Energy Replenishment Strategies for Robot Swarms

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***Abstract*— The utility of swarms of robots would greatly increase if they could operate over extended periods of time. Here, we consider two strategies for swarms of robots to replenish their energy while performing work in a remote location. In the first, each robot commutes to work and replenishes at its base. In the second, some robots perform work, whereas others commute to provide them with energy. We present results from extensive physics-based simulations. The first strategy performs 92.8% of the work at only 12.6% lower energy efficiency than an optimal strategy. The second strategy is beneficial for low charging rates or if the robots providing energy are permitted increased amounts of storage. We provide proof-of-concept validation using the CapBot swarm robot platform.**

I. INTRODUCTION

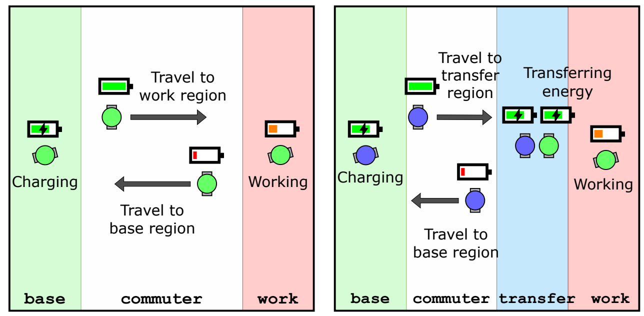
Robot swarms are required to operate autonomously over long periods, in applications such as environmental monitoring, surveillance, agriculture, construction, and mining [1], [2], [3]. Energy management is crucial, requiring careful attention to both energy replenishment (in-flow) and energy usage (out-flow). Robots must balance their energy between performing tasks and securing additional energy.

Several studies consider swarms where each robot alternates between performing work and visiting charging points to replenish its energy storage [4], [5], [6], [7], [8]. Others consider robots capable of swapping their batteries against fully charged ones [9], sharing energy with one another [10], [11], [12], [13], or charging stations that move [14].

This paper compares two strategies for replenishing the energy required by a swarm of robots working remotely over extended periods. It presents a series of physics-based simulations to identify conditions (e.g. the charging rate) in which either strategy becomes favorable, as well as a basic proof-of-concept validation using a CapBot robot [15].

II. METHODS

Consider the 2D environment illustrated in Fig. 1. It consists of three areas: *(i)* a *base* area (green), *(ii)* a *commuter* area (white), and *(iii)* a *work* area (red). The environment is populated by n_w robots (green circles), referred to as *workers*. Each robot has a maximum capacity to store energy, $c_{w,max}$, and consumes different amounts of energy depending on whether it is idle, moving, or performing work. While residing within the base area, a worker can accumulate (gross) energy at a specific rate. To reach the work area from the base area, the worker has to travel through the commuter area and vice versa.



(a) (b)

Fig. 1. Energy replenishing strategies. (a) The workers (green disks) travel from their work area (red area) to replenish their energy at the base (green area). (b) Mobile chargers (blue disks) transport energy from the base and supply it to the workers in the transfer area (blue area).

We consider a mission over a finite duration. Initially, each worker's energy storage is assumed to be at full capacity. The workers' objective is to perform as many units of work as possible without any worker depleting their energy storage while outside the base area.

For one of the strategies considered, we have a fourth area (blue) called *transfer* area, which sits in-between the commuter and work areas. This area is used by *mobile chargers*, which supply energy to workers but are unable to perform any work.

We consider two energy replenishing strategies.[1]

- **Fixed charging stations** strategy (see Fig. 1a): A worker travels from the base to the work area to perform work. Once its energy drops below a certain threshold, it travels back to the base area to recharge, and so on.
- **Mobile charging stations** strategy (see Fig. 1b): The workers perform work at the work area, while the mobile chargers recharge in the base area. Each mobile charger travels to the transfer area where it can recharge

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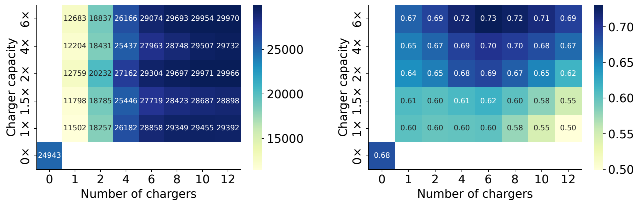
[1] The source code can be found at https://github.com/openswarm-eu/swarm-energy-replenishment



(a) (b)

Fig. 2. The effect of the number of mobile chargers and their storage capacity on (a) the amount of work performed and (b) the proportion of energy used to perform work. The results of the static charger strategy are shown in 0 chargers and 0× charger capacity cells.

any worker whose energy drops below a certain threshold.

