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RESEARCH ARTICLE

Nature-Inspired Drone Swarming for Wildfires Suppression Considering Distributed Fire Spots and Energy Consumption

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ABSTRACT Wildfires are among the biggest problems faced worldwide. They are increasing in severity and frequency, causing economic losses, human death, and significant environmental damage. Environmental factors, such as wind and large forest areas, contribute to the fire spreading over multiple fire spots, all of which grow continuously, making fire suppression extremely difficult. Therefore, fire spots should be coverage simultaneously to contain the spread and prevent coalescence. Therefore, this study presents a new model based on the principles of nature-inspired metaheuristics that uses Swarm Intelligence (SI) to test the effectiveness of using an autonomous and decentralized behaviour for a swarm of Unmanned Aerial Vehicles (UAVs) or drones to detect all distributed fire spots and extinguishing them cooperatively. To achieve this goal, we used the improved random walk algorithm to explore the distributed fire spots and a self-coordination mechanism based on the stigmergy as an indirect communication between the swarm drones, taking into account the collision avoidance factor, the amount of extinguishing fluid, and the flight range of the drones. Numerical analysis and extensive simulations were performed to investigate the behaviour of the proposed methods and analyze their performance in terms of the area-coverage rate and total energy required by the drone swarm to complete the task. Our quantitative tests show that the improved model has the best coverage (95.3%, 84.3% and 65.8%, respectively) compared to two other methods Levy Flight (LF) algorithm and Particle Swarm Optimization (PSO), which use the same initial parameter values. The simulation results show that the proposed model performs better than its competitors and saves energy, especially in more complicated situations.

INDEX TERMS Random walk algorithm, swarm intelligence, stigmergy, UAVs, wildfires suppression.

I. INTRODUCTION

Due to the increasing frequency of wildfires in many parts of the world, their severity and magnitude, and the potentially dangerous impacts they can have on people, infrastructures, and the environment, wildfire control has attracted considerable attention and has been considered an important global environmental issue [1], [2]. A comprehensive report confirms that forest fires have forced the evacuation of 6 million people worldwide and killed 3753 people in the last

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century [3]. On the other hand, forest fires cause environmental pollution, release large amounts of carbon, and increase the temperature of the Earth's atmosphere [4]. Fires are considered one of the greatest threats to wildlife, nature, and urban environment, and are one of the main factors that seriously affect a country's economy. In addition, firefighting involves many people in dangerous activities, which unfortunately cause many casualties every year.

A. FOREST FIRE SUPPRESSION IN LARGE AREAS: METHODS AND TECHNOLOGIES

Forest fire suppression is based on highly complex tasks using many traditional methods, such as human firefighters, helicopters, and seaplanes [5]. However, human firefighters are highly exposed to toxic smoke, flames, and high temperatures, which poses a risk to their health and lives [6]. Apart from that, the main problem is to bring firefighters and related resources to places that are hard-to-reach places. Moreover, helicopters are indispensable tools to support firefighters on the ground and perform tasks. However, these aerial systems have some limitations and disadvantages when used for firefighting (e.g., high risk due to low-altitude, difficulty in conducting firefighting operations at night, and the high cost of acquiring and maintaining the aircraft) [7], [8]. Therefore, recent research has been conducted on solutions to help remotely detect, track, and extinguish wildfires remotely [9], [10], [11], [12], [13], [14], [15], [16]. In this scenario, autonomous mobile robots represent a solution with great potential, as they can overcome all these limitations and challenges and fight fires from the outset without risking human lives. Moreover, these robots can be equipped with devices and sensors that allow them to operate at night and at short distances, thereby increasing the firefighting efficiency [17], [18]. An example of a special type of robot is a UAVs, or drones that move in a three-dimensional space.

B. USING UAVs FOR FOREST FIRE SUPPRESSION: CHALLENGES AND LIMITATIONS

Nowadays, UAVs are widely used and rapidly developing in many application areas, such as surveillance, exploration, disaster management, search and target detection, and monitoring [19], [20], [21], [22], [23], [24], [25], [26]. According to recent studies, most approaches that apply drone-based systems in fighting forest fires are techniques that use a single drone to detect and track forest fires [27]. The use of a single remotely piloted drone has many limitations, such as the fact that a human operator is required for each drone, which is close to the fire area and therefore exposed to the fire hazard. Moreover, the capabilities of a single drone are limited in terms of the area it can cover in a given time. Despite these possibilities, most researchers have focused on UAV-based technologies that are now used for wildfire detection and monitoring [28], fire hazard mapping, brush fire detection [29], forest monitoring [19], and disaster response support [30]. However, research and development on UAV-based extinguishing are still scarce [26], [27]. Therefore, real-time wildfire suppression is an important issue requiring the development of advanced control strategies.

On the other hand, a Multi-Robot System (MRS) has been proposed in several studies to develop autonomous capabilities in forest firefighting [10], [21], [22], [31], [32], [33], [34], [35]. Based on the coordinated use of a team of UAVs, this technological solution creates a versatile tool capable of performing more complex tasks and improving the overall resilience, efficiency, and independence of the system. Despite the promising results of these studies on forest firefighting, they have three main limitations.

(i) The complexity of coordination in MRS requires advanced software and hardware technology, and direct communication between members in real-time, which is a major challenge in forest firefighting.

(ii) In situations with multiple hot spots, current studies show a major limitation regarding area coverage. For example, the drones converge on each other owing to the attraction factor in the deployed PSO algorithm [32], which results in the coverage area being limited to a single spot and the inability to scan other possible hot spots in the search space.

(iii) Existing firefighting models lack the flexibility to optimize time and resources in a mission because the combat protocol dictates that all drones must follow each other to work on a single task. The limitation is that a drone that has dropped its load cannot leave the site to reload until all other drones have completed their current task, resulting in the poor use of time and resources [27].

To overcome these limitations, several research directions have emerged in the field of MRS, such as swarm intelligence [36].

C. METAHEURISTIC OPTIMIZATION TECHNIQUES

Metaheuristic optimization algorithms are used to find optimal solutions to optimization problems [37] by mimicking behaviour in natural, physical phenomena, and ethological, or biological processes [38].

