute the mobile robots and reach a new convergence state, thus providing a good test of how capable the system is of spreading robots between shelters. The length of the second phase is set to 750 s.

As we explained in Sec. 5, upon activation and deactivation, a shelter broadcasts a signal to its neighbours. The neighbours of a shelter are those shelters in direct line of sight. The signal forces the recipients to reset the leaving probability to l^{hi} and to restart the decay process.

An important aspect in our system is the transmission range of the reset signal. In Sec. 6.3.1, we analyse the results we obtained in experiments in which the reset signal is broadcast globally throughout the system. In Sec. 6.3.2, we discuss the results we obtained when the transmission range of the signal is limited.

6.3.1 Global Reset Signal

In this section, we analyse the results we obtained with a global broadcast of the reset signal across the shelters. In these experiments we use 9 shelters and 180 robots.

To study whether the starting point of the (de)activation event affects the system behaviour, we explore the cases in which the event occurs at the corner and at the centre of the shelter grid.

The results are reported in **Fig. 9**. In all the experimental settings, at the end of phase 1 the system reaches

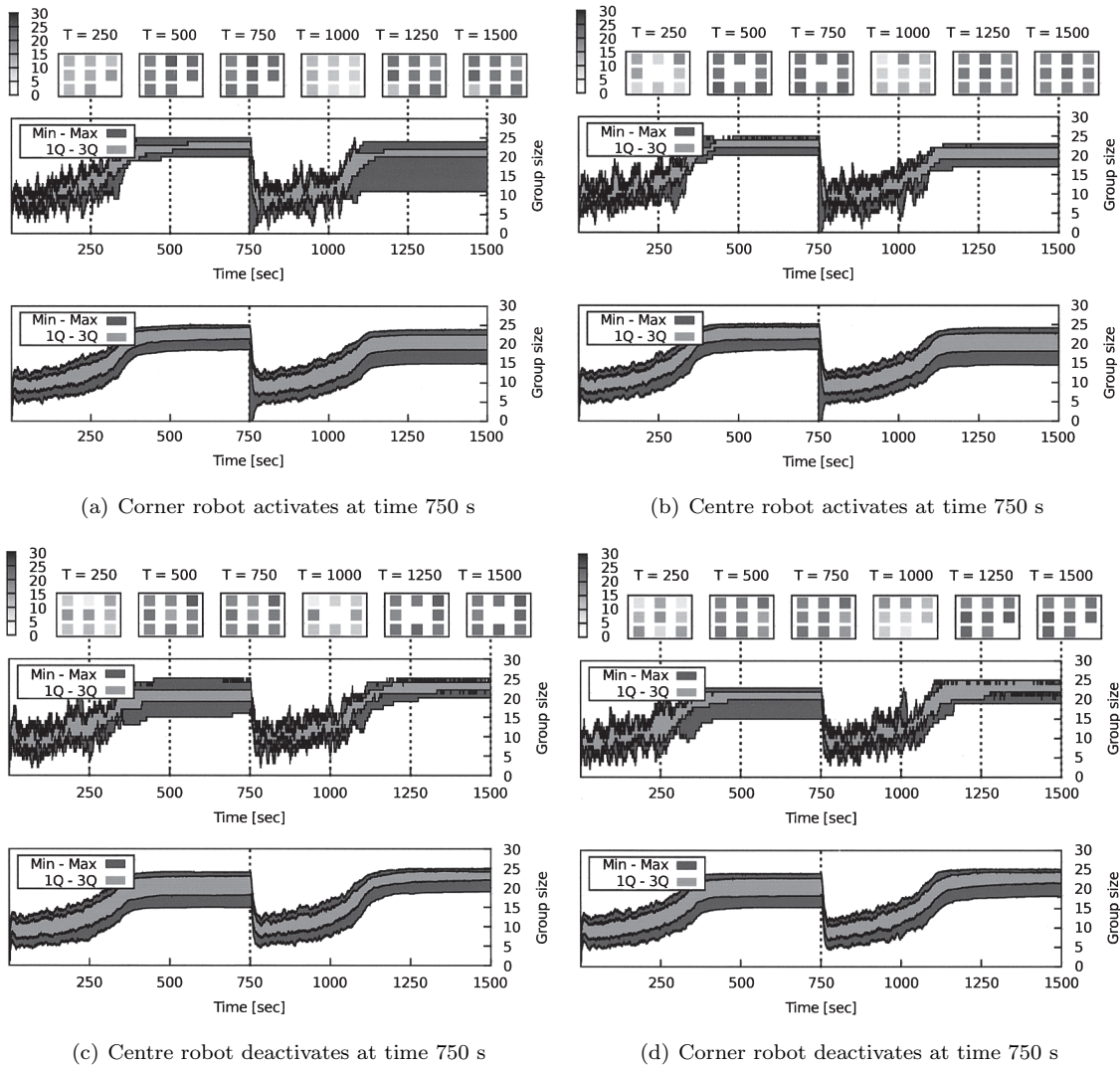


Fig. 9 Set of experiments testing the *spreading* property of the system. All experiments run with 9 shelters and 180 mobile robots in a recruitment area consisting of a 3x3 shelter formation. Results are shown for four sets of experiments (a,b,c,d). Each experimental run lasts for 1,500 s. 20 experimental runs were conducted for each set of experiments. Top plots in each set represent selected sample runs, while bottom plots represent data averaged over all 20 runs. For a more detailed explanation of the plots see previous caption from Fig. 8.

