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Simulating Collaborative and Autonomous Persistent Surveillance by Drones for Search and Rescue Operations

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Abstract

In search and rescue operations, time plays a critical role in saving lives. To address this challenge, a multi-drone surveillance system has emerged as a valuable tool for first responders, enabling them to cover large areas efficiently. However, for optimal effectiveness, such a system needs to be collaborative and autonomous, allowing first responders and operational rescue teams to focus on crucial tasks. This paper presents a simulation framework designed to assist in the selection of optimal design characteristics for a multi-drone collaboration system in a specific search and rescue environment, the objective of this simulation framework is (i) to optimize coordination and continuity in large scale missions while (ii) taking into account various factors and considerations to guide the decision-making process and (iii) adapt to dynamic in the resource allocation. By leveraging this simulation framework, stakeholders can evaluate and choose design features that enhance situational insight, optimize resource allocation, and streamline rescue operations in their unique context.

Keywords: Search and Rescue, Drones, Multi Agent Systems, Smart Mobility.

1. Introduction

Drones sometimes also denoted as “Unmanned Aerial Vehicles” (UAVs) or “Re-motely Piloted Aircraft Systems” (RPAS), play an important role in increasing safety and productivity across different urban search and rescue operations, such as mountain avalanches rescue operations, industrial accidents, desert rescue search, search and rescue under collapsed buildings after earthquakes…. UAV technologies have been successfully used in many search and rescue projects (ICARUS, Airborne, CUR-SOR, CHEMSAR, SARA, TRADR, MOBile NETwork …). The development of UAV capabilities like onboard processing, flight duration, maximum load, camera resolutions as well as enhanced features like dual control, automation and obstacle avoidance, making it a promising future technology to enhance complex and large-scale operations like search and rescue operations.

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Drones dedicated for such time-critical operations should have good resistance to different adverse weather conditions, long flight endurance, large payload handling and a camera with high resolution. On top of all these hardware challenges, the drones need an efficient automated processing and an efficient collaboration approach (processed onboard or using edge-processing) which could be more challenging than hardware requirements. Many available drone solutions require a dedicated pilot for each drone, which is also linked to regulations such as EU Regulation 2019/947. For large scale missions which require the participation of more than one drone, this requirement provides challenges to the ability to execute complex and repetitive missions. Based on discussion groups with first responders, the automated aerial area monitoring im-proves the visibility of the operational team and helps to make better decisions [1]. For time critical missions or missions that span a large geographical area, collaboration not only can allow coverage of larger areas but also increases the reliability of the sensed data. Also, the autonomy of the drone will allow rescue workers to focus on the operational field rather than flying drones. Due to its importance, the shift towards an autonomous collaborative drone system attracted many research in various industries. Existing software ground control applications allow to design waypoint missions for one drone. By executing a waypoint mission, the drone autonomously follows a set of locations and could execute a specific task at each location. Some commercial companies have also implemented multi drone features in their software solutions. For example, *DJI Flighthub* allows to manage multiple drones, but the software mainly focuses on team and fleet operations and does not offer any autonomous flying features such collaboratively searching an area [2]. Some other ground control station programs such as e.g. Mission Planner and *QGroundControl* focused also on multi drone applications. Some recent research projects worked on designing multi drone testbeds like Group Autonomy for Mobile Systems (GAMS) and OpenUAV. The following section reviews some of the studies and projects that focus on autonomous drone collaboration specifically for search and rescue operations.

2. Related works

Research works and projects addressing drone collaboration focus on a variety of challenges in collaboration, including task allocation [3], path planning, team formation [4], scheduling, communications [5], coordination.... Here we will not focus on communication or team formation but on mainly reviewing the coordination and continuity in large scale missions.

In [6] and [7] the authors proposed a collaborative drone system where multiple drones are simultaneously deployed to capture and transfer pictures to a central unit which creates a global mosaicked image for the first responders. The authors focus on path planning and task allocation strategies, taking into account sensing and communication constraints. The authors considered that the drones' waypoints are generated at the ground station based on the picture points which define the location where the drone should take a picture. They used multi-rotors drones with different capabilities (load, flight time...) and different sensors. The heterogenous drones communicate with the ground station to report sensed data and transfer onboard processed images. This work was developed to suit commercial drones that will use the generated waypoints. In [8] the authors propose a complete and modular solution for controlling multiple drones aiming to enhance the autonomy of drones. It enables an inexperienced user to create, execute and monitor simple and complex missions. The proposed model includes a fail-safe system component that detects and alerts anomalies such as low battery warnings. Once the ground station receives the alert, it deploys another drone. For task planning, the authors use a mission planner which automatically selects the drones which are connected to the platform, and which are available prioritizing the drone with maximum battery energy level.