Overall, there are various classifications in the literature, such as in [39], where they are divided into two main classes: swarm intelligence algorithms and evolutionary algorithms. In [40], they were divided into three classes: swarm intelligence algorithms, evolutionary algorithms, and physical algorithms. Meanwhile, there are no specific criteria by which metaheuristic algorithms are classified, but they are usually based on different sources of inspiration. However, based on these considerations, the author in [41] made classification into four types of algorithms:

(1) Swarm Intelligence-Based Algorithms (SIs) are a new area of research that aims to create a system capable of performing a task from the interaction of individual agents with each other and their environment. SI is inspired by the study of the behaviour of groups or swarms of organisms,

such as animals and social insects. Although insects that live in colonies or swarms, such as ants, bees, and termites, and each member of the colony works for its specific purpose, they appear to be well organized [42]. The individuals (agents) in these swarms, despite their simplicity, exhibit complicated collective behaviour, which is one of their most unique features. Aggregation [43], foraging [44], flocking [45], cooperation [46], and stigmergy [47] are some of the most common and complicated collective behaviours. Animals work together to accomplish tasks by developing a form of collective intelligence that allows them to achieve the goal of a task that is difficult for an individual to accomplish alone. Some of the well-known algorithms, such as (Particle Swarm Optimization (PSO) [48], Bees Algorithm (BA) [49], Artificial Bee Colony Optimization (ABC) [50], Ant Colony Optimization (ACO) [51], [52], Bacterial Foraging Optimization (BFO) [44], Glowworm Swarm Optimization (GSO) [53], Firefly Algorithm (FA) [54] and Biased Random Walk (BRW) [55]);

(2) Evolutionary-Based Algorithms (EAs) are mimicked by the principles of biological/natural phenomena but do not include SIs. The search process in an EAs starts with the generation of an initial random population. The fitness function is then used to evaluate the overall fitness of the individuals. After each generation, the fitness function is driven by the evolution of the individuals toward the greatest possible global solution. This process continues until either the maximum number of iterations is reached or a near-optimal solution is found. Some of the most popular algorithms, such as (Genetic Algorithm (GA) [56], Differential Evolution (DE) [57]);

(3) Physics-Based Algorithms (PAs), unlike SI and EA, PAs are inspired by some chemical laws or physical phenomena (e.g., electric charges, gravity, river systems, ionic motion, etc.). Some of the most popular algorithms, such as (Archimedes Optimization Algorithm (AOA) [58], Henry Gas Solubility Optimization (HGSO) [59], Bald Eagle Search (BES) [60], Honey Badger Algorithm (HBA) [61], Harris Hawk Optimizer (HHO) [62], Runge Kutta Method (RUN) [63], Weighted Mean Of Vectors (INFO) [64] and Slime Mould Algorithm (SMA) [65]);

(4) Human-Based Algorithms (HA), this type of algorithms the source of imitation is not natural, but from various properties and actions related to humans such as (Teaching–Learning-Based Optimization (TLBA) [66] and Harmony Search (HS) [67].

More specifically, the optimization achieved through this research felid for MRS has led to the emergence of a new field called Swarm Robotics (SR) [42]. SR is an approach for designing multi-robot systems based on the decentralized self-organization and self-coordination of large groups of relatively simple, homogeneous robots. It relies on local interactions between individuals to generate collective behaviour to achieve a common task [68]. This approach inspired his basic principles in the field of multiple robotics, such as coordination among themselves, cooperation, and other interactions directly emerging from natural systems such as (birds, fish, ants, bees, etc.). It tends to capture the characteristics of biological swarms, such as (autonomy; a large number; limited capabilities; scalability and robustness; distributed coordination), making them appealing for use in various applications [69]. It should be noted that all basic criteria (referred to in [69]) must be met to overcome the confusion caused by the term ''swarm'' in relevant studies and the overlapping meaning applied in the field of MRS to determine the extent to which SR can be applied and how it differs from other MRS.

The analogies between the search algorithms of SR and the SI are immediately obvious, as both attempt to find the ''best locations'' in a given search area or environment using swarms. Because they involve the decision process, many tasks, such as task assignment, path planning, formations and target search, and basic MRS capabilities, can be formulated as optimization problems [70]. For this reason, biologically inspired algorithms can be used to find near-perfect solutions to these problems. The main features, such as local communication, the emergence of global behaviour, and decentralized local control, i.e., self-organization, naturally fit SR their algorithms, making them more effective in target search Zakiev et al. [71].

By reviewing studies that have dealt with the task of extinguishing fires shown in Table 1, only two studies have been found [31], [32] that meet the standards of the swarm robotics approach mentioned above that used the PSO algorithm to handle the search space. The PSO algorithm was initially developed for social behaviour as a model inspired by earlier bird-flock simulations [72]. Every particle in a swarm population in the PSO algorithm moves and changes its position through the problem space based on several factors, usually an attraction factor toward the best position related to the target and attraction to the position related to neighbouring swarm members (or neighbourhood) [31], [32]. However, while executing a PSO run, the canonical algorithm does not detect changes in the optimal position where the particles are under the influence of outdated memory. Moreover, as swarm convergence and search progress, diversity is proactively lost, making the swarm unable to explore the dynamic environment of optimum moving tracking.

Moreover, as swarm convergence and search progress, diversity is proactively lost, making the swarm unable to explore the dynamic environment of optimum moving tracking. For this, the spread of fire leads to multiple dynamic hot spots, frequent environments, and severe changes in location and severity. In addition, the swarm suffers from momentum; therefore, it is difficult to change the direction immediately. In the approaches mentioned earlier, drones converge on each other because of the attraction factor, which limits the area coverage and cannot survey all locations in the search space. In other words, the swarm of drones moves to one hot spot and leaves the rest of the area. Hence, researchers

TABLE 1. Summary of studies that have used multiple UAVs in fighting wildfires.

Ref.	Coordination Control	Robot Type	Team Type	Approach Type	Description
[10, 73]	Distributed	UAV/UGV	Heterogeneous	Not SR	Did not meet the SR criteria
[35, 74, 75]	Centralized	UAV/UAV	Heterogeneous	Not SR	
[76, 77]	Decentralized	UAV/UGV	Heterogeneous	Not SR	
[31, 33, 78-87]	Decentralized	UAV	Homogeneous	Not SR	
[31, 32]	Decentralized	UAV	Homogeneous	SR	Meet the criteria

have chosen random walk algorithms as the best target search strategy in the field of SR [88]. The main features, such as local communication, the emergence of global behaviour, and decentralized local control (i.e., self-organization), naturally fit SR algorithms, making them more effective in target search. Zakiev et al. [71]. This type of research is of special interest, given the environmental hazards that firefighters face and the potential to save people from dangerous activities by using a swarm of drones instead of humans. The main motivation for this study is the lack of research on the firefighting capabilities of drone swarms in forests [26]. Finally, previous studies have indicated the need for further investigation into drone firefighting.

