Multi-Agent Systems using UAV's for Surveillance in the Disaster Management

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Abstract Rescue and recovery operations are critical in disaster management. For the speedy rescue process in order to save the lives, proper surveillance of the disaster affected area is essential. In this regard, surveillance using Unmanned Aerial Vehicles (UAV's) are predominately helpful in such circumstances for speedy surveillance. In this context, for faster surveillance, multiple UAV's are deployed in the disaster affected region. In this paper, the multiple UAV's are considered as multi-agent systems and explored the algorithms such as UAV back-and-forth algorithm, UAV FA algorithm and UAV random algorithm. The simulation results are carried out and evaluated the algorithms with respect to various parameters such as, residual battery in the drones, number of targets, average hit time and energy consumption. Based on the simulation results, the requirements and the need of the multi-agents for overall efficient surveillance for disaster management can be analysed based on the gathered information.

Keywords Multi-Agent Systems · Disaster Management · Unmanned Aerial Vehicles

1 Introduction

A disaster is a large-scale event that causes major physical harm or devastation, fatalities, or significant environmental change. Determining the extent of the damage after flood waters have receded becomes difficult. Communities can begin to recover by deciding which places need cleaning and repairs most urgently. Conventional methods for disaster management suffer from detailed

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information gathering and initial estimation of the degree of demolition. Those methods are also very time-consuming for victim search and identification. The damage revealed by receding water is frequently easier and more affordable to see using drones than with typical plane or helicopter-based examinations. Since drones can map damage to a finer precision than satellites, they can also complement large-scale evaluations of damage using satellite data. Decision-makers can evaluate where and how much assistance is required by using comprehensive, timely, and accurate flood damage assessments. Decision-makers can more easily decide if additional support should be asked for and the number of funds that may need to be applied for by quickly determining the extent of the flood damage. Additionally, it can also avoid wasting time and money. In this context, the proposed work uses the drones for surveillance for disaster management to provide efficient coverage and surveillance.

According to the National Crime Records Bureau's (NCRB) most recent data on disaster and unintentional fatalities in India, Bihar had the greatest number of deaths caused by floods in 2021. A total of 15,405 unintentional fatalities were reported in the state in 2021, an increase of 6.4% over the 14,474 accidental deaths reported in 2020 [14]. The earthquake in Valdivia Chile on 22 May 1960, killed 1655 people, injured 3000, and displaced two million. It caused US$550 million in damage in Chile [3]. In June 2013 in Uttarakhand, more than 6,054 people lost their lives and 4,550 villages were damaged when a midday cloudburst that was centered on the Indian state of Uttarakhand in the north of the country triggered deadly floods and landslides [1]. As CRED1 announced, from 1998 to 2017, 1.3 million people died and 4.4 billion were injured, lost their homes, or needed emergency assistance as a result of natural disasters including tropical storms, hurricanes, sandstorms, landslides, avalanches, tsunamis, wildfires, floods, and earthquakes. Different countries reported more than 2908 billion dollars in direct financial losses during this 20-year. According to published information, climate-related disasters account for 91% of all recorded events, and among them, floods were the most frequent type of disaster, 43% out of all [2].

Drones have many uses outside of the military and industry, but their effectiveness in aiding emergency management is undeniable. Monitoring flooding is a major challenge. The uncertainties associated with land-based methods and remote sensing approaches affect the levels of accuracy, reliability, and usability of the output maps generated. While you're unlikely to see anything in traditional aircraft and helicopters that you wouldn't be able to see from drones, moreover, the latter is often much cheaper and easier to operate. Unlike traditional aircraft, drone flights can be conducted by trained volunteers rather than requiring more skilled and licensed pilots. Drones can also be deployed flexibly and on short notice, like during a short break in dangerous weather that would otherwise ground aircraft. Using drones to take footage of flood events also means that manned aircraft can focus on finding and evacuating people that have been stranded by flooding without having to worry about collecting footage at the same time. The satellite can also be used to assess the scale and extent of natural disasters. But during flood events, cloud cover often prevents satellites from capturing any useful images. In the event of a damaged dam, people may get trapped in the flooded area. The evacuation is necessary, even if people can locate a higher spot nearby, like sitting on the roof. A tiny drone in the hands of local or regional management can assist in finding trapped persons. Floods are a tragedy that slowly develops thus, drones can assist in controlling and managing in many ways. With drone observation, it is possible to foresee how flooded the area would be, what buildings are at risk, where to start the evacuation of the population, etc. The fundamental problem with this application is the lack of manned aerials, however, drones can provide a satisfactory fix. There is still a need for innovative ways that can efficiently identify the correct tasks for the right drones at the right times while optimizing the overall advantages derived from the drone's operations.

This paper primarily focuses on designing algorithms that may help in improving the overall efficiency of multi-UAV surveillance systems for information analysis and crisis management in case of a disastrous situation via stimulating various multi-drone surveillance algorithms with the help of GAMA platform and exploring the conditions or situations best suited for using these algorithms.

2 Related Works

In this section, from the literature, the existing work has been explored and few observations are presented. In the paper [4], natural disasters or man made calamities, providing the required medical assistance physically through land is not possible most of times, and hence unmanned aerial vehicles are now being used at some places to provide the required medical aids easily and in less time. In this research paper its been discussed about the available path planning algorithms which are used in planning the most efficient path for providing medical aids at various nodes along with the capacity UAV's will be holding. The four different algorithms which are: CVRP(capacitated vehicle routing problem), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Genetic Algorithm (GA) have been discussed and the comparison between the algorithms was carried out at different vehicle capacities and numbers. The CVRP was found to outperform other algorithms with a runtime of 0.06 sec and cost of 419 at vehicle capacity 10, which is 50 percent less having the same number of the vehicles but increasing the capacities to 20. The results indicate that the effective path planning method could be applied to provide medical aid in real-time with efficacy. In this paper [5] When a disaster happens, it makes it hard for people to communicate with each other. Drones are being looked at as a solution to this problem, as they can help people communicate. This paper suggests two things to make this work better. First, it suggests using special technology to find places where a lot of people need help communicating. Second, it suggests mathematical model to figure out the best way to send out drones so that they can help the most people while using the fewest drones possible. Two methods are discussed in this paper to solve this problem, a B and B algorithm, which has complexity exponential to the network size, and a low complexity heuristic. In this paper [6] the goal of the algorithm is to distribute a group of drones in areas affected by disasters to establish communication This algorithm gives the deterministic positions of drones along with their height at which they should be deployed such that the average leftover energy of the drones is minimum and area covered is maximised. Region filling is the core part of the algorithm. Here the rectangular area is covered by using circles, representing coverage area by drones. The algorithm begins to fill the area with drone coverage, i.e., the circles, from the origin to the other corner, by filling circles along the coordinate axes layer by layer. The working of the algorithm is:- at first the drone is placed at (0 , 0) then check if the whole region is covered. If Yes then, stop else place a drone at the opposite corner diagonally i.e. at (m, n) and check if the whole region is covered. If not then fill circles along the coordinate axes optimally from (0 , 0) to (m , 0) and (0 , 0) to (0 , n) then again check if the area is covered. If not then repeat the same thing for the inner layers until the whole region is covered. This paper [7] provides a method for using unmanned aerial vehicles (UAVs) to assess damage to distribution systems during disasters when communication coverage is lacking. The paper describe how the proposed method utilizes image processing techniques to analyze high-resolution images captured by the UAVs and identify damaged components in the distribution systems. The paper also discuss the development of a decision recommender system that can provide recommendations for repair and recovery efforts based on the identified damage. The paper suggest that this approach can improve the efficiency and effectiveness of damage assessment and repair efforts in disaster situations where traditional communication methods may be unavailable or unreliable. Overall, the paper presents a promising approach for enhancing the ability of responders to assess and repair damaged distribution systems during disasters. The paper does not explicitly mention the specific image processing algorithms used in the proposed method for UAV-enhanced damage assessment of distribution systems in disasters with a lack of communication coverage. However, it suggests that the method utilizes image processing techniques such as edge detection, feature extraction, and pattern recognition to analyze high-resolution images captured by the UAVs. This paper [8] proposes a joint optimization approach for UAV cluster deployment and resource allocation that can significantly improve the performance of real-time emergency communication systems. They use K-means clustering algorithm and jointly optimal power and time transferring allocation algorithm. The results showed that their method works better than other ways that people have tried before. Overall, their approach can help emergency responders communicate more effectively in critical situations. In this paper [9], in the event of disaster, identifying location and number of victims is of utmost importance for effective rescue operation. Normal communication services become obsolete due to damages to communication towers, network overloading, or remote area affected. A Ubiquitous Network architecture (UbiQNet) is proposed. UAVs can act as nodes for a mesh network using ESP32 (low power WIFI module). These would be deployed to the affected area and act as nodes of UbiQNet on which victims and first responders can connect via an app. A victim can relay necessary information such as name, nearby person count, location etc. to the first responder. Additionally, UAVs would relay videographic feed of the affected area which will help the rescue team formulate a strategy to rescue the victims efficiently. In this paper [10], the first problem is to setup the communication in the disaster affected region as the infrastructure on the ground is destroyed. To solve this problem we use UAV's because of their capabilities of hovering at the same place for long time so that users at the service points can communicate. First we take sufficient amount of UAV and air station for each UAV from where the UAV will take off and return back to under the constrained Energy limit. These problem is similar to Travelling salesman where the UAV has to start air station and cover the maximum service point within its energy constrained and come back to air station but this problem is NP hard so two other Heuristic approaches are proposed. Nearest Assignment Algorithm where the each UAV will be assigned the service points which are nearer to them and after that for each single UAV they all separately planned the trajectories for their assigned service points. In this paper[11], using UAVs enhanced with artificial intelligence in Disaster management environments has been proved to be a very efficient tool for assessing the situation and damage control. Sending relief teams on the basis of feeds received from UAVs helps in reduced response time to provide better medical and other aid. The use of AI further facilities assessing difficult areas or those regions where visuals are not upto the mark. Conclusively, There is no doubt that UAVs are an integral part of disaster management procedure. This paper [12], proposes a system architecture for disaster management in collapsed buildings that utilizes the IOT technology. The proposed system consists of a sensor network, a data center, and a decision-making system. The sensor network is composed of various types of sensors that can detect the physical conditions of the collapsed buildings, such as temperature, humidity, and gas concentration. The data center collects and processes the data generated by the sensor network and provides real-time information to the decision-making system. The decision-making system is responsible for analysing the collected data and making decisions to guide the rescue operations. In the paper [13], post disaster management issues has been addressed by using the real hardware of the drone in the Internet of Things network. However, the multi agent drones simulations are not carried out.

