UNIVERSIDADE ESTADUAL DE CAMPINAS
Faculdade de Tecnologia

Leonardo Grando

Study for Optimization of Battery Consumption for Unmanned Aerial Vehicles

Estudo Para Otimização de Consumo de Bateria Para Veículos Aéreos Não Tripulados

Limeira
2025

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Tese apresentada à Faculdade de Tecnologia da Universidade Estadual de Campinas como parte dos requisitos para a obtenção do título de Doutor em Tecnologia, na área de Sistemas de Informação e Comunicação.

Thesis presented to the School of Technology of the University of Campinas in partial fulfillment of the requirements for the degree of Doctor in Technology in Computer Science, in the area of Computing and Communication Systems.

Supervisor/Orientador: Prof. Dr. Edson Luiz Ursini

Este trabalho corresponde à versão final da Tese defendida por Leonardo Grando e orientada pelo Prof. Dr. Edson Luiz Ursini.

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Resumo

Veículos aéreos não tripulados, também chamados de drones, podem ser utilizados em aplicações críticas, como suporte à recuperação de desastres ou na agricultura de precisão. No entanto, sua autonomia é limitada devido ao seu pequeno tamanho e capacidade. Novas formas de energia podem aumentar a autonomia dos drones e melhorar a coordenação de seus processos, tanto de trabalho quanto de tomada de decisão para a recarga de suas fontes de energia. Este trabalho visa desenvolver propostas de coordenação para o processo de recarga desses dispositivos, visando aumentar sua autonomia. Nesta pesquisa, drones são considerados dispositivos Internet das Coisas, operando em conjunto, na forma de enxame. Os drones precisam decidir se devem ou não recarregar suas baterias em uma estação de recarga. Este trabalho apresenta dois principais resultados: primeiro, a identificação de três lacunas na literatura a partir de uma revisão sistemática sobre o processo de coordenação da recarga de drones no contexto de aplicações em agricultura e desastres. O segundo resultado foi o desenvolvimento e documentação de um modelo de simulação baseada em agentes no software NetLogo, no qual foram realizadas 12.000 rodadas de simulação. Nesse modelo, considera-se um enxame de drones atuando de forma autônoma e sem comunicação entre si no momento da decisão sobre a recarga. Para esse modelo, foram propostas duas políticas de tomada de decisão, denominadas *Baseline* e uma baseada na teoria dos jogos chamada de política *ChargerThreshold*, que foram desenvolvidas e testadas, além de três indicadores para avaliar a robustez e eficiência em diferentes situações. A revisão da literatura mostrou que existem poucos estudos práticos no contexto de recarga de enxames de drones. O desenvolvimento de uma base de simulação, como este trabalho, bem como a criação de indicadores para avaliar os cenários de simulação, são contribuições importantes para esta área de pesquisa, ao servirem de base para futuros desenvolvimentos. Os resultados evidenciaram três tipos de lacunas encontradas na literatura e mostraram que ambas as políticas funcionam bem em situações com menor demanda energética. No entanto, em cenários com maior consumo de bateria, a política baseada em teoria dos jogos se mostrou mais eficiente, possibilitando que o conjunto de drones realizasse o trabalho esperado de forma autônoma. Os resultados da simulação destacam o potencial das estratégias de tomada de decisão propostas para otimizar a coordenação de drones em cenários reais, além de mostrar o potencial de uso dessa abordagem em outras aplicações, como o processo de recarga de veículos elétricos.

Abstract

Unmanned aerial vehicles, also called drones, can be used in critical applications, such as disaster recovery support or precision agriculture. However, their autonomy is limited due to their small size and capacity. New forms of energy can increase the autonomy of drones and improve the coordination of their processes, both work and decision-making for recharging their energy sources. This work aims to develop coordination proposals for the recharging process of these devices, aiming to increase their autonomy. In this research, drones are considered Internet of Things devices, operating together as a swarm. Drones must decide whether to recharge their batteries at a recharging station. This work presents two main results: first, it identifies three gaps in the literature from a systematic review on coordinating drone recharging in the context of applications in agriculture and disasters. The second result was developing and documenting an agent-based simulation (ABM) model in NetLogo software, in which 12,000 simulation runs were performed. In this model, a swarm of drones is considered to be acting autonomously and without communication with each other when deciding whether to recharge. For this model, two decision-making policies were proposed, called Baseline and a game theory-based ChargerThreshold policy, which were developed and tested, in addition to three indicators to evaluate robustness and efficiency in different situations. The literature review showed few practical studies in the context of recharging drone swarms. The development of a simulation base, such as this work, and the creation of performance indicators to evaluate simulation scenarios are important contributions to this research area, as they serve as a basis for future developments. The results highlighted three gap types in the literature and showed that both policies work well in situations with lower energy demand. However, in simulation scenarios with higher battery consumption rates, the game theory-based policy proved to be more efficient, allowing the drones to perform the expected work autonomously. The simulation results highlight the potential of the proposed decision-making strategies to optimize drone coordination in real-world scenarios, showing the potential for using this approach in other applications, such as the electric vehicle recharging process.

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Simbol List

UAV	Unmanned Aerial Vehicle
PA	Precision agriculture
DR	Disaster Recovery
IoT	Internet of Things
ABMS	Agent-Based Modelling System
BL	Baseline policy
SOC	Battery Status of Charge level
EFBP	El Farol Bar Problem
SLR	Systematic Literature Review
ABS	Agent-Based Simulation
MTOW	Maximum Take-off Weight
kg	kilograms
GPS	Global Position System
MAV	Micro or Miniature Air Vehicles
NAV	Nano Air Vehicles
m	meters
min	minutes
VTOL	Vertical Take-Off & Landing
LASE	Low Altitude, Short Endurance
sUAS	Small Unmanned Aircraft System
h	hour
LALE	Low Altitude, Long Endurance
MALE	Medium Altitude, Long Endurance
HALE	High Altitude, Long Endurance
ACL	Autonomous Control Levels
WPT	Wireless Power Transfer
RF	Radio Frequency signal
SWIPT	Simultaneous Wireless Information and Power Transfer
MAPA	Brazilian Agriculture and Livestock Federal Gov. Ministry
RBS	Radio Base Station
RFID	Radio Frequency Identification
BRT	Bias and Raising Threshold

ICE	Internal combustion engine
EMS	Energy Management System
EBM	Equation-based models
GIS	Geographic Information System
UML	Unified Modeling Language
AML	Agent Modeling Language
ODD	Overview, Design Concepts and Detail Protocol
DOE	Design of Experiments Technique
ANOVA	Analysis of Variance
OFAT	One Factor at a Time
B	EFBP comfort level
N	Simulation agent quantity
m	EFBP last attendance data windows value
AR	Autoregressive estimators
MDPI	Multidisciplinary Digital Publishing Institute
SLR-RQ1	Systematic Literature Review research question 1
SLR-RQ2	Systematic Literature Review research question 2
IEEE	Institute of Electrical and Electronics Engineers
PIOC	Population, Intervention, Outcome, and Context
PICOC	Population, Intervention, Comparing, Outcome, and Context
QA	Quality Assessment
QTY	Simulation Initial Quantity of drones
BC	Quantity of energy used during simulation working process
BC_SD	Standard deviation (normal) of BC
BG	Quantity of energy replaced during effective recharging
CT	Charger Threshold policy
UP	Upper reload limit SOC value
LW	Lower reload limit SOC value
k	Quantity of internal predictors
GUI	Graphic User Interface
xcor	NetLogo x coordinates
ycor	NetLogo y coordinates
pcolor	NetLogo patch colors
t	Netlogo discrete time unit (tick)
KPI	Key performance indicators
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
CoMP	Coordinated Multi-Point Clusters Technique.
NFV	Network Function Virtualization
CBDN	Cloud-Based Drone Navigation Algorithm
SDS	Social Drone Sharing

SCS	Social Charging Station
NA	Not available
MT-UAV	Maximum throughput with unmanned aerial vehicles
SWIPT	Simultaneous Wireless Information and Power Transmission
MAS	Multi-Agent System
BDI	Belief-Desire-Intention architecture
SUAV	Swarm-based and Mobility Prediction Scheme for UAVs
MAEI-CPP	Multi-agent Endurance Limited Coverage Path Planning algorithm
MAC	Multi-agent mission coordinating architecture

Contents

Chapter 1

Introduction

1.1 Objective

Unmanned aerial vehicles' (UAVs) flight autonomy is a difficult problem in drone usage in real-world swarm implementation. Their autonomy is limited in some minutes. Some solutions include energy sources (Shehu et al., 2021; Celik; Eren, 2018), hybrid powers (Berradi; Moutaouakkil; Medromi, 2016; Boukoberine; Zhou, Z.; Benbouzid, 2019) and recharging management (Sanchez-Aguero et al., 2020; Boggio-Dandry; Soyata, 2018).

Precision agriculture (PA) and disaster recovery (DR) solutions can be supported with a swarm of drones, but their flight autonomy capacity was a barrier to their implementation.

This research proposes a solution to the IoT device's energy supply problem, considering their recharging coordination process. Optimizing the consumption process is also associated with greater flight autonomy for these devices. Swarms of Unnamed Aircraft Vehicles, also known as drones, were used to illustrate these solutions.

This work aims to create a framework to simulate a swarm of UAVs' recharging coordination process using an Agent-Based Model Simulation (ABMS) without any communication about their recharging process. However, in other emergencies and/or unforeseen situations, the usual communication between drones must be carried out.

This framework considers a recharging place and a working place, where the agents make decisions in every simulation cycle. To make this decision, the agents can initially have two recharging policies.

The first Policy, called Baseline (BL), uses the drone's battery state of charge (SOC) limits and simplification concerning the recharging quantity. The second Policy also uses the drone

SOC level; in an intermediate SOC level, they use a game theory approach called El Farol Bar Problem (EFBP) (Arthur, 1994) decision process.

The El Farol Bar Problem approach was already used in congestion problems (Sharif; Huynh; Vidal, 2011) and Drone behavior coordination (Manrique; Johnson, D.; Johnson, N., 2017; Grando; Ursini, E. L.; Martins, P. S., 2020).

1.2 Research Question

This work presents two main results. The first is the current literature on agriculture and disaster drone recharging coordination process studies. The second is about the development and documentation of an agent-based simulation of a swarm of drones.

The first research question of this work concerns state-of-the-art research on drone coordination recharging in precision agriculture and disaster recovery. This will be developed in 3.1, and the results will be presented in Subsection 4.1.

The second research question is how to create a simulation to evaluate the decentralized coordination procedures of a swarm of drones. Assessing the reliability and the efficacy of 120 simulation cases and propose two decentralized coordination policies. This is assessed in the Subsection 3.2 and the results in the Subsection 4.2.

1.3 Outlook

Chapter 2 has a literature review of IoT devices (drones), an overview of drones usage in precision agriculture, disaster recovery, dengue disease flight, complex systems, Agent-Based simulation, and the simulation policies model.

Chapter 3 presents the Systematic Literature Review (SLR) methodology about the energy supply coordination procedures to agriculture and disaster recovery drones usage, the simulation model and parameters description, the experiment description, and the documentation.

Chapter 4 shows the Systematic Literature Review and the Agent-Based Simulation (ABS) results,

Chapter 5 is about the results' discussion, work conclusions, and future development of the work.

Finally, Appendix A compares this thesis work with the dissertation work, and Appendix C describes the research activities done during the four years of the Doctorate.

Chapter 2

Literature Review and Background

This chapter presents a literature review of drone technology, simulation, and complex system definition, the modeling approaches used in this work.

The Internet of Things and drones' definition, classification, usages, and energy supply techniques were presented in this section.

2.1 Drones

The Internet of Things model allows devices to be interconnected whenever and anywhere on the planet (Want; Schilit; Jenson, 2015). Some important elements in IoT devices are network complexity and scale. The IoT enablers are low-latency real-time interactions, peer-to-peer connections, and the integrations of low or no-processing-capability devices (Want; Schilit; Jenson, 2015).

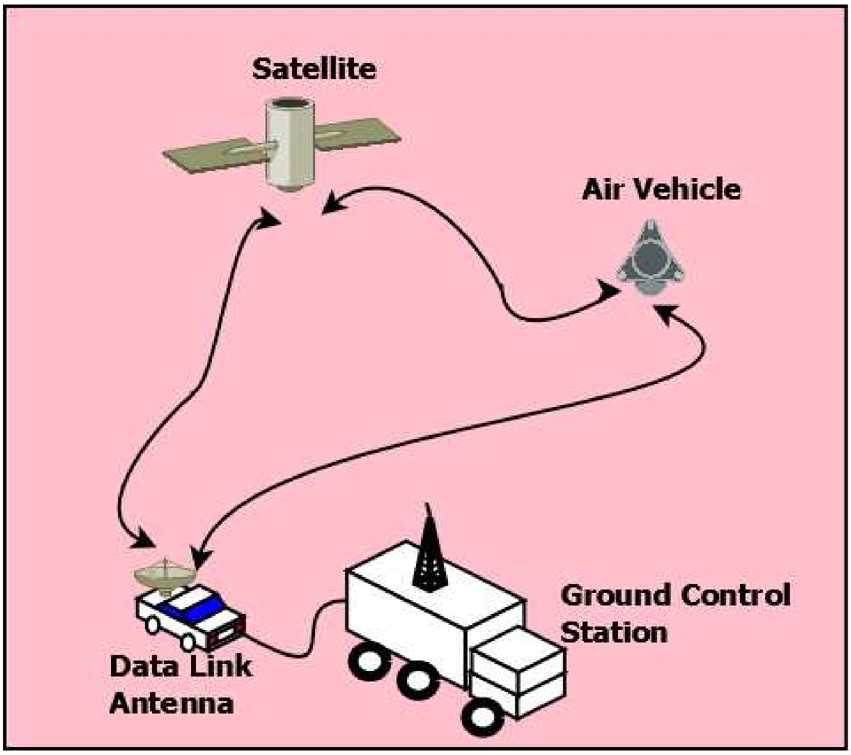
The number of IoT devices in 2022 is about 13,2 billion, and the 2028 forecast is expected to reach 34,7 billion devices (Ericsson Mobility, 2022).

This work uses drones as IoT devices as entities in the simulation. Due to the agent-based model approach, other device types can be modeled using their characteristics (states and actions).

UAVs are aircraft that operate without a human pilot onboard. Drones can perform their tasks in remote-controlled, pre-programmed missions, or autonomously (Fahlstrom; Gleason, 2012).

Figure 2.1 illustrates a generic UAV system with its Ground Control Station, the data link antenna, the UAV, and a satellite (Fahlstrom; Gleason, 2012).

Figure 2.1: Graphical representation of UAV architectures



Source: Adapted from (Fahlstrom; Gleason, 2012)

UAVs can act independently or together in a multi-UAV configuration. The Multi-UAV configuration can carry out multiple and simultaneous interventions, improve the efficiency in the action's execution time, and create a reliable system by redundancy (Valavanis; Vachtsevanos, 2015);

Using a fleet of small devices instead of a big one can be less costly because the drone's energy consumption depends on its weight and physical size. When considering a drone swarm, their architectures can be classified into four types (Valavanis; Vachtsevanos, 2015):

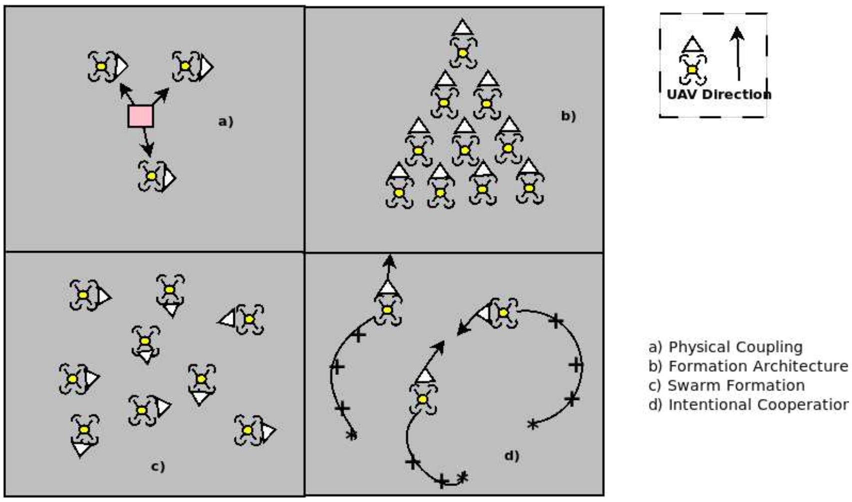
Figure 2.2-a shows physical coupling. When UAVs are connected with physical links, their movements are limited by forces that depend on other types of UAVs. Their Application can be the transportation of a single object by multiple autonomous vehicles.

Figure 2.2-b presents formation architecture. In this case, the UAVs are not physically connected, but their movement is restricted to maintain the predefined formation.

Figure 2.2-c shows swarm formation. In this case, it is a homogeneous vehicle team whose interaction generates collective emergent behavior. They have decentralized control as the example of this work simulation.

Figure 2.2-d shows intentional cooperation: The team of UAVs moves independently to perform their task in a global mission context.

Figure 2.2: Four types of Multi-UAV architectures



Source: Adapted from (Valavanis; Vachtsevanos, 2015)

In a swarm behavior, a simple interaction between large relative numbers of unintelligent agents can emerge a global complex collective behaviors (Valavanis; Vachtsevanos, 2015).

This thesis simulation model uses the Agent-based Model Simulation paradigm, widely used to simulate complex systems (Wilensky; Rand, 2015; Mitchell, 2009), as a swarm of drones. In this model, are evaluated the decision performance of internal policies can be considered internal intelligence to define when drones will recharge or continue their work. As critical applications such as precision farming can be difficult to communicate between drones, and our approach considers that the drones will not communicate, in this case, the decision process will be decentralized.

2.1.1 Drones Classification

Drones can be classified by their physical characteristics, rotors, maximum takeoff weight (MTOW), their degree of autonomy, and operational altitude (Valavanis; Vachtsevanos, 2015).

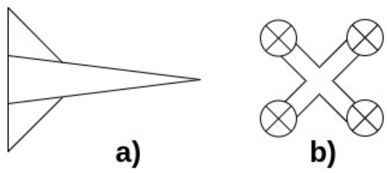
The Brazilian National Agency of Civil Aviation classifies drones according to their MTOW capacity. Class 1 considers UAVs with more than 150 kg; Class 2 considers UAVs with MTOW between 25 and 150 kg; and Class 3 corresponds to UAVs less than 25 kg (ANAC, 2023).

Another UAV classification considers the number of rotors. Regarding their application, the number of rotors can limit their ability to perform a mission. In the context of precision agriculture usage, drones with fewer than three rotors are often excluded due to concerns over aerodynamics and stability. Drones with four rotors are more commonly used, while those with six or eight rotors have also found applications, particularly in larger payload situations. However, these multi-rotor designs can be more challenging to control (Rahman et al., 2021).