D. RELEVANT METAHEURISTIC OPTIMIZATION ALGORITHM APPLICATION AREAS

The applications that used the aforementioned metaheuristic optimization algorithms were not exclusively on swarms of robots but included many other applications. For example, in [89], melanoma predictions model were proposed using machine learning. The imbalance of the melanoma dataset is taken into account by the proposed approach. This result was obtained using the BES algorithm [60], a metaheuristic optimization algorithm. BES is an advanced optimization algorithm based on the hunting abilities of bald eagles. The authors [90] developed a method that can accurately and quickly determine the severity of COVID-19 infection through chest X-ray images and improve the diagnosis degree based on a modified Whale Optimization Algorithm (WOA) [91]. In contrast, a novel approach to breast cancer prediction was presented by the authors of [92], which based their work on using both of Ant Lion Optimization Algorithm (ALO) [93] and the Butterfly Optimization Algorithm (BOA) [94]. To address the Feature Selection (FS) issues the author in [95] proposed a binary version based on Horse Herd Optimization Algorithm (HOA) [96] while [97] used the HHO algorithm [62] to achieve the same goal.

E. THE SCOPE OF THE STUDY

In the context of studies that deal with wildfire research and forest fire prevention, there are two aspects to this study [98]: (a) the fire spread model and (b) the suppression of forest fires in a complex and noisy environment. The former can either be based on physics [98], [99] or experiments (see, e.g., [100], [101]). In this paper, we have only improved the fire spread model based on the same principles as in [102] and [103] and using cellular automation, a programmable multi-agent modelling environment. However, it is based on simple assumptions and uses a limited number of model parameters considered in our approach, such as fuel density, fire intensity, wind speed, wind direction, and flat topology, which are compatible with available literature [104]. See section III-B for details and motivation. This study aimed to assess as best as possible the power of collective intelligence on the impact of using a swarm of drones to suppress forest fire propagation, a difficult phenomenon influenced by a variety of factors. Although there is a wealth of information on fire propagation models, few studies have addressed how fire suppression tools affect the fire front. Therefore, instead of proposing innovative methods that would also require a validation phase, the best-established theories were applied here.

In this study, we focus exclusively on perimeter coverage and an effective search for multiple fire spots and then use a self-coordination mechanism for the drone swarm to extinguish the fire. We assume that fire spots can be detected by appropriate sensors (e.g., thermal imaging cameras); however, we will not address the details of these sensors. Because we are interested in developing a firefighting system, we instead focus on how to achieve cooperative behaviour with the decision-making system when each drone has only partial knowledge of the environment. Finally, this study proposes a model for self-firefighting using a team of drones based on a bio-inspired swarm robotics approach. Then, the descriptive properties of different approaches are compared with two algorithms applied to a swarm of robots that must cover an unknown environment to search for multiple fire spots and extinguish them cooperatively.

F. THE MAIN OBJECTIVES AND CONTRIBUTION OF THIS STUDY

This article is based on a systematic study of collective behaviour resulting from the performance of a swarm of drones controlled by a fully decentralized approach in the context of autonomous wildfire suppression. The main objectives of this study were (i) to achieve the most realistic results in a complex task, such as self-extinguishing a fire using a swarm robotics approach that is robust, scalable, and flexible; (ii) to detect all the distributed fire hotspots in an unknown environment by improving a more effective coverage algorithm; and (iii) to propose an autonomous model of firefighting that allows individuals to decide on the course of events at a local level in order to better use and manage time and resources. Finally, it is important to note that all of the proposed approaches for each phase are the main contributions of this study. In contrast to the results in the literature, the main contributions of our study are summarized as follows:

1- A mathematical formulation of a new self-firefighting model is presented to develop an effective autonomous system with a swarm of UAVs.
2- An efficient bio-inspired algorithm was developed to detect dispersed fire spots in an unknown environment and to consider obstacle avoidance during a fire search mission based on flight behaviour.
3- Develop an effective swarm coordination strategy based on indirect communication, considering the amount of extinguishing fluid and flight range capacity, and use stigmergy approaches to cooperatively suppress a fire spot once the drone has detected it.

The rest of the paper is organized as follows: Section II describes the framework and basic assumptions. The essence of bio-inspired search algorithms and design models for swarm coordination is described in Section III. Section IV describes the simulation results of several experiments, and Section V summarizes the main findings of the study.

II. THE FRAMEWORK AND BASIC ASSUMPTIONS

This section describes the environment and capabilities of drones in detail. Thus, the framework proposed to address the problem in this study using swarm robots can be described by the following steps, as shown in Figure 1, which are divided into two phases:

Step 1: Use the fire propagation model to start fires at several random locations based on the FARSITE model [103].

Step 2: Use the improved random walk (RW) algorithm in the detection phase to detect distributed fire spots.

Step 3: Using a method to avoid collisions with nearby obstacles and drones.

Step 4: Use the pheromone as an indirect means of communication when a fire spot is detected by one of the drones to engage neighbouring drones to cooperate in extinguishing the fire in the firefighting phase.

Phase 1: **Coverage State**. This state aims to cover the area and detect randomly distributed fire spots in an unknown environment (forest). Because no fire spots were detected in the coverage phase, it would be more effective to distribute the drones over the entire area simultaneously and assign a suitable number of drones to cover multiple fire spots while avoiding collisions. At each step, a drone uses sensors to sense its neighbouring cells from its current position to determine its next steps. Drones do not use indirect communication in this phase; they make decisions based only on available information about the environment.

TABLE 2. The fundamental component of the model.

id	Component/s	Discerption
1.	Environment	the search area on which another component is placed;
2.	Drones	a mobile entity that performs specific tasks to achieve its goal;
3.	Fire spots	the fire spot entity to be detected by the drone;
4.	Obstacles	an obstacle entity that the drones must avoid;
5.	Stigmergy	the indirect communication mechanism used by the drone;
6.	Flight Pattern	The flight mechanism used by drones;

Phase 2: **Firefighting State**. This state aims to autonomously extinguish wildfires. When a drone detects a fire source, it begins fighting the fire and sends requests for help via indirect communication (stigmergy). The basic element of stigmergy is pheromones, which are chemical substances that can attract drones to places where they are released. When they sense pheromones from one or more neighbouring drones, the drones, using mechanisms based on concepts of swarm intelligence, decide individually and independently whether or not to move to the source of the fire based on a strategy based on available payload or flight range. It is important to note that the coverage and firefighting states are not necessarily separate. For example, a drone can simultaneously perform both tasks. The basic components of the simulator are listed in Table 2.

The environment can be viewed simply as a two-dimensional bounded area, where drones can move continuously. Consequently, fire spots with dynamic positions and obstacles (trees and towers) with static positions usually cover multiple cells, as shown in Figure 1. Drones are the only units that move continuously in a search space. Typically, the search space includes many obstacles and the number of drones in a swarm can be high. Therefore, a collision-avoidance mechanism is required to make the simulation more realistic. The drones, organized in a swarm, aim to detect fire spots in the exploration area and avoid obstacles and other drones use stigmergy as a self-coordination mechanism during the search. Fire spots are unknown places and must be discovered by drones within a certain time.

