



# A Bio-inspired Approach for Collaborative Exploration with Mobile Battery Recharging in Swarm Robotics

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**Abstract.** Swarm Robotics are widely conceived as the development of new computationally efficient tools and techniques aimed at easing and enhancing the coordination of multiple robots towards collaboratively accomplishing a certain mission or task. Among the different criteria under which the performance of Swarm Robotics can be gauged, energy efficiency and battery lifetime have played a major role in the literature. However, technological advances favoring power transfer among robots have unleashed new paradigms related to the optimization of the battery consumption considering it as a resource shared by the entire swarm. This work focuses on this context by elaborating on a routing problem for collaborative exploration in Swarm Robotics, where a subset of robots is equipped with battery recharging functionalities. Formulated as a bi-objective optimization problem, the quality of routes is measured in terms of the Pareto trade-off between the predicted area explored by robots and the risk of battery outage in the swarm. To efficiently balance these conflicting two objectives, a bio-inspired evolutionary solver is adopted and put to practice over a realistic experimental setup implemented in the VREP simulation framework. Obtained results elucidate the practicability of the proposed scheme, and suggest future research leveraging power transfer capabilities over the swarm.

**Keywords:** Swarm robotics · Battery recharging · Routing · NSGAI

## 1 Introduction

Robotics have evolved dramatically over the years to feature unprecedented levels of intelligence, resulting in an ever-growing number of scenarios benefiting from their widespread application to accomplish complex missions, e.g. structural

health monitoring, oil and gas industry, manufacturing, disaster management, precision agriculture and logistics, among many others. Providing robots with smart sensing, communication and organization functionalities allows them to capture information, operate, reason and infer knowledge from the environment in a collaborative manner. Research aimed at enhancing such functionalities by embracing elements from Artificial Intelligence and Distributed Computing has coined the so-called Swarm Robotics concept, which refers to the deployment of a set of robots that collaborate with each other so as to collectively perform a mission in a computationally efficient fashion [1,2].

In general, Swarm Robotics may rely on several key technologies to attain higher levels of autonomy, optimized operation and self-organization. Unfortunately, it is often the limited battery lifetime of robots not only what restricts most the autonomy of the swarm, but also what puts at risk the feasibility of complex missions where robots operate without any human intervention, as in e.g. the exploration of collapsed infrastructures after a massive disaster [3] or the structural assessment of undersea drilling equipment [4]. Despite notable advances in energy efficient robot mechanics, the battery capacity poses severe operational constraints to Swarm Robotics, to the point of jeopardizing their potential use in complex endeavors.

To overcome this issue, many research efforts have been devoted towards augmenting the power capacity of robot batteries, either by proposing new materials and chemical components or by deriving new mechanical improvements that extend further their lifetime by virtue of a lower power consumption [5]. For this same purpose, the community has also focused its attention towards the consideration of the aggregate battery power of the entire robotic swarm as a whole, an unique resource whose management is to be optimized globally over all robots rather than locally. This approach grounds on advances in wireless/mobile robotic charging [6] and the deployment of mobile charging stations in the swarm [7], which can be exploited as a resource to actively locate and replenish the battery of other robots. This research topic has been very active in this regard, as evinced by the short literature review provided in what follows.

## 1.1 Related Work

A remarkable amount of interesting studies has been published in the last decade focused in power charging and battery consumption of swarm robots. Haek et al. discussed in [8] the importance of swarm robustness, defining this concept as the ability of the robotic swarm to perform a complex task avoiding the total drainage of their batteries. In this work authors present a solution to allow robots to robustly achieve their assigned tasks, which mainly consists of the use of power stations or power banks. In [9], a collective energy distribution system is proposed for a dust cleaning swarm of robots. Authors of this study explore the concept of *trophallaxis*, previously introduced in [10], which refers to individual robots donating an amount of their own energy reserve to other robots of the swarm. This same concept of altruistic behavior is explored in [11], materializing the idea in a specific robot architecture called CISSBot. Apart from

battery charging, sharing and consumption, several additional features are also considered and studied in this contribution, such as a collision-free proximity motion control. Additional research on this topic can be found in [12].