Drones can be attached with several sensors and payloads for their movement, communication, and activities: cameras, Global Position System (GPS), accelerometer, altimeters, and implements for their working mission. (Rahman et al., 2021)

The three main types of UAVs were fixed wings, rotary-wing, and hybrids. Fixed-wing drone applications include carrying heavy payloads at high speeds, sensing images from higher altitudes, and great area coverage, but this drone type is not recommended for stationary inspection. The rotary-wing drones have better maneuverability and lower launching time, but this device motion can cause vibrations (Pakrooh; Bohlooli, 2021). Figure 2.3 shows schematics about these two main types of UAVs.

Figure 2.3: Main Types of drones representation a) fixed wings and b) rotary wings



Source: Author elaboration

A type of UAV nomenclature according to their size, flight endurance, and capabilities (Watts; Ambrosia; Hinkley, 2012) :

- MAV (Micro or Miniature or NAV (Nano) Air Vehicles): Classified because of their size, operates at low altitudes (less than 330 m), and short flight times (5 to 30 min.) due to battery and size limitations;
- VTOL (Vertical Take-Off & landing): UAVs with no take-off or landing run, can operate at varying altitudes but normally fly at low altitudes. The hovering flight requires high power capacity and high fuel capacity;
- LASE (Low Altitude, Short Endurance): also known as sUAS (small unmanned aircraft systems) with wingspans less than 3 m and weighing about 2 to 5 kg, can be launched by hand or catapult systems. Their range was a few km from the ground stations and 1 to 2 hours;

- LASE Close: Small UAS that require runways, but this type of drone has increased capabilities because of its size and weight. Can operate up to 1500 m and fly for multiple hours.

- LALE (Low Altitude, Long Endurance): Can carry payloads of several kg at a few thousand meters altitude for an extended period.

- MALE (Medium Altitude, Long Endurance): Aircraft much larger than low-attitude UAVs classes, operating up to 9000 m and hundreds of km flights from the ground stations with many hours.

- HALE (High Altitude, Long Endurance): The most complex UAS, with dimensions larger than manned aircraft. Can fly, 20000 m of altitude with thousands of km. The flight duration can be over 30 hours.

Another way to classify drones, through their Autonomous Control Levels (ACL). The authors (Dalamagkidis, 2015) describe eleven ACL, as in Table 2.1:

Table 2.1: Drones Autonomous levels.

Autonomous control levels	Level descriptor
0	Remotely piloted vehicle
1	Execute preplanned mission
2	Changeable mission
3	Robust response in real-time faults/events
4	Fault/event adaptive vehicle
5	Real-time multi-vehicle coordination
6	Real-time multi-vehicle cooperation
7	Battle space knowledge
8	Battle space cognizance
9	Battle space swarm cognizance
10	Fully autonomous

Source: Adapted from (Dalamagkidis, 2015)

Our proposal model solution considers a swarm of drones with at least an ACL level 5.

2.2 Drones Applications

UAVs were primarily employed for dull, dirty, or hazardous tasks. They have applications in both military and civilian sectors, as well as in environmental monitoring and other fields such as forest surveillance, inventory management, wildlife surveys, avalanche detection, air quality monitoring, plume tracking, groundwater discharge monitoring, mine surveying, precision agriculture, logistics delivery, and wireless coverage (Watts; Ambrosia; Hinkley, 2012; Boukoberine; Zhou, Z.; Benbouzid, 2019).

UAVs are also used as a way to supply energy to IoT network nodes, or UAV-assisted Wireless Power Transfer (WPT), UAVs can send Radio Frequency (RF) signals to recharge batteries and the UAV-assisted Simultaneous Wireless Information and Power Transfers (SWIPT) (Pakrooh; Bohlooli, 2021).

2.2.1 Precision Farm UAVs Applications

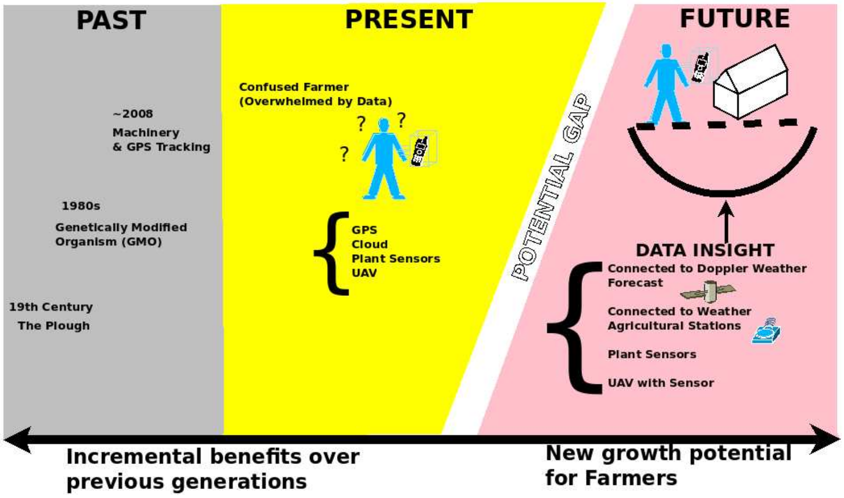
The agriculture sector significantly impacts Brazil's economy (FAO, 2022). The agriculture activities of automation can lead to sustainable productivity gains, reducing land use and deforestation (an undesirable ecological outcome).

Drones can be considered robotic tools that can enhance agriculture's productivity alongside other autonomous machines such as harvesters, planters, and irrigators. By allowing for more uniform and precise seeding and spraying, drones enable farmers to manage their crops better. Additionally, they facilitate monitoring of irrigation systems, crop coverage, and water stress, while also supporting animal and livestock management tasks, including locating animals, detecting sick ones, reading tags, and maintaining fences and water points (Fathallah; Abid; Hadj-Alouane, 2017; Rahman et al., 2021).

Figure 2.4 presents the evolution of agriculture over recent decades, from manual labor with plows to the use of cell phones, mobile networks, sensors, and IoT technologies today. This transition gave rise to precision agriculture (PA), simplifying decision-making by optimizing factors such as water and fertilizer application across different plantation sectors .

In agriculture, drones can collect data using sensors and obtain information through images. This step is important so farms can make data-driven operational decisions. Literature reports drone applications for PA as herds and crop monitoring, image capturing, seeding, fruit

Figure 2.4: Agriculture Evolution



Source: adapted from (Fathallah; Abid; Hadj-Alouane, 2017)

harvesting, and spraying with the correct quantity and location. (Fathallah; Abid; Hadj-Alouane, 2017; Hartanto et al., 2019; Radoglou-Grammatikis et al., 2020)

The Brazilian Agriculture and Livestock Federal Goverment Ministry (MAPA) ordinance MAPA Nº 298 is a Brazilian law that regulates the UAV operation for spraying, spreading, and fertilizing (Brasil, 2021).

The utilization of agriculture drones is constrained by several challenges, including privacy concerns, intricate farming environments, environmental challenges, and difficulties maintaining long-distance positioning and communication. Moreover, unexpected users can disrupt the data link connection between drones and the base station, compromising the stability of the swarm system. Furthermore, nano and micro drones are not ideal due to their limited battery capacity and weight-load capacity (Rahman et al., 2021).

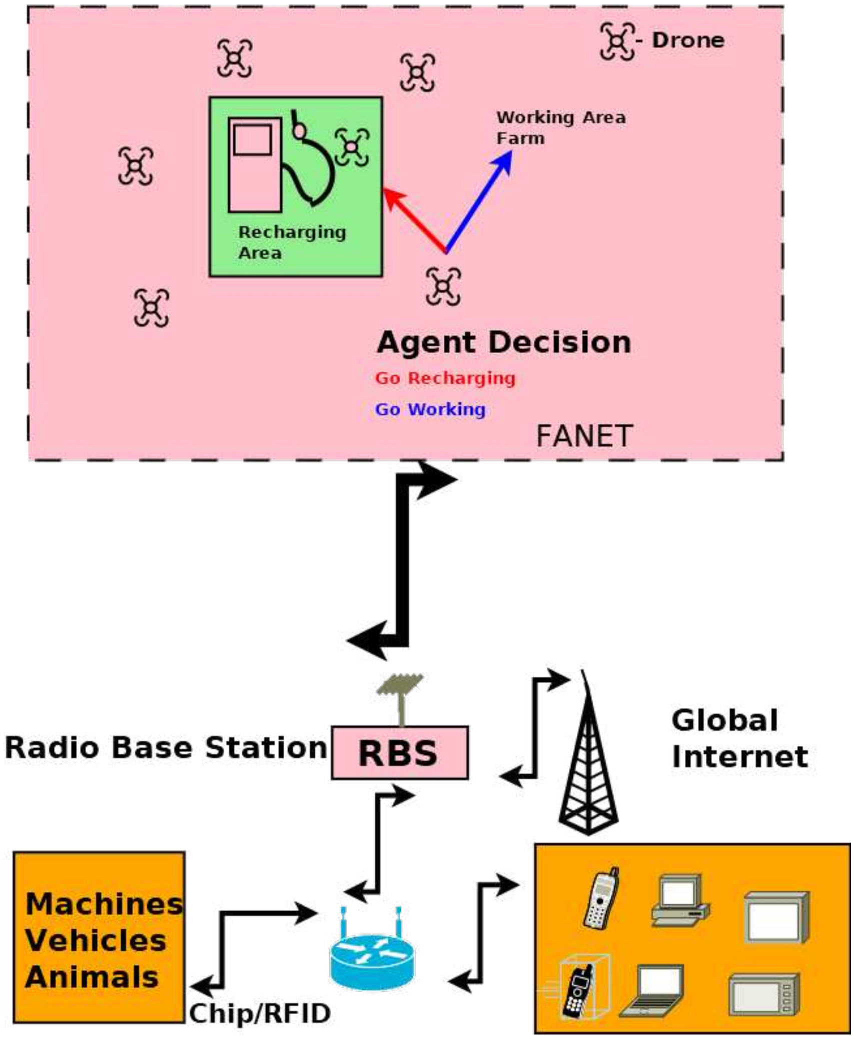
This difficulty in controlling and coordinating drones is another favorable aspect of the swarm and decentralized recharging approach proposed in this work.

Figure 2.5 presents a connected farm concept that integrates all equipment with a Radio Base Station (RBS), which serves as a central hub linking the farm to the internet, showing the communication flow between the RBS, the farm equipment, and external entities.

The 4G and 5G networks enable seamless connectivity between employees, equipment, and suppliers via the RBS. This facilitates communication and allows the connected farm to adopt Industry 4.0 context, featuring autonomous systems such as tractors, harvesters, irrigators, and drones.

Radio Frequency Identification (RFID) chips can enhance security and authentication if applied in animal tags and necklaces, serving as unique badges for employees and machines.

Figure 2.5: Connected Farm Concept.



Source: Author elaboration

2.2.2 Disaster Relief UAVs Applications

Drones and advanced mobile networks, including 4G and 5G technologies, can play a crucial role in facilitating natural disaster recovery efforts (ITU, 2014). Recovery processes can occur during and immediately after a disaster event, which can be caused by various factors such as earthquakes, tsunamis, storms, dam failures, hillside falls, and flooding - all of which are increasingly frequent due to global warming.

Smartphones can serve as early warning systems, notifying populations about impending disasters and providing critical escape routes. Drones can provide additional assistance, capturing visual evidence of the affected areas and emitting audible alarms to alert people of potential dangers. Furthermore, drones can film and transmit high-quality photos and footage, enabling comparisons of "Before and After" scenarios to assess the extent and severity of the disaster (ITU, 2014).

The information flow from smartphones during the disaster can also be leveraged to improve situational awareness, with timely updates providing critical insights for responders and affected communities. Moreover, accurate modeling and simulation of drone battery recharging and duration can provide valuable data on achieving critical missions assigned to these devices, ensuring optimal performance in emergencies (ITU, 2014).

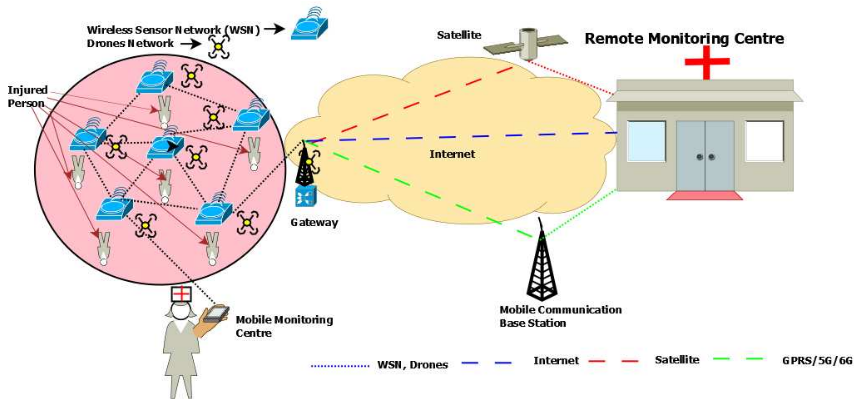
Authors from (Horio et al., 2019) propose a simulation method using drones to recreate disaster scenes, where drones can perform various tasks, such as detecting fires and rescuing people, as well as transferring information and even recharging their batteries when necessary.

Their approach employs the Bias and Raising Threshold (BRT) algorithm as its policy framework. In BRT, distributed agents can make autonomous decisions without a central leader, allowing for decentralized decision-making. This is similar to the concept described by (Arthur, 1994), where agents have limited communication capabilities, as this work is also inspired. The authors use a scoring system to simulate the health and performance of each drone, enabling them to compare and evaluate their effectiveness in various scenarios.

Figure 2.6 shows the use of IoT environmental sensors, as humidity, displacement, pressure, temperature sensors, and disaster victim vital signs sensors, such as smartwatches with temperature, blood pressure, oxygen, and glucose level, heart rate measurements can be used to predict the occurrence of accidents and identify which patients' care need. However, population alert failures are a major contributor to disasters, resulting in many deaths. To mitigate this, sirens, smartphones, and alarms can alert the population, emergency, and government bodies, which include governments, states, city halls, fire departments, and civil defense agencies. In addition, escape route panels, cell phone signals, and drones can provide critical information to guide disaster victims toward the safest evacuation paths, thereby reducing fatality rates (ITU, 2014).

Moreover, drones can also be equipped with advanced sensors to identify the most affected areas by a disaster and provide real-time information on alternative routes to reach specific locations. By issuing drone warnings, authorities can alert populations in high-risk zones to evacuate the area quickly.

Figure 2.6: Disaster Recovery Scenario.



Source: Adapted from (ITU, 2014)

2.2.3 Dengue Mosquito disaster Flight UAVs Application

In 2024, Brazil remained vigilant in response to the ongoing dengue virus epidemic, driven by the rapid spread of Aedes aegypti mosquito outbreaks. The country reported a significant public health crisis, with 6,041 deaths and an estimated 6,666,336 probable disease cases (Brasil, G. F., 2025).

The explosion of dengue cases was attributed to climate change that induced the rising of temperatures and increased rainfall. The Aedes aegypti mosquitoes, the primary vector for dengue, also transmit other infectious tropical diseases, including Chikungunya and Zika virus. (Amarasinghe; Wijesuriya, 2020).

A significant proportion of Aedes aegypti mosquito breeding sites are found within residential areas, with approximately 75% located in homes, backyards, gardens, and rooftops. Given the importance of identifying these breeding sites to prevent dengue transmission, drones can be utilized for visual pattern recognition and spot identification (Brasil, G. F., 2024).

In the fight against dengue, the literature suggests two primary approaches to utilizing drones:

1. monitoring new breeding sites using aerial imagery to detect Aedes Aegypti mosquito populations (Amarasinghe; Wijesuriya, 2020; De Mesquita et al., 2021);

2. deploying drones to release sterile male mosquitoes, thereby disrupting the insect's reproductive cycle (Ackerman, 2017; FAPESP, 2024).

Therefore, this simulation could also evaluate how to improve the drone's flight time, resulting in an improved capacity for searching for more dengue spots and delivering more sterile Aedes aegypti mosquitoes.

2.3 UAVs Energy Supply

Drones' flight time capacity is a main issue in the swarm application. Improving battery or energy technology, their energy replenishing supply, or improving coordination can extend the drone's flight time.

2.3.1 UAV Energy Types

Drones' energy supply can be done by electric battery storage, solar photovoltaic, Power line tethering, super capacitor, fuel cells, wireless power transfer (Shehu et al., 2021), wind shear layer (using earth gravity), laser beam recharging methods (Pham et al., 2022), Internal combustion engine (ICE) (Boukoberine; Zhou, Z.; Benbouzid, 2019).

Electric Unmanned Aerial Vehicles possess several desirable characteristics, including zero pollutant emission, self-starting capabilities, exceptional maneuverability, reduced noise levels, and minimal thermal signatures. In contrast to electric-powered UAVs, ICE-powered drones offer higher power and energy density. This results in improved endurance capacity, as the drone can sustain longer flights with less recharging or refueling. However, this advantage comes with increased complexity in ICE control, necessitating an auxiliary starting motor to facilitate start-up. Internal combustion engines produce high emissions and thermal signatures, posing potential environmental concerns (Boukoberine; Zhou, Z.; Benbouzid, 2019).

UAV batteries have limitations such as low energy density and lengthy charging times. Using more batteries can reduce the overall drone's dynamic capacity. Supercapacitors can provide high power density and quick peak power during takeoff and sudden maneuvers (Boukoberine; Zhou, Z.; Benbouzid, 2019).

Another solution is the use of fuel cells. This energy source has a high specific energy output, an estimated 10 hours flying capacity, and better refueling capacity than traditional battery recharging (Pakrooh; Bohlooli, 2021).

In addition to these solutions, drones with fixed wings can harness photovoltaic energy by incorporating solar cells. This technology allows the drone to generate power from sunlight during flight (Boukoberine; Zhou, Z.; Benbouzid, 2019).

Hybrid energy architecture has the advantages of both energy supply types. This type of architecture needs an Energy Management System (EMS), to control the onboard power to achieve the mission requirement (Boukoberine; Zhou, Z.; Benbouzid, 2019).

A laser beam can be used to recharge a drone battery remotely. In this method, a generator sends light power to a flying drone. Tethered UAVs can have unlimited endurance due to their continuous wire connection from a ground station. (Boukoberine; Zhou, Z.; Benbouzid, 2019).

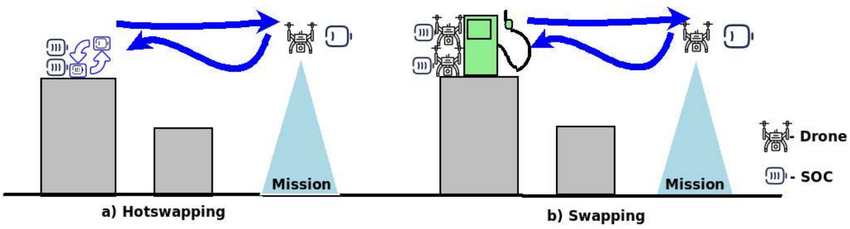
2.3.2 Drones Battery recharging techniques

Battery-powered drones can fly for an average of about 20 to 30 minutes (Mohsan et al., 2022), and this autonomy can be extended by battery recharge using the battery swapping methods.