Among the biologically inspired methods in the literature, *stigmergy* and *flight pattern* are commonly used to coordinate a swarm of UAVs during a targeted search [105]. Grassé [106] introduced the term stigmergy to describe a type of indirect communication mediated by environmental changes, which he found in two termite species, Cubitermes and Bellicositermes Natalensis. The Stigmergy-based swarming method, in which simulated pheromones are deposited on a

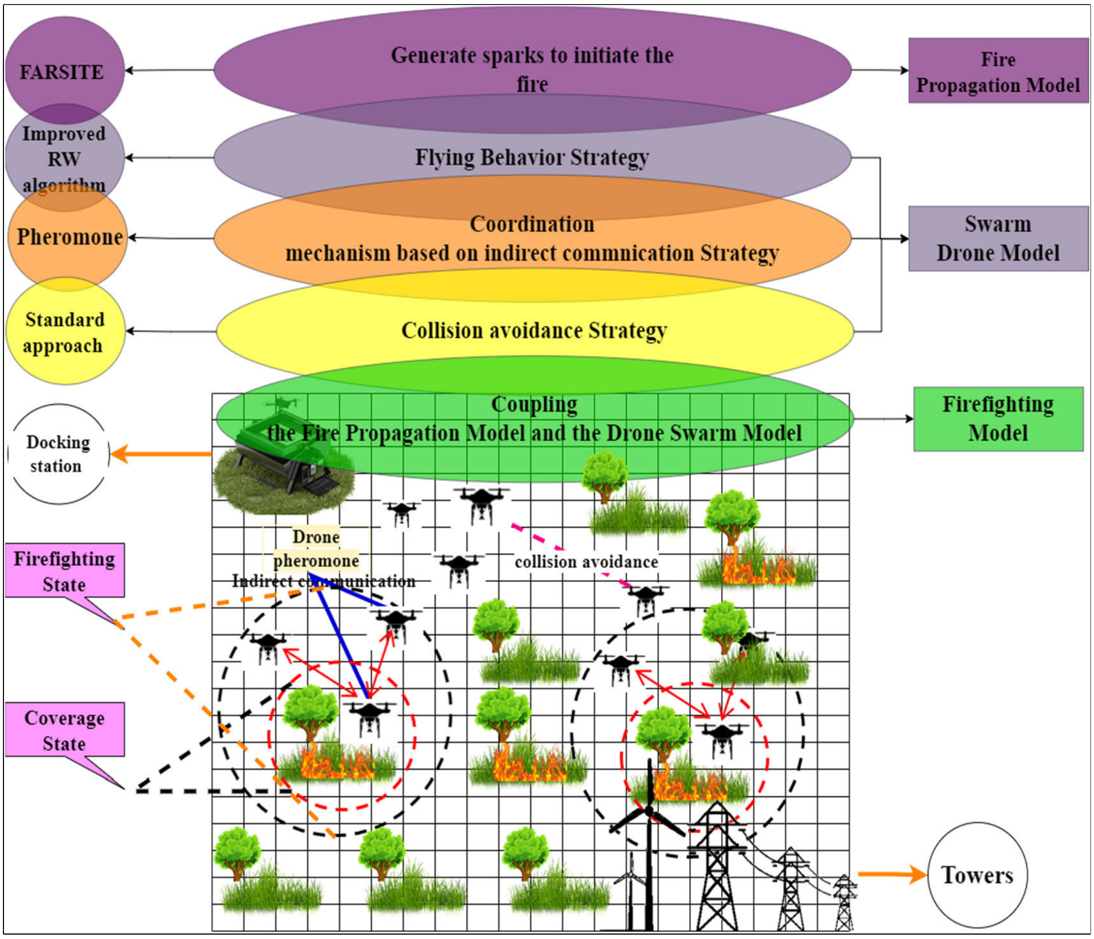


FIGURE 1. A representation of the structure of the proposed firefighting system the environment and its components simulation.

pheromone map and observed by agents, was investigated, and the results were confirmed [107].

A flight pattern is the behaviour of drones that move in the search space to search for targets defined by the mission through specific mechanisms that allow them to explore or cover the environment effectively.

In addition, the problem studied in this paper is based on the following assumptions: (1) the drones operate in a dynamic environment; (2) the number of fire spots is smaller than the number of drones to avoid blockage; (3) the drone fuel needs to be recharged every 600 steps; and (4) each drone is equipped and provided ball-release mechanism with a payload up to 40 small-sized fire extinguishing balls that are activated by heat and are environmentally friendly and can effectively extinguish short grass fires (each ball of 0.5 kg can extinguish a circuit equivalent to (1) m^2 of the total area) [108] and back to the docking station after dropping all balls to reloaded;(4) Assuming thermal imaging cameras are already in use, the drone model predicts that these cameras will be able to identify fire spots edge of forest fires. We use the term ‘‘tick’’ to refer to the time unit, the cycle of the environment, and the drones being updated simultaneously. Time t was discretized into time intervals defined as ticks (c = 1 m and t = 1 s). The search operation was modelled in two dimensions, due to the development environment. However, UAVs are assumed to fly above the ground. The drones did not go beyond the boundaries of the area and had the same speed. The power consumption of the sensors and communication devices was not included in the calculations, and it depended only on the number of steps.

III. ENVIRONMENT DESIGN AND COORDINATION MODELS

In the design phase, assumptions were made regarding the environment, drones, and other entities involved in the simulation. These assumptions concern the main characteristics of the environment and entities themselves. The environment can be considered as a two-dimensional bounded grid with n and m cells in the x and y directions, respectively. Each basic element cell (also called a patch) in the grid of dimension $\Omega \subset \mathbb{R}2$ represents as $c \in \Omega$, and its coordinates uniquely determine it (x, y), where $x \in \{1, 2, \ldots, m\}$ and $y \in \{1, 2, \ldots, n\}$ elements, as a symbolic representation of the working environment. To make the simulation as realistic as possible, a swarm drone model and a fire propagation model are required. The problem is then defined as a constraint-based optimization problem. For the area-coverage task, we focused on modelling the different factors of UAV coordination. The search area contained several drones, targets (fire spots), and barriers (obstacles), as shown in Figure 1. The coordination logic of a UAV is based on avoiding collisions, stigmergy, flying, and SR approaches.

A. SWARM DRONE MODEL

The self-firefighting model shows how drone agents interact with each other and with their environment. This includes the number of steps each drone has and the amount of extinguishing fluid it has. In addition, the model specifies how drones interact with fire spots and a mechanism for cooperating with another drone to locate a fire spot and extinguish it. The following sections explain how these elements fit together, as well as the model's motivations and assumptions.