Several contributions have been made to design algorithms to optimize multi-agent surveillance systems many of which are inspired by nature like flashing patterns and behavior of tropical fireflies or the motion of bird flocks and schooling fish which helped in designing and implementing algorithms useful in performing multi-agent surveillance efficiently. Particle swarm optimization (PSO), one of the bio-inspired algorithms that draw its inspiration from the movements of bird flocks, is a straightforward tool for identifying the best solution in the problem space, which is analogous to locating objectives in a surveying area has also been proposed [22]. Firefly algorithms is a nature-inspired meta-heuristic optimization algorithm developed by Xin-She Yang that is inspired by the flashing behavior of fireflies. In this algorithm, two entities (maybe solutions) attract each other based on many factors such as distances, and based on such attraction, along with a degree of randomness entities change and update their position [19].

Recent research has suggested teamwork strategies to help drones achieve objectives beyond their own capacities. Numerous approaches have been made in this area to deal with cooperative patrolling [25] and tracking operations [23,24], cooperative surveillance [15], and cooperative rescue missions [16]. In this context, a number of difficulties have been addressed, including path overlap avoidance [28], scheduling trajectories [17], and obstacle avoidance [26,27]. Numerous works have emphasized the use of artificial intelligence systems, including Multi-Agent Systems, to cooperatively generate harmony within a swarm of drones and carry out the expected activities in accordance with particular criteria [29,30] like time, energy limits, quality of service, etc. A 5-step drone collaborative planning approach where an algorithm involving assessment, setup, bidding, agreement, and feedback has been proposed [18] where factors like distances, and battery levels of drones were considered in order to select the best cell at the instants and results were analyzed in the GAMA platform with simulation. To optimize a distributed UAV swarm formation system, a distributed robot 3D formation system has been developed and its parameters have been optimized by a hybrid evolutionary algorithm (EA) [21]. This has improved the system's efficiency and robustness and helped to achieve stable formations in the majority of the scenarios. Also, Algorithms to find the best coverage paths to be followed by the UAVs to efficiently cover the areas of different shapes [20] to be surveyed using region optimal decomposition have also been proposed where decomposition of concave polygonal regions and the merging of sub-regions and the optimal algorithm to reduce the number of UAV turns.was discussed. Inspired by these algorithms, three algorithms were designed and studied namely back-and-forth Algorithms, firefly Algorithm, and Random Algorithm which were analyzed under various parameters and situations to find out the best scenario suited for a given algorithm.

3 Proposed Work

The proposed work includes developing and setting up a simulation environment to design, analyze, and test various Search and Rescue (SAR) algorithms for multi-agent systems in disaster management and exploring the conditions or situations best suited for using those algorithms. In the proposed work we have assumed that all agents are equipped with the necessary hardware to provide them the ability to communicate with each other to share surveillance information and required data to avoid collision during the movement of drones. These assumptions were made in order to mainly focus on the analysis

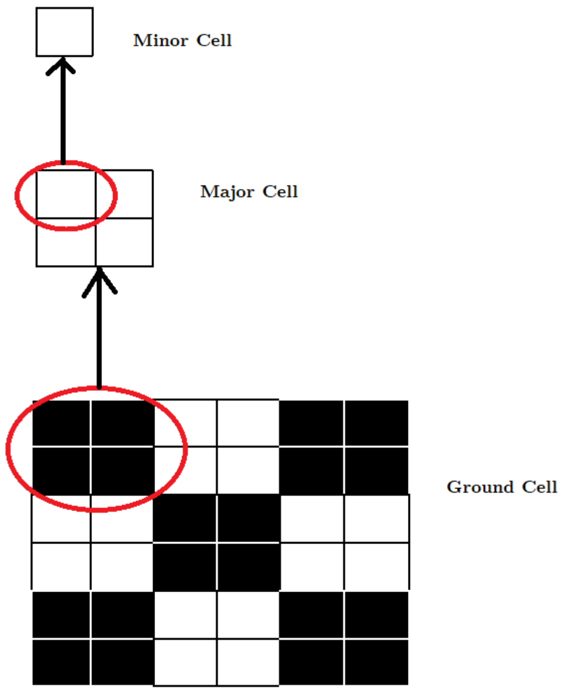

Fig. 1 Instance of a Ground Cell

of the algorithms used rather than accounting for the hardware capabilities of agents used.