Localization systems like GPS (Global Positioning Systems), GIS (Geographic Information System) and LiDARs play an vital role in the search and rescue operations. In [9] the authors suggested multi-agent perception model using heterogeneous SAR robots in different environment. The various arial, underwater and ground robots form an multi-agent collaborative system for environment mapping. The integration of GPS and GIS provide detailed and accurate data that can be exploited in emergency management applications. The review in [10] provided a detailed review about the deployment of drone-integrated GIS applications in different fields. The collaboration of drones has also been addressed in a search and rescue context. In [2], the authors proposed a semi-autonomous drone platform that allows in-structing multiple drones to collaboratively undertake a searching task. The drone collaboratively monitors the environment, and each drone sends real-time video to detect people and objects of interest. This work was a part of EU project titled SWIFTERS. The platform included a ground control application and multiple mobile applications. Each mobile application was linked to ground control and used to control drones. The paths of the drones are created by the user on the ground control application. In [11], the authors also implemented a multi-UAV application and propose a general control and monitoring platform for a cooperative UAV fleet. The idea of this study was similar to [12], i.e. to design a more cooperative model instead of leader-follower model to achieve cooperative services. In the application, each drone is linked to a software agent which interacts with the flight monitoring application. The flight monitoring application could generate control messages to enable cooperation services such as path planning, collision avoidance, synchronization... A recent literature review found that the complete coverage path planning problem in the persistent surveillance task is rarely considered [13]. Some other research addressed the persistence of continuous surveillance or monitoring mission and suggested a path planning approach for large environments by heterogeneous vehicles. In [13] a collaboration between areal and ground robots has been proposed to complete the persistent surveillance task in urban environments. The coverage problem was first formulated as large zero-one optimization, then a hybrid algorithm integrating the estimation of distribution algorithm (EDA) and a genetic algorithm (GA) has been used to solve the cooperative path planning problem. The area to cover was modeled as a grid and the examined scenario included grid cells that need to be covered from the ground, grid cells that need to be covered from the air and grid cells that need to be covered with special capturing resolution. For search and rescue operations, coverage path planning has been addressed in some works [14] to ensure the collect of the information from all the region of interest. Also, in [15] the authors proposed planner as generic tools allowing a drone operator to define and generate a coverage trajectory for any specific task.

In multi-agent system modeling and simulation, the collaboration of drones has also been investigated to mimic real scenarios. In [16] the authors developed a simulation to test the performance of a multi-UAV system using different possible configurations like type of aircraft and their degree of autonomy. The designed system modeled two types of UAVs: fixed wing UAVs and quadcopters. The task of a quadcopter is to capture specific points of interest while the mission of a fixed wing UAV is to patrol the area and detect threads in the environment. The human operator has also been modeled in this simulation to evaluate the workload and the fatigue level. The task of the human operator is to assign a point of interest to the quadcopter and to analyze the captured pictures. In [17], the authors suggested a simulation-based study to evaluate the resilience alternatives in real-time during system operation. The focus of the paper is to explore the feasibility of evaluating the resilience alternatives during the system operation using a multi-UAV system. This system consists of one UAV commander and other UAVs following the order of the commander. The commander UAV is responsible for making the informed decision for the system based on a utility function. This function ranks the resilience alternatives based on their usefulness. This utility function considers three criterions: safety, the resources and the goal of the mission. In [18], the authors simulate the simultaneous deployment of multiple autonomous UAVs for searching victims in a large environment where the UAVs coordinate between each other to accomplish the mission. The environment is divided into a set of layers and attributed to drones. The proposed approach also used a centralized design using a cloud control server. In the simulation, the authors measured the number of victims detected using the proposed approach and compared it to existing search algorithms. However, the authors focus mainly on coordination and do not address alternative tasking between collaborative drones. For multi agent systems, a variety of agents architecture have been proposed in the literature like cognitive agents and Belief-Desire-Intention (BDI) agents. The BDI architecture offers a straightforward description of logic model which makes it easy to understand, use and extend [19]. Beliefs, Desires and Intention describe the main intentional states that allow the agent to choose an action to perform and to execute based on the world knowledge which is the knowledge of the agent about his environment, the state of other entities and his state. Many extensions of BDI aiming to enhance variety of aspects like uncertainty in beliefs, plan restrictions, goals maintenance, belief revision… have been proposed in literature [20].