Another interesting approach to energy consumption is the one recently proposed in [13], where an Energy-Aware Particle Swarm Optimization (EAPSO) bioinspired solver is designed to optimize the movement strategy of aerial micro-robots. Interestingly, the optimization process considers the energy levels of the robots for their efficient movement. Although authors do not propose any charging mechanism, the designed method renders a considerable reduction of the total energy consumption, making the robotic swarm more reliable and robust. Another bioinspired scheme sensitive to the consumed energy is the Honey Bee inspired swarm in [14], which improves the energy efficiency and is proven to be effective for foraging environments, such as the collection of crops of materials.

Also interesting to mention is the preliminary research presented by [15], in which an immune system response is studied for the development of energy sharing strategies. In that case, the granuloma formation is explored, which is a process in which undesired components are removed by immune systems. This behavioral concept is mapped to the components of a Swarm Robotics system, enhancing the fault tolerance of the deployed robots. A further step was taken in [16], where another immune system mechanism is proposed based on the use of contact-less energy charging areas and their simulation-based comparison to other energy charging mechanisms. A similar technique was proposed in [17] to add self-healing capabilities to robotic swarms.

As stated in [18], an usual trend in the literature for dynamic energy charging of robots is based on the deployment of power banks or removable chargers. Despite being quite effective, this approach has its own disadvantages, such as the resulting weight increase of the robot equipment, often crucial in critical missions. With the intention of overcoming these issues, [18] describes initial research on the implementation of an energy-sharing scheme using a two-way communication mechanism. Finally, in [19] an energy-encrypted contact-less system is described for improving the charging performance and the energy transmission mechanism of swarm robots. To this end wireless power transfer is used, enabling robots to charge their batteries even in moving situations. Other contributions related to dynamic energy charging include [20], which elaborates on a novel tree-based schedule for mobile charger robots, which minimizes the travel distance without causing energy depletion; and [21], which presents a versatile mobile charging station capable of actively locating and replenishing the battery of inactive robots.




## 1.2 Contribution

Even though the literature has been profitable in what regards to Swarm Robotics with mobile battery recharging nodes, to the best of the authors' knowledge routing for exploration missions in Swarm Robotics has so far been addressed without considering such nodes as assets whose routes over the scenario at hand can be jointly optimized with those of exploring robots.


Furthermore, when dealing with overly complex scenarios to be explored, the total area sensed by exploring robots can be intuitively thought of as a conflicting objective with the remaining battery margin; in this sense, enforcing the swarm to explore the entire area spanned by the scenario could create a risk of any robot to run out of battery on site, and be left dead and unrecoverable. This work aims at addressing this research niche by modeling and solving a bi-objective routing problem for mobile swarm robotics considering the minimization of this risk as a second fitness metric that quantifies the quality of a generated route plan. The problem formulation also includes the search for optimal routing plans for mobile battery recharging nodes along with the routes of exploring robots. Both are solved efficiently by means of a bi-objective bio-inspired solver driven by the aforementioned objectives. Results obtained from a realistic simulation framework implemented in VREP [22] are shown to be promising, with several future research lines stemming therefrom.

The rest of this paper is structured as follows: first, Sect. 2 formulates mathematically the optimization problem under study, including the conflicting objectives to be maximized. Next, Sect. 3 delves into the utilized bi-objective solver, followed by Sects. 4 and 5 detailing the simulation setup and discussing the obtained results, respectively. Section 6 concludes the paper.

## 2 Problem Statement

Following the schematic diagram depicted in Fig. 1, we assume a swarm  $\mathcal{N}$  of  $|\mathcal{N}| = N$  robots, with time-dependent positions  $\{\mathbf{p}_n^{\Delta,t}\}_{n=1}^N \doteq \{(x_n^{\Delta,t}, y_n^{\Delta,t})\}_{n=1}^N$  (with  $t$  denoting time) over a square area  $S^\square \doteq [X_{min}, X_{max}] \times [Y_{min}, Y_{max}]$ . Each of such robots is equipped with sensors that allow them to explore an area  $\{S_n^{\Delta,t}\}_{n=1}^N$  around its location at time  $t$ , e.g. if the area is circular with radius  $R_n^\Delta$ , then  $S_n = \{(x, y) \in S^\square : (x - x_n^{\Delta,t})^2 + (y - y_n^{\Delta,t})^2 \leq R_n^2\}$  (areas shaded in ,  and  in Fig. 1). The total area  $S^T(t)$  explored by the robotic swarm at time  $t'$  will be then given by

$$S^T(t') = \bigcup_{t=1}^{t'} \bigcup_{n=1}^N S_n^{\Delta,t}. \quad (1)$$

Another set of  $M \leq N$  robots  $\mathcal{M}$  with battery recharging capabilities is deployed in the same location jointly with  $\mathcal{N}$ , with coordinates  $\{\mathbf{p}_m^{\circ,t}\}_{m=1}^M \doteq \{(x_m^{\circ,t}, y_m^{\circ,t})\}_{m=1}^M$ . A robot  $m \in \mathcal{M}$  will recharge the battery of a robot  $n \in \mathcal{N}$  whenever (1) their distance  $d_{m,n}^t$  falls below a certain threshold  $D_{max}$  (area in , i.e.

