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MODELING AND SIMULATION OF BATTERY RECHARGING FOR UAVS APPLICATIONS: SMART FARMING, DISASTER RECOVERY, AND DENGUE FOCUS DETECTIONS

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ABSTRACT

The applications of Unnamed Aerial Vehicles (UAVs) or Drones have been increasing in areas such as Smart Farming, Disaster Recovery, and combat of tropical mosquito diseases such as Dengue. Due to the short duration of the electrical battery capacity, at most 20 to 30 minutes in some cases, most UAVs have low battery capacity to carry out missions. This work presents two contributions: i) a description of the characteristics observed in three drone applications (agricultural, disaster, and against dengue disease), and ii) the creation of an Agent-Based Simulation Model considering energy supply simulation. This model considers that the agents will not collude about their recharging decisions.

1 INTRODUCTION

The Internet of Things (IoT) enables the automation of several sectors of the economy, including Precision Agriculture and recovery from Natural Disasters in risk regions: in prevention, in action during the occurrence, and in assistance, to rescue victims and for monitoring damaged structures; and recently, IoT is also used to help combat diseases due to insect bites (Brazil 2024; Amarasinghe and Wijesuriya 2020).

An Unmanned Aerial Vehicle (UAV), also known as a drone, is an aircraft with the capacity to fly without a pilot inside it (Fahlstrom and Gleason 2012). This device can be operated autonomously or controlled telemetrically and can have fixed, rotary, or hybrid wing types. Drones can be classified according to their number of rotors and their maximum takeoff weight (MTOW). Drones can carry several payloads and sensors to perform their desired mission. Drones can act alone or in joint, with the advantage of working as a swarm (Valavanis and Vachtsevanos 2015).

Initially, our work focused on the main characteristics highlighted by relevant articles about three types of drone applications. While doing this, we found limitations in drones' battery capacity (Mohsan et al. 2022). To deal with this situation, we proposed an approach for collective battery recharging, focusing on the characteristics observed for each type of IoT application.

To coordinate this recharging process, we evaluated two viable approaches: i) using a centralized model in which there would be a separation between the control flow and the data flow, as in Software Defined Networks (SDN), or ii) proposing a decentralized approach, where agents do not communicate with each other about the decision process, yet they define their turn for charging using a model based in a game theory approach called El Farol Bar (Arthur 1994). For now, we decided to use this last approach, as communications can drain the battery faster during UAV usage in hostile or remote environments.

The main objective of our model is to find a way to increase the time of activity performed by a swarm of drones. To this end, we proposed to develop a strategy to coordinate a swarm of drones in their decision to recharge or continue their work. We performed a sensitivity analysis to compare our proposed internal recharging policy Charger Threshold (CT Policy), and a baseline policy (BL Policy). For this purpose, we carry out 60 simulation sets, each with 100 replications, resulting in 6000 simulations.

We proposed three Key Performance Indicators (KPIs) to evaluate the reliability and effectiveness of the 60 simulation runs.

The remaining paper structure is: Section 2 addresses bibliographical and drone applications analysis; Section 3 presents the methodology and parameters description of the simulation; Section 4 is devoted to showing the results and discussions of the simulation runs; Finally, Section 5 addresses the work conclusions, research limitations, and future work suggestions.

2 RELATED WORK

This section presents selected research works related to the application of drones and their energy consumption in agriculture, disaster recovery, and monitoring and combating dengue disease.

2.1 UAV System and Energy Supply Procedure

A typical UAV system comprises a Ground Control Station (GCS), a data link antenna, the UAV itself, and a satellite (Fahlstrom and Gleason 2012). The energy capacity of UAVs can be increased by enhancing their battery technology or by providing energy to these batteries through recharging or battery replacement.

UAVs' higher-capacity batteries application negatively influences the flight capacity due to the system weight-increasing (Mohsan et al. 2022). Jain and Mueller (2020) show a relationship between the battery mass and the total mass of the drones increases, and if this relationship exceeds a limit, the battery duration of the drones begins to reduce. The use of new materials may result in increased battery energy density. Other technologies like supercapacitors (Khan et al. 2021), the use of photovoltaic power supply (Aissi et al. 2020), and fuel cells (Gong et al. 2018), or hybrid forms of energy (Avila et al. 2018), have also been researched. Cables (tethered) (Fauzi and Rahim 2022) or a wireless power transfer (WPT) system (Campi et al. 2019) can also supply UAV drone energy.