Models/Agents: For developing and implementing the simulation, the models which were defined along with their characteristics are as follows:

- Ground Cells: The model represents the ground on which the targets will be present and for which drones will be performing surveillance. Ground cells comprise two types of cells, i.e., Minor cells (smallest cells) and Major cells (group of minor cells) as shown in the Fig 1. In this figure, minor Cell - smallest cell & major Cell - larger cell are of the same color.
- Target: The model represents the entity/event which is aimed to be detected during surveillance. This target can be static, i.e., always at a fixed location, or dynamic, i.e., changing its location with time. Both types of targets can be the representation of various scenarios in real life. For instance, the static target can represent a human stuck in a post-earthquake situation whereas the dynamic target can represent conditions like prisoners escaping a prison or fire/flood spreading in an area that needs to be surveyed for analysis. Also, for dynamic targets effect of starting location being the same or different for all targets was also studied. In order to achieve the same, dynamic targets were categorized into the same sourced targets (all targets starting from the same initial locations) and different sourced targets (all targets starting from different initial locations). These

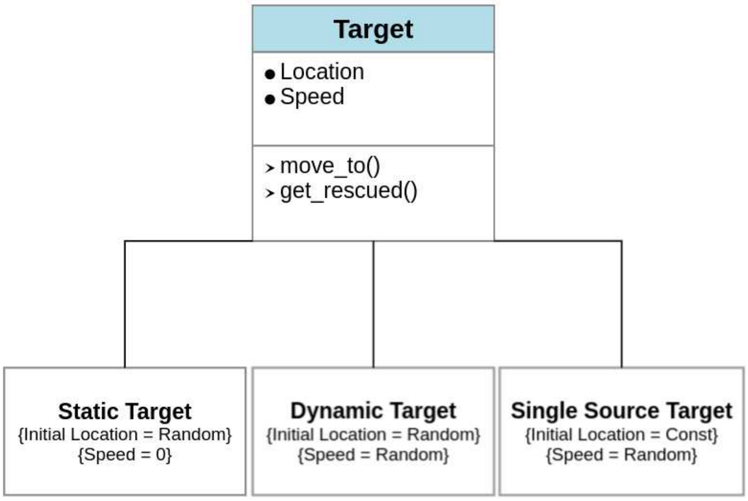

Fig. 2 Class Diagram of Target Model

categories can also be a portrayal of real-life situations like fire originating at a single source and spreading or random animals roaming around fields. The class diagram of the target model is shown in Fig 2.

– Drone: The model represents the real-life drone that will be performing the actual surveillance. The model performs the surveillance by allocating a particular cell, reaching the selected cell while updating its instant locations and battery levels, and performing surveillance upon reaching the selected cell. While the movement of the drone, the location and battery levels are updated according to the speed of the drone i.e. since the motor speed is expected to be lesser while surveillance than the speed while moving from one cell location to another hence battery is consumed according to this assumption. The allocation of cells to be surveyed is decided by the algorithms which are to be analyzed. The main 3 types of algorithms implemented were Firefly Algorithm, Back & Forth algorithm, and Random Algorithm, accordingly different drone models were implemented. The class diagram of the agent model is shown in Fig 4.

3.1 UAV Back-and-Forth Algorithms:

In the UAV back-and-forth algorithms, all drones follow a back-and-forth path to cover the surveillance area until the complete area is covered or all targets are identified. The algorithms for determining the condition when the drone moves in the right direction from the current location, left of the current location, upwards and downwards from te current location of the drone to survey the disaster affected area is given in the following algorithms. These

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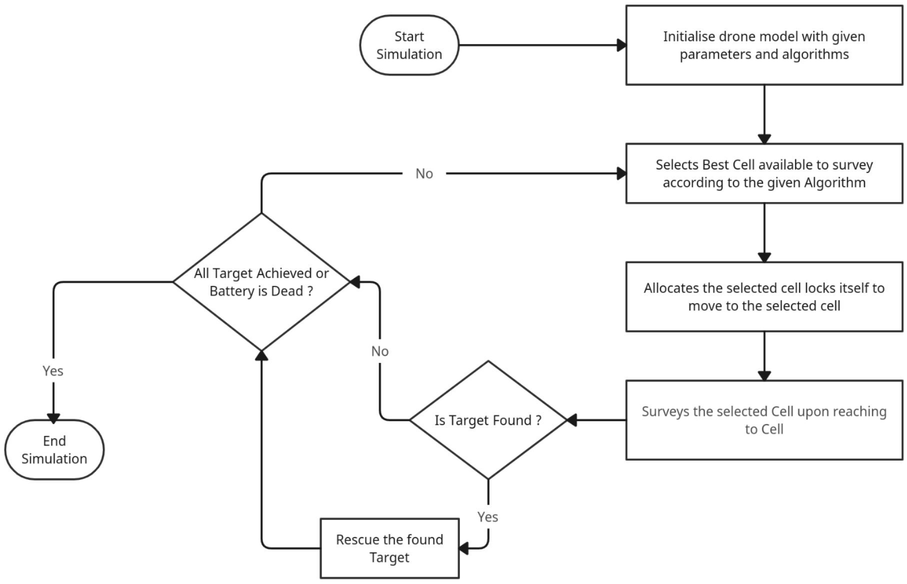

Fig. 3 Flow chart of the Simulated Agents

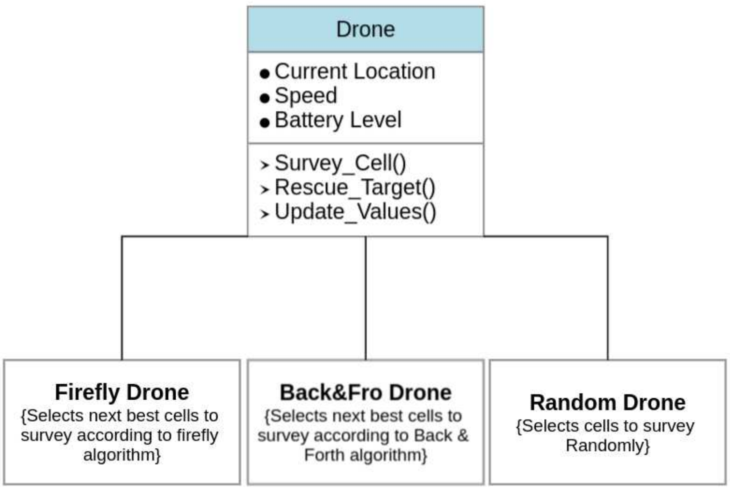

Fig. 4 Class Diagram of Agent Model

are the algorithms to decide the next move (right, left, up, or down) of the drone based on the current location of the drone to survey.

Algorithm 1 Pseudo code for Back-and-Forth algorithm

```
Input as change_direction, grid_X, grid_Y
procedure PSEUDOCODE: TO_MOVE_RIGHT
    (condition_move_right) ← (change_direction and grid_Y%2 = 0) or
        (!change_direction and grid_X < cell_side − 1 and grid_Y%2 = 1)
    return(grid_X < cell_side − 1) and condition_move_right
end procedure
procedure PSEUDOCODE: TO_MOVE_LEFT
    (condition_move_left) ← (change_direction and grid_Y%2 = 1) or
        (!change_direction and grid_Y%2 = 0)
    return(grid_X > 0) and condition_move_left
end procedure
procedure PSEUDOCODE: TO_MOVE_LEFT
    (condition_move_down) ← (grid_X = cell_side − 1 and
        grid_Y% = 0)or(grid_X = 0 and grid_Y%2 = 1)
    return(change_direction and grid_Y <
        cell_side − 1) and condition_move_down
end procedure
procedure PSEUDOCODE: TO_MOVE_LEFT
    (condition_move_down) ← (grid_X = cell_side − 1 and
        grid_Y% = 0)or(grid_X = 0 and grid_Y%2 = 1)
    return(change_direction and grid_Y <
        cell_side − 1) and condition_move_down
end procedure
procedure PSEUDOCODE: RETURN_NEXT_BEST_CELL
    Input: drone
    current_location ← drone.location
    grid_length ← ground_side/cell_side
    grid_X ← current_location.x/grid_length
    grid_Y ← current_location.y/grid_length
    best_grid_X ← grid_X
    best_grid_Y ← grid_Y
    if to_move_right() then
        a. best_grid_X ← grid_X + 1
        b. best_grid_Y ← grid_Y
    else if to_move_left() then
        a. best_grid_X ← grid_X − 1
        b. best_grid_Y ← grid_Y
    else if to_move_down() then
        a. best_grid_X ← grid_X
        b. best_grid_Y ← grid_Y + 1
    else if to_move_up() then
        a. best_grid_X ← grid_X
        b. best_grid_Y ← grid_Y − 1
    end if
    if is_curr_cell_surveyed() then
        a. change_direction ← true
    end if
    return (best_grid_X, best_grid_Y)
end procedure
```

3.2 UAV FA Algorithm:

UAV FA algorithm is inspired by the firefly algorithm first cells are divided into two categories major and minor cells. The attraction between major cells and drones decides the next best major cell to be surveyed and the attraction value depends upon which cells have a history of more targets, which drones have more battery levels and are closer, and many other factors. Once the best major cell is selected the unsurveyed minor in the selected major cell is randomly chosen. The above algorithm determines the attraction value between a given drone and all major cells based on the mentioned equation. The algorithm determines the coordinates of the next best cell to be surveyed based on the attraction values calculated using Algorithm 6. The algorithm pseudo code is given as follows.