$$d_{m,n} = \sqrt{(x_m^{\circ,t} - x_n^{\Delta,t})^2 + (y_m^{\circ,t} - y_n^{\Delta,t})^2} \leq D_{max}, \quad (2)$$

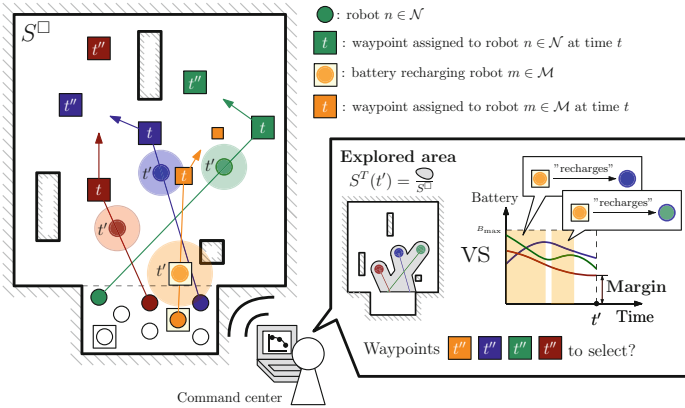
and (2) the above condition holds for a minimum of  $T_{min}$  seconds, comprising the power plug coupling/uncoupling along with physical maneuvers to align connectors. If both conditions hold, energy is transferred from robot  $m \in \mathcal{M}$

to  $n \in \mathcal{N}$  at a rate of  $\beta$  units of energy per second (measured in e.g. Watts). Furthermore, the movement of the robot itself involves a battery consumption of  $\gamma$  units of power per unit of distance, so that in a certain time gap  $\Delta T$  measured from time  $t$  the remaining amount of battery  $B_n^{\Delta, t+\Delta T}$  in robot  $n$  can be mathematically expressed as

$$B_n^{\Delta, t+\Delta T} = \min \{ [1 + I_D \cdot I_T \cdot \beta] \cdot B_n^{\Delta, t} - \gamma V_n^{\Delta} \Delta T, B_{max} \}, \quad (3)$$

where  $V_n^{\Delta}$  denotes the cruise speed of the robot (in units of distance per unit of time), and  $I_D$  and  $I_T$  are binary indicator functions such that  $I_D = 1$  if  $d_{m,n}^{t'} \leq D_{max} \forall t' \in [t, t + \Delta T]$ , and  $I_T = 1$  if  $\Delta T \geq T_{min}$  (0 otherwise in both cases). In the above expression  $B_{max}$  stands for the nominal maximum battery load (in units of power) of the robot model, which without loss of generality is assumed to be equal throughout the entire robotic swarm.

With this definition in mind, the goal of the routing optimization problem is essentially the determination of an optimal set of routes composed by  $N + M$  waypoints  $\mathbf{W}^{\Delta, t, \heartsuit} \doteq \{\mathbf{w}_n^{\Delta, t, \heartsuit}\}_{n=1}^N = \{(x_n^{\Delta, t, \heartsuit}, y_n^{\Delta, t, \heartsuit})\}_{n=1}^N$  and  $\mathbf{W}^{\odot, t, \heartsuit} \doteq \{\mathbf{w}_m^{\odot, t, \heartsuit}\}_{m=1}^M = \{(x_m^{\odot, t, \heartsuit}, y_m^{\odot, t, \heartsuit})\}_{m=1}^M$  for all robots in the swarm (both explorers and battery chargers). Here optimality of the set of discovered routes refers to the Pareto relationship between the explored area and a quantitative measure of the *risk of no return* taken when the entire swarm is commanded to follow a certain route. Intuitively, the more area the swarm explores, the more likely is the chance that any of the robots in the swarm lacks enough battery to return to the point  $\{(x^{\Delta, 0}, y^{\Delta, 0})\}$  where robots had been initially located. This risk is crucial in many practical situation, e.g. disaster events where the topological characteristics of the facility to be explored remain unknown to the command center before and while the mission is performed by the robotic swarm.