Figure 1 shows the battery replacement process. The hot swapping process is when drained batteries are exchanged for charged batteries, allowing the drones to continue working. In the swapping process, drones with drained batteries are replaced by other drones with recharged batteries and enter the recharging process. A swapping process is composed of three elements: i) the battery swap station, ii) the available block of batteries, and iii) a control system to manage the swarm of UAVs (Mohsan et al. 2022).

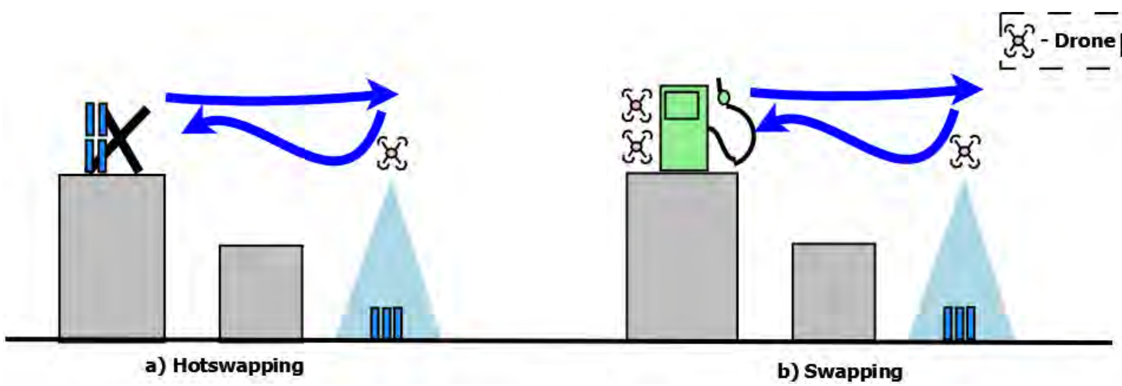

Figure 1: Battery exchange techniques based in Mohsan et al. 2022.

Concerning the modeling of drone swarms and recharges, Boggio-Dandry and Soyata (2018) presented a proposal for coordinating a swarm of drones for its continuous operation, considering a finite state analysis considering seven states. Each drone chooses whether to charge after assessing its situation. Grando et al. (2020) use a model based in El Farol Bar for recharging drones. This work follows a similar approach, adding more details as the amount of energy used for each drone, and proposing new recharging decision-making policies.

William Brian Arthur created the El Farol Bar model to simulate inductive reasoning (limited rationality) instead of deductive and logical behavior, as it is traditional in economics to solve theoretical problems (Arthur 1994).

This economic game theory model considers a bar called El Farol Bar and their neighborhood in Santa Fe city. This bar presents a musical show each week, as this bar has limited space, if the sum of bar-goers is less or equal to a defined comfort threshold, the attendees will have a good night. Bar attendees want to know if they will have benefits from going to the bar each night. For this, they follow strategies using the attendance values from recent weeks, spread in a local newspaper, and try to predict if they will have a good night. These agents don't talk to each other about their decisions, making the attendance records the only information available.

2.2 Drone Application Analysis

This subsection analyzes three drone applications in which the swarm of drones operates and can be allowed by two proposed decentralized recharging coordination processes. Our work considers that the swarm systems can perform some level of their Autonomy Control Level (ACL), of at least Level I according to (Dalamagkidis 2015), meaning execute a preplanned mission capacity.

2.2.1 Smart Farming

The agriculture sector impacts the Brazilian economy (FAO 2022). Drones are robotic tools that, in addition to other automated machines such as harvesters, irrigation systems, and planters can become autonomous, boosting agricultural productivity and enhancing crop yields. Drones allow farmers to seed and spray more homogeneously and precisely to their crops. The farmer will be able to identify the functioning of irrigation equipment, possible failures in crop coverage, and hydrical stress. It can also help monitor animals and livestock equipment, locate animals, identify sick animals, read tags, and monitor fences and water fountains.

In agriculture, drone utilization can obtain information through images or by collecting data using sensors. This information can make data-driven operational decisions. Drone applications for precision agriculture (PA) can be herds and crop monitoring, image capturing, seeding, fruit harvesting, and spraying (Hartanto et al. 2019; Radoglou-Grammatikis et al. 2020). A Brazilian law regulates the UAV operation for spraying, spreading, and fertilizer (Brazil 2021).