The UAV battery recharging process can be done by Hot Swap, as shown in Figure 2.7-a, with an exchange of drained batteries for charged batteries. Figure 2.7-b presents the Swap that was the battery recharging, by exchanging drones with low battery charge with other charged drones. The drained battery drone will enter the recharging process (Campi et al., 2019; Boukoberine; Zhou, Z.; Benbouzid, 2019; Williams; Yakimenko, 2018; Delgado; Bergel, 2019).

A swapping process comprises the battery swap station, the available batteries, and a control system to manage the swarm of UAVs (Mohsan et al., 2022).

Figure 2.7: Battery exchange techniques,



Source: Adapted from (Campi et al., 2019)

The recharging process can be done using a wireless recharging pod (Jung; Ariyur, 2017; Jawad et al., 2019).

This work simulation model considers the hot-swapping method. The drones have a battery's internal energy charge quantity (SOC) value. The SOC range is between 0 and 100%.

In each simulation run drones lose some of this SOC value, and if they achieve 0%, they will stop working by starving.

2.4 Simulation

Simulation can be defined as a process of building a model of a system containing a problem and conducting model experiments on a computer for the specific purpose of solving it. A model can be defined as a representation or abstraction of anything such as a system, concept, problem, or phenomenon.

A model can have inputs, parameters, and outputs. A system contains the problem to be solved. (Balci, 1994), or be considered an intelligible, artificial, symbolic representation of situations (Bouquet; Chipeaux, et al., 2015).

During a simulation, an artificial history of the system is generated, with the main points investigated, and it is possible to develop inferences of the operating characteristics of the real system represented. Simulation can be used to describe and analyze the behaviors of a system and a problem-solving methodology for many real problems (Banks, 1998).

A model should be complex enough to answer the modeling question and can be classified as dynamic if the time passage is important, or static if it is considered a fixed point of time (Banks, 1998).

When a real-world system is abstracted in a conceptual model, it is verified whether this representation is accurate using two iterative components: verification and validation. The verification process is the determination of whether the computer conceptual implementation was correct, and the validation process determines if the conceptual model can be replaced by the real system for experimentation purposes.

2.4.1 Agent-Based Simulation Modeling

A complex system comprises multiple individual elements that interact, and their behavior or properties are not predictable from each component. The whole can be more than the sum of the parts (Wilensky; Rand, 2015).

A complex system is one in which broad networks of components without central control and simple rules of operation can rise to complex collective behavior, with internal and external sophisticated information processing, and with adaptation capacity via learning or evolution processes. (Mitchell, 2009)

Six characteristics can define a complex system (De Domenico; Sayama, 2019):

1. Interactions – Complex systems components interact with each other and their environment in several ways;

2. Emergence – The properties of whole complex systems are different and sometimes unexpected, from the sum of the properties of the individual components, or “the whole is more than the sum of its parts”;

3. Dynamics – This system tends to change its states dynamically also presenting unpredictable long-term behavior;

4. Self-organization – Complex systems can self-organize producing spontaneous and non-trivial patterns without a blueprint;

5. Adaptation – A complex system can adapt and evolve.

6. Interdisciplinary – Can be used in managing and understanding various systems in several domains.

Examples of complex systems are insect colonies, stock markets, pandemics, the immune system, the brain, ecosystems, economies, human societies, and the World Wide Web (Mitchell, 2009; Janssen, 2020).

Approaches like difference and differential equations, also known as Equation-Based Modeling (EBM), complex systems, and agent-based modeling can be used to study complex systems (Janssen, 2020).

Comparing ABM with other modeling approaches, like equation-based models (EBM), the ABM has some advantages, such as the ability to consider heterogeneous and discrete population elements. ABM doesn’t require prior knowledge of the aggregate phenomena, unlike EBM. ABM’s results are more detailed than EBM’s because they can provide micro (for individuals) and macro (aggregate level detail) results. ABM provides a rich and detailed description of a system’s process during the simulation time, not only the final states of the system (Wilensky; Rand, 2015).

Agent-Based Modeling (ABM) can be defined as computational modeling that's a complex system that is modeled considering agents and their interactions. The ABM aims to create agents and rules to generate a target behavior (Wilensky; Rand, 2015).

Three elements compose an agent-based model: the agents, the environment, and their interactions (Wilensky; Rand, 2015).

Agents are the basic units of agent-based modeling. They can be defined as autonomous computational individuals or objects with specific properties (agents' current state) and actions (agents' behavior) (Wilensky; Rand, 2015). The authors (Bouquet; Chipeaux, et al., 2015) define agents as physical or virtual entities with some characteristics such as being able to act in an environment, communicating directly with other agents, having skills, and offering services. (Wooldridge, 1997).

Different types of agent cognition can be found in agent modeling such as reflexive agents, which follow if-then rules, utility-based agents, which try to maximize a utility function, goal-based agents, and adaptive agents which change their strategies based on prior experience. (Wilensky; Rand, 2015).

The environment is the conditions and the habitats that surround the agents. The environment can be affected by agent decisions. Several types of environments, such as a geographic information system (GIS), 3D worlds, Network-based Environments, several boundary conditions (topologies), square lattices, and hex lattices can be used in the ABM modeling (Wilensky; Rand, 2015).

Five types of interaction classes are found in the Agent-Based Modeling, agent-self (e.g., the agent considers its current state and decides what to do), environment-self (environment alters or changes themselves), agent-agent (e.g., agent communicating with other agents), environment-environment (e.g., diffusion), and agent-environment (agent examines and manipulates part of the world in which it exists, or when the environment affects the agents) (Wilensky; Rand, 2015).

(Wilensky; Rand, 2015) describe eight main uses for agent-based models:

1. **description** of a real-world system. Models are simplified descriptions of the real world.;

2. **explanation** of essential mechanisms underlying a phenomenon, or clarify the power of emergence.;

3. **experimentation**. Models can be run to verify their dynamics and outputs.;

4. providing sources of **analogy**. Find similarities with other models already modeled that appear to be different;

5. **communication/education**. ABM can expand static knowledge, allowing students to conduct experiments;

6. providing **focal objects** for scientific dialogue. The ABM is considered as a “glass box”, in opposition to “black box” models;

7. as **though experiments**. Models such as cellular automata, fractals, and particle swarms are examples of phenomena that do not represent real-world phenomena but can be simulated in ABM.;

8. **prediction**. ABM can be used to discuss future results of a complex phenomena model.

And this approach has benefits of the ABM (Wilensky; Rand, 2015) as:

- ABM can be used to model any natural phenomenon;

- agent-based models are more useful when used to model a medium of (ten to millions) of interacting agents;

- agent-based models are more useful when the agents are not homogeneous, and the heterogeneity of the agents affects the overall performance of the system;

- ABM is useful when the interaction between agents (agent-to-agent) and agents’ interaction with the environment is complex;

A trade-off of using ABM is that the rich individual-level data details can be computationally intensive and can require the modeler to have a great knowledge of the low-level elements (Wilensky; Rand, 2015).

Agent-based modeling was used in several fields, such as chemistry, biology, material science, psychology, sociology, physics, business, medicine, economics, anthropology, philosophy, history, and law (Wilensky; Rand, 2015).

Agent-based simulation has two levels of results that describe the interactions between entities. The micro-level results describe a simple local behavior, and the macro-level, derived from the micro-levels, describes the interaction of more elements (Remondino; Correndo, 2006).

Agent-Based Modeling Simulation Software

In this work, using the software NetLogo (Wilensky, 1999). NetLogo is considered as a "low threshold" when novices can quickly employ it to do meaningful and useful things, and a "high ceiling" that scientists and researchers can use to designate cutting-edge scientific models (Wilensky; Rand, 2015).

The authors (Abar et al., 2017) made a state-of-art evaluation of 83 Agent-Based Modeling Simulation Software, regarding their computational modeling strength (their scalability level), the model development effort, the type of agents based on its interaction behavior, and the program scope or domain.

The NetLogo (Wilensky, 1999) was considered to be a simple/easy model development effort, with a medium/broad modeling strength and with active objects with simple goals implemented as mobile agents (turtles, patches, links, and the observer) (Abar et al., 2017).

Agent-Based Modeling Simulation Programming Documentation

Formalizing a model aims to gain an understanding of the system, abstracting not only technical considerations about the simulation components, and generating the code, by the transition from model to implementation. The documentation of a model is fundamental to the mobilization, understanding, and sharing of knowledge and its efficient usage (Bouquet; Sheeren, et al., 2015).

Formalizing a model can (Bouquet; Chipeaux, et al., 2015):

- Instructive description of knowledge obtained using the model;
- Explaining the structure and operation of the model without ambiguity;
- Taking the multiplicity of model users' expertise into account;
- Describe the meta-knowledge (e.g., model's hypotheses) of the model;
- Making the replication model possible;
- Working alongside the model development cycle, the writing and reading model, and their submodels;
- Developing model visualization resources.

(Bouquet; Sheeren, et al., 2015) describe three modeling tools that can be used to formalize Agent-Based Models. The Unified Modeling Language (UML), Agent Modeling Language (AML), and Overview, Design Concepts, and Details (ODD) Protocol.

UML is generally oriented to object programming, and AML supplements UML with agent concepts. Both implementations are good examples of how to describe a model visually.

The authors (Grimm; Berger; Bastiansen, et al., 2006) presented the Overview, Design Concepts, and Details (ODD) protocol as a formal way to describe agent-based models. According to (Bouquet; Sheeren, et al., 2015) ODD is the current standard manner to explain and communicate an agent model.

Table 2.2 presents the ODD protocol has three blocks (Overview, Design Concepts, and Details) and 7 elements (Grimm; Berger; DeAngelis, et al., 2010)

Table 2.2: ODD Blocks and Elements Protocols

Blocks	Elements	Description
Overview	Purpose and Patterns	Description of the model's question or hypothesis and their use.
	Entities, State Variables, and Scales	Description of the model's entities, state variables, and attributes.
	Process Overview and Scheduling	List of the processes that build the model and their scheduling.
Design	Design Concepts	The model's design characteristics, including basic principles, emergence, adaptation, objectives, learning, prediction, sensing, interaction, stochasticity, collectives, and observation.
Details	Initialization	Description of the simulation parameters and their initial values.
	Input Data	Input data that needs to be defined.
	Submodels	A mathematical or full description of the submodels.

Source: Adapted from (Grimm; Berger; DeAngelis, et al., 2010)

2.5 Verification, Validation & Testing Techniques.

The Model Verification, Validation, and Testing techniques are an important and necessary methodology to be used during the life cycle simulations studies to avoid the three main errors when conducting simulation studies (Balci, 1994):

1. Error type I – Reject the model credibility when the model is sufficiently credible. Also, known as the model builder's risk;

2. Error type II – Accept the model credibility when in fact the model is not sufficiently credible, or the Model User's risk;

3. Error type III – Error of solving the wrong problem.

The consequence of error Type I is that it increases the model development costs. In the cases of error type II and III, the consequences can be catastrophic. (Balci, 1994)

The model validation process ensures that the model behaves satisfactorily and consistently with the study objective. This technique checks whether the model is built correctly.

The model verification process checks whether the model is built with sufficient accuracy or if the computerized model is implemented correctly. Model Testing demonstrates if there exist some inaccuracies in the model under several situations. Testing is conducted to perform validation and verification model process (Balci, 1994), (Sargent, 2010).

There are several validation techniques according (Sargent, 2010), as listed next:

- Animation – operational behavior graphically displayed as the model moves through time.
- Comparison to other models – simulation output models are compared to valid results from differents models.
- Event Validity – This assessment involves comparing the simulated "events" of occurrences in the model with those that occur in the real-world system, to determine their similarity.
- Extreme Condition Tests – The model structure and outputs should be plausible for any extreme and unlikely combination of levels of factors in the system.
- Face Validity – Individuals with system expertize are asked whether the model and/or its behavior are reasonable.
- Historical Data Validation – If historical data exist, part of the data is used to build the model and the remaining data are used to determine (test) whether the model behaves as the system does.
- Internal Validity – Several replications (runs) of the stochastic model are made to determine the amount of (internal) stochastic variability in the model. Lack of consistency can result in a questionable model.
- Parameter Variability or Sensitivity Analysis -changing the values (qualitatively or quantitatively) of a model input and internal parameters to determine the effect upon behavior or output.

The author (Kleijen, 1999) proposes three approaches using statistical techniques to validate simulation models according to real-life data availability.

If no real data is available, the author suggests using the Design of Experiments (DOE) approach to detect simulation errors and interaction among the factors. In the case of real data, output data indicates the usage of a two-sample t-student statistic for normal data or distribution-free test in the non-normality. If the input and output real data are available, he recommends regression analysis usage.

Regarding the Agent-Based Models (ABM) some validity issues can be found as multi-level properties with a missing link between the micro and macro system level. their non-linearity, number of assumptions, over-parametrization, level of details, and the lack of appropriate data statistical validation (Klügl, 2008).

The author (Klügl, 2008) proposes a validation framework for Agent-Based Models with these steps:

From a run-able model, a face validation can be performed using animation assessment – A human with process expertise assesses the animation of the overall simulated system (or parts of it) and whether the simulated system appears to behave like the original system, the output assessment.

A sensitivity analysis can evaluate the effect of the different parameters and their values. In ABS, scaling problems can happen because of the number of parameters (high level of detail). Based on this analysis, a simpler model can be implemented by deleting parameters without effect and connected parts, resulting in a minimal model.

Calibration model parameters have to be set so that a structurally correct model produces a valid outcome. In ABS, until the size and missing data, how to deal with problematic reasonably parameter structure and how to avoid the tuning trap, resulting in a calibrated model

That can be performed through statistical validation, which must use different data sets to ensure that the model is not merely tuned to reproduce given data but may also be valid for inputs that it was not provided before, resulting finally in a deployable model.

(Remondino; Correndo, 2006) describes three macro areas for validation. The **empirical validation** was based on comparing the results obtained from the model and the real system. The **predictive validation** that evaluates the results of a model will have validity in situations that aren't observable in the real world, and the **Strutural validation** that assesses how the results are obtained. A model should be examined and decomposed, evaluating that the interaction parts are identical to the corresponding real parts.

2.5.1 ABM Analisys Methodology

Machine Learning and Data mining can be used in agent-based simulation context in endogenous modeling when these tools provide a sort of intelligent behavior to agents, e.g., when agents evaluate past results to improve future behaviors and exogenous modeling, when the final results of a simulation are analyzed using data mining techniques to find patterns. Data mining tools can support a model building based on statistical evidence to validate or refute the system's hypothesis (Remondino; Correndo, 2006).

The authors (Remondino; Correndo, 2006) describe the analysis of variance (ANOVA) to discover unknown relationships between the variables of the system, linear regression to estimate a linear conditional relation between the independent variables and the free variables, multiple regression, to find relationships between variables of a system as ANOVA, cluster analysis to retrieve some collections of individuals whose behavior is alike, and the association rules, to find regular patterns to describe categorical data and find patterns using "if-then" rules.

The authors (Broeke; Voorn; Ligtenberg, 2016) study three sensitivity analysis approaches. The extended One-factor-at-a-time (OFAT), proportional assigning of output variance employing model fitting and the means of Sobol's decomposition. Agent-based models have some properties such as multiple levels, nonlinear interaction, and emergent properties, making classical methodologies for sensitivity analysis not always sufficient. The sensitivity analysis in ABM can be used to evaluate how patterns and emergent properties are generated in ABM, examine the robustness of emergent properties, and quantify the variability in ABM outcomes model parameter changes. The authors evaluate these three sensitivity analysis techniques in terms of three aims. For the examine patterns aim, the OFAT and regressions-based methods were recommended, as in the examination of the robustness aim. The authors suggest the regression-based and Sobol methods to quantify outcome variability due to parameters. But some restrictions can restrain any usage.

2.6 Modeling Approaches

2.6.1 Baseline Approach

The baseline model aims to imitate the common recharging procedure similar to a normal recharging process of a cell phone or car refueling when the energy reaches a determined threshold. This work considers this recharging coordination process the simplest way an agent makes their recharging decision.

2.6.2 Game Theory Approach

This work simulation's model uses as internal logic an adapted El Farol Bar Problem (EFBP) (Arthur, 1994) process decision algorithm. This process internal algorithm model was inspired from (Rand; Wilensky, 2007) NetLogo's EFBP default models library model. This model are used to avoid logic verification problems, but other algorithms will be used in future work development to make process decisions.

The EFBP has already been used in some congestion problems as reported in some literature:

- (Challet; Zhang, Y.-C., 1997) Simplification of the EFBP approach using the $EFBP$ comfort threadshold B is the half of the simulation agents quantity N in a model called Minority Game. In this model, the agents want to choose the side with fewer agents.
- (Sharif; Huynh; Vidal, 2011) - A terminal gate congestion problem is modeled using the EFBP. The authors also use NetLogo to model the problem.
- (Manrique; Johnson, D.; Johnson, N., 2017) Drone Systems congestion simulations using minority game and many-body physics.
- (Grando; Ursini, E. L.; Martins, P. S., 2020) Drone Swarm recharging simulation using EFBP approach. Because EFBP agents don't use information collusion about their recharging decisions, this can result in less battery usage. The current work has detailed improvements below regarding this work. More details in Appendix A.

This problem was developed to study a method to apply inductive rationality against deductive rationality in economics. Perfect and logical deductive rationality was great for solving theoretical problems, but human rationality behavior is bounded. Humans are superb at pattern recognition, hypothesis formation, deduction using these hypotheses, changing these hypotheses when needed, and discarding lower-performance strategies (Arthur, 1994).

In this model, N agents want to decide whether to go to a bar each party's night. El Farol bar space is limited, and agents only feel comfortable with a ratio B of N. There is no collusion or communication about agents attending decisions.

The unique information agents have for their decision is the last m week's bar attendance history. With this history, agents use their k internal estimators to evaluate and compare the best performance estimator. This performance comparison is made by the k estimator's values calculation errors, considering the last m week's values.

The best-performed estimator value is used to decide the bar's attendance decision. If the agent's best estimator predicts that the attendance decision is less or equal to B, the agent will attend the next bar event, otherwise, they will not participate and stay at home.

The original EFBP paper doesn't describe the agents' predictors used in the paper's simulation, (Arthur, 1994) named some possibles as the same as the last week's, a mirror image of the last week's, a rounded average, the same as the previous 2 weeks ago.

(Rand; Wilensky, 2007) NetLogo's model uses auto-regressive (AR) estimators, with some defined weights before simulations start. This is the same approach used in this Thesis simulation model.