III. RESULTS

We conduct simulation trials with $n_w = 6$ workers.[2] For the strategy involving mobile chargers, we vary the number of mobile chargers n_m, and the size of the storage capacity $c_{m,max}$, to examine their effect on the aforementioned metrics. For details, see [16].

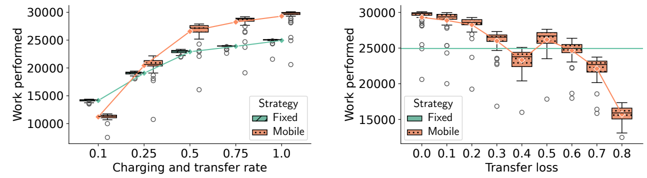
Fig. 2a shows that 24943 units of work are performed if the workers charge at the base. This is 92.8% of the theoretical upper bound reported in [16], suggesting that the workers perform close to optimal in embodied simulations. When workers obtain their energy from mobile chargers, the amount of work performed increases with the number of mobile chargers n_m, and plateaus after around $n_m = n_w$. Performing substantially more work would require additional workers.

Fig. 2b shows the energy efficiency: the portion of total energy consumed that was devoted to performing work. Workers that charge at the base achieve an energy efficiency of 68.2%. This is only 12.6% less efficient than the upper bound [16]. For workers obtaining energy from mobile chargers, the highest energy efficiency is consistently observed when $n_m = n_w$. This suggests that using fewer or additional mobile chargers would result in them or the workers wasting energy due to the time they spend waiting for each other. Moreover, deploying many mobile chargers with small capacity proves inefficient. Nevertheless, mobile chargers are able to help perform more work and even improve energy efficiency when their storage capacity is larger than that of workers.

In Fig. 3a, we explore the effect of the rate at which the agents charge and transfer energy, on the amount of work performed. For the mobile charger strategy, we use $n_m = 6$ and $c_{m,max} = 2c_{w,max}$. For both strategies, the amount of work performed decreases as the charging and transfer rate decreases. This is because robots need to spend a longer time to charge, reducing the time available for working.

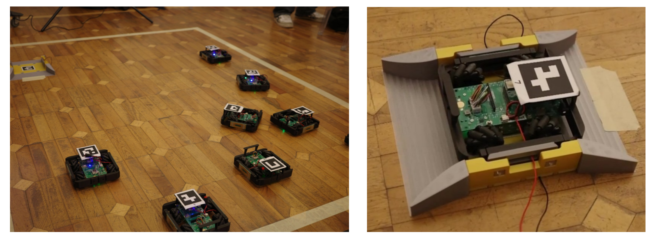
Fig. 3b examines the effect of energy transfer loss on the amount of work performed. We consider $n_m = 6$ and $c_{m,max} = 2c_{w,max}$. Results are non-monotonic: the work performed first decreases as the transfer loss increases up to 40%, then increases at 50%, and finally decreases again from 60%. Close inspection reveals that this is caused by the particular timings of the chargers and workers' activities. At a transfer loss of 50%, the mobile chargers can only transfer available energy to a single worker, and then have to return to the base. At a transfer loss of 40%, they attempt to transfer energy to a second worker but have to abort the process prematurely to return to the base. For full details of the results, refer to [16].

[2] Video recordings of the simulation can be found at `https://doi.org/10.15131/shef.data.25561923`



(a) (b)

Fig. 3. Comparison of the two strategies: (a) across different charging and transfer rates, (b) for different levels of transfer losses.



(a) (b)

Fig. 4. Proof-of-concept validation. (a) A swarm of CapBots [15] and charging base. (b) A CapBot arriving at the base.

We conduct a proof-of-concept validation using CapBot [15] – an education swarm robotics platform developed at KU Leuven. Each CapBot features a pair of super-capacitors. It charges in about 16 s, thereby realizing duty cycles around 99% [15]. Fig. 4a shows the experimental setup: a group of CapBots and a drive-through charging station. The real-time positions of these entities are tracked using a camera-based system and ArUco-markers. Using this information, a CapBot is programmed to autonomously move through the charging station, effectively topping up its energy storage (see Fig. 4b).