2.2.2 Disaster Recovery

Humanitarian relief drone operations can support medical interventions, remote sensing and monitoring, logistics, search, and rescue operations. Maghfiroh et al. (2023) describe some drone disaster application barriers as their limited battery and consequently flying endurance, susceptibility to extreme weather, data transfer, and cargo capacity.

Regarding the energy problem, Noguchi and Komiya (2019) propose a UAV replacement process of low-energy devices to ready devices to provide persistent UAV networks disaster relief. Golam et al. (2021) propose an energy allocation technique to mitigate energy limitation in post-disaster drone usage. Selim and Kamal (2018) propose a post-disaster rehabilitation 4G / 5G framework using different types of drones for disaster applications.

2.2.3 Monitoring of Dengue Breeding Places With the Use of Drones

Brazil is on alert regarding the Dengue virus epidemic caused by the proliferation of outbreaks of Aedes aegypti mosquitoes. On March 5, 2024, Brazil recorded 299 deaths from dengue and 1,253,919 probable cases (Brazil 2024).

The explosion of dengue cases occurred early this year in Brazil due to climate change, increasing temperature, and rain. The Aedes Aegypti mosquito is also the vector for other infectious tropical diseases, such as Chikungunya and Zika Virus. About 75% of mosquito breeding sites are found in homes, making it necessary to constantly monitor lands, backyards, gardens, and roofs of residences. Drones can do this pattern recognition about dengue spots using computer vision techniques (Valdez-Delgado et al. 2021).

Another way to fight against this disease is by delivering sterile males in nature, to avoid reproduction (Ackerman 2017; FAPESP 2024). Ali et al. (2022) propose a framework to evaluate the disease occurrence and use drones to spray the infected location if necessary. Our model can allow drone swarms to improve their flight time to improve the surveillance, spraying, and infertile male mosquito delivers, fighting against the Aedes aegypti mosquitoes.

3 METHODOLOGY & MODELING

This work performs an Agent-Based Modeling Simulation (ABMS) using NetLogo as modeling software (Wilensky 1999).

We evaluate 15 different battery demands, two different recharging place sizes, and two recharging policies resulting in 60 scenarios, and repeated 100 times, or 6000 simulation runs. We perform a sensitive analysis, by changing the parameters to evaluate how each simulation sets behave in three KPIs.

The two first KPIs evaluate the reliability of the system. The third KPI is related to the effectiveness of the simulation of each set. In all KPIs, their higher values were related to the best performance system:

1. **Quantity of Finished Simulations:** Quantity of times each simulation set concludes the 100 replications. The simulation run can halt when one of two simulation stop criteria happens. This is discussed further in Section 3.3.
2. **Average Remaining Drones:** Mean drone quantity that finishes the simulations. This KPI evaluates the mean survivor's drones that remain in each finished simulation;
3. **Average Utility:** Mean survivor drones' working decision values concerning the total simulation time. This KPI evaluates the decision performance of each policy. The higher the value represents that the agent performs more of their mission.

3.1 Variable and Decision Process

An initial quantity (QTY) of drones that are doing a determined mission, e.g. spraying, obtaining images, serving as a source of connectivity in case of disasters, dengue spraying, needs to decide whether they will continue to work or go to the charging station, to refill their energy. In this model, the charging station has a limited capacity B, a fraction of the drone QTY value.

Figure 2 visually presents this decision process and the integration of the drone swarm system and the connected farm. The Radio Base Station (RBS) sends information to drone swarms, and their internal intelligence defines if they go recharging or do their work (mission).

Although our agents do not have an explicit interaction between them, they act in a coordinated way to achieve their objectives, described in Subsection 2.2, so they can be defined as autonomous agents type according to the Macal (2016) definition.

The simulation model parameters are related to the application's demand, the system's recharge capacity, and the agents' decision-making process.

The application (farm, disaster assistance, fight against dengue) demands a quantity (QTY) of agents necessary to perform the mission. Aiming to simulate this application demand, we consider an average energy expenditure for each agent (Battery Consumption — BC). This BC value is randomized using a Gaussian distribution with a standard deviation (SD) in a simulation cycle time.