About original papers results, (Arthur, 1994) uses $B = 60$ and their bar mean attendance convergence outcomes to these values, considering as a natural "attractor" of this problem. Another outcome is a Nash equilibrium in which an average of 60% of the population forecasts below the mean attendance value and 40% above 60.

Chapter 3

Development

This chapter describes the methodological development to answer the two thesis research questions. The first research question is about the current literature status-of-art of drone research coordination process in agriculture and disaster relief recovery context. For this, a systematic literature review was conducted. The second research question is about the development of a drone swarm agent-based simulation model description and the model and parameter descriptions. This is done using the ODD Documentation protocol and the experiments' description and performance indicator development.

3.1 Systematic Literature Review Methodology and Results.

This section is based on our full paper (Grando; Jaramillo, et al., 2025b) published in January of 2025 in Multidisciplinary Digital Publishing Institute (MDPI) Drones Journal.

This work aims to evaluate the state-of-the-art of these two applications and the energy supply recharging coordination procedure using a Systematic Literature Review process based on (Kitchenham; Charters, 2007) developed for SLRs in Software Engineering. A Systematic Literature Review (SLR) is a secondary study that identifies, analyzes, and interprets all available evidence from primary studies related to a specific research question. A systematic literature review process involves planning, conducting, and reporting the review activities. The tool used to perform this SLR is the Parsifal (Freitas; Segatto, 2024) to conduct this research.

The review aims to study two SLR research questions. The first research question of the systematic literature (SLR-RQ1) concerns the application context, and the second (SLR-RQ2) is related to the energy supply methods found in the selected study.

3.1.1 Literature Review

The SLR process is performed in three phases:

- Define the need for the review, and perform the planning of the review.
- Conducting the Review to get as many primary studies related to the research question.
- Reporting the Review. This phase focuses on writing the results of the SLR and publishing them to the interested parties

3.1.2 Planning Phase

The SLR study research questions were:

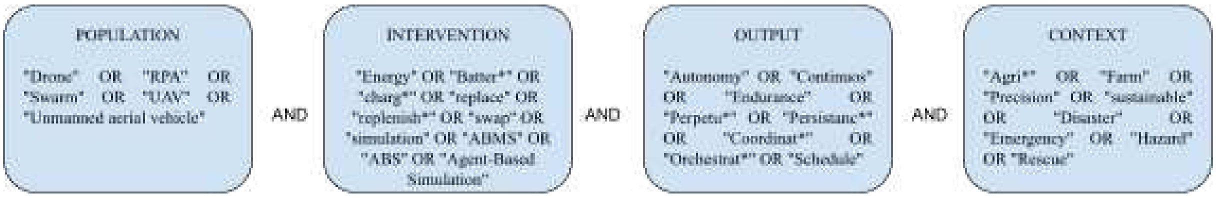
- SLR - RQ1: What disaster or agriculture context is described in the literature?
- SLR - RQ2: What types of energy mitigations were used in the studies?

Three databases are chosen for article searching: the Institute of Electrical and Electronics Engineers (IEEE) Digital Library (Electrical; Electronic Engineers, 2024), Scopus (Elsevier, 2024), and Web of Science (Clarivate, 2024).

For the keywords strategy, the Population, Intervention, Outcome, and Context (PIOC) keyword strategy is used as shown in Figure 3.1. The PIOC strategy is derived from the PICOC strategy but without the comparing term.

- Population terms include items related to the object of study;
- Intervention terms include energy supply and simulations;
- Context terms are related to agriculture and disasters;
- Desired outcome terms are related to autonomy and the coordination process.

Figure 3.1: PIOC search string strategy.



Source: Author elaboration

Table 3.1: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Articles that use Simulation based on agents or other techniques	Studies that describe energy method generations
Studies that present ways for UAV continuous flight	retracted articles
Studies that present ways to supply UAV energy	not aerial devices
Studies that present disaster context UAV simulations	Studies about device communication
Studies that present farm context UAV simulations	Secondaries or tertiary studies
Studies about IoT devices coordination problem	Studies published out of time range (2017 to 2023)
	Duplicated studies
	Out context studies
	Studies that languages are not English
	Grey literature (Manuals, reports, theses, dissertations)
	Conference Proceedings
	Short Paper (less than 4 pages)
	Studies not available for download

Source: Adapted from (Grando; Jaramillo, et al., 2025b)

Table 3.1 presents the 6 inclusions and 12 exclusion criteria used in the initial screening of papers found using the PIOC keyword in the three databases.

The selected studies are fully read, and a quality assessment (QA) checklist is performed to select the study that most adheres to our research questions. The quality questions have three answer levels: "Yes", "Partial", and "No", and their weights are 1, 0.5, and 0, respectively. These three weight values were defined arbitrarily. Table 3.2 presents the seven quality assessment questions:

Table 3.2: Quality assessment questions

Sort	QA questions
1	Does the study include the UAV context?
2	Does the study consider drone recharging simulation?
3	Does the study include use in agriculture or disasters?
4	Does the study include any simulation?
5	Does the study use agent-based simulation?
6	Does this article describe any validation criteria?
7	Data results quality. Is data available? (Source, repositories, and quantity of data)?

Source: Adapted from (Grando; Jaramillo, et al., 2025b)

The quality threshold of more than 5 points is a cutoff for selected articles.

3.2 Model and Parameters Description

In this model, a predetermined quantity (QTY) of drones must make decisions about their actions when visiting a work environment, where they make determined missions such as agriculture spraying treatments, collecting images, and providing connectivity during disasters. or the drones can go to a recharging station. This place has a limited capacity and can accommodate only a fraction of the current working drones.

The variables in this simulation model are related to the problem's demand, the system's recharge capacity, and the agents' decision process.

The demand variables for the swarm of drones were the number of Agents (QTY), the average energy expenditure of each agent (*BC*), and the *BC* standard deviation (*SD*) value.

To supply this energy demand, there are supply parameters as the capacity of the recharging station (*B*), and the amount of energy supplied with each recharge (*BG*).

About the agent decision policies there are two decision-making policies, the base policy (*BL*) and the Charger Threshold (CT) policy.

Figure 3.2 presents graphically the decision process of these policies.

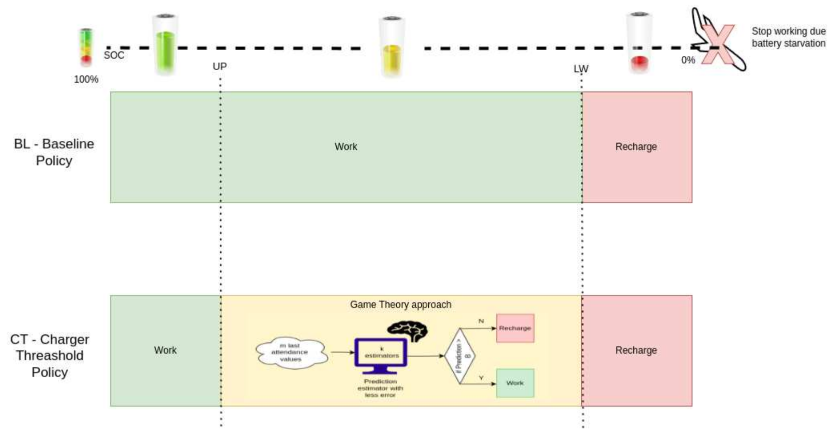
The *BL* policy considers an analogous decision process to fill up a car or recharge a cell phone when these devices' battery energy reaches a critical limit of the amount of energy (*SOC*) each agent has to define whether or not to recharge. This critical limit is called the Lower Reload Limit (LW) in this model.

CT Policy also considers *LW* to recharge, but they also have an upper reload limit UP value, which, if the agent battery is more than this, will not recharge. In an intermediate *SOC* value, the decision process is based on a Game Theory approach called El Farol Bar. In this model, drones watch the attendance recharging place history to make a decision. This history is the number of drones in the last m weeks that tried to recharge their batteries. This information can be sent as a small signal by the Radio Base Station (RBS).

With this information, each agent can use their k internal predictors, which in this model is as autoregressive as (Rand; Wilensky, 2007) model, and calculate the predicted value. The predicted value that has less error using the m last weeks will be used as the internal predicted value.

If the drone's internal predicted value is less than the current *B* value, this agent decides to try to recharge the batteries.

Figure 3.2: Recharge Policy Decision Process



Source: Author

As the charging station has limited positions. If the current number of drones that attended the recharging place is more than the B value, all drones inside will not recharge. This is a model abstraction created to emulate a real recharging case with limited resources.

The drones' *SOC* decreases over time as they experience an abstracted battery consumption (*BC*), which is influenced by various factors such as environmental conditions and operational characteristics. To account for these uncertainties, there are incorporate a normal distribution with standard deviation (*BC_SD*) as a way to simulate random fluctuations in BC.

Additionally, using the NetLogo internal clock's tick unit to represent time in simulation, allowing to track changes in drone *SOC* over discrete time intervals.

In simulation, drones move randomly in a 2D space, according to their decision state, to the recharging or working patches.

The model was divided into two sub-models when the first model (*BL* policy) was a baseline and *CT* a more complex:

- Policy *BL* — Baseline policy: The agent decision was a simple if-then based-rule. If the battery SOC is below a threshold, the drones decide to recharge. This simple model will be used as a baseline to compare future improvements (queue implementation, fuzzy, neural networks).

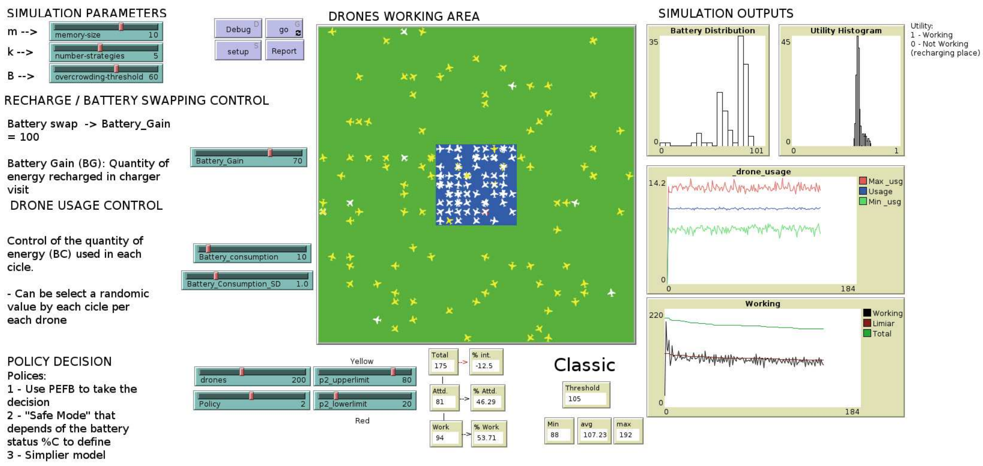
- Policy *CT* — Charger Threshold policy: Use as recharging decision process as the NetLogo El Farol logic but include superior and inferior recharging thresholds. If the drone battery status (SOC) exceeds this superior threshold, they reject the recharging decision and continue working. If SOC is lower than this battery threshold, the drone will try to recharge. This threshold was implemented to improve the fairness of the model.

Policy *CT* uses an inspired NetLogo El Farol bar (Rand; Wilensky, 2007) as a decision algorithm. Differently from (Grando, 2020) work that was different estimators to the decision recharging, in this work, the (Rand; Wilensky, 2007) is used as a well-known model to calibrate the other model differences such as drones' *SOC*, Battery usage, and other parameters.

The experimental model was implemented in the NetLogo, an Agent-Based Model Simulation Software (Wilensky, 1999) in their version 6.4.0.

Figure 3.3 shows a view of NetLogo's experimental model Graphic User Interface (GUI), with simulation control switches, real-time agent position visualization, and simulation outputs.

Figure 3.3: NetLogo Model Interface



Source: Author NetLogo Model

3.3 ODD ABM Model Documentation

In this section, the simulation model was formally described using the ODD paradigm.

3.3.1 Purpose and patterns

This model simulates a swarm of Unmanned Aerial Vehicles (UAV) to guarantee their service continuity. It considers that the drones are working in a swarm and need to decide whether to go or not to refill their batteries.

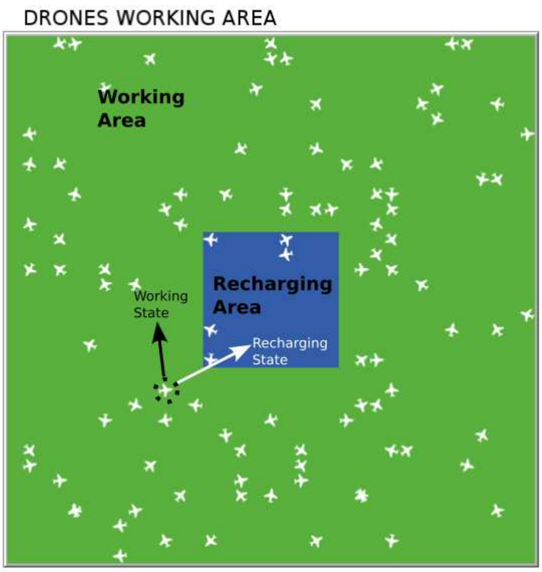
3.3.2 Entities, state variables, and scales

This model has three entity types, the *drones (UAVs)*, *recharging places*, and the *working area*. Drones are the agents of the simulation, and they can have two states:

When the drones are in *working* state, they will make an activity in their neighborhood, e.g. surveillance, internet offer in a remote position, delivery, etc. In this current work development, during this state, the agent movement will occur randomly in some place of the green area in Figure 3.4.

When the *attend* state was selected, the drones go to the recharging place, the blue area in Figure 3.4, to try to recover their energy (under Policy CT) or recharge their battery (all policies).

Figure 3.4: Working and Recharging area Simulation GUI Representation



Source: Author elaboration

In this work, are simulate, the recharging and the battery swap process using the mean quantity of battery slider BC. The recharging place doesn't have a limit on their lot in the recharging place (Policy BL) or an overcrowding limit of B in the case of Policy CT. An initial quantity (QTY) of 100 drones in swarm mode start the simulation.

The simulation/service time is one NetLogo unit of time (tick). Simulate the hot swapping case considering the 100% SOC recharging case because there are no waiting times or queues; in this model, the recharging procedure occurs in a one-time tick.

The environment model topology is a torus with a dimension of 35 x 35 cells. The environment has its sides closed. At the moment, the model doesn't consider any dimensional measure of the cell size because the drone movement was considered randomly. The distance concept is not currently included in this simulation model.

As a temporal resolution, each simulation cycle was called a “tick”, a NetLogo discrete time resolution concept that can be defined in second, minutes, hours, etc. A tick represents a discrete unit of time. In the current state of the simulation, this value is considered arbitrary.

In the future, with literature resources, this value will be calibrated. A possible strategy to calibrate this temporal resolution is using the ratio of the battery capacity and the simulation tick’s mean battery consumption (*BC*). For example, if a drone battery has 20 minutes to be juiced, and the simulation parameter’s Battery Consumption was an average value of 10%, considering each tick as 2 minutes.

Table 3.3 presents the four categories of variable types regarding the agents, the patches, the simulations parameters, and global variables.

The agent’s variables (the drones) decide to go or not recharge their batteries, their x and y coordinates, represented by *xcor* and *ycor* respectively. The drone’s battery level *SOC*, and their simulation *shape*, an internal NetLogo airplane shape.

In NetLogo, a patch is a small area representation, and each small place has an x and y coordinate. Our simulation is 35 × 35 patches (a total of 1225), 81 patches for the recharging area and 1144 remaining patches for the working area.

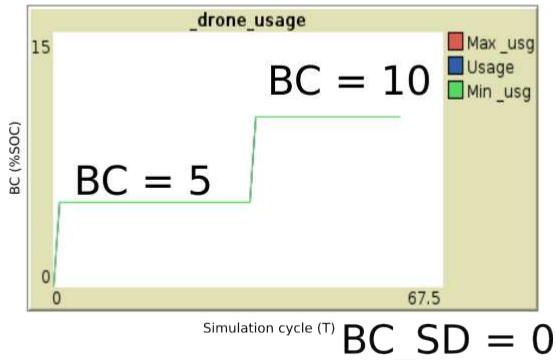
The simulation parameters were the initial drone population is QTY, the two recharging policies, the maximum battery gain per each effective recharging *BG*, the EFBP limit overcrowding-threshold *B* values in case of Policy 1 or 2, the mean battery consumption value in each cycle is *BC* and their standard deviation value is *BC_SD*.

Figure 3.5 shows the mean battery consumption profile for two cases. The vertical axis of this graph is the mean *BC* value and the horizontal axis is the simulation time. When $BC = 5$ %, all drones lose this % *SOC* for each simulation time cycle. The same idea is true to $BC = 10$ %.

This standard deviation value was used to simulate a variation of the necessary power for drone flight in each simulation time. This power usage distribution encapsulated the drone’s real-life usage, such as wind resistance, speed variation, hoover, and other features.

Figure 3.6 shows three *BC_SD* cases for the same *BC* values. The vertical axis represents the mean *BC* consumption the red line shows the max value of *BC*, the blue line is the mean

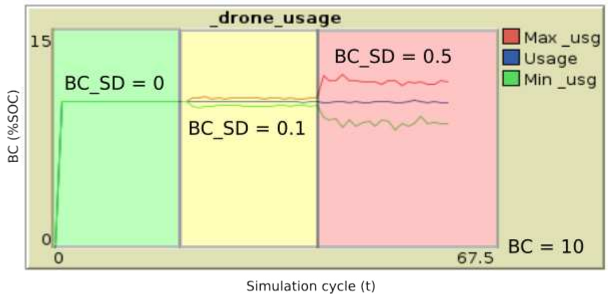
Figure 3.5: Mean battery consumption profiles



Source: Author elaboration

value, and the green line is the minimum value. When increasing the *BC_SD* value, a more *BC* profile diversity was also increased.

Figure 3.6: Battery Standard Deviation differences



Source: Author elaboration

The baseline *BL* policy uses the *LW* value as a recharging threshold. If an agent's *SOC* value is below that threshold, they will go recharging.

The *CT* policy agents use the *UP* and *LW SOC* threshold values to agent's decision taking and the EFBP in an intermediate *SOC* values. The upper value is the SOC Battery limit that the drone doesn't recharge, and the lower threshold forces the drone to recharge if its SOC value is below this value.

Global simulation parameters include the discrete simulation time count tick (t), the number of drones that stop working due to battery starvation *die*, and the total drones that were *working* yet in the simulation.

3.3.3 Process overview and scheduling

Table 3.4 shows the parameters the user needs to define according to their policy decision. The possible value range was already described in Table 3.3.