Algorithm 2 Pseudo code for FA algorithm:

```
procedure PSEUDOCODE: RETURN_ATTRACTION_VALUE
    Input: drone,cell_X,cell_Y
    drone_location ← drone.location

    major_cell_location ← get_major_grid_location(major_grid_X, major_grid_Y)
    distance_bet ← get_distance_bt_points(drone_location, major_cell_location)
    battery_life ← given_drone.batteryLife
    reputation ← 1 + drone.targetRescued
    surveillance_factor ← get_surveyed_percentage(major_grid_X, major_grid_Y)
    attraction_power ← (distance_bet^(0.5)) * (random(1))/(battery_life *
        reputation)
    attraction ← attraction_constant * exp(−1 * attraction_power) * (1 −
        surveillance_factor)
    return attraction
end procedure
procedure PSEUDOCODE: RETURN_NEXT_BEST_CELL
    Input: Agents/Drone
    update_attraction_matrix()
    current_attraction_value ← 0
    cell_X ← random(cell_side − 1)
    cell_Y ← random(cell_side − 1)
    for i ← 0 to major_cell_side − 1 do
        for j ← 0 to major_cell_side − 1 do
            attraction_value ← attraction_matrix[i][j][drone.idx]
            if current_attraction_value ≤ attraction_value then
                a. current_attaction_value ← attraction_value
                b. cell_X ← i
                c. cell_Y ← j
            end if
        end for
    end for
    return(return_random_minor_cell(cell_X, cell_Y))
end procedure
```

3.3 UAV Random Algorithm:

In the UAV random algorithm, all drones randomly select the next cells to be surveyed without taking into account the factors like distance between the drone and the cell, or energy consumed. The algorithm randomly selects the coordinates of the next cell to be surveyed until all targets are detected or all cells are surveyed (only for static targets).

Pseudo codes for Random algorithm:

Algorithm 3 Pseudo codes for Random algorithm

```
procedure PSEUDOCODE: RETURN_NEXT_BEST_CELL
    Input: Agents/Drone
    if (TARGET_MODE!="Static") then
        return[random(cell_side − 1), random(cell_side − 1)]
    end if
    for times ← 1 to cell_side^2
    a. cell_X ← random(cell_side-1)
    b. cell_Y ← random(cell_side-1)
    if (!is_cell_surveyed(cell_X,cell_Y) and !is_cell_allocated(cell_X,cell_Y)) then
        return[cell_X, cell_Y]
    end if
    return[random(cell_side − 1), random(cell_side − 1)]
end procedure
```

4 Results and Analysis

For developing and setting up the simulation environment we used the GAMA platform which is a modeling and simulation development environment for building spatially explicit agent-based simulations in which we have defined various agents like ground cells, targets, and drones along with specifying their attributes and methods required to simulate a given algorithm for using them in the multi-agent system for surveillance and various results like average time to detect a target or energy consumed were plotted across various drone algorithms.

Various input parameters which were defined during simulations. Firstly, with respect to the ground parameters for governing the characteristics like shape and size of the ground to be surveyed. Ground side parameter for the length of the ground side in meters, minor cell side for the number of minor cells in any one major cell side and major cell side for the number of major cells in any one ground side. Regarding drones or agents parameter, number of agents or drones viz., number of drones available to perform surveillance, drone origin mode, whether all drones are to be launched from the same (Sourced Mode) or different locations (Random Mode), drone algorithm mode refers to the algorithm to be followed during surveillance like Firefly Algorithm, Back-and-forth Algorithm, or Random Algorithm. Likewise, battery capacity refers to the measure of the maximum capacity of energy that can be stored in a drone's batteries and rescue sensitivity refers to the measure of the minimum distance from which drones can detect the given target are considered.

Subsequently, with respect to the target parameters, number of targets present on the ground to be detected during surveillance and target mode refers to whether targets are static or dynamic are considered.

Srveillance simulation where the actual motion and movements of drones and targets according to input parameters while monitoring the output parameters are performed. For instance, in the Fig 5, surveillance simulation snapshot is shown.

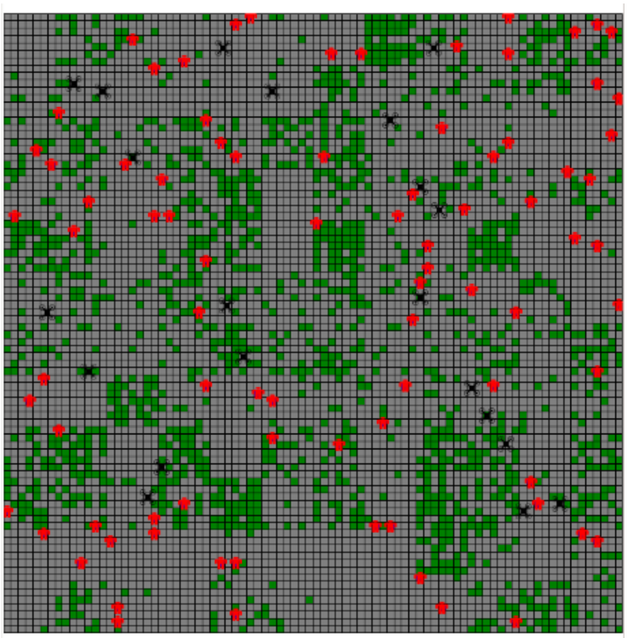

Fig. 5 Surveillance Simulation

Output entities that were monitored and plotted over time. Average hit time is the time taken by the drones to detect target, percentage of energy consumed refers to the average percentage of energy consumed in the drones and percentage of targets left, which are undetected at the instance are considered as output parameters. The comparative analysis of the target's and remaining battery is shown in Fig 6. Likewise, the average hit time is shown in Fig 7.

4.1 Results

For analyzing the given algorithms the simulations were executed in batches over various input parameters and average hit time as well as average energy

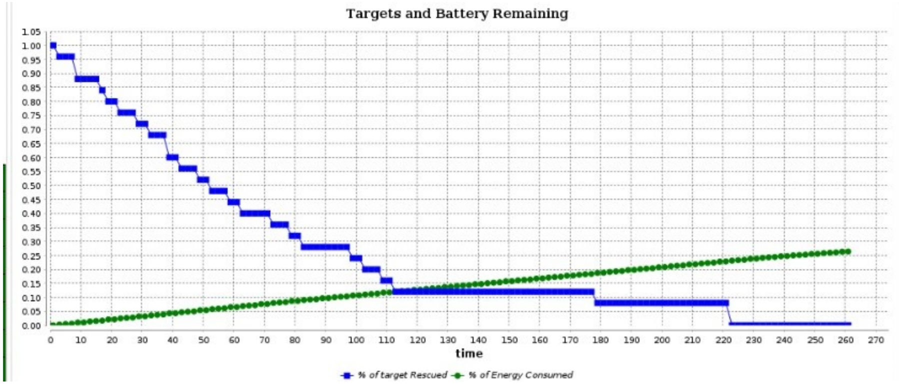

Fig. 6 Comparative observations for Targets and Remaining Battery

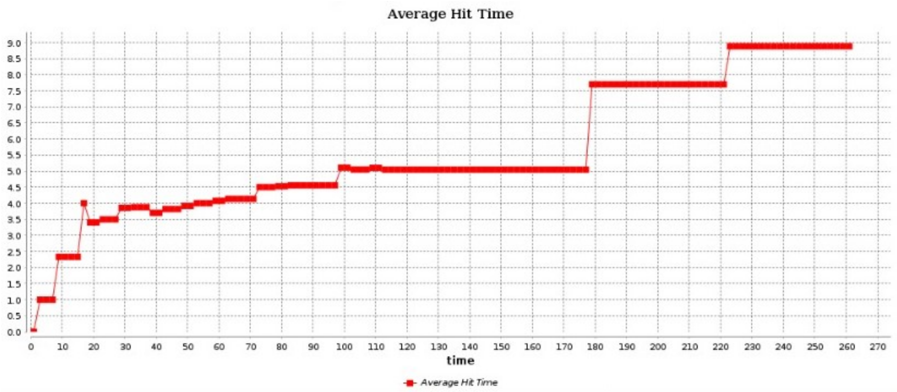

Fig. 7 Average Hit Time

consumed were recorded and plotted against all the given algorithms in the form of a violin graph (where the width of the plot represents the frequency of the provided data) and bar chart. The output parameters that were monitored and plotted for all simulations across all algorithms for different drone origins are hit time as the average time it took to detect a target and percentage of battery consumed as in the average percentage of the battery it consumed for surveillance. The results were analyzed across different parameters which are as follows:

Drone origin location, whether all drones are to be launched from the same location i.e., sourced origin or different locations i.e., random origin. If sourced origin, then all drones are starting from the same given location and are not well distributed over the area to be surveyed (which is the case in real life due to the availability of ground stations at limited locations) initially. If random origin, then all drones start from a random location and are well distributed over the area to be surveyed.

Surveillance algorithm to be followed during surveillance of the ground. In the back-and-forth algorithm, all drones are following the Back-and-Forth algorithm as explained in algorithm 1. Likewise, in the firefly algorithm, all drones are following the firefly algorithm as explained in algorithm 2. Similarly, in the random algorithm, all drones are following the random algorithm as explained in algorithm 3. Target movement is determined based on the movement of targets that need to be detected while surveillance. In the case of static target, all targets are at rest throughout the surveillance. In the case if sourced target, all targets are moving in random directions throughout the surveillance but starting from the same location. Likewsie, in the case of dynamic target, all targets are moving in random directions throughout the surveillance but starting from different random locations. The hit time (the average time it took to detect a target) was averaged out for all simulations and plotted across all three given algorithms (firefly algorithm, back-and-forth algorithm, and random algorithm) for both drone origin modes (sourced origin and random origin).

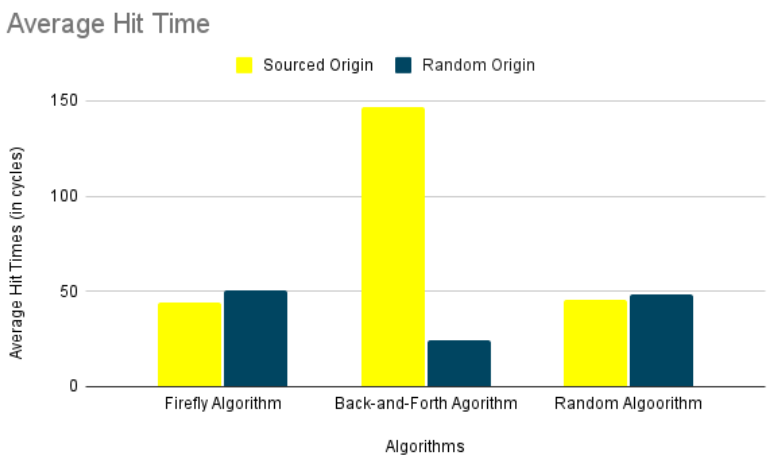

Fig. 8 Average Hit Time Vs Drone Algorithms

As shown in the Fig 8, it can be concluded the back-and-forth algorithm is performing best in the case of drone random origin whereas for sourced drone origin firefly algorithm performs the best. The percentage of battery consumed (the percentage of the battery it consumed for surveillance) was averaged out for all simulations and plotted across all three given algorithms (firefly algorithm, back-and-forth algorithm, and random algorithm) for both drone origin modes (sourced origin and random origin). As shown in Fig 9, it can be concluded the back-and-forth algorithm is performing best in the case of drone random origin whereas for sourced drone origin firefly algorithm performs the best in terms of efficient energy consumption.

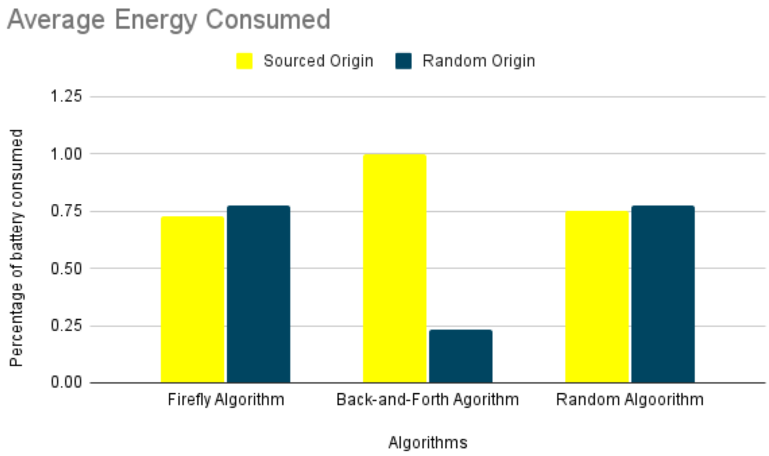

Fig. 9 Average Energy Consumed Vs Drone Algorithms

The hit time (the average time it took to detect a target) was monitored and plotted in a violin graph (where the width of the plot represents the frequency of the provided data) across all three given algorithms (firefly algorithm, back-and-forth algorithm, and random algorithm) for the random drone origin and dynamic targets as shown in Fig 10, for the random drone origin and sourced targets as shown in Fig 11, for the random drone origin and static targets as shown in Fig 12, for the sourced drone origin and dynamic targets as shown in Fig 13 and for the sourced drone origin and sourced targets as shown in Fig 14. Likewise, the hit time or the average time it took to detect a target was monitored and plotted in a violin graph for all three algorithms for the sourced drone origin and static targets as shown in Fig 15 and for the random drone origin and dynamic targets as shown in Fig 16.

The percentage of battery/energy consumed was monitored and plotted in a violin graph (where the width of the plot represents the frequency of the provided data) across all three given algorithms (firefly algorithm, back-and-forth algorithm, and random algorithm) for the random drone origin and sourced targets as shown in Fig 17. Likewise, the graph was plotted for the random drone origin and static targets as shown in Fig 18. Similarly, the results were depicted for the sourced drone origin and dynamic targets as shown in Fig 19. With respect to the sourced drone origin and sourced targets, all the three algorithm results are presented in the Fig 20. Further, for the sourced drone origin and static targets with respect to all the three algorithms are as shown in Fig 21.

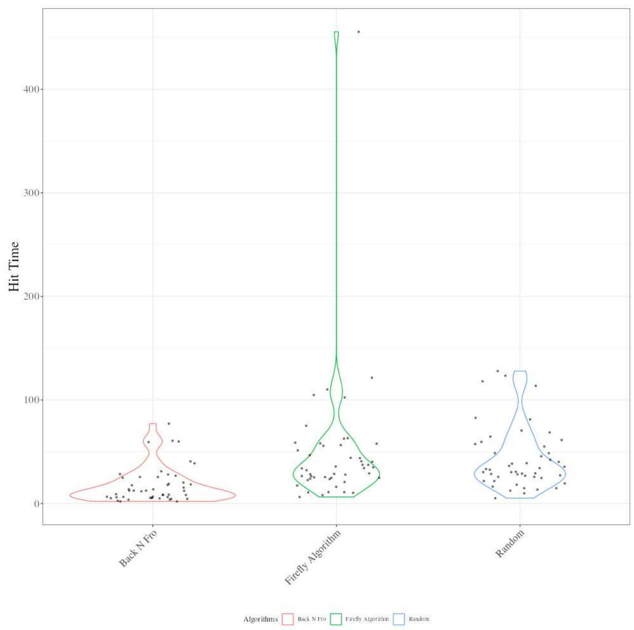

Fig. 10 Hit Time vs Drone algorithm (For random drone origin and dynamic targets)