The recharging station (B) has a limited capacity to supply energy to the drones. This energy amount is defined by the Battery Gain (BG) parameter.

The variables and their ranges of variation in the experiments are described in Table 1.

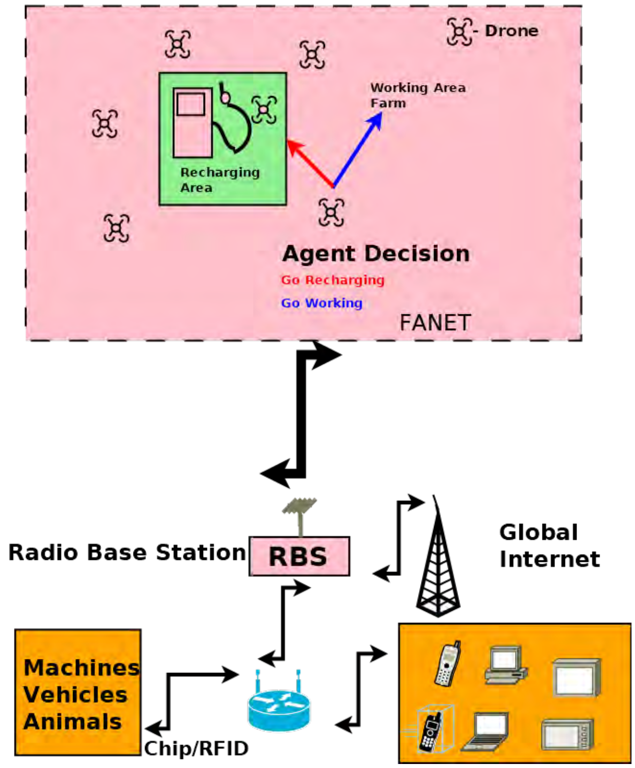

Figure 2: Agents' decision process in each simulation cycle.

Table 1: Parameters and variables of the simulation experiments.

Parameters	Descriptions	Symbols	Value
Status of Charge	Drones' energy quantity	SOC	0 to 100 %
Memory size	CT policy memory value	m	10
SOC upper limit	CT policy SOC threshold	UP	80 %
SOC lower limit	Emergency recharging SOC threshold	LW	25 %
Battery Gain	Effective recharging SOC value gain	BG	0 to 100 %
Drones	Simulation drones quantity	QTY	100
Policy	Recharging decision policies	PLC	BL and CT
Battery Consumption	Drone SOC usage per simulation cycle.	BC	1 to 15 %
Battery Consumption SD	BC Gaussian standard deviation	SD	0.1
Recharging place capacity	Recharging place capacity (ratio QTY)	B	20 or 50%
Ticks	Simulation discrete temporal value	t	1500

3.2 Policies and Decisions

The agents have two internal policies to make the recharge or work decisions. Both policies are decentralized, which means that agents make your decision without colluding with other drones or receiving an order from the RBS to recharge, This means: (i) the reduction in communication between drones when carrying out their missions (but which can occur in other situations), with the consequent reduction in battery consumption and improvement of system data security, and (ii) minimizing the need for remote control to recharge drones which can facilitate continuous work on farms or in disasters.

3.2.1 BL Policy

The BL policy uses the UAV batteries' State of Charge (SOC) as a parameter for drone internal decisions. Each agent has to define whether to recharge, analogous to the decision to fill up a car or recharge a cell phone when reaching a critical limit. The critical limit is called the Lower Reload Limit (LW). If the SOC battery level is less or equal to this value, the UAV will try to recharge its batteries. This policy uses less computational power than the CT policy.

3.2.2 CT Policy

The CT Policy considers both the amount of energy present in the drone battery and the decision process based on the El Farol Bar, based on the history of agents who went to recharge at the charging station to make a decision. Regarding the history of agent updates, the Radio Base Station (RBS) will broadcast the m previous attendance information to each agent. Each agent has, in turn, in its memory "k" internal autoregressive algorithms (AR) that evaluate and predict a possible next simulation attendance value.

This policy approach is based on the El Farol Bar model (Arthur 1994), which can be found in the NetLogo library (Rand and Wilensky 2007). This model is widely used in resource congestion (blocking) problems (Sharif et al. 2011; Bell and Sethares 1999).

