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MODELING AND SIMULATION FOR FARMING DRONE BATTERY RECHARGING

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ABSTRACT

The Connected Farm is composed of several elements that communicate with each other through a 4G/5G Radio Base Station (RBS) placed in the middle of the farm. This RBS is connected to the Internet, allowing communication for all kinds of autonomous devices, performing uninterrupted tasks. This work simulates the Connected Farm environment for an autonomous drone. Our model intends to define when each drone needs to recharge its batteries, with no collusion regarding this recharging decision, reducing the drone's battery usage due to the absence of this communication.

1 DISCUSSION

Drones, also known as Unmanned Aerial Vehicles (UAV) are crucial for Connected Farms because they perform several activities, such as herds and crop monitoring, image capturing, seeding (Radoglou-Grammatikis et al. 2020), and fruit harvesting (Hager 2023), among others. However, their energy capacity can limit the performance of drones in these tasks.

The farming sector has a significant economic impact on Brazil's gross domestic product (GDP). For example, Brazil is responsible for 40% of the world's sugar cane production. Brazil's meat production (chicken and beef) impacts global world production (FAO 2022).

Figure 1-A represents the Connected Farm concept. The RBS connects all devices to the Internet. Drone communication is a three-dimensional Flight Ad-Hoc Network (FANET). In our model, the agents (Drones) didn't share their energy supply with other agents, reducing the battery usage. Figure 1-B presents the Agent-Based Simulation Graphic User Interface (GUI) implemented in Netlogo (Wilensky 1999). In both figures, the green space represents the working/productive area, and the blue area represents the recharging area.

In this simulation, the agents (Drones) want to decide, in each simulation cycle, whether or not they will recharge, according to pre-defined internal policies. This work uses the El Farol Bar Problem (EFBP) (Arthur 1994) logical approach to coordinate the recharging agent decision. **Policy 1** uses the EFBP, similar as found in (Rand and Wilensky 2007), and **Policy 2** includes an extra decision layer for Policy 1, considering each drone battery Status of Charging (SOC) to decide, if they recharge or not according to their SOC level. If a drone has a SOC higher than a pre-selected value (in our experiments 80%), this drone will ignore the EFBP decision and will not recharge. Also, if SOC is lower than a lower value (20%), the drone's decision is to recharge independently of the EFBP decision.

Recharging occurs when the attendance value is less than a recharging place over-crowding threshold as in an ant swarm behavior. This behavior simulates recharging place space limitation. As each drone has

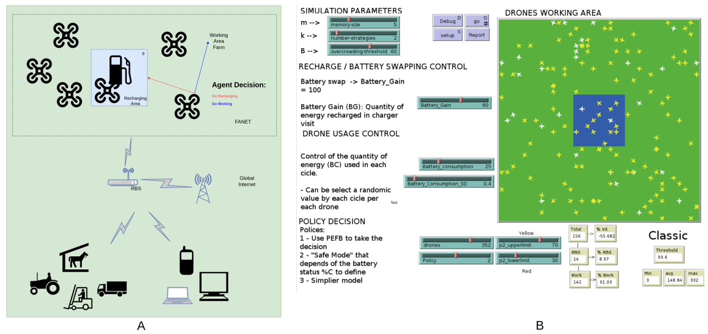

Figure 1: A - Connected Farm Concept. B - Simulation Model GUI.

a limited battery capacity, each cycle, the drones use parts of this SOC capacity to emulate their usage. This value has some randomness to simulate different real-world conditions, such as wind speed and direction, drone speed and movement direction, UAV load, and other parameters. With the effective functioning of this proposal over time, we will optimize these parameters implementation in future works.

In this simulation, we consider five parameters with two possible values for each parameter. These parameters are the initial quantity of simulated drones, the battery recharge rate, the UAV's mean battery usage, the UAV's mean battery usage standard deviation, and the two recharging policies. We performed 3200 (2^5 and 100 replications) simulation runs.

We found two types of results. First, a **reliability measure**, the mean survivor's drone's quantity remaining in 1000 simulations cycles. The simulation results show that Policy 2 agents' results (89.21%) were better than Policy 1 (32.53%) survival rate. Second, an **effectiveness measure**, the average time the agents were not attending the recharging place (working). Policy 2 has better effectiveness performance (66.9% versus 9.35%) than Policy 1. In both results, Policy 2 performed better than Policy 1.

2 CONCLUSIONS

This ongoing work proposes an energy supply process in farming solutions drone swarms. Experiments show that Policy 2 presents better performance results than Policy 1. This finding is an opportunity for new policy decision usage. Future works will consider different UAV internal cognitive processing, environment, and recharging simulation behaviors improvements. Other recharging policy decisions, e.g., Reinforcement Learning, Fuzzy Logic, and Deep Learning, can be tested in the future.

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