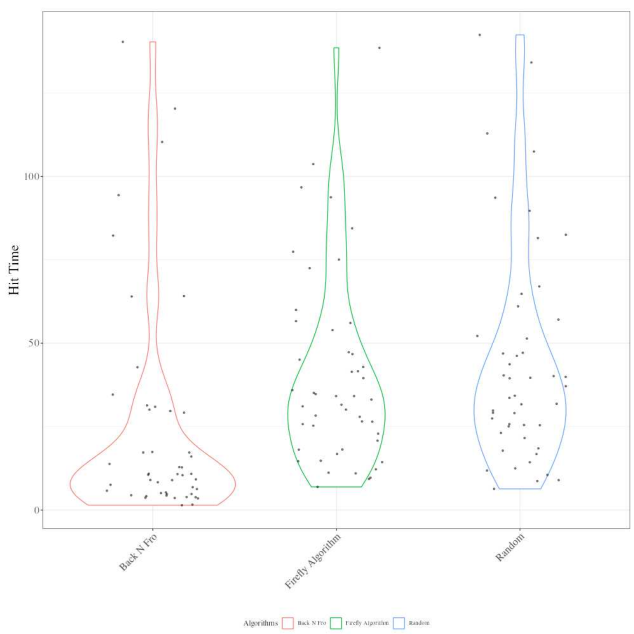

Fig. 11 Hit Time vs Drone algorithm (For random drone origin and sourced targets)

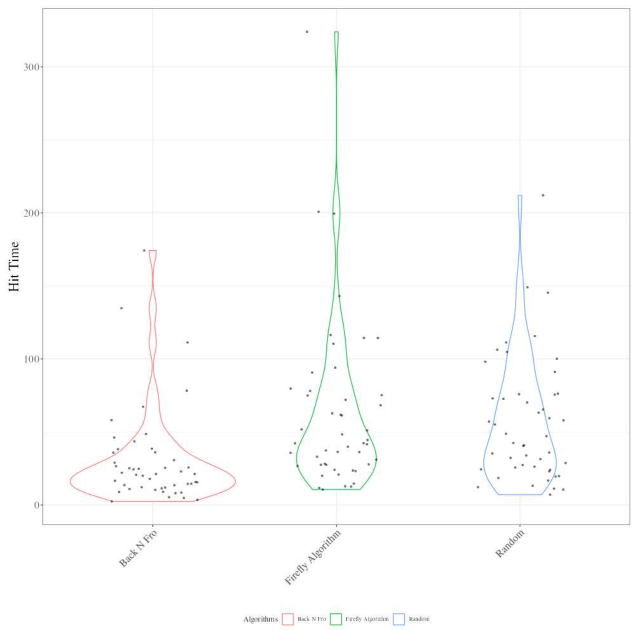

Fig. 12 Hit Time vs Drone algorithm (For random drone origin and static targets)

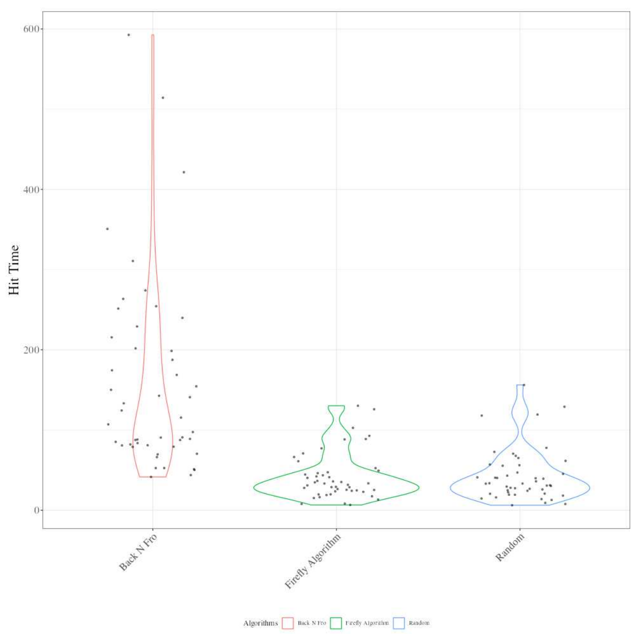

Fig. 13 Hit Time vs Drone algorithm (For sourced drone origin and dynamic targets)

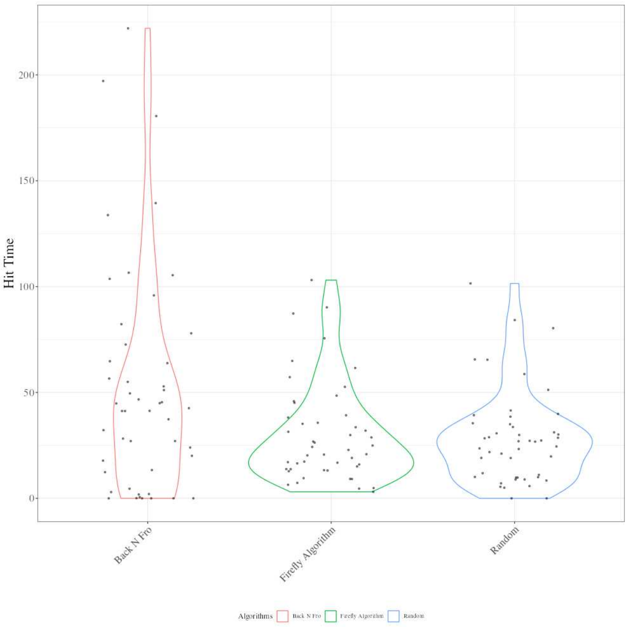

Fig. 14 Hit Time vs Drone algorithm (For sourced drone origin and sourced targets)

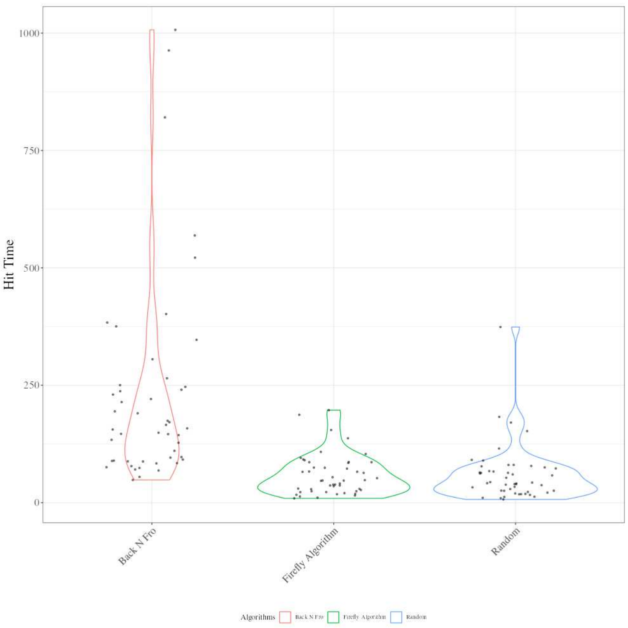

Fig. 15 Hit Time vs Drone algorithm (For sourced drone origin and static targets)

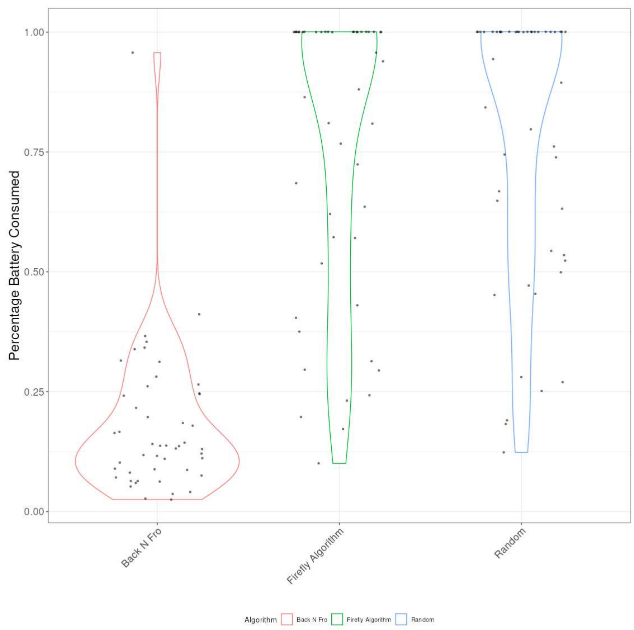

Fig. 16 Percentage of battery consumed vs Drone algorithm
(For random drone origin and dynamic targets)