**Fig. 1.** Schematic diagram of the scenario tackled in this paper. (Color figure online)

Mathematically this risk can be modeled by accounting, over the whole robotic swarm, for battery margin  $B_n^{\Delta, t}$  expected to be left for every robot should

it proceed and move to the assigned waypoint and return safely to  $\{(x^{\Delta,0}, y^{\Delta,0})\}$ . Assuming that the route optimization is performed at time  $t$ , the value of the battery margin  $B_n^{\Delta,t}$  for robot  $n \in \mathcal{N}$  when commanded to go to waypoint  $\mathbf{w}_n^{\Delta,t,\varrho} = (x_n^{\Delta,t,\varrho}, y_n^{\Delta,t,\varrho})$  can be estimated as

$$B_n^{\Delta,t}(\mathbf{p}_n^{\Delta,t}, \mathbf{w}_n^{\Delta,t,\varrho}, \{\mathbf{p}_m^{\Delta,t}\}_{m=1}^M, \{\mathbf{w}_m^{\Delta,t}\}_{m=1}^M) = B_n^{\Delta,t} - B_n^{\Delta,t+\Delta T_{\mathbf{p},\mathbf{w}} + \Delta T_{\mathbf{w},\mathbf{p}_0}}, \quad (4)$$

where  $\Delta T_{\mathbf{p},\mathbf{w}}$  and  $\Delta T_{\mathbf{w},\mathbf{p}_0}$  are the times taken for robot  $n \in \mathcal{N}$  to travel from its current point  $\mathbf{p}_n^{\Delta,t}$  to the assigned waypoint  $\mathbf{w}_n^{\Delta,t,\varrho}$  and therefrom to its initial position  $\{(x^{\Delta,0}, y^{\Delta,0})\}$ . This estimation is made by assuming that the robot goes straight without colliding with any object nor any other robot along its path. It should be remarked that as per (3), the battery expenditure reflected in  $B_n^{\Delta,t+\Delta T_{\mathbf{p},\mathbf{w}} + \Delta T_{\mathbf{w},\mathbf{p}_0}}$  takes into account not only the power consumed by the robot dynamics (which depends on its speed  $V_n$  and the traversed distances), but also time periods along the path during which the relative position between battery recharging robots and robot  $n \in \mathcal{N}$  fulfill conditions  $I_D$  and  $I_T$  required to recharge the battery of robot  $n$  on the move. The total duration of such recharging periods can be computed as  $\sum_{(t_s, t_e) \in \mathcal{T}_n^{\Delta,t}} (t_e - t_s)$  over the set of periods  $\mathcal{T}_n^{\Delta,t}$ , defined as

$$\begin{aligned} \mathcal{T}_n^{\Delta,t} &\doteq \{(t_s, t_e) \in [t, t + \Delta T_{\mathbf{p},\mathbf{w}} + \Delta T_{\mathbf{w},\mathbf{p}_0}]\} \text{ such that :} \\ (1) \quad &t_e > t_s; \quad (2) \quad \exists m \in \mathcal{M} : d_{mn}' \leq D_{max} \forall t' \in [t_s, t_e]; \quad \text{and} \quad (3) \quad t_e - t_s \geq T_{min}, \end{aligned} \quad (5)$$

with  $[t'_s, t'_e] \cap [t''_s, t''_e] = \emptyset \quad \forall (t'_s, t'_e), (t''_s, t''_e) \in \mathcal{T}_n^{\Delta,t}$ . Therefore, the swarm-wide battery margin  $B^T(t)$  to be maximized at time  $t$  so as to keep the aforementioned risk to its minimum is given by

$$B^T(t) = \min_{n \in \mathcal{N}} \left\{ \max \left\{ 0, B_n^{\Delta,t}(\mathbf{p}_n^{\Delta,t}, \mathbf{w}_n^{\Delta,t,\varrho}, \{\mathbf{p}_m^{\Delta,t}\}_{m=1}^M, \{\mathbf{w}_m^{\Delta,t}\}_{m=1}^M) \right\} \right\}, \quad (6)$$

from where the formal statement of the problem tackled in this work follows:

$$\mathbf{W}^{\circ,t,\varrho}, \mathbf{W}^{\Delta,t,\varrho} \left\{ S^T(t), B^T(t) \right\}, \quad (7a)$$

namely, as the simultaneous maximization of two conflicting objectives: the surface explored by the robotic swarm and the minimum expected battery margin over the robots should it be commanded to return to the initial deployment point after reaching the enforced waypoint.  $\mathbf{W}^{\Delta,t,\varrho} \in S^{\square}$  and  $\mathbf{W}^{\circ,t,\varrho} \in S^{\square}$ .