The coordination of the decision process occurs without collusion between agents (they do not communicate) about their decision, being an advantage in adverse environments such as agriculture or disaster recovery, and reducing the consumption process of computational and communication resources for decision-making. Internal decisions regarding recharging policies consist of estimators that guide UAV choices, recharging, or continuing working.

In the adaptation/analogy for our ABS model, we consider the drones as agents and the charging station as the El Farol Bar in the original model. We use the predictors as estimators so that the agents' internal policies can make their decisions (Rand, W and Wilensky, U 2007).

This algorithm compares the best performance k internal predictors and compares with the current B value as shown in Figure 3-b. If the predicted value is less than the B value, the agent will try to charge the battery in the recharging place.

In addition to this calculation, the CT policy considers drone battery values (SOC) about the lower value threshold (LW). In a simulation run, if an agent's battery level drops below LW, the agent will attempt to recharge at the recharging station. Conversely, if the agent's battery level exceeds the upper-value threshold (UP), the drone will continue its operations.

Figure 3-a illustrates the difference between both policies related to the battery SOC level. In this figure, the green area represents the UAV work decision, the red area UAVs' recharge decision, and the yellow area represents the use of the El Farol Bar strategy to make the decision.

3.3 Recharging Process

In each simulation run, each active drone decides if to try recharging or working. If they decide to try to recharge, they will attend the charging station. The charging station has a limited position quantity (B). If the number of drones that try to recharge is greater than the B value, the drones that attend the charging station will not recharge, because this model considers that if the recharging is overcrowded they will not have the capacity to recharge the drones. An effective recharge process is considered when the station is not overcrowded and can supply energy to drones inside the recharging place. Figure 4 presents this recharging process model.

Our current model considers the hot-swapping battery change process because the effective recharging SOC value battery gain BG is 100. The battery capacity was limited between 0 and 100% SOC values. Agents will be inoperable if the battery reaches a SOC value below 0%.

In each time step, the SOC values are subtracted from a battery consumption rate (BC). This BC value is randomized by a normal random variable with a Gaussian standard deviation called Battery Consumption

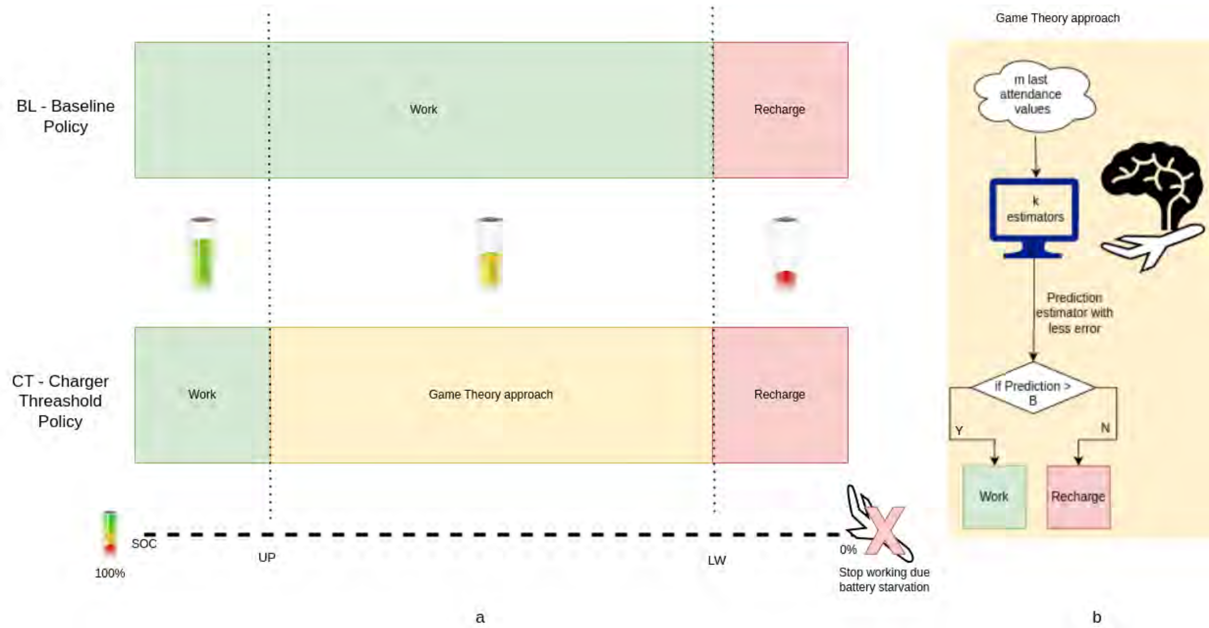

Figure 3: Recharging policies descriptions.