In this work we suggest the simulation of a fully autonomous collaborative drone platform that allows to monitor a given area within a given period and with a given update frequency to assist first responder in a disaster situation. In the proposed implementation, the time and resource constraints have been taken into consideration in addition to alternative tasking. The simulation framework can assist in the selection of optimal design characteristics for a multi-drone collaboration system in a specific search and rescue environment, in order to optimize coordination and continuity in large scale missions. The framework takes into account various factors and considerations to guide the decision-making process. By leveraging this simulation framework, stakeholders can evaluate and choose design features that enhance situational insight, optimize resource allocation, and streamline rescue operations in their unique context.

3. Methodology

During the search and rescue operations, the first responder needs to cover a specific area in a specific timeframe to search for victims, explore and identify the sources of danger in the environment and monitor changes. The use of multiple drones definitively allows the first responders to cover a larger area in a shorter timeframe. How-ever, the performance of the collaborative drones depends on many factors like the optimization of task coordination (e.g. patrolling and charging or swapping batteries), the availability of resources (the number of drones available, the number of charging stations and battery swapping stations, path planning, etc.). In the realized simulation we set up a scenario with eight drones (four active drones and 4 idle drones) and four battery charging stations (BCS), four battery swapping stations (BSS) and one ground control station (GCS). All these parameters (except the number of GCSs) could be customized by the user before starting the simulation. Table 1 shows the parameters used in the simulation. Each swapping station includes a number of fully charged batteries and a set of free charging slots. The BSS and the charging stations are considered as shared resources which are randomly distributed in the environment, and which could be used by any drone. Although the placement of the charging and swapping station could play an important role in the optimization of time, in after disaster context, it could be difficult to optimize this factor and set a specific location for each station, therefore, the distribution of these stations is simulated by a random placement...

As shown in Figure 2, the area to monitor is modeled as a grid with 2 levels (meso grille (region) and nano grille (cells)). The global area is divided into the number of active drones (drones ready to take off). Each drone will be assigned to a region. Based on the assigned region, the drone will generate the patrolling path. The GCS will be responsible for coordinating the tasks of the drones and guiding the drone to the charging activity. The model was implemented using multi-agent system simulations. The realized simulation is implemented in GAMA platform and is based on GAML agents, i.e. a variety of GAMA BEN (Behavior with Emotions and Norms) agents. The BEN agent uses the BDI architecture which will execute the plan based on the desire and the beliefs of the agent. Algorithms 1, 2 and 3 describe the reasoning of the drone, ground control station and the swapping station agents.

Algorithm 1. Drone Agent

```
plan patrol belief: not lowBattery
status ← "active"
path ← findPath (area, NbDrone, DroneFoV)
do follow path
reflex battery when: lowBattery
    remove_desire patrol
    add_belief lowBattery
    add_desire charge
    sendMessage (coordinationCenter, "Where")
    wait
    after (time_limit)
      do goHome
reflex message when: MessageReceived
        station ← MessageReceived.content
plan charge belief: lowBattery and station
status ← "charging"
if location = station
    if station one_of (swapingStations)
        ask station:
            status ← busy
            do swapBatteries
            if currentCapacity=batteryCapacity
                remove_belief lowBattery
```

```
            add_desire patrol
  if station one_of (chargingStations)
      ask station:
        status ← busy
        do charge
        if currentCapacity=batteryCapacity
        if not one_of (Drones) in self.region where status = "active"
            remove_belief lowBattery
            add_desire patrol
        else
                do goHome
                self.status ← "idle"
```

The GCS will be responsible for the task allocation and the coordination of the drone's action. As represented in Figure 1 the GCS will communicate with the drones using FIPA Agent Communication Language Specifications (FIPA-ACL) messages. The drones have to report their status and location repeatedly to the GCS. The BCS and the BSS will also report their availability to the GCS. In a real-world situation (not in a simulation) with hardware drones this communication could be designed as an extremely lightweight publish/subscribe messaging protocol. Within the simulation, where drones are modeled as agents, FIPA ACL messages are used. Based on the re-ported information, the GCS will be able to make the decision about the action/ task allocated to the drone. Under some circumstances (e.g., low battery), the drones can communicate with the GCS to ask for instructions. In case the drone did not receive any instruction from the GCS, it executes the goHome plan to return to the home location.