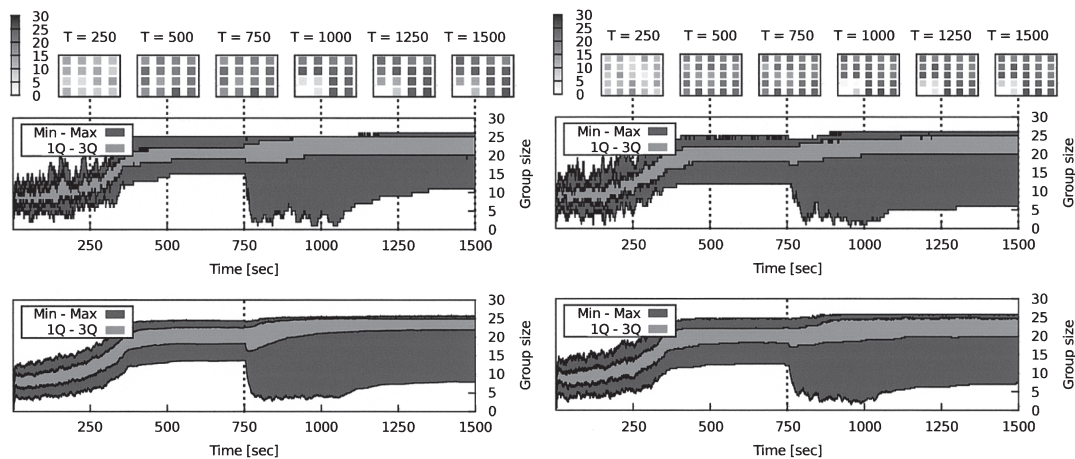
convergence to a state in which the group size distribution is tightly packed around the target value 20. The event causes the shelters to release the grouped robots. The subsequent dynamics, in the average plots, shows that, regardless of the location of the event and its type (activation/deactivation), the system is able to reach a new convergence state. The final distribution of the group sizes is tightly packed around 20 robots.

The snapshots in **Fig. 9** of the sample experiments show that the initial location of the event does not affect the final distribution of the robots. The grey levels in the snapshot do not display any visible bias towards a specific region of the group formation area, thus indi-

cating that spreading is fair.

6.3.2 Local Reset Signal

Although a global reset signal allows for fair spreading after the activation and deactivation of shelters, its application to real scenarios is problematic. In fact, if the frequency of these events is too high, the system may have insufficient time to reach convergence, resulting in constantly fluctuating group sizes. To prevent constant fluctuations, the convergence results of Sec. 6.2 suggest that the time between activation/deactivation events must be greater than the decay period δ . As the size of the scenario grows, and with it the number of group formation requests per time unit, the frequency



(a) 16 shelters, 320 mobile robots.

(b) 25 shelters, 500 mobile robots.

Fig. 10 Set of experiments on local perturbation. In these experiments, the propagation of the reset signal is limited to the direct neighbours. Results are shown for two sets of experiments (a,b). 20 experimental runs were conducted for each set of experiments. Each experimental run lasts 1,500 s. Top plots in each set represent selected sample runs, while bottom plots represent data averaged over all 20 runs. For a more detailed explanation of the plots see previous caption from Fig. 8.

of the events is likely to exceed δ^{-1} , thus causing constant fluctuations. A possible solution to this problem is to limit the range of transmission of the reset signal.

In this series of experiments, we test the impact on the spreading ability of the system when the reset signal is not globally broadcast. We use 16 and 25 shelters (to which correspond 320 and 500 mobile robots, respectively) and deactivate only one corner shelter.

Short range. **Fig. 10** shows the results of experiments in which the reset signal was transmitted only to the closest neighbours of a perturbed shelter (i.e., the shelters in the Moore neighbourhood). The final state reached by the system presents two regions, one affected by the perturbation and one not affected by it. In the region affected by the perturbation, the final group sizes are visibly lower than in the other region. Thus, spreading is not fair. This phenomenon can be explained by observing that, upon leaving a group, the direction chosen by a robot is random and uniformly distributed. Thus, part of the robots leaked from the perturbed region to the unperturbed one.