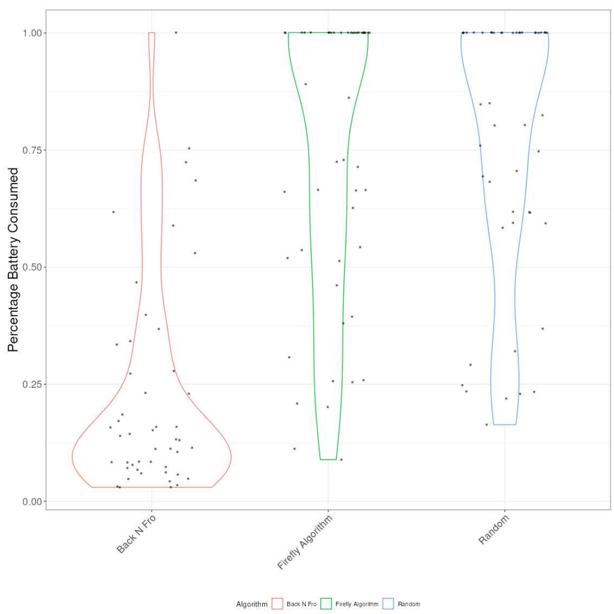

Fig. 17 Percentage of battery consumed vs Drone algorithm
(For random drone origin and sourced targets)

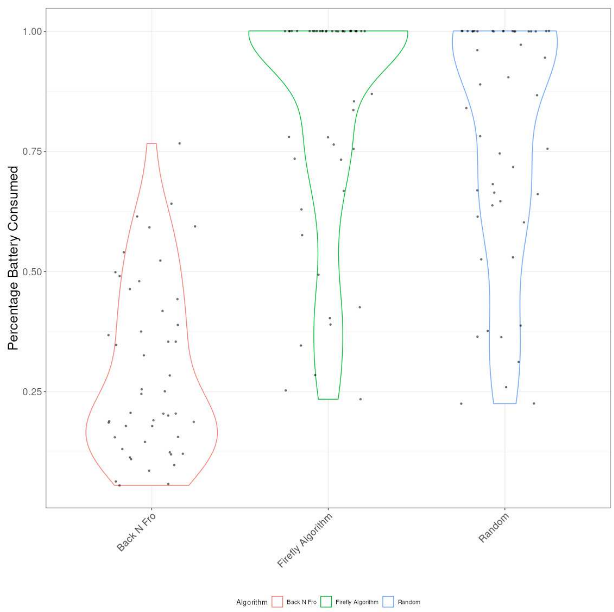

Fig. 18 Percentage of battery consumed vs Drone algorithm
(For random drone origin and static targets)

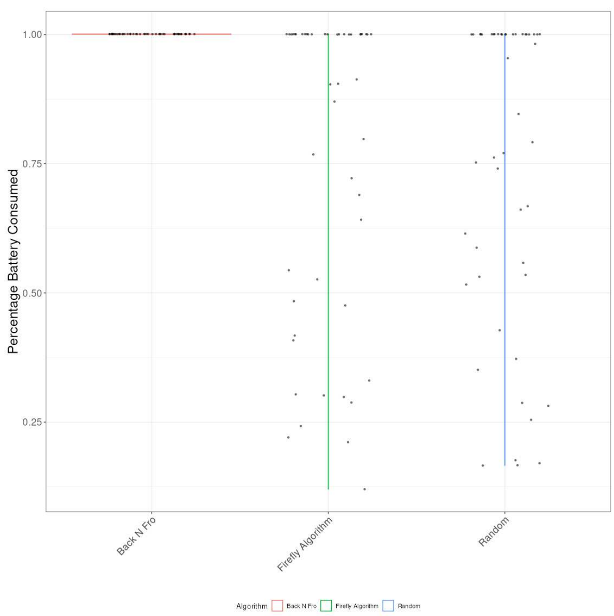

Fig. 19 Percentage of battery consumed vs Drone algorithm
(For sourced drone origin and dynamic targets)

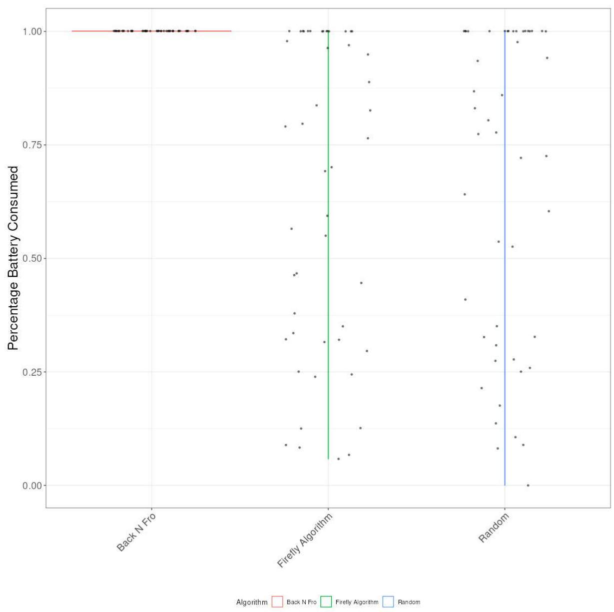

Fig. 20 Percentage of battery consumed vs Drone algorithm
(For sourced drone origin and sourced targets)

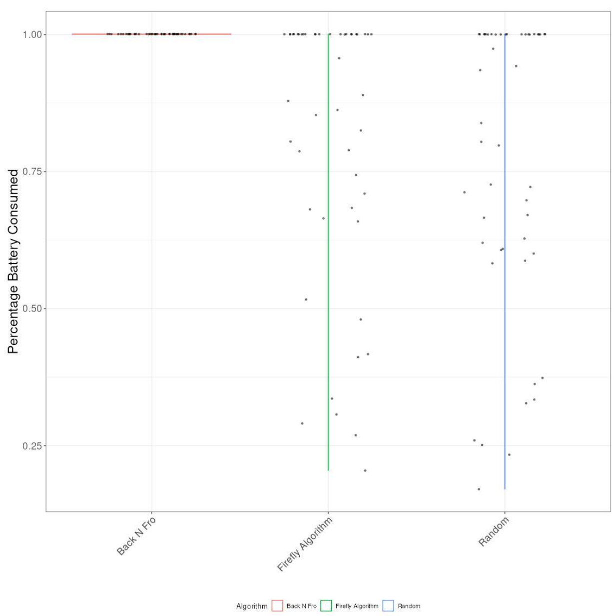

Fig. 21 Percentage of battery consumed vs Drone algorithm
(For sourced drone origin and static targets)

5 Conclusion and Future Work

In the case of drones starting from the random location or are well distributed over the area to be survey then on the basis of the average hit time back-and-forth algorithm performs better then firefly algorithm which performs better than the random algorithms. In case of drones starting from the a given location or are not well distributed over the area to be surveyed (which is case in real life due to availability of ground stations at limited locations) then on the basis of the average hit time firefly algorithm performs better then back-and-forth algorithm which performs better then the random algorithms. On basis of energy consumption back-and-forth algorithm performs better then the rest of the algorithms therefore in cases which are not time critical this algorithm can be used.

Implementation of static as well as dynamic charging stations and blind spots for better simulation of real-world situations, collision avoidance algorithm on drones and analysis of these algorithms in a 3-dimensional simulation environment, implementation of the given algorithms on physical hardware to study the efficiency of multi-drone surveillance systems were considered as future work.