Algorithm 2. Ground Coordination Center

```
reflex readReplyMessage when: MessageArrived and availableResource
    sender ← readMessage.sender
    if availableResource is one_of(swappingStations)
        reply ("Swapin", closest (swappingStation, sender)
    else
        if availableResource is one_of(chargingStations)
        reply ("Chargein", closest (chargingStation, sender)
        if (availableIdleDrone)
            takeOverDrone ← closest (availableIdleDrone, sender)
            sendMissionToDrone (sender.Mission, takeOverDrone)
```

Algorithm 3. Swapping Station

```
state ← free
size ← swapSize
chargedBatteries ← []
chargingBatteries ← []
reflex chargeBatteries
    for b in chargingBatteries
        if fullBattery
        add b to chargedBatteries.
reflex swapBattery when: DroneInSwapStation and size(chargedBatteries)>=1
    add battery to chargingBatteries.
    first ← removeFirstFromchargedBatteries
    drone.battery ← first
reflex resetFree when: DroneLeaveSwapStation
    state ← free
reflex resetBusy when: DroneInSwapStation
    state ← busy
```

The whole system will be modeled as a fully autonomous system with centralized control since the ground station will generate the paths of the regions and assign it to the drones. The mission of the drone will be to patrol the assigned region. Once the battery level reaches a threshold the drone will communicate with the GCS, which will send to the drone the action to perform. The GCS will check the location of the drone and identify the closest BSS with fully charged batteries. If no batteries are available in the BSSs, the GCS will identify the closest free charging station and reply with the action plan of the drone (“swap” or “charge”) and with the geo-coordination of the BSS or the charging station. If the drone is instructed to charge its battery and not to swap it, the GCS will check the availability of an idle drone (D2) to take over the patrol mission of the first drone (D1). If there is an idle drone, the GCS will send the start location and the path to the idle drone. If no drone is available, D1 will execute the charging plan and the GCS will repetitively check the availability of a charged idle drone. If the used swapping station has no available charged batteries and the swapping station is busy, the GCS center informs the drone to wait. Drone D1 will remain in waiting mode until one of the swapping becomes available for use or one of the charging stations becomes free.

Table 1. Parameters and Values used in the implemented simulation.

Area	52.803 kilometers2
Field of view of the drone	83 degrees
Altitude of the drone	20 meters
Width of each meso region	1,981,5 meters2
Area of region	13.200 kilometers2
Battery lifetime	2000 cycles (2 minutes)
Number of Batteries in swapping stations	2 batteries
Battery charging time	4000 cycles (4 minutes)
Number of drones used	8 drones
Number of charging stations	4 stations
Number of swapping stations	4 stations
Speed of drone	30 km/h
Area covered per minute	990.75 m2

The paper presents a use case that applies the developed framework to a concrete environment and location. The modeled search and rescue scenario is a forest fire scenario where a fire could spark from a random location with a parametrized probability. The defined as a two-dimensional cellular automaton on a grid of cell which will then be extended to neighboring cells based on a random distribution (across neighboring cells). The main goal is to allow the available resources to coordinate their tasks of charging the batteries and execution the patrolling mission and reduce the time in which the cells are without surveillance. Here, we do not consider prioritized region or area since in some scenarios the first responders need to monitor the whole area. Figure 1 shows the modeled use case. To evaluate the performance of the collaborative mission, we measure the number of nano-cells that have been visited with a predefined frequency (1600 cycles, or ~1.6 minutes) and we calculate the percentage of the area which was not visited within the specified frequency (Figure 4)