Table 3.3: Simulation Variables Values

Variable Types	Variable names	Possible values
Agents (Drones)	Attend?	true or false
	Battery level (*SOC*)	0 to 100
	Shape	airplane
Patches (Places)	*xcor*	-17 to 17
	ycor	-17 to 17
	Recharging place	81 patches
	Working area	1144 patches
	pcolor	blue / green
Simulation Parameters	Qtd. drones (QTY)	0 to 100
	Policies	BL and CT
	Battery gain (*BG*)	0 to 100
	% overcrowding-threshold (*B*)	0 to 100
	Available data windows for agent decision (m)	0 to 10
	Quantity of estimators per agent (k)	0 to 10
	Battery Consumption (*BC*)	0 to 100
	Battery Consumption Stand. Dev. (*BC_SD*)	0,1
	CT policy SOC upper threshold (UP)	0 to 100
	CT policy SOC low threshold (*LW*)	0 to 100
Global	step-time (ticks)	0 to 1500
	die	0 to Qty
	Working	0 to Qty

Source: Author elaboration

Figure 3.7 presents the agent's simulation workflow to make their decisions. After program startup, agents check the simulation stop criteria, make their decision about recharging according the select police, check their status, and update simulation global values.

About the internal program working, after the simulations parameter definition using NetLogo GUI, the model *"Setup"* procedure will create the agents and set their internal agents' initial values.

In the *"Go"* procedure, the agents update their cycle battery usage variable, using the procedure *"battery-consumption"* and define if it goes working to recharge using the procedure *predict-attendance* in case of policy *CT* define the prediction value and compare with the overcrowding-threshold *B* values in policies *CT* or compare the drone value with the *LW* in case of BL policy.

Table 3.4: Necessary Parameter Selection to run the Simulation

Description	BL policy	CT policy
Available data windows for agent decision (*m*)	No	Yes
Quantity of estimators per agent (*k*)	No	Yes
Recharging threshold of the total of Agents (*B*)	No	Yes
Battery Upper Threshold (*UP*)	No	Yes
Battery Lower Threshold (*LW*)	Yes	
Quantity of drones	Yes	
Mean Battery consumption (*BC*) % per cycle	Yes	
Mean Battery consumption normal Std Dev (*BC_SD*)	Yes	
Battery Gain in an effective recharging (*BG*):	Yes	

Source: Author elaboration

In the case of Policies *BL*, the simulation uses the *EFBP* auxiliary procedures *"update-strategies"*, *"random-strategy"*, and *"predict-attendance"* from (Rand; Wilensky, 2007) model to try to predict the attendance value and compare with *B* value.

Regarding *CT* policy, the drones will use the LW and UP values as decision support. If the drone's SOC is less than LW, it will go recharging, and if the drone's SOC is more than UP, they don't go recharging, independently of the *"predict-attendance" EFBP* value predicted value. The procedure *"move-to-empty-one-of"* is responsible for moving the drones to the decision place (working or recharging).

The battery level *(SOC)* is also checked in each simulation cycle. Its limit is from 0 to 100%. If it is less than 0% the drone will stop working (the agent dies).

To verify the recharging policy efficiency results in the Working Ratio (UTL), the ratio of times the drone worked.

Figure 3.8 presents the simulation program Unified Modeling Language *(UML)* code diagram. In case of *BL* policy don´t considers the *random-strategy*, *update-strategies*, and *predict-attendance* methods.

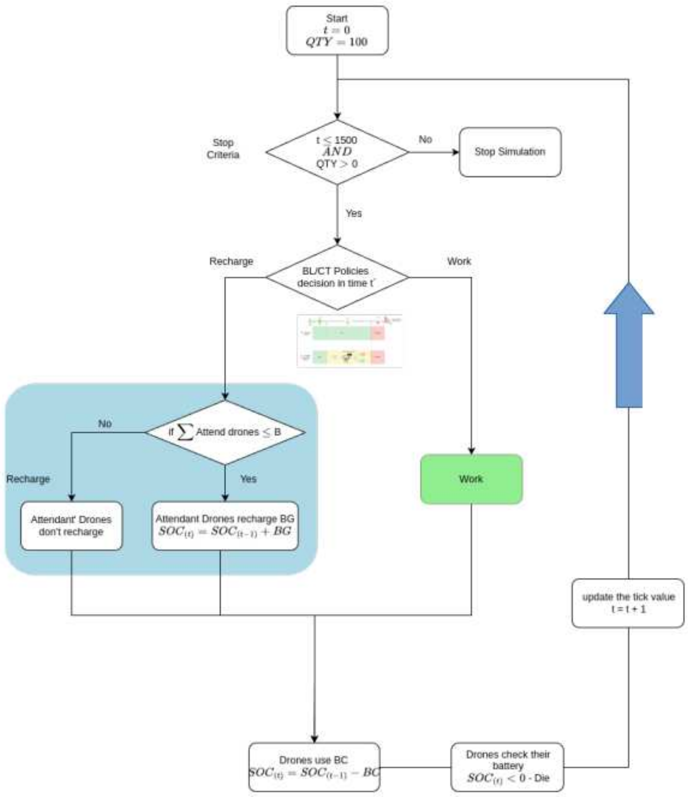
3.3.4 Design concepts

During simulations, CT policy simulation scenario results mimic the *EFBP* (Arthur, 1994) known behavior. More investigations should be done in future works.

3.3.5 Input data

Section 3.4 details the experiment input data. Table 3.5 presents these fixed values according to the policy of recharging chosen.

Figure 3.7: Simulation data flow



Source: Author elaboration

A sensitivity analysis, considering the BC values variation and the size of the recharging place B was performed to evaluate how each policy performs in each case. A total of 12000 simulation runs are performed, considering 120 simulation sets and 100 repetitions.

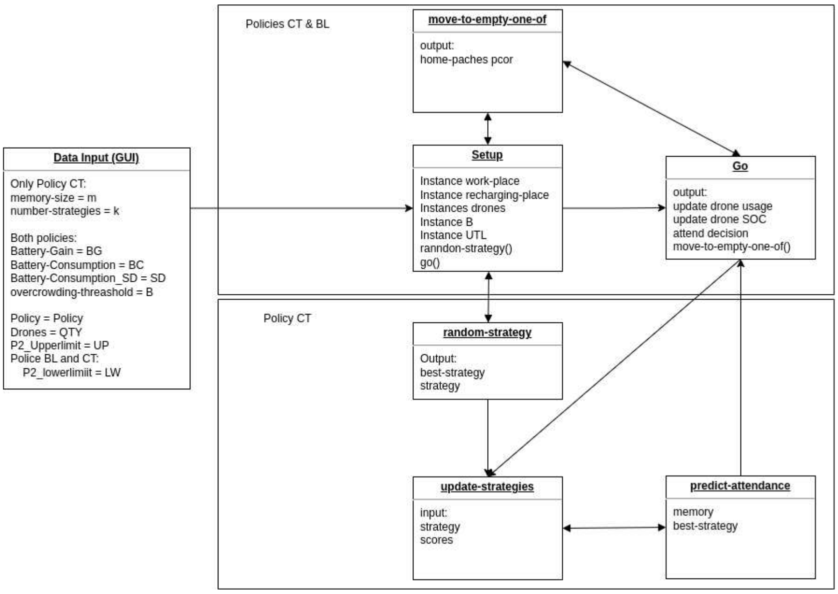
Table 3.6 shows the variable simulation parameter values. There are two policies (BL and CT). The recharging place size **(B)** has four recharging possibilities: 20, 30, 40, and 50% of the QTY value.

The B value varies following the QTY value in each tick. For example, if the B is set to 20% and there are 50 remaining drones, the recharging space is 10.

The Battery Consumption can take 15 values, going from 1% to 15% of SOC. This evaluates how policy behavior is better in different drone usage conditions.

The stopping criterion for each round is no agent with a remaining battery or 1500 rounds of simulation.

Figure 3.8: Simulation Software UML Diagram



Source: Author elaboration

Table 3.5: Experiments Fixed Parameters

Description	*BL* policy	*CT* policy
Available data windows for agent decision (m)	-	10
Quantity of estimators per agent (k)	-	5
Battery consumption normal Std Dev. (SD)	0,1	
Battery Upper Threshold (UP)	-	80%
Battery Lower Threshold (LW)	25 %	
Quantity of drones (QTY)	100	
Experiment time simulation limit	1500 ticks	
Experiments simulation replications	100 runs	

Source: Author elaboration

3.3.6 Submodels

The CT policy submodel uses the El Farol Bar Problem NetLogo library model as an agent internal decision (Rand; Wilensky, 2007). The agents (drones) access the last recharging attendance history, calculate their attendance decision, and compare with B value:

Regarding the original model, several changes and abstractions have been made as described next:

Table 3.6: Experiment Parameters Levels

Variables	Values	Levels
Drone recharging decision Policies	*BL* & *CT*	2
Mean *SOC* decreases in every simulation run *(BC)* % per cycle	1,2,3,...,14,15	15
Ratio of *QTY* that represents the recharging place capacity *(B)*	20,30,40,50	4

Source: Author elaboration

- The two-dimensional area simulates the recharging and the working area;
- The El Farol Bar was now the recharging place (blue area);
- The neighborhood (green area) was the drone's working area;
- Figure 3.4 presents the bar-goers (agents) decision flow if drones want to decide whether they recharge or stay working in each simulation cycle;
- The recharging area has a limit (B) that, in the original model, is the comfort threshold. A model premise is abstracting the idea that the recharging place has limited resources;
- The recharging procedure, when in the El Farol Bar Problem (EFBP) mode, only occurs when the drones' attendance L is less or equal to the B (EFBP "good night" idea);
- In this model, the principal indicator of the model decision is the battery state of the charger (*SOC*) of each agent, and not only the last bar attendance. Because of this, the drones can stop working due to starvation;
- There are two recharging policies (the way that the drones decide if it goes recharging in each simulation circle), one following the $EFBP$ decision and another that depends on the drones' battery *SOC*;

3.4 Experiments Description

The drone recharging environment model experiments were run in NetLogo software version 6.4. NetLogo's Behavior Space simulation was used to perform the sensitivity analysis. Figure 3.9 shows their interface and the parameters used in this experiment.

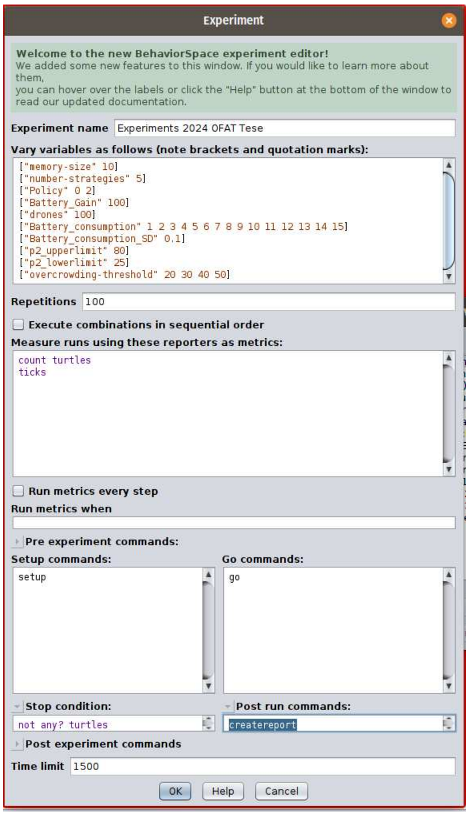
Figure 3.10 represents the experiment data mining process. The data was synthetically generated in the NetLogo. The text files created during the simulation were analyzed in Python, permitting statistical analysis and creating visual representations of this data.

To evaluate each simulation set performance, three experiment results Key Perfomance Indicators (KPI) concerning the reliability and efficiency of each simulation set.

The reliability results (KPI 1 and KPI 2) consider the macro-level simulation results and consider the result of all simulations as one. In turn, the efficiency result (KPI 3), which aims at the micro-level result, considers each agent's individual results.

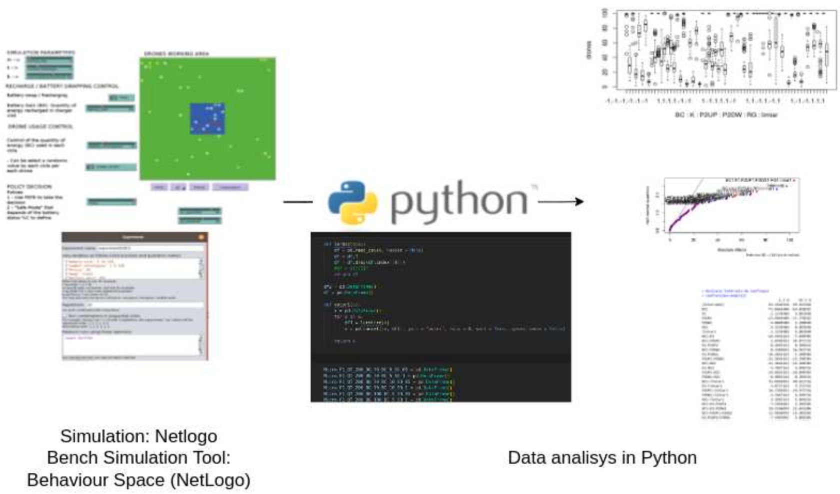
These results are described as follows:

Figure 3.9: Behavior Space Experiment Configuration



Source: Author elaboration

Figure 3.10: Data Mining Process.



Source: Author elaboration

- KPI 1 - Percentage of the ratio of finished simulations in the 100 repetitions for each 120 simulation set;

- KPI 2 - Average Simulation Remaining Drones is calculated by dividing the total number of drones that completed the simulation by the average number of drones that participated in each iteration. It represents the capacity of mission coverage for each simulation set;

- KPI 3 - Average Utility is the agent work/recharge decision ratio, times drones decide to work instead of recharging, during all simulations. A higher utility represents that this simulation set does more work than a lower utility.

KPI 3 considers the individual drone results. They counted how many times the agents worked during the process; for example, if in 10 runs, a drone goes two times to the recharging area, its utility was 80%.

Chapter 4

Case Studies

This section presents the two main results of this thesis. First, the current literature on state-of-the-art drone recharging coordination process PA and DE usage context, and a swarm of drones agent-based simulation recharging scenarios results.

4.1 Systematic Literature Review about Drones and their applications.

A Systematic Literature Review (SLR) is performed to evaluate the drone coordination recharging in precision agriculture (PA) and disaster relief. The methodology and main results are in the Subsection 3.1. This result were adapted from (Grando; Jaramillo, et al., 2025b).

4.1.1 Study Selection Phase

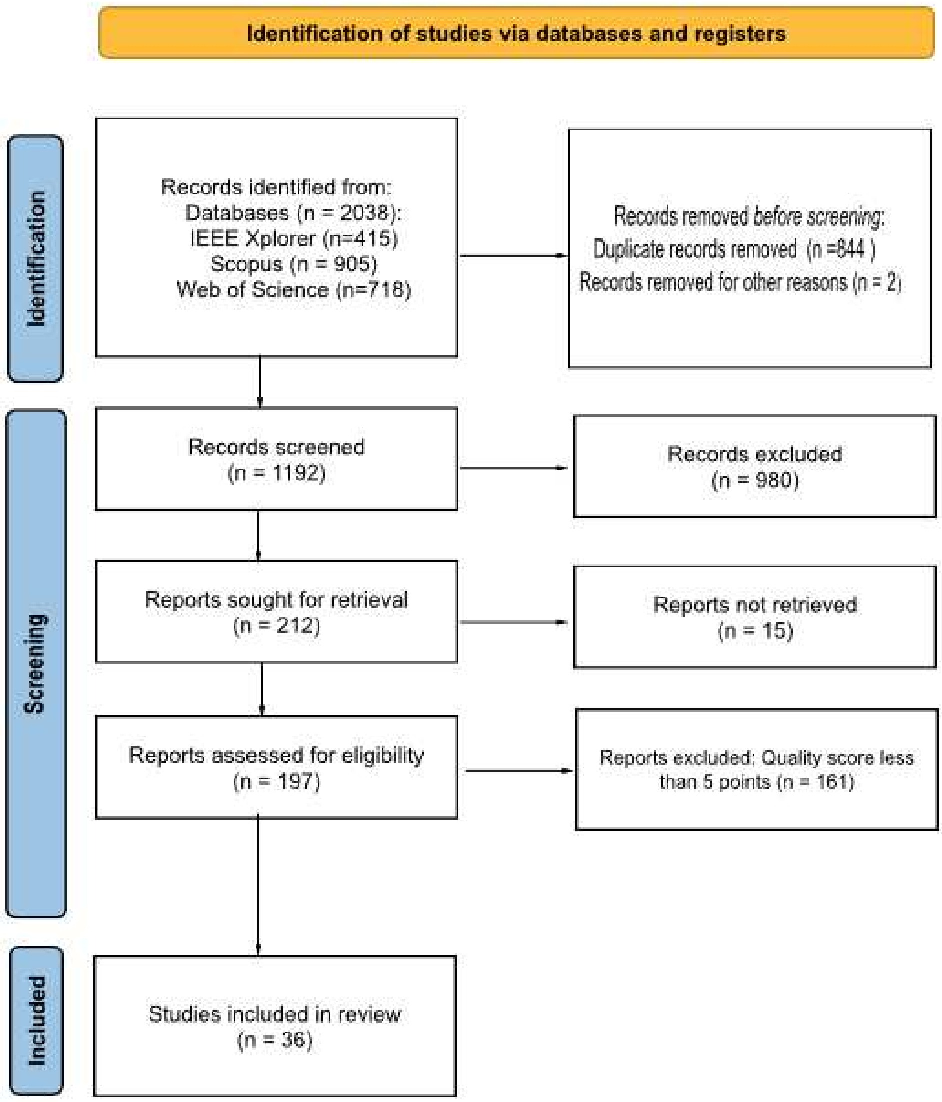
The keyword search was performed on 09 February 2024. A total of 2038 records were found in the three databases: IEEE Digital Library (415), Elsevier Scopus (905), and Clarivate Web of Science (718).

The Preferred Reporting Items for Systematic Reviews and Meta-Analysis Statement (PRISMA 2020) is designed for systematic reviews that assess the effects of health interventions. It focuses on evaluating any study design, regardless of its methodology or type. This work uses the PRISMA 2020 Flow (Page et al., 2021) to present the selection articles' flow during the research process in Figure 4.1, and the PRISMA 2020 checklist can be found in Appendix B

A total of 844 duplicates, 2 retracted studies, and 267 studies out of this study timeline were rejected and removed from the pool of studies. After reading the remaining 925 studies' abstracts, 713 studies were included or excluded due to the inclusion and exclusion criteria. Of the 212 remaining studies, 15 studies were not downloadable.

Then, perform the quality assessment process, read the full papers, and score according to the seven quality questions. The selected 36 studies achieved a quality threshold of at least five points. Finally, the data from the remaining 36 studies are extracted and used to answer the two SLR Research Questions.

Figure 4.1: PRISMA 2020 Flowchart.