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Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

References

1. D. Vallejo , J.J. Castro-Schez, C. Glez-Morcillo, J. Albusac, "Multi-agent architecture for information retrieval and intelligent monitoring by UAVs n known environments affected by catastrophes",Engineering Applicationsof Artificial Intelligence, vol 87, pp.4-13, 2020.
2. P. Wallemacq and R. U. House, "CRED report: Economic losses, poverty & disasters (1998–2017)," Brussels: Centre for Research on the Epidemiology of Disasters (CRED), 2018, pp 10-17
3. Haghighi, R., Cheah, C.-C.,"Multi-group coordination control for robot swarms",Automatica, vol. 48 No. 10, pp: 2526–2534 and pp.6-14, 2012.

4. Khan, Sara Imran and Qadir, Zakria and Munawar, Hafiz Suliman and Nayak, Soumya Ranjan and Budati, Anil Kumar and Verma, Keshav D and Prakash, Deo, "UAVs path planning architecture for effective medical emergency response in future networks", Physical Communication, Elsevier, vol 47, p: 101337, 2021.
5. Akram, Tallha and Awais, Muhammad and Naqvi, Rameez and Ahmed, Ashfaq and Naeem, Muhammad, "Multicriteria UAV base stations placement for disaster management", IEEE Systems Journal, vol 14, no 3, pp: 3475–3482, 2020.
6. Varghese, Bivin Varkey and Kannan, Paravurumbel Sreedharan and Jayanth, Ravilal Soni and Thomas, Johns and Shibu Kumar, Kavum Muriyil Balachandran, "Drone Deployment Algorithms for Effective Communication Establishment in Disaster Affected Areas", Computers, MDPI, vol 11, no 9, p: 139, 2022.
7. Qanbaryan, Mostafa and Derakhshandeh, Sayed Yaser and Mobini, Zahra, "UAV-enhanced damage assessment of distribution systems in disasters with lack of communication coverage", Sustainable Energy, Grids and Networks, Elsevier, vol 33, No 9, p: 100984, 2023.
8. Do-Duy, T., Nguyen, L.D., Duong, T.Q., Khosravirad, S.R. and Claussen, H., "Joint optimisation of real-time deployment and resource allocation for UAV-aided disaster emergency communications", IEEE Journal on Selected Areas in Communications, vol 39, no. 11, pp.3411-3424, 2021.
9. Ganesh, S., Gopalasamy, V. and Shibu, N.S., "Architecture for drone assisted emergency ad-hoc network for disaster rescue operations", in the proceedings of IEEE International Conference on Communication Systems & NETworkS (COMSNETS), pp: 44-49, 2021.
10. Lin, Yu, Tianyu Wang, and Shaowei Wang. "Trajectory planning for multi-UAV assisted wireless networks in post-disaster scenario." in the proceedings of IEEE Global Communications Conference (GLOBECOM), pp. 1-6, 2019.
11. Oren, Camille, and Andrej Verity. "Artificial Intelligence (AI) Applied to Unmanned Aerial Vehicles (UAVs) and its Impact on Humanitarian Action." Digital Humanitarian Network, May (2020).
12. Lakshmi, P., Gopika Rejith, Tom Toby, Sai Shibu NB, and Sethuraman N. Rao. "A Resilient IoT System Architecture for Disaster Management in Collapsed Buildings." In 2022 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), pp. 282-287. IEEE, 2022.
13. J Sathish Kumar, Saurabh K Pandey, Meghavi Choksi and Mukesh A Zaveri,"Collaborative data acquisition and processing for post disaster management and surveillance related tasks using UAV-based IoT cloud", International Journal of Ad Hoc and Ubiquitous Computing, vol. 34, no. 4, pp. 216-232, 2020
14. Hollinger, G.A., Singh, S., "Multirobot coordination with periodic connectivity: Theory and experiments", IEEE Trans. Robot, vol. 28, no. 4, pp:967–973, 2012.
15. Albusac, J., Vallejo, D., Castro-Schez, J.J., Remagnino, P., Gonzalez, C., Jimenez, L.,. "Monitoring complex environments using a knowledge-driven approach based on intelligent agents" IEEE Intell. Syst., vol. 25, no. 3, pp 24–31, 2010.
16. X. Zhou, W. Wang, T. Wang, X. Li, Z. Li, "A research framework on mission planning of the UAV swarm", in the IEEE Proceedings of 12th Syst. Syst. Eng. Conf. SoSE, 2017, pp. 1-6, doi: https://doi.org/10.1109/SYSOSE.2017.7994984.
17. Burgard, W., Moors, M., Stachniss, C., Schneider, F.E.,"Coordinated multi-robot exploration" IEEE Trans. Robot, vol. 21, no. 3, pp.376–386, 2005.
18. Hana Gharrad, Nafaa Jabeur, Ansar Ul-Haque Yasar, Stephane Galland, Mohammed Mbarki. "A five-step drone collaborative planning approach for the management of distributed spatial events and vehicle notification using multi-agent systems and firefly algorithms", Computer Networks, Elsevier, vol 198, no 108282, 2021.
19. Yang, Xin-She. "Firefly algorithms for multimodal optimization." In Stochastic Algorithms: Foundations and Applications", in the proceedings of 5th International Symposium, Springer, pp. 169-178, 2009.
20. Tang, Gang, Congqiang Tang, Hao Zhou, Christophe Claramunt, and Shaoyang Men. "R-DFS: A coverage path planning approach based on region optimal decomposition." Remote Sensing, vol. 13, no. 8, p: 1525, 2021.
21. Stolfi, Daniel H., and Grégoire Danoy. "An Evolutionary Algorithm to Optimise a Distributed UAV Swarm Formation System." Applied Sciences, vol. 12, no. 20, p: 10218, 2022.

22. J. Kennedy and R. Eberhart, "Particle swarm optimization," in the proceedings of ICNN'95 - International Conference on Neural Networks, 1995, vol.4, pp. 1942-1948, doi: 10.1109/ICNN.1995.488968.
23. Y. Altshuler, A. Pentland, A. Bruckstein, "Swarms and network intelligence in search", Studies in Computational Intelligence, vol 729, pp 5-15, 2018.
24. Wang, Duo, Zhihong Peng, Xiaojie Ju, Tao Yu, and Xue Wang. "Multi-UAV cooperative target tracking strategy based on formation control." In the proceedings of IEEE Chinese Control Conference (CCC), pp. 6224-6229, 2019.
25. T. Samad, S. Iqbal, A.W. Malik, O. Arif, P. Bloodsworth, "A multi-agent framework for cloud-based management of collaborative robots", International Journal of Advanced Robotic Systems, vol 15, no 4, p.1729881418785073, 2018.
26. Rajashekharaiah, Puneeth Hulikunte, Archana Menon, SenthilRajan Subramanian, Paavai Arun, Shiksha Murthy, and Arpan Vasavada. "Coordinated UAV for efficient field inspection." In the proceedings of INCOSE International Symposium, vol. 29, pp. 363-377. 2019.
27. N. Paula, B. Areias, A.B. Reis, S. Sargento, "Multi-drone Control with Autonomous Mission Support", in the proceedings of IEEE Int. Conf. Pervasive Comput.Commun. Work. PerCom Work, 2019, pp.121-132.
28. Y. Qiao, J. Yang, Q. Zhang, J. Xi, L. Kong, "Multi-UAV Cooperative Patrol, "Task Planning Novel Method Based on Improved PFIH Algorithm", IEEE Access, vol. 7, pp:167621-167628, 2019.
29. Beck, Zoltán, Luke Teacy, Alex Rogers, and Nicholas R. Jennings. "Online Planning for Collaborative Search and Rescue by Heterogeneous Robot Teams." in the proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems, pp. 1024-1033. 2016.
30. Beck, Z., Teacy, W.L., Rogers, A. and Jennings, N.R., "Collaborative online planning for automated victim search in disaster response", Robotics and Autonomous Systems, vol. 100, pp.251-266, 2018.