Standard Deviation (SD). This BC variation value is intended to create a drone battery random usage in simulation. This usage is not explicitly considered in this work and can be by payload, environmental conditions, and the drone's three-dimensional movement (Sierra et al. 2019).

There are two simulation-stopping criteria, whichever is reached first: i) the presence of a single agent with a remaining battery in the simulation run, or ii) The run achieves the t = 1500 ticks (one tick is a discrete-time unit).

Each agent starts the simulation with an initial battery level (SOC). Each agent was assigned a mission workload, and during the simulation, their battery level was subtracted from the Battery Consumption level (BC). In a successful recharging case, the agents' battery level will be increased to 100% (hot-swap process). If this battery level achieves zero percent, the drone will stop working because it did not have energy. A drone with enough battery to reach the simulation end (stop-criteria ii) is defined as a "survivor drone".

4 CASE STUDY

We conducted a sensitivity analysis of the model based on battery demand values (BC), evaluating 60 simulation scenarios, 30 for each policy (BL and CT). This analysis involved 15 different battery demand values and two recharging station capacities (20 and 50 places). Each scenario simulation was repeated 100 times, resulting in a total of 6,000 simulation runs.

To evaluate the simulation results, we develop three KPIs. The two first KPIs evaluate the reliability of the system. The third KPI is related to the effectiveness of the simulation of each set. In all KPIs, higher values mean a better performance system than others with a low KPI value:

1. Quantity of Finished Simulations (percentage);
2. Average Remaining Drones (percentage);
3. Average Utility (percentage).

Figures 5 to 8 contain a graphical representation of the results for each set of policies, battery expenditure, and space available for recharging. Figures 5 and 7 present the average values of the results of the two