Source: (Grando; Jaramillo, et al., 2025b)

4.1.2 Selected Studies Reading Results

Table 4.1 presents the selected literature reading and summarization to answer the two research questions. The first column of Table 4.1 presents a sort of the studies. The second column presents the author's names, and the third column is the studies' summaries. The fourth column shows the agriculture or disaster recovery approaches described in the selected articles. This column is related to the SLR - RQ1. Only two articles are unrelated to these applications, and column number five is related to SLR - RQ2 and describes the energy mitigation methods described in the literature. A discussion of these two results questions is presented after Table 4.1.

Table 4.1: Selected literature data extraction about each work research question

No.	Authors	Research Work	Application Context	Energy mitigation Context
1	(Abdelhakam et al., 2023)	The study aims to optimize the system's energy consumption, including propulsion and communication energy, using a coordinated multi-point (CoMP) cluster's beamforming vectors.	Disaster context. Internet of Things (IoT) networks can have your performance degraded during a disaster	Mission planning to reduce energy consumption.
2	(Akbari et al., 2023)	Coordination of a Network Function Virtualization (NFV).	Possible uses: Smart agriculture surveillance and environmental monitoring.	Minimizing total network energy consumption.
3	(Alatas et al., 2022)	The study considers implementing the Cloud-Based Drone Navigation (CBDN) algorithm.	Application of CDBN algorithm in land fertilization simulation.	It is expected that CBDN can reduce blockages/queues at the charging stations.
4	(Bisio et al., 2022)	This article proposes the novel concepts of social drone sharing (SDS) and social charging stations (SCS).	Disaster context.	Citizens can volunteer to recharge a drone or replace its batteries
5	(Boggio-Dandry; Soyata, 2018)	A charge replenishment mechanism to allow a swarm of drones to stay in the air perpetually.	NA	Changing and drone replacement coordination

(continued)

Table 4.1 – *Selected literature data extraction about each work research question*

No.	Authors	Research Work	Application Context	Energy mitigation Context
6	(Boroujerdian et al., 2021)	The authors evaluate the impact of computing on the UAV mission time and energy consumption.	Disaster context (search and rescue operations)	Impact of the battery on mission completion.
7	(Bouhamed et al., 2020)	The Study proposes a spatiotemporal scheduling framework for autonomous UAVs using reinforcement learning.	In a disaster, the flying units can wirelessly exchange messages and communicate with a control center.	Path, recharging planning, and UAV decision to return to charging stations when necessary.
8	(Calamoneri; Corò; Mancini, 2022)	The study considers a graph model considering recharging and heuristics, evaluating how to completely fly a fleet of Unmanned Aerial Vehicles (UAVs)	Yes. Rescue operations after an earthquake	Mission planning, estimating the best number of UAVs and additional batteries that guarantee the rescue
9	(Chiaraviglio et al., 2019)	Managing the UAV network throughput by formulating a maximum throughput with the unmanned aerial vehicles process (MT-UAV).	Users are located in a set of areas affected by the disasters.	Mission energy consumption optimization.

(continued)

Table 4.1 – *Selected literature data extraction about each work research question*

No.	Authors	Research Work	Application Context	Energy mitigation Context
10	(De Rango et al., 2017)	The study proposes a simulator suitable for the agriculture domain for a UAV team that monitors the land to destroy plant parasites.	UAVS (also called drones) are used in agriculture in situations where it is necessary to monitor lands.	Mission planning, considering that each drone is equipped with battery energy to fly and move in the interested area
11	(Fei et al., 2022)	The study considers a multi-UAV scheduling problem and suggests a method of rolling-inspired scheduling for emergency tasks by heterogeneous UAVs.	Emergency task scheduling context	Task scheduling model
12	(Feng et al., 2020)	Creation of an emergency communication framework of UAV-enabled Simultaneous Wireless Information and Power Transmission (SWIPT) for IoT networks.	Disaster context. IoT devices can stop working due to a lack of energy.	Energy improvement by path planning
13	(Gharrad et al., 2021)	Intelligent drone collaboration approach using the Multi-Agent System (MAS) paradigm based on a new generic Belief-Desire-Intention (BDI) architecture.	Disaster monitoring and road traffic within a restricted geographic area.	Simulation of the performance of the two collaboration approaches with drones, charging stations, and a contaminated zone.

(continued)

Table 4.1 – *Selected literature data extraction about each work research question*

No.	Authors	Research Work	Application Context	Energy mitigation Context
14	(Goyal et al., 2019)	The authors propose a network architecture for the scalable solution of UAVs in an urban environment.	Architecture can be used in farming or disaster relief contexts	Path planning.
15	(Grishin et al., 2022)	Modeling a communications system for emergencies based on UAVs, optimizing the required network elements.	Emergency disaster context.	Radio coverage. UAV location clustering methods.
16	(Li, J. et al., 2022)	The study evaluated the endurance of agricultural unmanned aerial vehicles, considering their structural composition.	Agricultural UAV endurance	A calculation method of equivalent endurance for model verification and validation by hover tests.
17	(Lin et al., 2021)	The authors suggest a hybrid compressed-sampling-based WSN node clustering model	Agricultural wireless sensor network monitoring.	Improvement of network energy consumption.
18	(Medeiros; Boukerche; Cerqueira, 2022)	The authors propose an energy-aware swarm-based and mobility prediction scheme for UAVs, called SUAV.	Disaster context. SUAV provides a unique UAV-based system for rescue scenarios.	Reduce the dependence on energy-intensive computer vision services to identify the target's position.
19	(Ming; Li, K., 2023)	Applying a heterogeneous graph neural network to a real-time reconfiguration approach.	Disaster recovery context.	Drones can receive energy bt wireless energy network, reducing battery recharging needs.

(continued)

Table 4.1 – *Selected literature data extraction about each work research question*

No.	Authors	Research Work	Application Context	Energy mitigation Context
20	(Niu et al., 2022)	The proposition of a task scheduling problem as a two-stage Lyapunov optimization problem.	Possible application in natural disaster relief.	System energy consumption is reduced.
21	(Pradeep; Park; Wei, 2018)	Considers the optimal path planning for maximizing farm field area coverage.	Precision Farm agriculture sensing applications.	Path planning can reduce energy
22	(Puangpontip; Hewett, 2022)	Managing search and rescue drone autonomy to decide on its actions based on energy consumption.	Disaster context, by using drones to help find disaster victims.	System energy consumption is reduced.
23	(Qin; Pournaras, 2023)	Scalable and energy-aware model for UAV planning and coordination of spatiotemporal sensing.	Possible use of swarms in disaster response and traffic response	Mission planning approach to reduce energy consumption.
24	(Shinkuma; Mandayam, 2020)	The Authors suggest a wireless mesh network design that depends on UAVs' mechanized automation.	Provision of flexible data transmission from sensors in disaster areas.	Developed a battery discharge model mission and mathematical formulations.
25	(Song et al., 2022)	Multi-agent endurance-limited coverage path planning (MAEI-CPP) problem.	Use of heatmaps of the pre-disaster environment to perform Search and rescue Algorithms.	Route planning using a priori knowledge of the heatmap of the disaster area, reducing energy usage.

(continued)

Table 4.1 – *Selected literature data extraction about each work research question*

No.	Authors	Research Work	Application Context	Energy mitigation Context
26	(Souto et al., 2023)	Proposes a heuristic that uses three reinforced learning methods to reduce UAV power consumption in disaster scenarios.	Power consumption of UAV missions in disaster scenarios	Path optimization of UAVs in urban scenarios to reduce energy usage.
27	(Sun et al., 2023)	The study investigates energy-efficient communication in the UAV wireless power transfer (WPT).	UAV energy consumption in the emergency communication context.	Wireless power transfer can reduce the dependence on stopping drones from recharging.
28	(Wang, K. et al., 2023)	The study considers the design and analysis of cooperative path-planning algorithms of a large UAV swarm.	NA	Study how battery charging affects UAV swarm cooperation in path planning.
29	(Terzi et al., 2019)	The paper presented a multi-drone tasking algorithm.	Emergency response missions	Mission planning (battery requirements for a delivery task)
30	(Tipantuña et al., 2019)	A drone scheduling model for short and long-term applications.	Considers drone swarms providing network connectivity in disaster situations.	Drones recharging scheduling.
31	(Trethowan; Wang, Z.; Wong, 2023)	The study focuses on trajectory planning to efficiently make birds fly away from crops.	Pest bird control in agriculture	Use of a tethered UAV strategy to supply energy to drones.

(continued)

Table 4.1 – *Selected literature data extraction about each work research question*

No.	Authors	Research Work	Application Context	Energy mitigation Context
32	(Yang et al., 2022)	The authors evaluate the UAV energy consumption in data dissemination in the post-disaster areas.	Data dissemination in post-disaster areas.	Network energy usage
33	(Yu et al., 2023)	The authors suggest using aerial drones for triangular oblique photography to construct a realistic 3D model.	Agriculture context. Pest and disease prevention in orchard management	The study considers path planning and energy consumption calculation for the six-rotor plant protection UAVs.
34	(Zadeh et al., 2023)	Multi-agent mission coordinating architecture (MAC) to provide a redundancy-free multiple UAV mission plan.	Disaster context	Missing Planning. Unbalanced workloads can result in different residual battery energy.
35	(Zhang, T. et al., 2023)	Consider the mobile edge computing technologies enabled by UAVs in disasters;	Disaster context. Ground terminals are usually used to perform search and rescue tasks.	Task scheduling optimization.
36	(Zhou, M. et al., 2022)	Unmanned Aerial Vehicle Assisted Sleep Scheduling algorithm in a Wireless Sensor Network (WSN) nodes.	Agricultural IoT benefits from wireless sensor networks (WSN)	Wireless sensor network optimization is putting unused sensors to sleep.

Source: Adapted from: (Grando; Jaramillo, et al., 2025b)

4.1.3 SLR - RQ1: What disaster or agriculture context is described in the selected studies?

From the 36 selected studies, nine studies were found to be related to Precision Agriculture (PA), 25 related to Disaster Recovery (DR), and two without context. Table 4.3 summarizes these applications in each context.

Table 4.2: Precision Agriculture Studies Applications in SLR

Type	Application	Quantity	Studies
PA	General farm activities such as land fertilization and pest control	4	(Alatas et al., 2022; De Rango et al., 2017; Trethowan; Wang, Z.; Wong, 2023; Yu et al., 2023)
	IoT network deployment	3	(Lin et al., 2021; Pradeep; Park; Wei, 2018; Zhou, M. et al., 2022)
	Surveillance Activities	1	(Akbari et al., 2023)
	UAV drone autonomy evaluation in farm activities	1	(Li, J. et al., 2022)
DR	Communication and networks in disaster recovery	13	(Abdelhakam et al., 2023; Bouhamed et al., 2020; Chiaraviglio et al., 2019; Feng et al., 2020; Grishin et al., 2022; Medeiros; Boukerche; Cerqueira, 2022; Ming; Li, K., 2023; Niu et al., 2022; Shinkuma; Mandayam, 2020; Sun et al., 2023; Tipantuña et al., 2019; Yang et al., 2022; Zhang, T. et al., 2023)
	Path-planning and device coordination in disaster context	12	(Bisio et al., 2022; Boroujerdian et al., 2021; Calamoneri; Corò; Mancini, 2022; Fei et al., 2022; Gharrad et al., 2021; Goyal et al., 2019; Puangpontip; Hewett, 2022; Qin; Pournaras, 2023; Song et al., 2022; Souto et al., 2023; Terzi et al., 2019; Zadeh et al., 2023)

Source: Adapted from: (Grando; Jaramillo, et al., 2025b)

Two studies (Boggio-Dandry; Soyata, 2018; Wang, K. et al., 2023) are not related to disaster or precision farming contexts but were selected due to their drones and recharging coordination process descriptions.

This evaluation reveals an imbalance in the research focus, with disaster relief receiving more attention in energy supply studies than precision agriculture. Studies on network-related issues and mission planning have been the most extensively explored.

4.1.4 SLR - RQ2: What energy mitigations were used in the studies?

Optimization strategies such as path and mission planning are well-researched and dominate energy usage mitigation strategies. There is still a need to explore more innovative methods for reducing energy usage such as internal drone energy usage to make decisions and effective recharging coordination processes as this simulation proposed work.

Table 4.3: Precision Agriculture Studies Applications in SLR

Application	Quantity	Studies
Reduce UAV energy usage by optimizing UAV's path and mission planning	16	(Abdelhakam et al., 2023; Bouhamed et al., 2020; Calamoneri; Corò; Mancini, 2022; Chiaraviglio et al., 2019; De Rango et al., 2017; Fei et al., 2022; Feng et al., 2020; Goyal et al., 2019; Pradeep; Park; Wei, 2018; Qin; Pournaras, 2023; Song et al., 2022; Souto et al., 2023; Terzi et al., 2019; Yu et al., 2023; Zhang, T. et al., 2023; Zadeh et al., 2023)
Improve energy autonomy through UAV battery parameter improvements, endurance tests, or the recharging coordination process	10	(Bisio et al., 2022; Boggio-Dandry; Soyata, 2018; Boroujerdian et al., 2021; Gharrad et al., 2021; Li, J. et al., 2022; Ming; Li, K., 2023; Shinkuma; Mandayam, 2020; Tipantuña et al., 2019; Trethowan; Wang, Z.; Wong, 2023; Wang, K. et al., 2023)
Network and wireless power transfer process improvements	6	(Akbari et al., 2023; Lin et al., 2021; Medeiros; Boukerche; Cerqueira, 2022; Sun et al., 2023; Yang et al., 2022; Zhou, M. et al., 2022)
UAV system optimization	4	(Alatas et al., 2022; Grishin et al., 2022; Niu et al., 2022; Puangpontip; Hewett, 2022)

Source: Adapted from: (Grando; Jaramillo, et al., 2025b)

4.1.5 Research Gaps

This Systematic Literature Review shows three potential research gaps: knowledge, methodological, and practical.

The results of this systematic literature review indicate that the approach of this thesis simulation work has been underexplored, highlighting a significant gap in the existing research. These three gaps underscore the innovative potential of our simulation study.

Knowledge Gap

The SLR reveals a gap in studies addressing drone battery recharging. In the current research (Grando; Jaramillo, et al., 2023), were explore a drone battery recharging coordination simulation using agent-based modeling, specifically focusing on scenarios where drones and ground stations make in-flight recharging decisions without communication. Applying a game theory approach to the internal decision-making process, where drones reduce communication frequency and energy consumption by waiting before recharging.

Methodological Gap

The SLR shows that drones' energy and recharging coordination rely on communications-based models; this work suggests a decentralized approach.

Practical Gap

There is a lack of real-world applications, including real disaster cases and precision validation research. Most research in this SLR was theoretical applications of the recharging coordination process.

4.2 Simulations Results

These results were adapted from our work (Grando; Jaramillo, et al., 2023) and two papers that will be published, a Winter Simulation Conference 2024 (Grando; Jaramillo, et al., 2024) and a preprint in arXiv (Grando; Jaramillo, et al., 2025a). More information in Appendix C.2.

The case studies include a sensitivity analysis of the quantity of mean energy necessary during the simulation runs. The BC values start at in average 1% and go to 15%. The higher this value is, the more extreme the environment. In agriculture, an extreme case can be spreading seeds and fertilizers, water irrigation, and medicine logistics in a disaster. A lower *BC* value can be considered for agriculture and disasters where photo taking, monitoring, and activities with fewer energy needs are involved.

The following sections present two types of simulation results. The reliability results relate to the capacity of the system to continue to work under stress, and the utility results show how this system delivers its work. These results are the statistical mean of 100 replications in each simulation set. There are 15 cases of energy usage scenarios, four sizes of recharging areas, and two coordination recharging policies, resulting in 120 scenarios.

4.2.1 Reliability Compliance

The reliability results are related to the capacity of the simulation to perform the predetermined mission. Table 4.4 presents the relationships between KPI 1 and KPI 2 to evaluate the simulation results. KPI 1 evaluates how many simulations reach the stop criteria of 1500 ticks for each simulation set, and KPI 2 evaluates the average agent's value remains in the simulation halt.

Figure 4.2 presents the mean numbers of finished simulations, which means that they have at least one drone working and achieve the 1500 ticks.