IV. DISCUSSION

Results show that mobile chargers are beneficial when there is a sufficient – though not excessive – number of them, and when they have a large energy capacity. Moreover, mobile chargers are beneficial when more energy is required while performing work than while navigating. However, slow recharging rates and energy transfer losses negatively affect the amount of work performed and energy efficiency. Future work will investigate the ability of CapBots to charge their peers directly.

REFERENCES

[1] J. V. A. Marques, M.-T. Lorente, and R. Groß, "Multi-Robot Systems Research: A Data-Driven Trend Analysis," in *Distributed Autonomous Robotic Systems*. Springer Nature Switzerland, 2022, pp. 537–549.

[2] S. Pearson, T. C. Camacho-Villa, R. Valluru, O. Gaju, M. C. Rai, I. Gould, S. Brewer, and E. Sklar, "Robotics and Autonomous Systems for Net Zero Agriculture," *Current Robotics Reports*, vol. 3, no. 2, pp. 57–64, 2022.

[3] L. Xie, Y. Shi, Y. T. Hou, and A. Lou, "Wireless Power Transfer and Applications to Sensor Networks," *IEEE Wireless Communications*, vol. 20, no. 4, pp. 140–145, 2013.

[4] K. Chour, J.-P. Reddinger, J. Dotterweich, M. Childers, J. Humann, S. Rathinam, and S. Darbha, "An Agent-Based Modeling Framework for the Multi-UAV Rendezvous Recharging Problem," *Robotics and Autonomous Systems*, vol. 166, p. 104442, 2023.

[5] B. Kannan, V. Marmol, J. Bourne, and M. B. Dias, "The autonomous recharging problem: Formulation and a market-based solution," in *2013 IEEE International Conference on Robotics and Automation*. IEEE, 2013, pp. 3503–3510.

[6] M. Rappaport and C. Bettstetter, "Coordinated recharging of mobile robots during exploration," in *2017 IEEE/RSJ international conference on intelligent robots and systems (IROS)*. IEEE, 2017, pp. 6809–6816.

[7] Y. Warsame, S. Edelkamp, and E. Plaku, "Energy-aware multi-goal motion planning guided by monte carlo search," in *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*. IEEE, 2020, pp. 335–342.

[8] K. Yu, A. K. Budhiraja, S. Buebel, and P. Tokekar, "Algorithms and experiments on routing of unmanned aerial vehicles with mobile recharging stations," *Journal of Field Robotics*, vol. 36, no. 3, pp. 602–616, 2019.

[9] F. Vaussard, P. Rétornaz, S. Roelofsen, M. Bonani, F. Rey, and F. Mondada, "Towards Long-Term Collective Experiments," in *Intelligent Autonomous Systems 12*, S. Lee, H. Cho, K.-J. Yoon, and J. Lee, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 683–692.

[10] M. Kubo and C. Melhuish, "Robot Trophallaxis: Managing Energy Autonomy in Multiple Robots," *Proceedings of Towards Autonomous Robotic Systems*, pp. 77–84, 2004.

[11] C. Melhuish and M. Kubo, "Collective Energy Distribution: Maintaining the Energy Balance in Distributed Autonomous Robots using Trophallaxis," in *Distributed Autonomous Robotic Systems 6*. Springer, 2007, pp. 275–284.

[12] C. Moonjaita, H. Philamore, and F. Matsuno, "Trophallaxis with Predetermined Energy Threshold for Enhanced Performance in Swarms of Scavenger Robots," *Artificial Life and Robotics*, vol. 23, no. 4, pp. 609–617, 2018.

[13] A. F. Winfield, S. Kernbach, and T. Schmickl, "Collective Foraging: Cleaning, Energy Harvesting, and Trophallaxis," in *Handbook of Collective Robotics*. Jenny Stanford Publishing, 2013.

[14] G. Li, I. Svogor, and G. Beltrame, "Long-Term Pattern Formation and Maintenance for Battery-Powered Robots," *Swarm Intelligence*, vol. 13, no. 1, pp. 21–57, 2019.

[15] M. Liu, L. Deferme, T. Van Eyck, S. Michiels, A. Abadie, S. Alvarado-Marin, F. Maksimovic, G. Miyauchi, J. Jayakumar, M. S. Talamali, T. Watteyne, R. Groß, and D. Hughes, "Capbot: Enabling battery-free swarm robotics," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2025.

[16] G. Miyauchi, M. S. Talamali, and R. Groß, "A Comparative Study of Energy Replenishment Strategies for Robot Swarms," in *International Conference on Swarm Intelligence (ANTS)*. Springer, 2024, pp. 3–15.