1) INDIVIDUAL DRONE BEHAVIOR

The behaviour of an individual drone is implemented using a swarm self-firefighting model. The behaviour of the drone agent during the simulation and its ability to respond to pheromones were included in this behaviour. In the environment, a set D of homogeneous drones evolves, where $D = \{k|k \in 1, 2, \ldots, N^D\}$ and at each step t, the current state of drone k can be represented by its coordinates (x_k^t, y_k^t). Consistent with our assumptions regarding the properties of drones, we assume that they operate in a discrete-time domain and can fly from cell to cell. The speed and angular velocity of the drone are considered, as well as the fuel amount, number of payloads, size of the drone, and sensor angle and radius, as listed in Table 3 in Section V. The drone flight altitude is an important factor in detection accuracy. In addition, drones can detect certain search areas more easily when they fly at a lower altitude. It is worth noting that there are several factors may affect whether a fire affects a UAV on a firefighting mission, including the type of drone being used, the altitude at which it is flying, the intensity and duration of the fire, and the distance between the flames and the UAV.

In general, fire can have several negative effects on UAVs, such as (fire damage, smoke and ash, interference with communication and turbulence) [109]. Therefore, drones equipped with specialized protective measures, such as protective shields, heat-resistant coatings, and advanced communication systems must be used to mitigate these effects. However, the loss of the drone and the risk of damage are still present during a firefighting mission.

However, due to the type of UAVs employed in this study as well as its main objectives, we didn't evaluate its response functions or the effect of fire on the UAV. Therefore, this should be taken into account by readers when interpreting the results of this study.

Except for the cells occupied by obstacles or other drones, drones can move in all cell spaces. Because we only allow a drone to move from one cell to one of its eight neighbouring cells when all the cells are free, we assume that the rotation unit for a drone is 45 °. An illustration of this process is shown in Figure 2.

TABLE 3. General simulation parameters.

Parameter Name	Parameter Value
Simulation Area	
Search area size (X * Y)	401 * 401 (i.e.,160,801 patches)
Cell size	1 m^2
Number of obstacles	5
Drone	
Drone.Speed	10 m/s
Drone. *StepRange*	600 steps
Drone. Payload	40 balls
Drone. size	1.4 m
Sensing.Radius	2 m
Pheromone coverage	10 [cells]
ObstacleVisionAngle	45°
ObstacleVisionRange	3 m
Fire model	
Tree density	[50%, 60%]
Tree size	1 m^2
Experiments	
Swarm size	[30...100]
Number of runs per experiment	20
Time at which drones are deployed	80 ticks

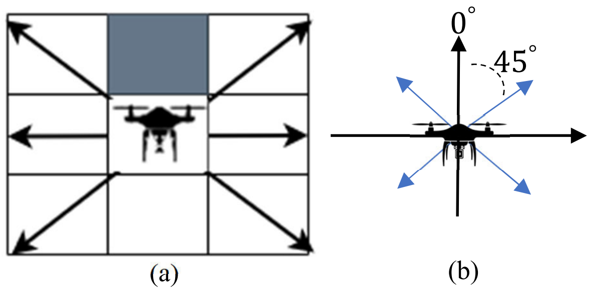


FIGURE 2. (a, b) Possible directions and turning for the drone.

However, for clarity, we assume that the drones have a simple set of common reactive behaviours that allow them to avoid obstacles and detect other drones to perform the task together. This is done so that the drones could work together to accomplish the task. They have limited computational and memory capacity and can perform tasks partially but not completely. Some of the parameters of the model were inspired by [110]. The behaviour of the drone agent consists of three strategies, each with increasing priority (*Flying behaviour, Coordination mechanism based on pheromone, and Basic collision avoidance*).

a: FLYING BEHAVIOR STRATEGY

In our study, three different variants of the random walk were considered and evaluated: Brownian motion (BM) [111], LF [112], and Levy taxis [113]. These variants were chosen because they have been described as completely random, exploitation-specific (exploring a specific area of the environment in detail), and/or coverage-specific (moderately exploring a large area of the environment). Indeed, we are interested in analyzing the differences between coverage-enhancing exploration and exploitation-oriented exploration in a drone swarm to support fire-spot coverage.

Before applying the proposed model, we conducted experiments in a simulated environment using swarm drones prepared in a closed environment. We used three different types of random walk: Brownian motion, Levy flight, and Levy taxis. The drone swarm successfully mapped the environment during the simulation. However, the experiments were less satisfactory and highlighted the need for better programming strategies for transfer control. The simulation results showed that the LF worked better because the swarm could better cover the environment. However, these results apply only to closed environments and are not transferable to open environments.

In contrast, other species showed dominant exploitation behaviour, which usually provided half-complete coverage. To this end, we made some simple improvements to the LF algorithm so that its general structure is not compromised. Drones move around the search space to cover hotspots without stimuli or information. In general, a method that uses random walks must have two features to be implemented or generated: step length and direction, both of which can be derived from a uniform distribution. Using the distribution equation (1), waypoints or movement points are generated for the drones, defined as follows:

$$p(\lambda) = \frac{1}{\pi} \int_{-\infty}^{\infty} \cos(\lambda t) . e^{-\lambda t^{c}} 0 < c \leq 2 \tag{1}$$

where c is the Lévy distribution index ranging between $0 < c \leq 2$ while p is the Levy flight waypoint generation function. The distribution turns into Brownian motion when $c = 2$, and then uses a Gaussian distribution. The symbol λ indicates the step size and t is the time between two successive steps. The step size was determined using (2).

$$\lambda = \frac{U}{V^{\frac{1}{c}}} \tag{2}$$

where u and v are regular random numbers.

The random-walk mechanism in our approach depends on the step length of the drone and the rotation angle, considering collision avoidance, which also allows changing the direction of the movement of the drone. Algorithm 1 illustrates the pseudocode of this function. *StepRange* is the maximum step range a drone can travel between refuelling operations while $N_{\text{Rand}}, P_{\text{steps}}$ are the number of steps the drone takes after each period and the number of steps the drone's movement is maintained in Lévy flight mode, respectively.