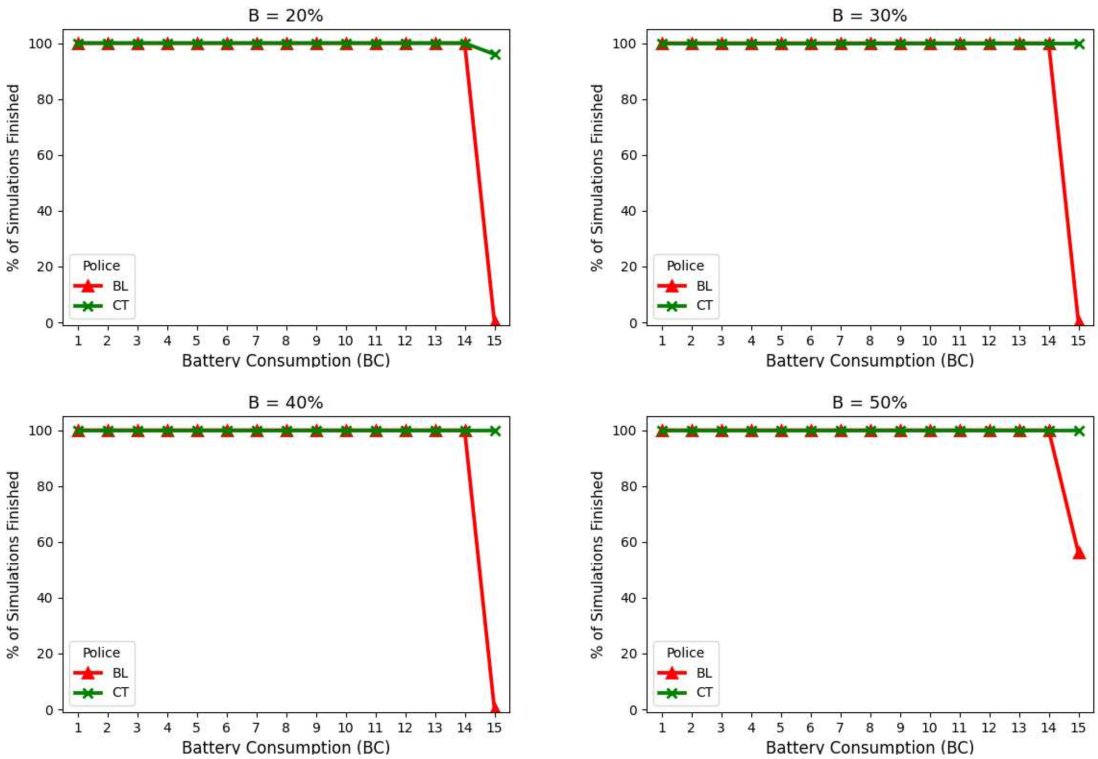
Figure 4.3 presents the mean number of drones that achieve the simulation finished

Table 4.4: Relationships about the simulation results

KPI 1	KPI 2	Results
High	High	Most of the simulations finished with a small loss of drones
High	Low	Most of the simulations finished with a significant loss of drones
Low	High	few simulations finished with a small loss of drones
Low	Low	Most of the simulations finished with a significant loss of drones

Source: Author elaboration

Figure 4.2: KPI 1 - Number of Finished Simulations (%)



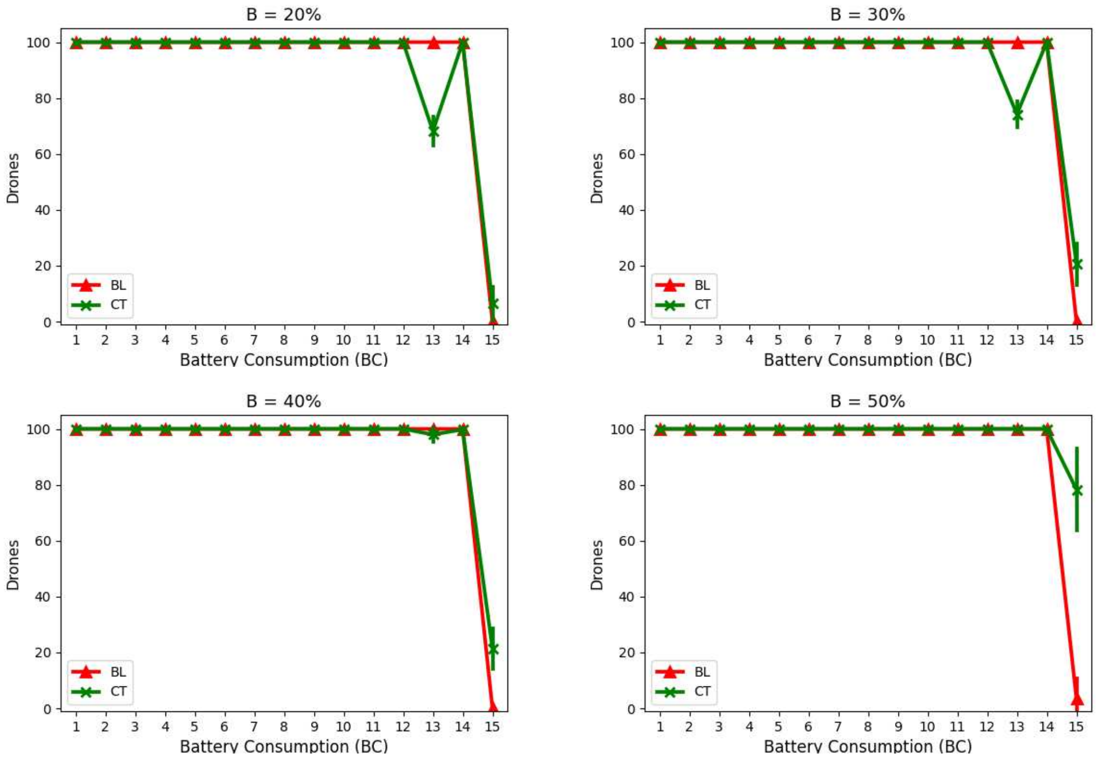
Source: Author elaboration

These results were reliability-related. When the BC value is less or equal to 12% of *SOC*, all simulations run results in 100% of simulations finished, and all drones finish the simulations run.

When the values of *BC* simulate extreme energy usage conditions ($BC > 12$), simulation setups suffer performance degradation. The baseline policy has a stronger degradation in the case of the hardest condition ($BC = 15\%$), when all situations besides $B = 50\%$ didn't finish the simulation.

Because the recharging threshold LW value (25%) is near extreme *BC* values and without any other intelligence, *BL* drones will achieve the stop-simulation conditions more than the *CT* drones.

Figure 4.3: KPI 2 - Average Simulation Remaining Drones



Source: Author elaboration

The recharging space (B) effect shows that increasing B increases the reliability performance results. *CT* policy drones are more sensitive concerning the B change with a case of KPI 2 lost performance when B = 20 and 30% in the BC = 13% case. As Agent-Based simulations, behavior can be complex and emergent, as in this case.

4.2.2 Efficiency Analysis

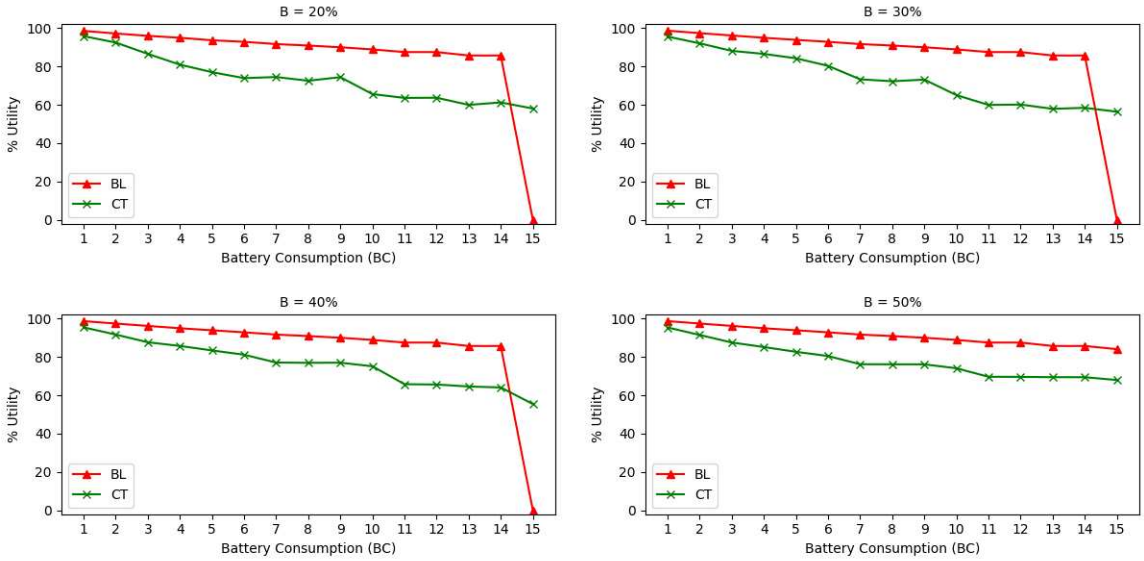
KPI 3 is related to system efficiency. One system can have good reliability results, but the remaining drones can only stay in the recharging place, avoiding work.

In this case, a high utility value means that the remaining drones in simulations stay more in the working area to make their agriculture or disaster recovery missions. A lower utility value means that the simulation agents are trying to recharge more often.

Figure 4.4 presents the average utility for each simulation set, considering the 120 simulation values.

The utility is the ratio that the simulation selects the work action in the 1500 simulation runs.

Figure 4.4: KPI 3 - Average Working rate (Utility) (%)



Source: Author elaboration

The utility shows a linear decrease in the BC value, which is expected because it is a more expensive energy situation. In the *BL* policy, when $BC = 15$, the utility is 0 in the case of $B =$ 20, 30, and 40% because, according to KPI 1, there are no finished drones in this situation. The $B = 50$ % of this utility shows their linear behavior.

CT policy case, until the utility is less *BL*, But in the case of more extreme situations $BC =$ 15, and a lower value of *B* will be unique that can reach the expected mission.

As expected, as *BC* increases, a reduction of the simulation set performances in the mean simulation runs, so our model has a validity behavior.

The *B* increase value shows less correlation between simulation set performance and more in *BL* policy.

These results show that *CT* police were more recommended than *BL* policies when agents needed more energy. These also show that a decentralized situation as a swarm of autonomous drones, will require adaptive control.

Chapter 5

Conclusions

This work describes two results: the first result evaluates the state-of-the-art research in the drone energy supply coordination process on the agriculture and disaster recovery drones usage, by performing a Systematic Literature Review, and the second result proposes an initial approach to simulate the swarm of drones' recharging process in a decentralized way.

The first result, the systematic literature review (SLR), evaluates the drone recharging coordination methods for precision agriculture and disaster relief using a methodology proposed by Barbara Kitchenham. The review followed these steps: paper search, duplicate removal, abstract screening, and quality assessment, ultimately analyzing 36 studies. These primarily focus on optimizing UAV energy usage via path planning, battery improvements, and coordination strategies.

Given the three research SLR gaps, particularly the limited energy capacity of UAVs, is recommended that future studies explore UAV applications in precision agriculture with a focus on energy supply methods. Additionally, further research should investigate the intersection of emerging technologies with agricultural and disaster contexts, specifically in recharging coordination processes.

Techniques include optimization algorithms, machine learning, reinforcement learning, multi-agent systems, and fewer simulation modeling studies. Despite advancements in technologies like wireless power transfer and solar recharging, challenges remain, particularly concerning the sustainability and scalability of operations. A lack of literature studies regarding swarm recharging coordination in the precision agriculture context has also been detected.

The Agriculture and disaster applications of drones can require that these devices work without communication, due to the application energy needs and the distance between devices and the Radio Base Station. This work proposed an evaluation of two decentralized energy supply coordination processes. The less complex decision process called the BL policy uses only the agent's SOC value to make their decision, the CT policy uses the SOC and the last recharging attendance history, with a game theory approach, called El Farol Bar Problem, to make their decision. This work explores three drone applications across (precision agriculture, disaster context, and Dengue disease fighting), and examines energy supply strategies for a swarm of drones using a game theory-based recharging coordination process.

Drones enhance agricultural resources by aiding farmers with informed decision-making. In disaster recovery scenarios, they provide vital services like communication, imaging, and mapping evacuation routes for victims. To combat dengue, drones can identify mosquito breeding sites and release sterile males to restrain the spread of the disease.

To address the recharging procedure, it is proposed to use agent-based modeling to analyze how a drone swarm autonomously makes recharging decisions. Two scenarios are evaluated: the Baseline (BL) Policy, where drones decide based on their battery levels (*SOC*), and the Charger Threshold (*CT*) Policy, which incorporates battery level with the El Farol Bar game theory approach. A total of 12000 simulation runs are performed, with 120 simulation sets, and 100 times replication.

In this work simulation, elements such as battery usage with standard deviation to reflect diverse drone operations and energy supply considerations are simplified, assessing two outcome types: reliability and efficiency results.

Both policies showed no significant differences in low UAV energy usage scenarios (*BC* less than 12% of *SOC*). However, the *CT* policy demonstrated superior performance at a 15% baseline capacity (*BC*), mainly in the KPI-1 results. In terms of efficiency, both policies achieved good results, with agents active for over 80% of the simulation time. Under more extreme conditions, the *CT* policy again outperformed in reliability metrics.

Overall, our study suggests that incorporating game theory into recharging strategies can enhance drone swarm operations across different scenarios and use cases.

5.1 Future Work

More development needs to be done, followed by limitations and future development descriptions.

Regarding this work's limitations, some simulation aspects, such as recharging place queue, network concept, coordinate movement, time, drones, and environmental characteristics, can be improved using this work as an initial mark.

Future practical usage of a swarm of drones in precision agriculture or disaster recovery will validate this type of work. In the current stage, we will need to use the design of experiments to evaluate the simulated results.

A multicriteria KPI analysis can be done to find the best simulation scenario results. Another possibility is the use of a real-time predictor as the KSL-X (Martins, P.; Ursini, E., 2018). Another suggestion for future work is to evaluate the recharging communication energy usage.

More studies in the precision farm context were needed, as shown SLR performed in this work.

Another limitation is the agent-based simulation verification and validation process. This simulation type can have a great number of parameters. This procedure is a challenge to future developments, as discussed in Section 2.5.

For future developments will require validation by searching the literature, thinking about an analogy (e.g., server, or processor), or a process mathematical evaluation (e.g., minority game), and improvements.

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Appendix A

Comparing this Thesis model work with Dissertation model work

This thesis work is a continuation of the (Grando, 2020) master dissertation work.

Current work implements drones' life cycle including battery usage, recharging process, and energy usage. In the thesis simulation, the drones will stop working due to battery starvation. The battery usage and standard deviation values variations parameters are an initial approach to future simulation improvements. For example, a validated mathematical model can include battery usage parameters such as the drone's size, weight, and environmental aspects.

The recharging parameters were also included, with an approach to full battery recharging replacement and battery recharging process, which is not present in the dissertation work.

Another model difference is between drone internal estimator types. In the dissertation work, diverse estimator types, and in this current work, the (Rand; Wilensky, 2007) autoregressive type helps the verification and validation process, because this model was used in the original Netlogo El Farol model. This is made to focus this work on the recharging and energy usage.

Appendix B

PRISMA 2020 CheckList

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Abstract
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	1. Introduction
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	2.1. Planning Stage
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	2.2. Selecting Phase
Information sources	6	Specify all databases, registers, websites, organizations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	2.1. Planning Stage
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	2.1. Planning Stage
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	2.2. Selecting Phase2.3. Quality Assessment and Data Extraction Phase
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	2.3. Quality Assessment and Data Extraction Phase
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	2.3. Quality Assessment and Data Extraction Phase
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	2.3. Quality Assessment and Data Extraction Phase
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	2.3. Quality Assessment

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
			and Data Extraction Phase
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	2.3. Quality Assessment and Data Extraction Phase
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	2.3. Quality Assessment and Data Extraction Phase
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	3. Results
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	3. Results
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	3. Results
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	3. Results
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	3. Results
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	3. Results
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	3. Results
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	3. Results
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	3. Results
Study characteristics	17	Cite each included study and present its characteristics.	3.3. Selected studies reading review
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	3.3. Selected studies reading review
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	3.3. Selected studies reading review

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	3.3. Selected studies reading review
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	3.3. Selected studies reading review
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	3.3. Selected studies reading review
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Not applicable
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Not applicable
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Not applicable
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	4. Discussion
	23b	Discuss any limitations of the evidence included in the review.	4. Discussion
	23c	Discuss any limitations of the review processes used.	4. Discussion
	23d	Discuss implications of the results for practice, policy, and future research.	Discussion
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Review was not registered
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Review was not registered
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Review was not registered
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Funding
Competing interests	26	Declare any competing interests of review authors.	Conflicts of Interest
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Data Availability Statement

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71.

Appendix C

Academic Production and Participation

C.1 Activities Mannagement

This section describes the current and future activities of this work. The Unicamp Technology School requisites for a Ph.D. degree:

- A total of 40 credits courses – Total: 46 credits
- English proficiency text – Approved on 03/02/2022;
- At least two-semester experience as a teacher intern program – PED (TT413 in the second semester of 2021 and 2023 and EB102 in the first semester of 2022) as shown in C.2.1;
- Qualification document presentation – Approved in 24/05/2023;
- A paper submission - Done, as shown in Appendix C.2;
- Final Ph.D. Thesis defenses in 21/02/2025, as shown in Figure C.1.

C.2 Academic Production and Participations

The current list of related academic works from this research and their status on 03/01/2025:

C.2.1 Unicamp Teacher Internship Program (PED) Participation

- 2021 Second Semester (Level C) - TT413 - Métodos Matemáticos para Telecomunicacões.

- 2022 First Semester (Level C) - Delivered lectures for EB102 - Geometria Analítica e Álgebra Linear.
- 2023 Second Semester (Level B) - Returned to teach TT413 - Métodos Matemáticos para Telecomunicações.

Certificates are present in Figure C.2

C.2.2 Mesa de Discusion in the 12° Congreso Internacional de Investigación - UVM

In this discussion panel, I presented the 2021 status of this work and discussed agent-based present and future applications with peers, as shown in Figure C.3

C.2.3 Unicamp School of Technology "Workshop da Pós-Graduação da Faculdade de Tecnologia"

ISSN 2527-256X

Participate in all editons during the Doctorate.

In the 2024 edition, I won the prize for the best work in oral mode in the Information System area with the work: "Análise de consumo de bateria de dispositivos usados em IoT (Internet das coisas)", as shown in Figure C.4

C.2.4 2023 Winter Simulation Conference editions

WSC 2023 Edition `https://meetings.informs.org/wordpress/wsc2023/`

Work: "Modeling and Simulation for Farming Drone Battery Recharging"

Extended Abstract as shown in Figure C.5. Link: `https://informs-sim.org/wsc23papers/satwcea107.pdf`

C.2.5 2024 Winter Simulation Conference editions

WSC 2024 Edition `https://meetings.informs.org/wordpress/wsc2024/`

ISSN: 1558-4305

Work: "Modeling and Simulation of Battery Recharging for UAV Applications: Smart Farming, Disaster Recovery, and Dengue Focus Detection"

Full Paper published in IEEE Xplorer during 2025, as shown in Figure C.6.

Link: `https://ieeexplore.ieee.org/document/10839001`

C.2.6 MPDI Drones

`https://www.mdpi.com/journal/drones`

ISSN: 2504-446X

Title: "Systematic Literature Review Methodology for Drone Recharging Processes in Agriculture and Disaster Management"

Submitted on 09/11/2024

Published in 08/01/2025 as show in Figure C.7

`https://www.mdpi.com/2504-446X/9/1/40`

C.2.7 Preprint: arXiv

Link: `https://arxiv.org/abs/2503.12685`

Title: "Agent-Based Simulation of UAV Battery Recharging for IoT Applications: Precision Agriculture, Disaster Recovery, and Dengue Vector Control"

eprint: 2503.12685

Submitted on 16/03/2025 as shown in Figure C.8.

Figure C.1: Ph.D Thesis defense section minute

UNIVERSIDADE ESTADUAL DE CAMPINAS
Faculdade de Tecnologia
Comissão de Pós-Graduação da Faculdade de Tecnologia

Ata da Sessão pública de defesa de tese para obtenção do título de Doutor em Tecnologia, na área de Sistemas de Informação e Comunicação, a que se submeteu o aluno Leonardo Grando - RA 189052, orientado pelo Prof. Dr. Edson Luiz Ursini.

Aos vinte e um dias do mês de fevereiro do ano de dois mil e vinte e cinco, às 14:00 horas, Sala de Defesa (Prédio da Pós-Graduação da FT) | meet.google.com/wsf-ufvp-evu, de forma híbrida, reuniu-se a Comissão Examinadora da defesa em epígrafe indicada pela Comissão de Pós-Graduação do(a) Faculdade de Tecnologia, composta pelo Presidente e Orientador Prof. Dr. Edson Luiz Ursini (FT/ UNICAMP) e pelos membros Dr. Kauê Tartarotti Nepomuceno Duarte (University of Calgary) (por videoconferência), Prof. Dr. Eric Alberto de Mello Fagotto (PUC-Campinas) (por videoconferência), Prof. Dr. Anibal Tavares de Azevedo (FCA/ UNICAMP) e Profa. Dra. Marli de Freitas Gomes Hernandez (FT/ UNICAMP), para analisar o trabalho do candidato Leonardo Grando, apresentado sob o título **" Study for Optimization of Battery Consumption for Unmanned Aerial Vehicles. " (Estudo Para Otimização de Consumo de Bateria Para Veículos Aéreos Não Tripulados.)**.