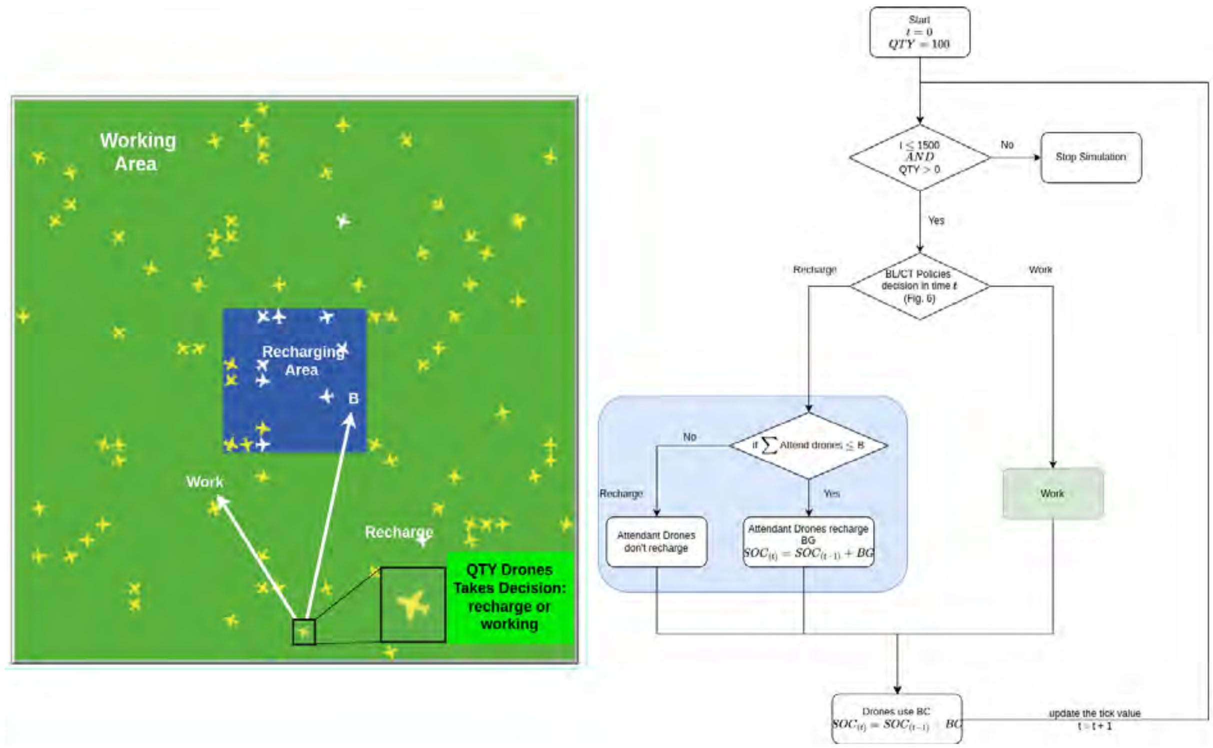

Figure 4: Recharging process flowchart.

indicators and their 95% confidence interval for each simulation set regarding the reliability indicators. Figures 6 and 8 show the mean average utility of the survivor's drones regarding the effectiveness KPIs.

4.1 Results When B = 20%

Regarding the reliability indicator, almost all simulation sets perform in their totality regarding the BC values below 14% SOC. For BC = 15%, the BL policy finished almost none of their simulation runs. CT policy finishes almost all of their simulation runs, but the remaining drones have a low value. That shows CT policy performing better than the BL policy.

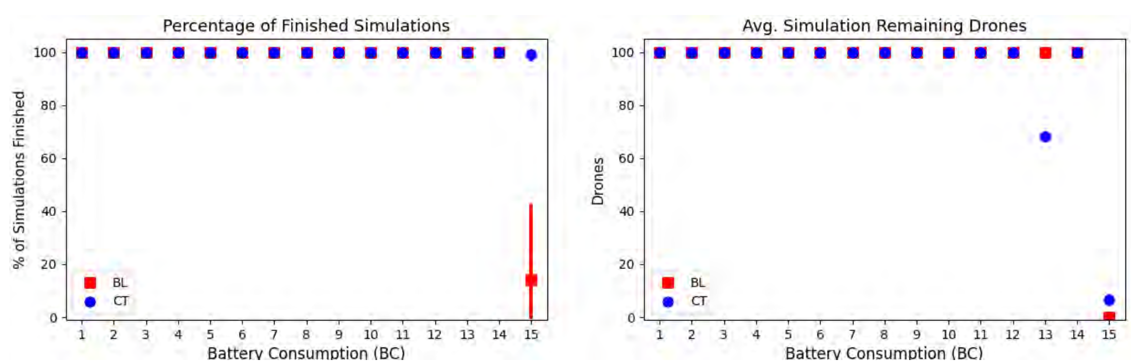

Figure 5: KPIs 1 & 2 results when B = 20%.

Figure 6 shows the mean efficiency results. BL policy has a similar performance in the working ratio. In both policies, there is almost a negative linear relation between the Utility and BC values. In the BC = 15% case, the CT policy performs better than the BL policy.

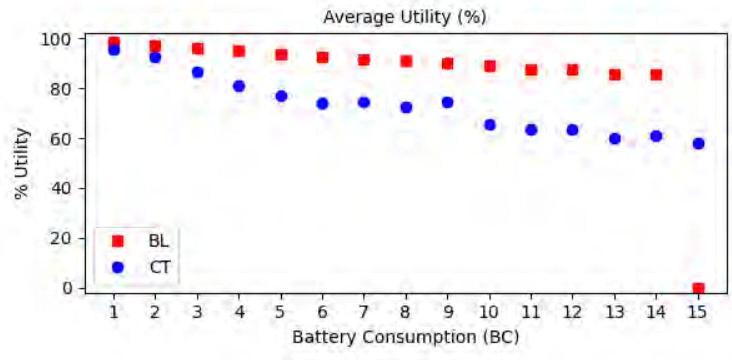

Figure 6: KPI 3 results when B = 20%.

4.2 Results When B = 50%

Figure 7 shows the value of B is set equal to 50% of the initial QTY, simulating a case in the recharging area that has more recharging capacity. As in the B = 20%, in values of small battery consumption, almost conclude all simulations runs, only in the case of BC = 15% SOC the indicators have inferior performance. A larger recharging area results in better results about the reliability indicators, but CT performs better.