### 3 Proposed Solver

In order to efficiently tackle the above problem, we propose to apply a centralized meta-heuristic solver capable of optimally balancing the two objective functions considered in its formulation. The optimizer relies on the renowned

Non-dominated Sorting Genetic Algorithm (NSGA-II, [23]), a bio-inspired approach that hinges on the concepts of non-dominance ranking and crowding distance to guide a multi-objective search over a set of potential candidate solutions (in this case, waypoints defining routes). In essence NSGA-II sorts a population of candidates according to (1) whether each solution within the population *dominates*, in terms of Pareto optimality, other solutions in the pool (yielding the so-called dominance rank of the Pareto front to which the solution at hand belongs); and (2) the closest distance from every individual to the rest of solutions (corr. crowding distance). By applying this dual selection procedure along with genetically inspired crossover and mutation operators (with probabilities  $P_c$

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**Algorithm 1.** NSGA-II solver applied to the problem under study.

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**Data:** Number of exploration robots  $N$ ; number of battery recharging robots  $M$ ; dimensions of the scenario  $X_{min}, X_{max}, Y_{min}, Y_{max}$ ; sensing radii  $\{R_n\}_{n=1}^N$ ; maximum distance  $D_{max}$  and minimum time  $T_{min}$  for battery recharge; nominal robot speeds  $\{V_n^\Delta\}_{n=1}^N$  and  $\{V_m^\ominus\}_{m=1}^M$ ; maximum battery capacity  $B_{max}$ ; battery charging rate  $\beta$ ; battery consumption rate  $\gamma$ ; crossover and mutation probabilities  $P_c$  and  $P_m$ ; population size  $P$ ; maximum number of iterations  $\mathbb{I}$ ; proportion of the minimum battery margin to the maximum battery capacity  $\lambda$ .

- 1 Deploy all robots on the initial location  $(x^{\Delta,0}, y^{\Delta,0})$ , and set waypoints  $\mathbf{w}_n^{\Delta,t_{ini},\heartsuit}$  and  $\mathbf{w}_m^{\ominus,t_{ini},\heartsuit}$  equal to  $(x^{\Delta,0}, y^{\Delta,0}) \forall n \in \mathcal{N}$  and  $\forall m \in \mathcal{M}$
- 2 Set  $t' = t_{ini}$  and  $\mathcal{T} = \{t_{ini}\}$
- 3 **while**  $B^T(t) \geq \lambda B_{max}$  **do**
- 4     **while**  $\mathbf{p}_n^{\Delta,t} \neq \mathbf{w}_n^{\Delta,t',\heartsuit}$  and  $\mathbf{p}_m^{\ominus,t} \neq \mathbf{w}_m^{\ominus,t',\heartsuit} \forall n, m$  **do**
- 5         Let robots move to their assigned waypoints  $\mathbf{w}_n^{\Delta,t_{ini},\heartsuit}$  and  $\mathbf{w}_m^{\ominus,t_{ini},\heartsuit}$
- 6         Update remaining battery  $\{B_n^{\Delta,t}\}_{n=1}^N$  as per (4) and (5)
- 7     **if**  $t' = t_{ini}$  **then**
- 8         Initialize  $P$  individuals in the population uniformly at random from  $\mathcal{S}^\square$
- 9     **else**
- 10         Retrieve the estimated Pareto from the previous run, introduce it in the population. and fill the remaining individuals randomly over  $\mathcal{S}^\square$
- 11     **for**  $it \leftarrow 1$  **to**  $\mathbb{I}$  **do**
- 12         Select parents, recombine them (w.p.  $P_c$ ) and mutate (w.p.  $P_m$ ) the produced new offspring that represent a new set of  $P$  waypoints
- 13         Evaluate explored area and battery margin of offspring as per (1), (6)
- 14         Sort previous and new waypoints by rank and crowding distance
- 15         Discard the worst  $P$  individuals in the sorted, concatenated population
- 16     The estimated Pareto is given by the  $P$  individuals remaining in population
- 17     Select the set of waypoints in the estimated front that best suits the commanding policy (e.g. maintain a battery margin above 10%), and assign them to robots
- 18     Set  $t' = t$ , and  $\mathcal{T} = \mathcal{T} + \{t\}$
- 19 All robots to initial position by  $\mathbf{w}_n^{\Delta,t_{ini},\heartsuit} = \mathbf{w}_m^{\ominus,t_{ini},\heartsuit} = (x^{\Delta,0}, y^{\Delta,0}) \forall n, m$