Algorithm 1 DroneFlay

1: **Input:** *CutrrentPosition*(k_i $(t+1)$), StepRange, N_{Rand}, P_{steps}
2: **Output:** *NewPosition*.
3: **Strat**
4: moveForward(drone)
5: **if** (StepRange <= (StepRange- N_{Rand})) and (StepRange > (StepRange - N_{Rand}) - P_{steps}) **then**
6: Generate Random Walk using Equation (2)
7: Calculate the step length λ based on Equation (3)
8: StepRange = StepRange-1
9: $N_{\text{Rand}} = N_{\text{Rand}}$ -1
10: While a target is not found and the recent waypoint was visited
11: ***NewPosition***$\leftarrow$ $\vec{k}_i$ $(t+1)$based Equation (4)
12: **Return*NewPosition***
13: else Go to step (4)
14: **Stop**

The proposed algorithm calculated the new position $\vec{k}_i(drone)$ using Equation (3).

$$\vec{k}_i\,(t+1) = L\acute{e}vy\_flight(k_i\,(t+1)\,, \boxed{\text{StepRange}}, N_{\text{Rand}}, P_{\text{steps}}) \tag{3}$$

b: COORDINATION MECHANISM BASED ON PHEROMONE STRATEGY

Drones must be able to coordinate and interact with each other to firefighting forests in a self-organized manner. Pheromones are used to attract drones to potential targets for cooperation. The stigmergic communication technology of digital pheromones satisfies these requirements. An effective strategy is to search for and cover multiple hotspots by conducting a rapid survey of the area and identifying the hotspots for which there is circumstantial evidence. In this strategy, a drone swarm must be dynamically organized such that each member that discovers a fire spot cell can effectively engage neighbouring members. For this reason, a drone that finds the fire spot cell releases a virtual pheromone mark for a limited period calculated by evaporation, which works as a traction potential for neighbouring drones. Figure 3. shows an example of a drone-finding pheromone in a circular area, defined as *SenceRadius.* Once the drone detects pheromones, it directs its heading toward the highest pheromone density, as shown in Figure 3.b. Figure 3.c shows the sensitivity required to reach the highest pheromone density to start the cooperative operation. Therefore, it is also assumed that drones have the sensors necessary to detect and release pheromones to cover hotspots.

As shown in Figure 4, the shades of grey represent different levels of pheromone intensity. The darker the shading, the higher the intensity. When the pheromone diffuses to neighbouring cells at a constant rate, its value is in the range of $\mu\epsilon[1, 0]$. The pheromone marks have the potential to aggregate to form pheromone tracks, and the track will eventually disappear when its level decreases linearly with each tick by

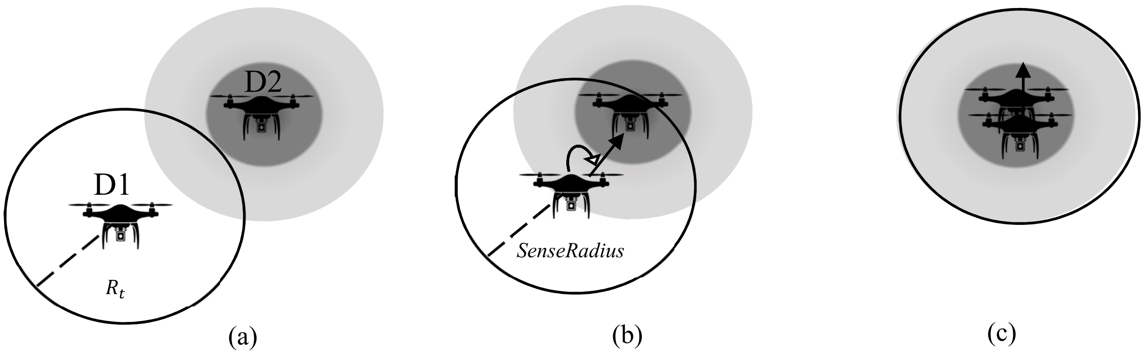


FIGURE 3. The Stigmergy strategy (a) Pheromone Release by D2, (b) Pheromone sensing by D1, (c) Olfactory habituation.

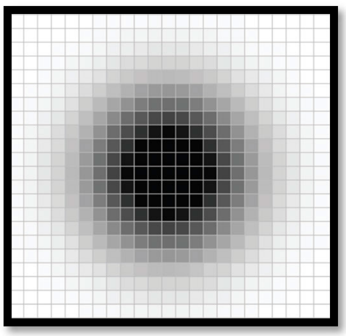


FIGURE 4. The different levels of pheromone intensity value are in the range of$\mu\epsilon$ [1,0].

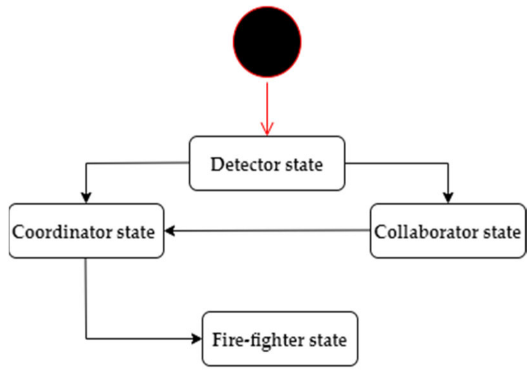


FIGURE 5. Possible states for each drone in our model.

a predetermined amount ∂ (evaporation rate) in the range of $\partial\epsilon[1, 0]$. The pheromone intensity ρ is represented at time t and on cell (x, y) according to the following equation:

$$\rho_{x,y}(t) = \partial \cdot [(1-\mu)\,.\rho_{x,y}(t-1) + \Delta\rho_{x,y}(t-1,t) + g_{x,y}(t-1,t)] \quad (4)$$

where $(1-\mu)\,.\rho_{x,y}(t-1)$ and $\Delta\rho_{x,y}(t-1,t)$ represent the amount remaining after diffusion to nearby cells and the additional deposits made within the interval $(t-1,t)$, respectively, while $g_{x,y}(t-1,t)$ represents the input pheromone diffused from all the nearby cells and can be formally calculated as

$$g_{x,y}(t-1,t) = \frac{\mu}{8}\sum_{i=-1}^{1}\sum_{j=-1}^{1}\rho_{x+i,y+j}(t-1)\,(i,j)\neq(0,0) \quad (5)$$

We assume that the pheromones for each of the eight cells near cell (x, y) are diffused in each update cycle. Considering evaporation, the total amount in (4) is multiplied by a factor ∂.

c: COLLISION AVOIDANCE STRATEGY

Collision-avoidance strategies prevent drones from leaving the area or colliding with objects or other drones. To avoid obstacles when using a drone, two parameters, *ObstacleVisionAngle* and *ObstacleVision*, are used to obtain a circular sector area called *ObstacleVisionArea*, installed in the centre of the drone. The drone changes its direction and speed when an obstacle or another drone is detected in the *ObstacleVisionArea*. Therefore, the collision avoidance solution is based on a standard approach [114], [115].

2) THE AGGREGATION OF SWARM MECHANISM AND ITS EVOLUTION

All drones follow simple rules of behaviour at each step, as shown in Figure 5, based on the events that occur and are described as follows.