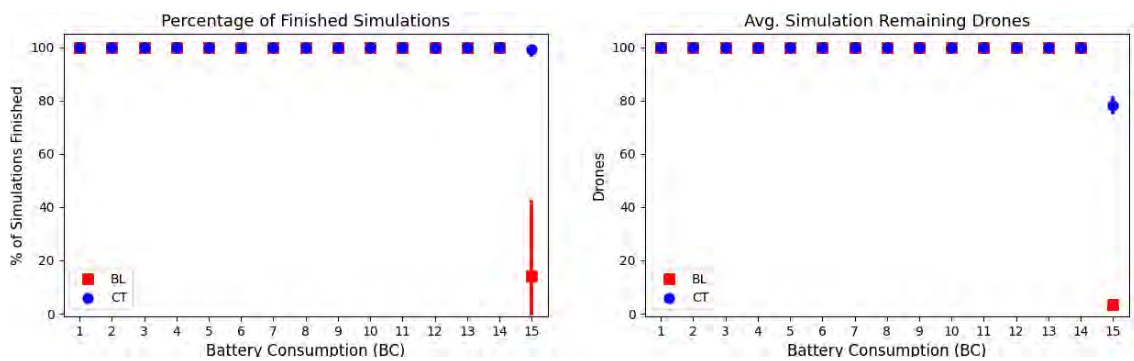

Figure 7: KPIs 1 & 2 results when B = 50%.

Figure 8 shows that in B = 50% case, BL policy performs better than CT policy in the effectiveness result.

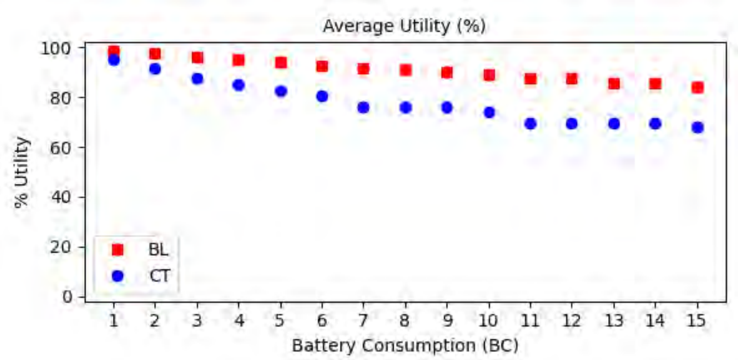

Figure 8: KPI 3 results when B = 50%.

The most significant differences regarding policy comparison happen in the KPI 3. In KPI 1 and 2, the results are similar.

Considering these results, the increase of BC shows a decrease in system performance, this is an expected behavior. Increasing the recharging capacity (B) also shows an increase in system performance. When comparing policies, BL has similar performance to CT in effectiveness, but in the case of more stress (higher values of BC), CT performs better, which can be helpful in stressful drone application situations.

5 CONCLUSIONS

This work focused on the development of coordination processes for recharging a swarm of drones. We created an Agent-Based model to propose two decentralized battery recharging procedures for a swarm of UAVs in precision agriculture, disaster relief, and dengue combat applications. We performed extensive simulation runs to evaluate the model in several drone usages. The first (BL) decision policy is less computationally complex than the second (CT) decision policy, but we observed that the CT policy performed better than the BL policy in cases where there is extreme drone usage.

Considering the existing applications in the literature, we highlight three critical missions—precision agriculture (PA), disaster relief, and dengue control, where drone swarms can be highly effective. Our proposed decentralized recharging decision strategy can enhance the coordination of remote applications and reduce battery consumption due to reduction of communication needs. Additionally, by reducing communication, the security of swarm data (device-to-device or device-to-base) can also be improved.

This work analyzes and proposes an approach to increase drone energy capacity to enable precision farming, disaster recovery, and dengue fighting concerning drone swarm applications. The game theory approach shows better performance in recharging coordination during extreme situations. The use of a decentralized approach can improve the autonomy and the data security of the system because of the communication reduction about the internal recharging decision.

Regarding work limitations, this simulation can be improved by real-world parameters data about the three application needs, considering new policy decisions and comparing with this current model. Another future work can be creating a guideline about drone usage in dengue fighting, and mapping where the disease is affecting. We propose in raining season Aedes aegypti mosquito's spot monitoring by using machine learning visual techniques by drone swarms.

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