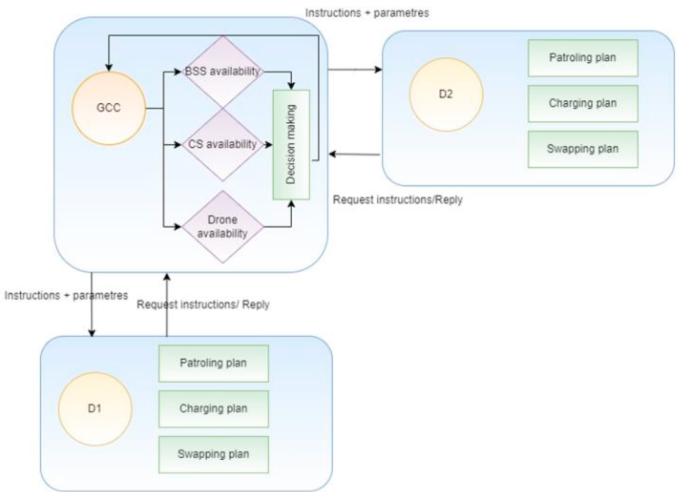

Fig. 1. Architecture of the Drones Collaborative Platform

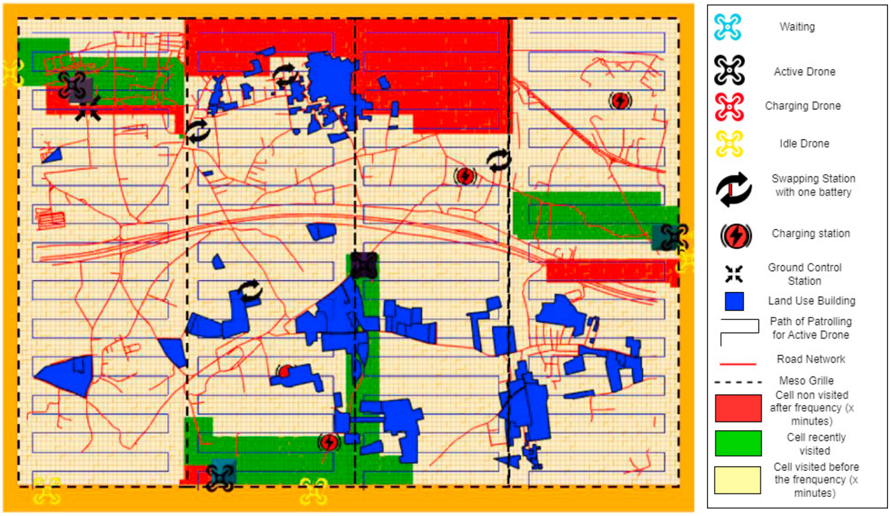

Fig. 2. Overview of Simulated Environment

4. Results

To evaluate the performance of the system with different configurations, the percentage of cells that were not visited after the required frequency has been recorded. The simulation is executed first using the listed configuration in Table 1. Afterward, the simulation is executed by applying 29 other hand-picked plausible configurations (30 in total). During these simulations, the size of the area, the size of the field of the view of the drone and frequency of the visits are fixed. The number of active and idle drones, the number of charging and swapping stations, the number of batteries and the number of charging slots in the swapping stations are variables. The drone should keep 30% of their battery for the goHome operation. Once the active drone confronts a low battery level event, the idle drone takes over the mission from the active drone after a request from the GCS. In some drones, the charging time is estimated to be triple the flight duration, for other drones it is estimated to be double the flight duration. Since fast charging could be an option in search and rescue, the charging time for the batteries is estimated to be double the flight time of the drone. Once a drone charged its battery, it notifies the GCS. The GCS checks if some regions of the mission are without an activated drone. If all the regions of the mission are already assigned to a drone. The charged drone returns to the idle state. Otherwise, the GCS re-assigns the drone to the mission, so patrolling is continued. The performance of the 30 simulations is shown in Figure 3. The drone generates his path based on the region assigned to him. For this reason, in the first simulation we have only one region, while for the second simulation where we have two active drones assigned to the mission, the mission area was divided into two meso-grille subregions. Each sub-region will be assigned to a different drone.

Table 2. Configurations of the best simulation in terms of performance.

Configuration	Simulation22	Simulation27
nbDroneActive	4	4
nbDroneIdle	4	5
nbChargeStation	4	4
nbSwapStation	4	4
nbChargeSlots	3	3
nbBatteries	4	4
Mean Performance	99.89%	99.88%