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and  $P_m$ , respectively), the Pareto optimality of solutions contained in the population becomes improved iteration after iteration, to eventually yield a Pareto front estimation after a number of iterations of this search procedure.

An algorithmic description of the NSGA-II approach designed in this work is provided in Algorithm 1. Individuals are encoded directly as  $N + M$  vectors  $\mathbf{w}_i^p$  denoting the waypoints of all robots in the scenario, where  $i \in \{1, \dots, N, N + 1, \dots, N + M\}$ ,  $p \in \{1, \dots, P\}$ ,  $P$  denoting the population size and  $\mathbf{w}_i^p \in \mathcal{S}^\square \forall i, p$ . A uniform crossover operator and a Gaussian mutation with standard deviation  $\sigma$  have been selected as heuristic operators. The iterative application of these operators and the NSGA-II selection scheme outlined above is stopped after  $\mathbb{I}$  iterations. It is important to remark at this point that the solver must be run incrementally at certain time instants, e.g. the solver is not run constantly along time but rather triggered at time ticks embedded in the set  $\mathcal{T} \in \mathbb{R}[t_{ini}, t_{end}]$ , where  $t_{ini}$  is the time at which the robotic swarm is first deployed and  $t_{end}$  is the time at which the battery margin  $B^T(t_{end})$  in the estimated Pareto front falls below a fraction  $\lambda$  of the maximum battery capacity  $B_{max}$ . For the sake of simplicity, the NSGA-II solver will be executed once all robots have reached their commanded waypoints  $\mathbf{W}^{\Delta, t, \eta}$  and  $\mathbf{W}^{\odot, t, \eta}$  optimized previously, which yields the time instants contained in  $\mathcal{T}$ . To match this incremental nature of the proposed optimization schedule, the population of individuals is accordingly initialized by including the best front found in the previous NSGA-II execution, randomly setting the remaining individuals until filling the population.

## 4 Simulation Setup

In order to assess the performance of the proposed bi-objective routing approach, a simulation setup has been constructed by resorting to VREP, a renowned software platform that permits to realistically model and perform experimental studies with swarms of robots. In order to extract valuable insights, we have kept the dimensions of the experimental scenario reduced to  $N = 5$  exploring robots and a single battery recharging node ( $M = 1$ ) deployed on a  $10 \times 10$  m<sup>2</sup> square area. The maximum distance and minimum time to recharge batteries are set to  $D_{max} = 1$  m and  $T_{min} = 3$  s, respectively. Robots with six mechanical legs (also referred to as *hexapods*) and diameter size equal to 0.5 m are utilized, with speeds equal to  $V_n^\Delta = 3.5$  cm/s  $\forall n \in \mathcal{N}$  and  $V_m^\odot = 2.6$  cm/s. Battery recharging is done at a rate of 1% per second with respect to the nominal maximum capacity  $B_{max}$  of exploring robots, whereas the recharging node is equipped with a total battery capacity equal to  $10 \cdot B_{max}$ . The battery depletion rate is fixed to  $\gamma = 1.5\%$  of  $B_{max}$  per linear meter. As for the parameters of the NSGA-II solver, crossover and mutation rates are set to  $P_c = 1$  and  $P_m = 0.1$ , with a population size of  $P = 20$  individuals and  $\mathbb{I} = 100$  iterations per run. The decision making criterion adopted to select a route among the estimated Pareto fronts was based on selecting the route whose associated battery margin is closest to 20% of  $B_{max}$ . If no route with margin greater than this threshold, the robot swarm is enforced to return to the origin position. Figure 2 illustrates, from two different



perspectives, the scenario generated in VREP and simulated to yield the results discussed in the next section<sup>1</sup>.