O Presidente declarou abertos os trabalhos, a seguir o candidato dissertou sobre o seu trabalho e foi arguido pela Comissão Examinadora. Terminada a exposição e a arguição, a Comissão reuniu-se e deliberou pelo seguinte resultado:

[x] APROVADO
[ ] APROVADO CONDICIONALMENTE (ao atendimento das alterações sugeridas pela Comissão Examinadora especificadas no parecer anexo)
[ ] REPROVADO (anexar parecer circunstanciado elaborado pela Comissão Examinadora).

Para fazer jus ao título de Doutor, a versão final da tese, considerada Aprovada ou Aprovada Condicionalmente, deverá ser entregue à CPG dentro do prazo de 60 dias, a partir da data da defesa. De acordo com o previsto na Deliberação CONSU-A-10 /2015, Artigo 42, parágrafo 1º, inciso II e parágrafo 2º, o aluno Aprovado Condicionalmente que não atender a este prazo será considerado Reprovado. Após a entrega do exemplar definitivo e a sua conferência pela CPG, o resultado será homologado pela Comissão Central de Pós-Graduação da UNICAMP, conferindo título de validade nacional aos aprovados.

Nada mais havendo a tratar, o Senhor Presidente declara a sessão encerrada, sendo a ata lavrada por mim, que segue assinada pelos Senhores Membros da Comissão Examinadora, pelo Coordenador da Comissão de Pós-graduação, com ciência do aluno.

Prof. Dr. Edson Luiz Ursini
Presidente da Comissão Examinadora

Dr. Kauê Tartarotti Nepomuceno Duarte

Prof. Dr. Eric Alberto de Mello Fagotto

Prof. Dr. Anibal Tavares de Azevedo

Profa. Dra. Marli de Freitas Gomes Hernandez

Leonardo Grando
Aluno(a)

Secretaria de Pós Graduação

Prof. Dr. Enelton Fagnani
Coordenador(a) da CPG

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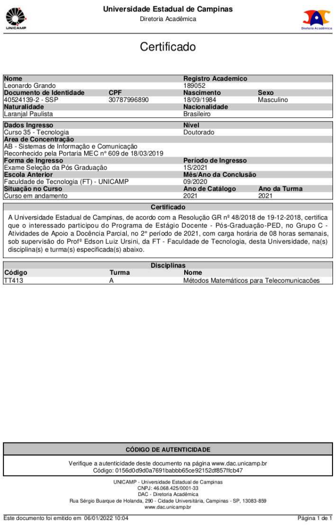
Figure C.2: Certificates of participations



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40524139-2 - SSP	30787996890	18/09/1984	Masculino
Naturalidade		**Nacionalidade**	
Laranjal Paulista		Brasileiro	

Dados Ingresso	Nível	
Curso 35 - Tecnologia	Doutorado	
Area de Concentração		
AB - Sistemas de Informação e Comunicação Reconhecido pela Portaria MEC nº 609 de 18/03/2019		
Forma de Ingresso	**Período de Ingresso**	
Exame Seleção da Pós Graduação	1S/2021	
Escola Anterior	**Mês/Ano da Conclusão**	
Faculdade de Tecnologia (FT) - UNICAMP	09/2020	
Situação no Curso	**Ano de Catálogo**	**Ano da Turma**
Curso em andamento	2021	2021

Certificado

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Disciplinas

Código	Turma	Nome
TT413	A	Métodos Matemáticos para Telecomunicacões

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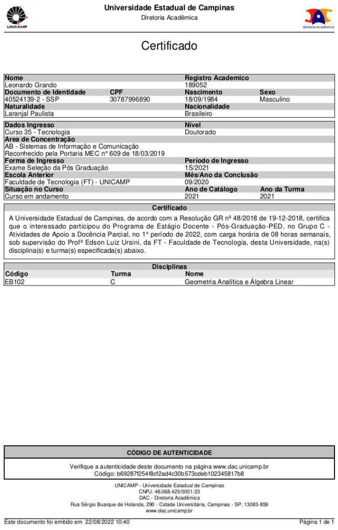

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Naturalidade		**Nacionalidade**	
Laranjal Paulista		Brasileiro	

Dados Ingresso	Nível	
Curso 35 - Tecnologia	Doutorado	
Area de Concentração		
AB - Sistemas de Informação e Comunicação Reconhecido pela Portaria MEC nº 609 de 18/03/2019		
Forma de Ingresso	**Período de Ingresso**	
Exame Seleção da Pós Graduação	1S/2021	
Escola Anterior	**Mês/Ano da Conclusão**	
Faculdade de Tecnologia (FT) - UNICAMP	09/2020	
Situação no Curso	**Ano de Catálogo**	**Ano da Turma**
Curso em andamento	2021	2021

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Disciplinas

Código	Turma	Nome
EB102	C	Geometria Analítica e Álgebra Linear

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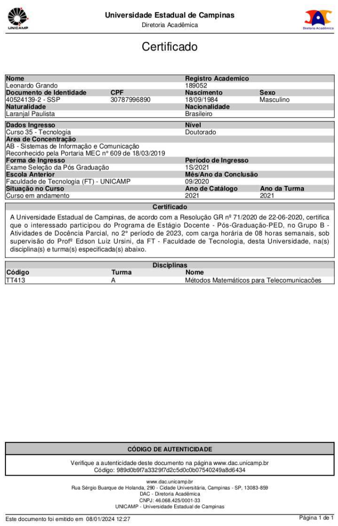

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Naturalidade		**Nacionalidade**	
Laranjal Paulista		Brasileiro	

Dados Ingresso	Nível	
Curso 35 - Tecnologia	Doutorado	
Area de Concentração		
AB - Sistemas de Informação e Comunicação Reconhecido pela Portaria MEC nº 609 de 18/03/2019		
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Escola Anterior	**Mês/Ano da Conclusão**	
Faculdade de Tecnologia (FT) - UNICAMP	09/2020	
Situação no Curso	**Ano de Catálogo**	**Ano da Turma**
Curso em andamento	2021	2021

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Disciplinas

Código	Turma	Nome
TT413	A	Métodos Matemáticos para Telecomunicacões

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Figure C.3: Certificates of participations

12 CONGRESO INTERNACIONAL DE INVESTIGACIÓN UVM
INNOVACIÓN SIN FRONTERAS

UVM

La Universidad del Valle de México
otorga la presente CONSTANCIA a

Leonardo Grando

Por su participación en Using a classical model to provide insights through Agent-based Simulation en el 12° Congreso Internacional de Investigación UVM, realizado con sede digital en Campus Tuxtla.

Dr. Gerardo Dubcovsky — Mtra. Rita Acosta Reyes — Dr. Nein Farrera Vázquez

Tuxtla Gutiérrez, Chiapas, México, a 7 de octubre de 2021.

Source: Author

Figure C.4: XV Workshop da Pós-Graduação Oral Best Presentation Certificate.

PPGT PROGRAMA DE PÓS-GRADUAÇÃO EM TECNOLOGIA

XV WORKSHOP DA PÓS-GRADUAÇÃO

Certificamos que

Leonardo Grando

recebeu o prêmio de melhor trabalho na modalidade Oral, na área de Sistemas de Informação, pelo trabalho intitulado "**Análise de consumo de bateria de dispositivos usados em Iot (Internet das coisas)**", realizado no dia 11 de setembro de 2024, no XV Workshop da Pós-Graduação da Faculdade de Tecnologia - UNICAMP, na cidade de Limeira - SP.

Enelton Fagnani
Coordenador do Programa de Pós-Graduação da Faculdade de Tecnologia - UNICAMP

Jacqueline Malvestiti
Representante discente da Comissão de Pós-Graduação da Faculdade de Tecnologia - UNICAMP

Rodrigo Cavalcante
Representante discente da Comissão de Pós-Graduação da Faculdade de Tecnologia - UNICAMP

Apoio:

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Figure C.5: WSC system approval and Congress Participation Certificate.

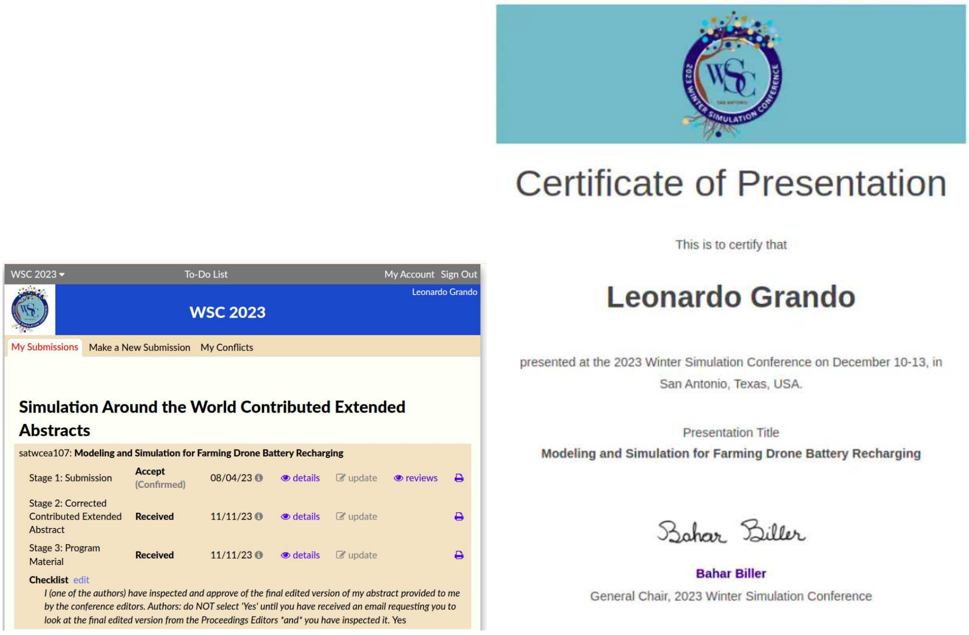

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Figure C.6: WSC system approval and Congress Participation Certificate.

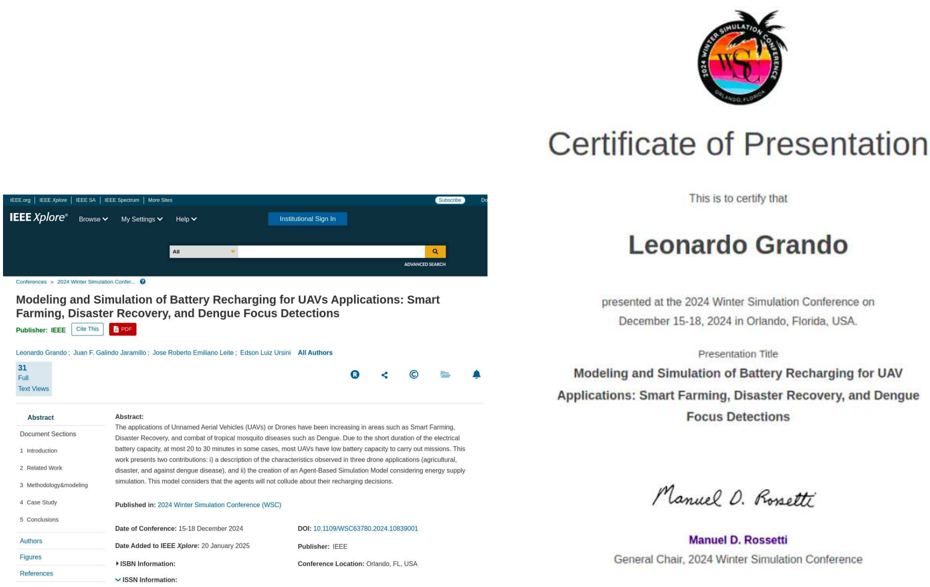

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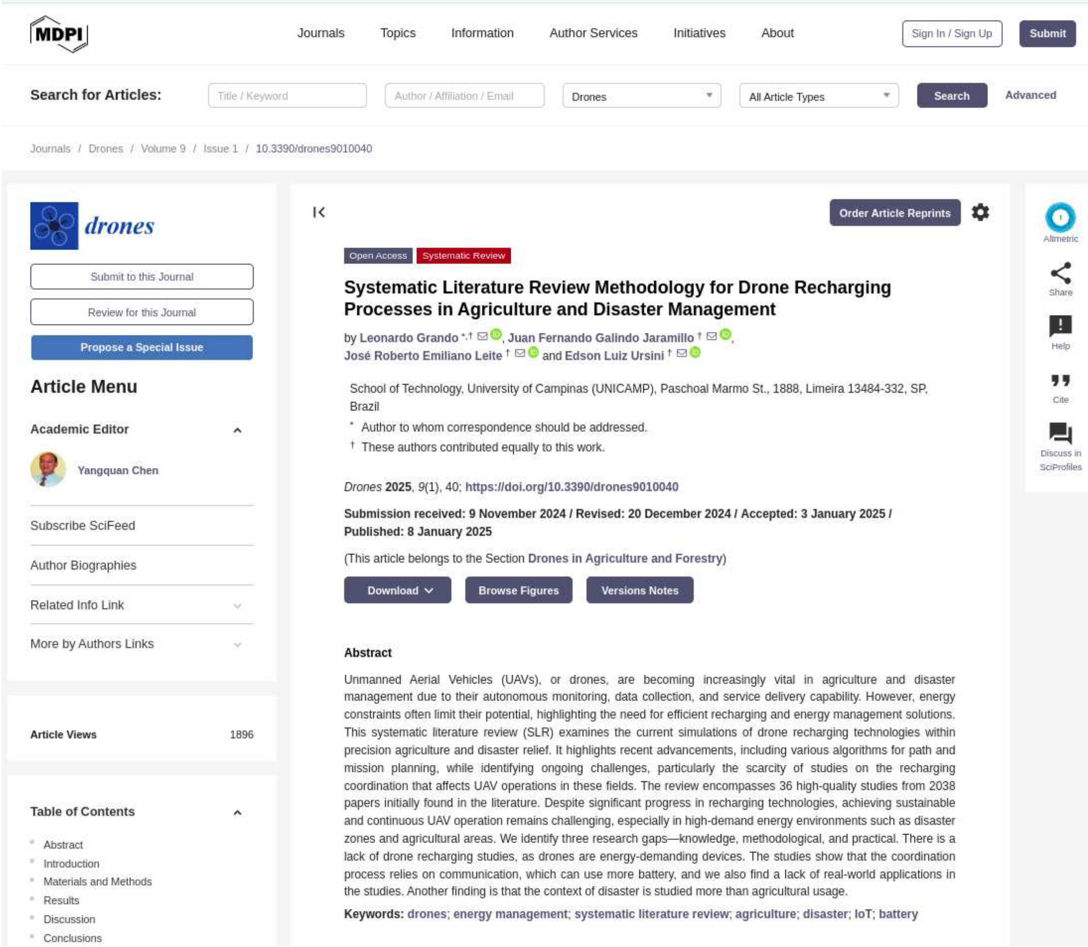
Figure C.7: MDPI Drones SLR Paper



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- Results
- Discussion
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Open Access Systematic Review

Systematic Literature Review Methodology for Drone Recharging Processes in Agriculture and Disaster Management

by Leonardo Grando *,†, Juan Fernando Galindo Jaramillo †, José Roberto Emiliano Leite † and Edson Luiz Ursini †

School of Technology, University of Campinas (UNICAMP), Paschoal Marmo St., 1888, Limeira 13484-332, SP, Brazil

* Author to whom correspondence should be addressed.

† These authors contributed equally to this work.

Drones 2025, 9(1), 40; https://doi.org/10.3390/drones9010040

Submission received: 9 November 2024 / Revised: 20 December 2024 / Accepted: 3 January 2025 / Published: 8 January 2025

(This article belongs to the Section Drones in Agriculture and Forestry)

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Abstract

Unmanned Aerial Vehicles (UAVs), or drones, are becoming increasingly vital in agriculture and disaster management due to their autonomous monitoring, data collection, and service delivery capability. However, energy constraints often limit their potential, highlighting the need for efficient recharging and energy management solutions. This systematic literature review (SLR) examines the current simulations of drone recharging technologies within precision agriculture and disaster relief. It highlights recent advancements, including various algorithms for path and mission planning, while identifying ongoing challenges, particularly the scarcity of studies on the recharging coordination that affects UAV operations in these fields. The review encompasses 36 high-quality studies from 2038 papers initially found in the literature. Despite significant progress in recharging technologies, achieving sustainable and continuous UAV operation remains challenging, especially in high-demand energy environments such as disaster zones and agricultural areas. We identify three research gaps—knowledge, methodological, and practical. There is a lack of drone recharging studies, as drones are energy-demanding devices. The studies show that the coordination process relies on communication, which can use more battery, and we also find a lack of real-world applications in the studies. Another finding is that the context of disaster is studied more than agricultural usage.

Keywords: drones; energy management; systematic literature review; agriculture; disaster; IoT; battery

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Figure C.8: Submission in arXiv

Cornell University

We gratefully acknowledge support from the Simons Foundation, member institutions, and all contributors. Donate

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Computer Science > Multiagent Systems

[Submitted on 16 Mar 2025]

Agent-Based Simulation of UAV Battery Recharging for IoT Applications: Precision Agriculture, Disaster Recovery, and Dengue Vector Control

Leonardo Grando, Juan Fernando Galindo Jaramillo, Jose Roberto Emiliano Leite, Edson Luiz Ursini

The low battery autonomy of Unnamed Aerial Vehicles (UAVs or drones) can make smart farming (precision agriculture), disaster recovery, and the fighting against dengue vector applications difficult. This article considers two approaches, first enumerating the characteristics observed in these three IoT application types and then modeling an UAV's battery recharge coordination using the Agent-Based Simulation (ABS) approach. In this way, we propose that each drone inside the swarm does not communicate concerning this recharge coordination decision, reducing energy usage and permitting remote usage. A total of 6000 simulations were run to evaluate how two proposed policies, the BaseLine (BL) and ChargerThershold (CT) coordination recharging policy, behave in 30 situations regarding how each simulation sets conclude the simulation runs and how much time they work until recharging results. CT policy shows more reliable results in extreme system usage. This work conclusion presents the potential of these three IoT applications to achieve their perpetual service without communication between drones and ground stations. This work can be a baseline for future policies and simulation parameter enhancements.

Comments: 22 pages

Subjects: Multiagent Systems (cs.MA); Robotics (cs.RO)

Cite as: arXiv:2503.12685 [cs.MA]

(or arXiv:2503.12685v1 [cs.MA] for this version)

https://doi.org/10.48550/arXiv.2503.12685

Submission history

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[v1] Sun, 16 Mar 2025 23:04:28 UTC (1,138 KB)

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