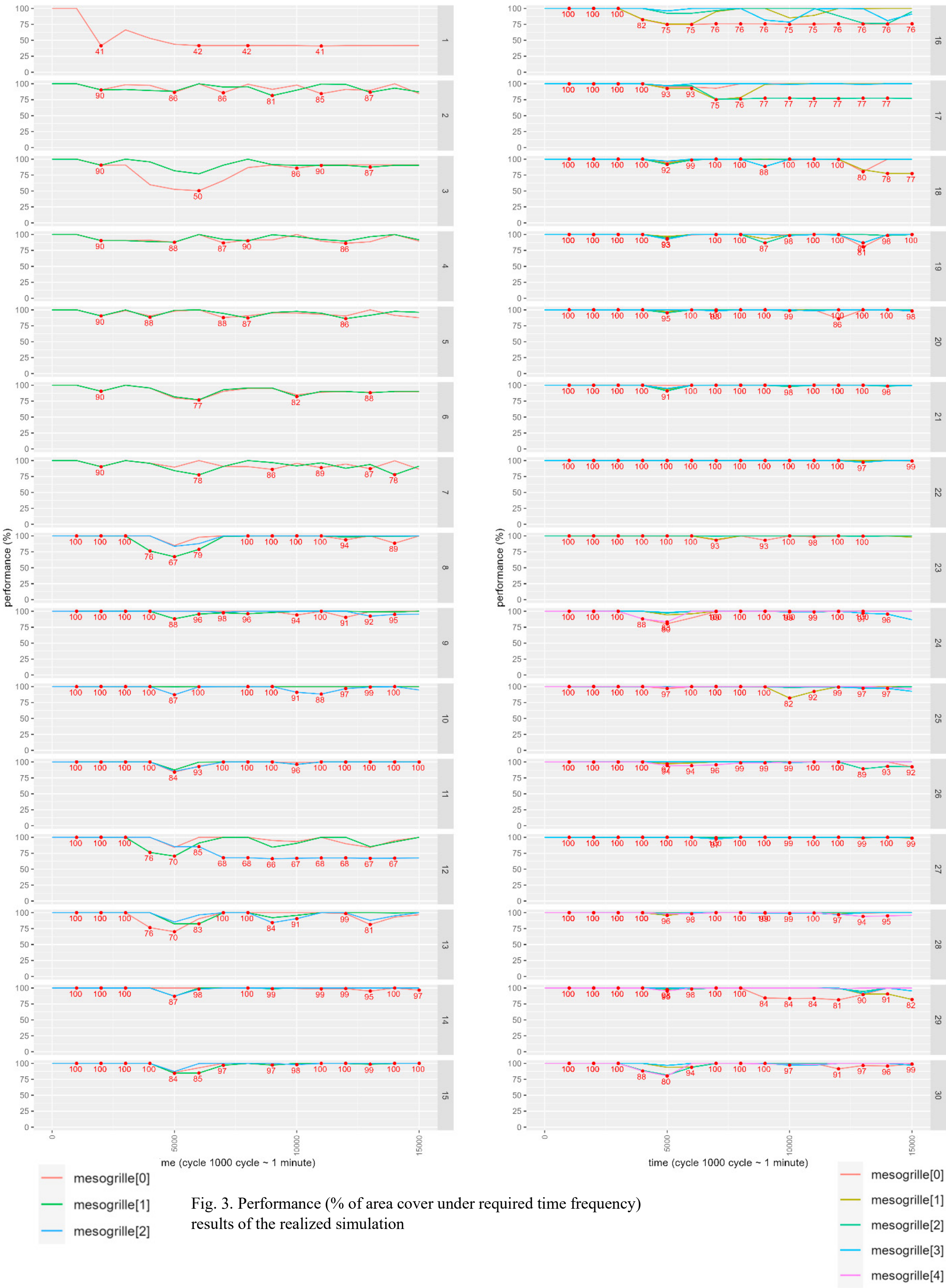

Fig. 3. Performance (% of area cover under required time frequency) results of the realized simulation

The simulation results were analyzed using a linear model to find the effect of each parameter on the global performance of the mission following the following formula where Yi is the performance of the simulation i.

$$Y\,i = \beta_1\,\mathrm{nbDroneActive} + \beta_2\,\mathrm{nbDroneIdle} + \beta_3\,\mathrm{nbChargeStation} + \beta_4\,\mathrm{nbSwapStation} + \beta_5\,\mathrm{nbBatteries} + \beta_6\,\mathrm{nbChargeSlots} \qquad (1)$$

The estimated value for the effect of each parameter shows that the most significant parameters are the number of active drones, the number of batteries used and the number of charging slots available in the swapping stations. The number of idle drones has a borderline p-value of 0.05. In the results we expected a correlation between the parameters nbBatteries and nbChargeSlots. However, the VIF (Variance Inflation Fac-tor) shows a low level indicating that multicollinearity should not be a problem, so both parameters are kept in the model. Figure 4 shows the variation of the performance by the number of active and idle drones and the number of batteries.