## 5 Results and Discussion

The discussion on the results obtained by the proposed scheme starts with Fig. 3, which illustrates the set of estimated Pareto fronts along time under different assumptions. Specifically, every plot in this figure contains a three-dimensional cloud of points – each representing a given route plan (set of waypoints) – which results from the aggregation of all fronts estimated in simulation time for a single experiment. A total of 10 executions of the NSGA-II solver have sufficed for illustrating the main benefit of our proposed routing scheme: by incorporating battery recharging functionalities, the autonomy of the entire robotic swarm is enhanced, so that a larger area can be explored for a given decision making criterion imposed on the minimum admissible battery margin for the robots to return back and safe to the base.

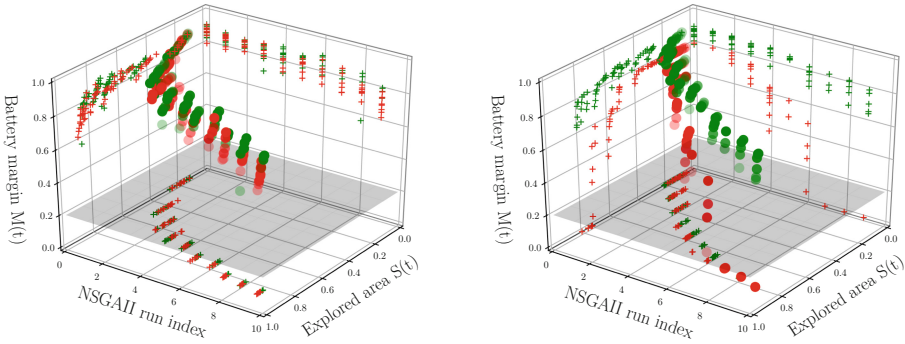


**Fig. 2.** Visual representation of the simulated setup yielding the results later discussed in the manuscript; (left) isometric view; (right) top-down view. The robot dynamics are provided by the VREP framework, whereas the NSGA-II routing approach has been implemented in Python and communicates with VREP via remote API functions.

To this end two different cases are assessed, depending on the exploration radii assumed for the sensing robots: (1)  $R_n = 0.9$  m, which should a priori render minimum gains due to a more efficient area exploration; and (2)  $R_n = 0.5$  m, smaller sensing radii for which the incorporation of battery recharging functionalities in the swarm should provide higher gains. Indeed, this intuition is confirmed by the results in the plots: as evinced by the plot on the left (higher exploration radii), almost no exploration gain is obtained by including battery recharging

<sup>1</sup> Videos showing how robots move over this scenario can be found at: <https://youtu.be/r31teMtWRF0> and <https://youtu.be/zewRVZQpvP8>.

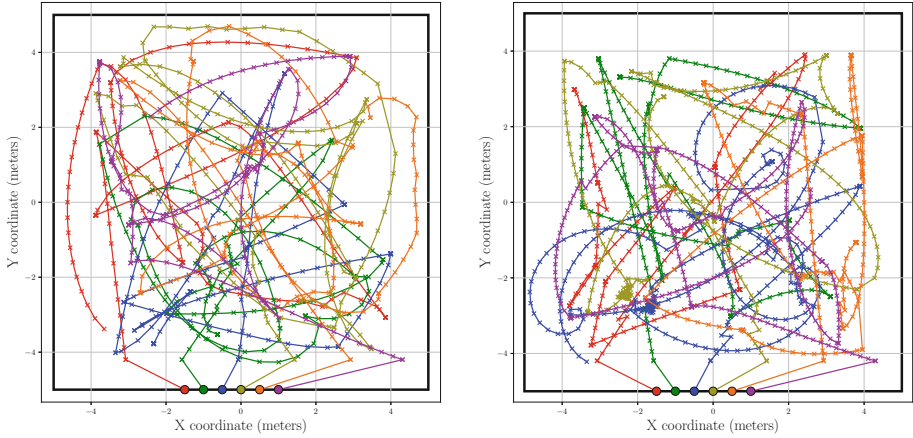
functionalities (■) when compared to a unassisted robot swarm (■). However, when reducing the sensing radius, robots must traverse longer distances in order to explore the entire scenario, which leads to higher battery consumption levels that could be compensated efficiently by including a battery recharging node. This is precisely what the plot on the right in Fig. 3 reveals: when inspecting the evolution of the maximum battery margin in the fronts computed along time, it is straightforward to note that the margin of the unassisted swarm (■) decreases much faster than that of its assisted counterpart (■), falling below the minimum admissible threshold (20%) imposed by the mission commander. As a result, the entire swarm is commanded to return to the base once 61% of the scenario has been explored. By including the mobile recharging node, the battery margin degrades smoothly along time, and is maintained above the threshold to explore a higher area percentage (ca. 80%) even for more conservative policies. For instance, should it have been set to 60% the unassisted swarm would have explored less than 50% of the area; in the assisted case robots would have been operative for a longer time, attaining explored area ratios close to 80%.