- **Detector State**: This first operational state of each drone. In this state, drones cover the fire spot by exploring the entire area to detect multiple fire spots. They can also communicate with other swarm members about the environment (indirect communication). Algorithm 2 illustrates the pseudocode of this function.
- **Coordinator state**: The process of coordinating the required UAVs begins when one of the drones detects a fire spot by releasing a virtual pheromone mark. The pheromone mark is usually a circular area defined as the *SenseRadius* of the detected fire spot and is only received by the neighbouring drones within their range.
  - **Collaborator state:**A drone switches to this state when it senses the pheromones from one or more neighbouring coordinators, and then directs its

Algorithm 2 DroneAgent Step

1: **if** Drone K is at the docking station, **then**
2: *StepRange* =600;
3: *Payload* =40;
4: **end if**
5: **if** *Payload*>0 and *StepRange*>0 **then**
6: Move as DroneFlay (Algorithm 1)
7: *MovementDirection* = SearchMethed (Algorithm 4)
8: **else** go to a docking station (step 2, step 3)
9: **end if**
10: Get context information
11: **if** *MovementDirection* is not null, **then**
12: **if** Within image bounds and not at the destination, **then**
13: Move one cell to the grid
14: Set xLoc, and yLoc based on position
15: **end if**
16: **if** At *MovementDirection*, **then**
17: **if** dropPayload **then**
18: dropPayload()(Algorithm 3)
19: **end if**
20: **end if**
21: *StepRange= StepRange-1*
22: **end if**

heading to the highest pheromone density to work as a collaborator to the predefined goals. Subsequently, the drone will decide whether to go to the fire spot individually and independently based on a strategy based on the amount of available payload or flight range.

– **Fire-fighter state**: Once all nearby drones reach the fire spot, the extinguishing process begins cooperatively by dropping its payload on the fire spots. Algorithm 3 illustrates the pseudocode of this function.

In each tick period, the drone executes the logic illustrated in figure 6. Here, coordination occurs through target detection, pheromone attraction, collision avoidance, and movement. The drone moves based on an improved random walk algorithm. The drone then started to detect obstacles and boundaries. When an obstacle is detected nearby (e.g., a tree, tower, or drone), the drone changes its direction to that of a free cell or moves to the next cell. After updating the environment, the drone attempted to search for fire spots.

If the drone detects fire spots, it immediately changes to the coordinator state mentioned above and then releases the pheromone to seek help from nearby drones to put out the fire. For example, suppose a pheromone is detected in neighbouring cells. In this case, the drone immediately switches to the collaborator state, reaching its highest pheromone intensity and releasing pheromones at fire spots to extinguish them with the coordinator drone. However, if no pheromone is detected, the drone moves randomly according to the improved random walk algorithm. Finally, the drones check whether the fire has been completely extinguished. If so, the drone moves to the end of the mission or returns to search for a fire spot again depending on the remaining payload and flight range.

Algorithm 3 DroneAgent dropPayload Decision

1: **if** FireSpot is not null and pheromone is not null, **then**
2: **if** the Color at FireSpot is Red, **then**
3: dropPayload =true
4: Payload=Payload-1
5: **end if**
6: **end if**

B. FIRE PROPAGATION MODEL

Due to the complexity of the chemical and physical phenomena of fire spread, which play a major role in heterogeneous environments, it is a great challenge to develop a detailed representative model of fire spread and unsolved yet [116]. Therefore, it should be noted that in this study, we focus exclusively on evaluating the ability and impact of the collective intelligence of a swarm of drones to suppress the spread of wildfires, which would meet the requirements of the problem (covering multiple hotspots) addressed in this study. Therefore, we do not claim that the fire spread model presented in this study is capable of efficiently predicting the rate and extent of fire spread. Rather, we only need to achieve a realistic performance to be able to test our approach in simulation in the context of autonomous drone swarms to fight forest fires, and predicting how a real fire will spread is beyond the scope of this study. This is crucial because it allows us to justify the limited number of model parameters considered in our approach, such as fuel density, fire intensity, wind speed, wind direction, and flat topology, which are compatible with the available literature [103], [104].

The fire model consists of a mechanism for the representation and propagation of a fire, which depends on certain rules that determine the behaviour of the fire in the simulation. In an agent-based simulation, individual behaviour is an important part of the fire-propagation model. Each cell in the grid space of the simulation corresponded to a single pixel on the terrain grid. In the simulation, the agent class fire spot specifies the behaviour and appearance of a single flame spot. To simulate how a fire spreads, each fire spot can create additional fire spots. Consequently, there is no requirement for a central control system, as global behaviour is determined by how the Fire Spots interact with their environment. In addition, various external aspects such as land height, terrain, wind, fauna type, and combustibility must be considered when simulating a fire. Because most of these factors are beyond the scope of this study, another method was used to develop the fire model.

Therefore, in this work, we made some real improvements to the agent-based modelling tool based on the basic forest fire model [102], which is a programmable multi-agent