Medium range. **Fig. 11** shows the results of experiments in which the reset signal was transmitted in a medium range. The reset signal reaches the neighbours of the neighbours of the originally perturbed shelter. Analogously to the previous case, the final state of the system is characterised by two regions, one affected by perturbation and one not affected. Since a larger part

of the system takes part into the redistribution process, the distribution of the final group size is more even than the non-propagated signal case, but still spreading is not very fair.

6.3.3 Discussion

The communication range of the reset signal characterises the ability of the system to redistribute the robots. Our experiments show that, when the frequency of the perturbations exceeds δ^{-1} , limiting the range of the reset signal is not enough, by itself, to ensure fair redistribution. This problem is due to the fact that the robots that leave the perturbed shelters tend to leave the group in all the directions. As a consequence, only a part of the leaving robots are directed towards other perturbed shelters. The other robots join already stable groups. In this way, two regions are formed in the system—one region with a surplus of robots, and a region with a deficit of robots. A possible solution for this problem, currently under study, is to prevent the robots from navigating towards the unperturbed regions of the system.

7. Conclusions

In this paper, we presented a novel, distributed approach to the formation of multiple groups of mobile robots. The main feature of our algorithm is the ability to fairly distribute robots across group of different target sizes even in presence of scarce resources.

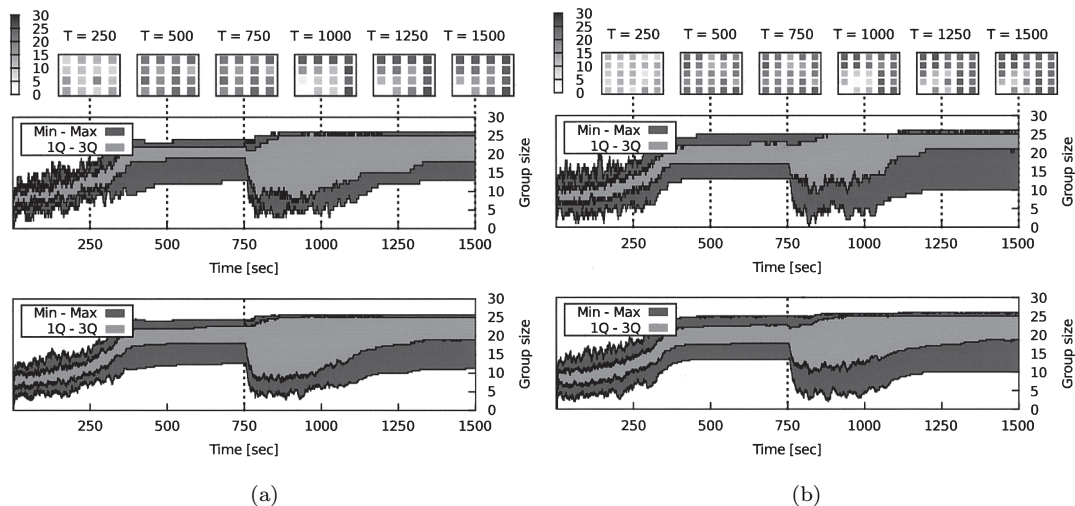


Fig. 11 Set of experiments on local perturbation. In these experiments, the propagation of the reset signal is limited to the second-level neighbours (i.e., the direct neighbours of the direct neighbours of the signal originator). Results are shown for two sets of experiments (a,b). 20 experimental runs were conducted for each set of experiments. Each experimental run lasts 1,500s. Top plots in each set represent selected sample runs, while bottom plots represent data averaged over all 20 runs. For a more detailed explanation of the plots see previous caption from Fig. 8.

The method takes inspiration from the behaviour of cockroach aggregation under shelters. In our system, shelters are simple, active devices able to monitor the number of aggregated robots, and calculate and locally broadcast probabilities for the robots to join and leave the aggregate.

We showed that the stability of the groups is mainly dependent on the leaving probability, and presented a system in which shelters vary this probability over time to control group size. We demonstrated that, to achieve group size convergence and fair robot spreading, it is sufficient to let the leaving probability decay gradually from a high value to a low value.

We assessed the performance of our system in a large, challenging scenario in which hundreds of robots must be aggregated into dozens of groups. Our results suggest that, due to its parallelism, the convergence time of the system is basically independent of the size of the scenario. Regarding spreading, the system is able to distribute the robots evenly among the shelters. In presence of perturbations, such as activation/deactivation of a shelter, spreading is fair if the time between two of these events is longer than the decay period of the leaving probabilities.

We are currently studying methods to modify our system to enhance spreading with a high frequency of perturbations. A possible way to improve our system is to keep the propagation of the perturbations local, and

prevent the robots that are temporarily freed from leaking to the non-perturbed region.

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