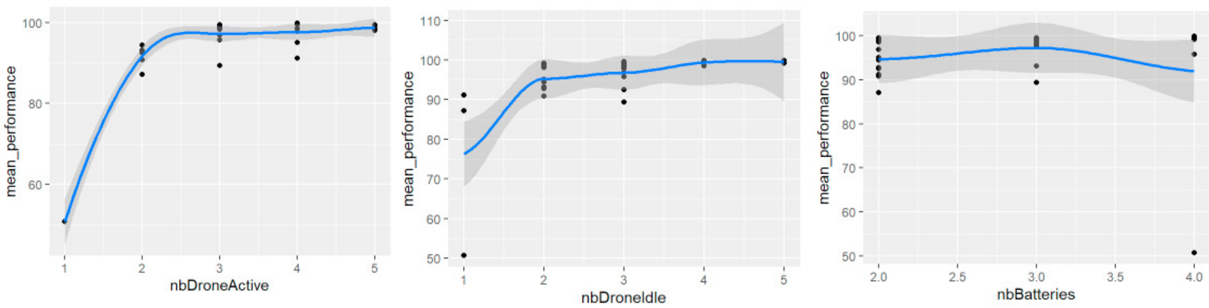

Fig. 4. Variation of the percentage of the performance based on the (a) number of the active drone (b) the number of idle drones and (c) the number of batteries.

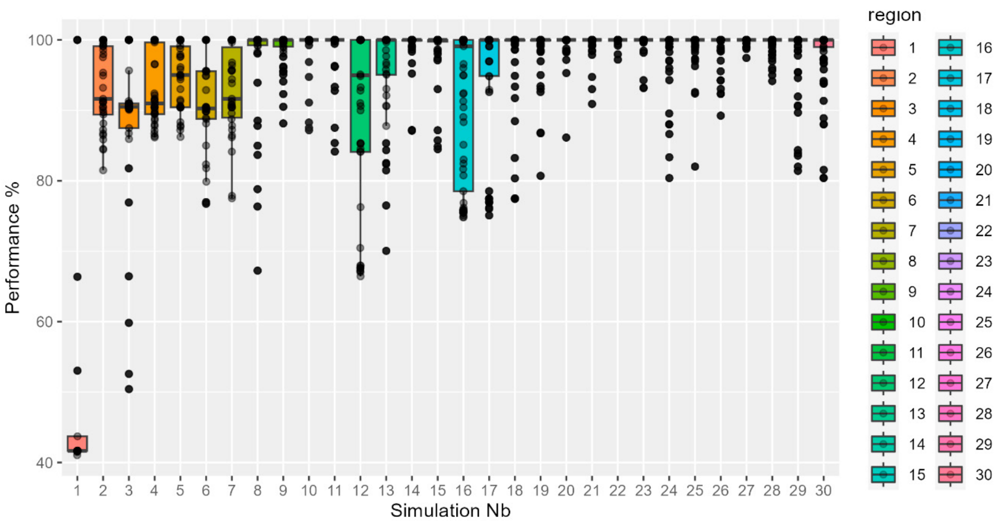

Fig. 5. Mean Performance of each simulation.

5. Conclusion

Collaboration network missions require intense communication of highly con-text-dependent information. The autonomous collaboration of drones can help to enhance the repetitive and continuous surveillance of search and rescue operations and alleviate the control of multiple drones by multiple pilots. The proposed simulation framework aims to showcase the continuous coordinated surveillance of a large area using multiple drones. The simulation could give an estimation of the efficiency of the collaboration based on the surveillance requirements and available resources. It also estimates the required resource to cover a specific area within a time frequency. The framework can be used to proactively simulate an area to design a collaborative drone system. In a concrete use case simulation concerning a forest fire search and rescue scenario, we focus on the autonomous coordination of the mission for a continuous monitoring using homogenous drones. To improve this work an optimized approach for the distribution of the charging stations and Battery Swapping Stations (possible mobile) could be included. Also, path planning could be prioritized dynamically based on events in the environment. Finally, additional aspects could also be taken into consideration for the identification of the optimal configuration, such as ground risks, as well as reporting resource costs and the resulting elasticity of the performance.

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