**Fig. 3.** Three-dimensional plot showing the Pareto trade-off between battery margin and explored area estimated by the NSGA-II solver as the simulation evolves (represented by the NSGA-II run index). The left plot corresponds to the case when  $R_n = 0.9\text{m}$ , whereas the right plot depicts the case when  $R_n = 0.5\text{m}$ , in both cases  $\forall n \in \{1, \dots, 5\}$ . Also are included in the plots the two-dimensional projections of the point cloud along every axis, so that the progression of the maximum achievable value of each metric. The plane shaded in gray indicates the minimum admissible battery margin imposed by the mission commander (20%). (Color figure online)

Besides the evidence provided by the above plots, further insights can be extracted by taking a closer look at the trajectories traced by the robots in the swarm for both cases. One should expect that for high values of the sensing radii  $R_n$ , nodes should feature relatively less dynamic mobility patterns over the scenario than those corresponding to lower values of this parameter. The plots in Fig. 4 go in line with this expected behavior. In particular mobility traces of the robotic swarm are shown for the assisted robotic swarm with  $R_n = 0.5\text{m}$

(left) and  $R_n = 0.9\text{m}$  (right). It can be noted that the former case features rectilinear trajectories composed by long segments, whereas in the latter all robots in the swarm describe topologically tangled traces, and few cases reach the boundaries of the scenario. In summary, the sensing radii plays a crucial role in the behavior of the swarm and ultimately, in the attainable performance gain from the introduction of mobile recharging nodes in the swarm.



**Fig. 4.** Trajectories followed by the robots in the swarm for  $R_n = 0.5\text{ m}$  (left) and  $R_n = 0.9\text{ m}$  (right). A visual inspection permits to infer that lower values of the sensing radius make all trajectories be shorter and more complex as a result of a lower overlapping between the sensing areas of robots in the swarm. On the contrary, when the sensing radius increases robots describe cleaner, rectilinear trajectories.

## 6 Concluding Remarks

In this paper, a routing problem for collaborative exploration in Swarm Robotics has been presented. An analysis of the recent literature supports that one of the main issues in these systems is the energy consumption and reliability of the swarm, which jeopardizes the performance of complex missions and tasks. This identified issue is what lies behind the rationale for this research work: to include a subset of robots in the swarm endowed with battery charging capabilities. The challenge resides in how to properly route the robots in the scenario considering the existence of such nomadic battery recharging nodes, which has been formulated as a bi-objective optimization problem where a Pareto equilibrium must be met between the explored area and the risk of battery outage. In order to solve efficiently this problem, a bio-inspired approach has been designed based on the well-known NSGA-II solver. A realistic experimental setup comprising the VREP robotic simulation framework has been constructed so as to shed light on how the proposed solver performs in practice. The obtained results have proven empirically the practicality and inherent utility of the proposed routing scheme,

which provides the commander of the mission with more valuable information for decision making than traditional schemes based on a single fitness function.

Several lines of research related to this work have been planned for the near future, e.g. the inclusion of other bioinspired multi-objective heuristic engines (e.g. SMP SO, MOEA/D) and their comparison to each other in terms of multi-objective indicators. Another research path that will be prospected will gravitate on relaxing and extending the assumptions and constraints defining the considered scenario towards, for instance, co-located exploration tasks (demanding different sensing equipment). Among them, the most challenging research direction to be followed focuses on distributing the intelligence among the robots in order to realize a *true* robotic swarm, namely, a swarm of robots that communicate to each other and exchange information, deciding on an optimal set of waypoints without requiring a centralized command center as the one assumed in this work.

**Acknowledgments.** E. Osaba and J. Del Ser would like to thank the Basque Government for its funding support through the EMAITEK program. Likewise, the involvement of A. Galvez and A. Iglesias in this work has been funded by the *Agencia Estatal de Investigación* (grant no. TIN2017-89275-R), the European Union through FEDER Funds (AEI/FEDER), and the project #JU12, jointly supported by the public body SODERCAN and European Funds FEDER (SODERCAN/FEDER).

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