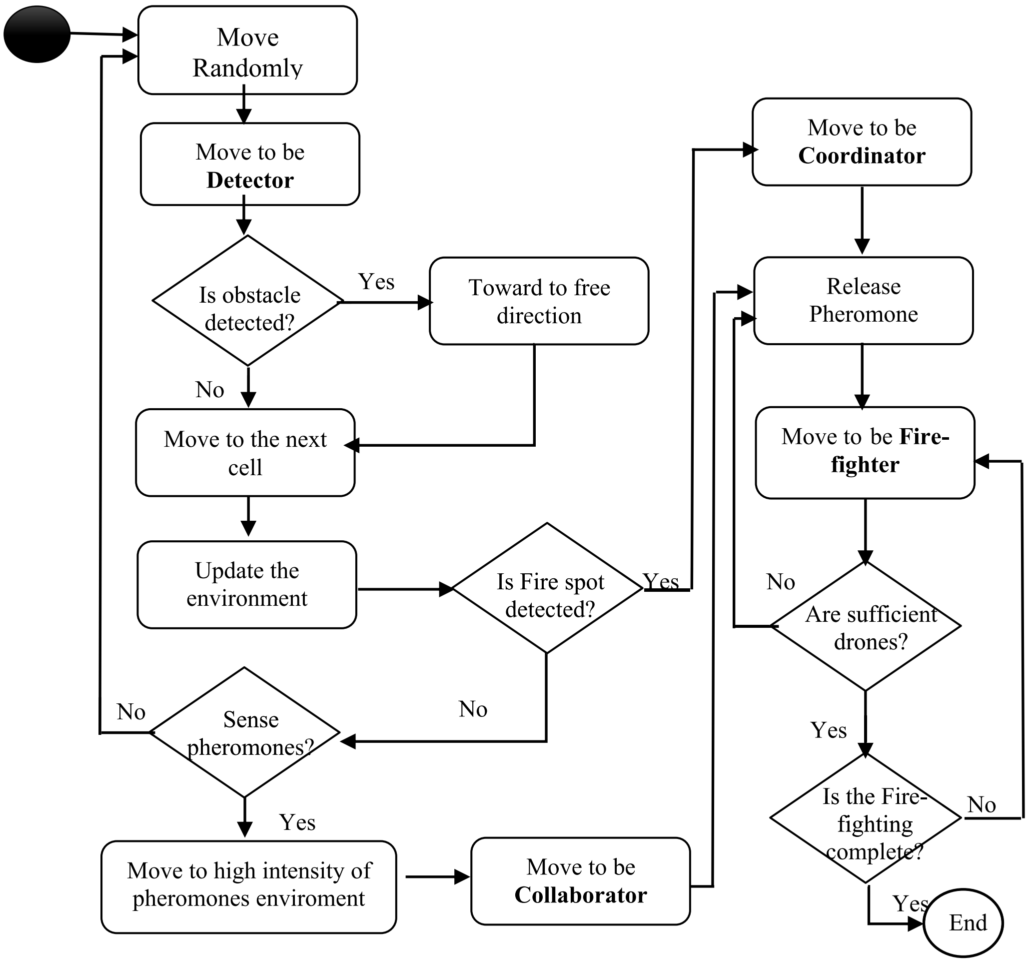


FIGURE 6. Flowchart of the proposed coordination logic strategy.

modelling environment for modelling fire spread. For example, if the simulation is run and obstacles are added at certain locations, fire can spread to different random locations each time. To simulate the developed model, a rectangular environment was used, in which the trees were randomly distributed over the terrain to simulate the forest. There are fire cell factors, each of which can start at any point in the simulation experiment. Using local rules and spread options, once a fire begins, it spreads to a random number of locations.

Thus, the simulation represents the spread of a real fire using distributed agent-based technology. Finally, the fire spreads to the cell itself and the surrounding cells through its influence on the factors and conditions provided by the environment.

Considering f_t^i as the location of the i-th fire spot on the forest at time t and $\dot{f}_t^i$ as the fire spot growth rate at the location f_t^i (i.e., fire propagation velocity), the wildfire propagation dynamics can be expressed as in Equation 6, where δt is the time step and $\dot{f}_t^i = \frac{d}{dt}(f_t^i)$ is a function of the fire spread rate. Figure 7 presents the simulation implementation of a forest fire and randomly distributed fire spots at multiple locations. When the dark green colour corresponds to the density of trees in the forest, the red colour corresponds to the spreading of fire spots, and the black colour corresponds to empty and non-flammable areas.

$$f_t^i = f_{t-1}^i + \dot{f}_{t-1}^i \delta t \tag{6}$$

The simulation of the spread of fire in the forest was represented by two main agents: tree agents and fire spot agents. The slider shown in Figure 8 controls the density of the randomly distributed grass. The rules for spreading fire between grasses can be described as follows: they look at their neighbours from all directions. If there are weeds in their neighbours, the fire will burn them.

C. COUPLING THE FIRE PROPAGATION MODEL AND THE DRONE SWARM MODEL

The proposed model of the drone swarm is coupled with the fire propagation model once it runs realistically and sufficiently fast, as illustrated in Algorithm 4. The swarm model aims to detect the boundaries of fire spots and suppress them by deploying fire suppressant balls. The drone drops payloads at the fire spots to establish a firebreak. It is assumed that dropped payloads on active fire spots will immediately

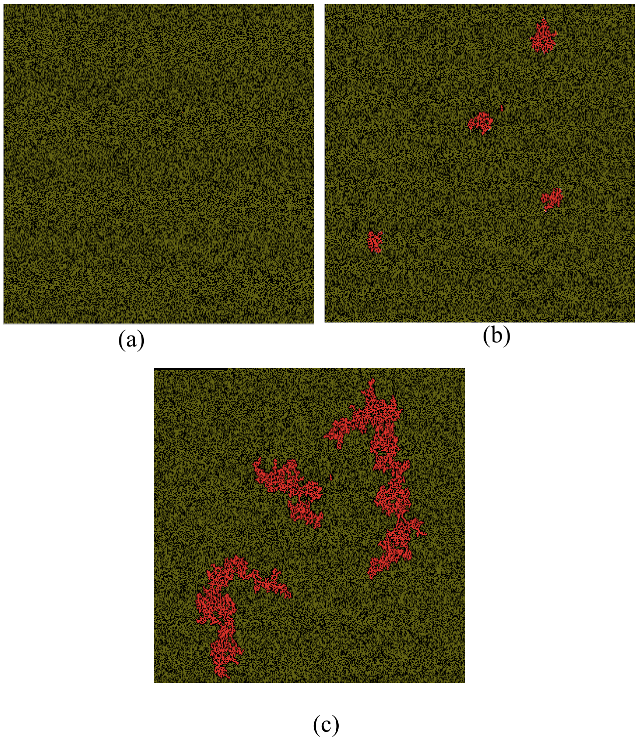


FIGURE 7. **Representation of the forest by simulation. (a) The initial state of the forest; (b) the generation of a spark randomly at multiple locations; and (c) fire propagation in the forest according to the fire model.**

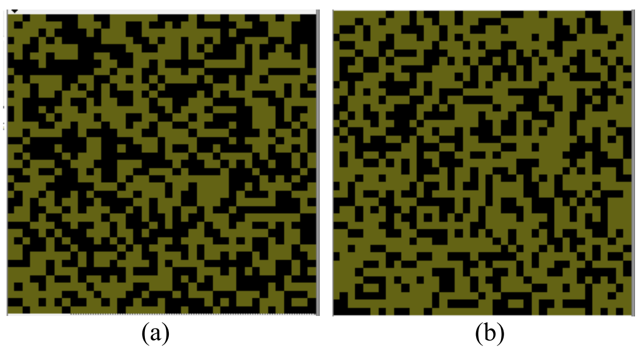


FIGURE 8. **The tree agents (a), and (b) when the density of trees is 50% and 60%, respectively.**

prevent the fire from spreading in all directions and that once a firebreak is established, the fire will not be able to cross it. The implementation of the self-firefighting model stepping method was similar to that of the fire propagation model, where the stepping method was executed once per tick of the simulation.

A simulation of the overall task is required to evaluate the performance of a single solution. As the drone moves randomly, the results are subject to a certain degree of randomness. Each evaluation was repeated 20 times (repeated trials). When 100% of the fire spots have been detected, the mission objective was achieved without loss of accuracy. Based on these factors, the fitness value for a given set of

Algorithm 4 Self -Firefighting model

```
Spread the fire spots to different random locations in Ω
   environment over five different places to start the
   process of fire propagation according to the model in the
   4.1 section
Placed Drones at their recharging station are fully charged
   and fully water-loaded at the start of the simulation
   (tick = 0; FirspotFound = 0;).
for each drone d in the swarm
   Input the swarm settings for the drones independently,
   as in (Algorithm 2) to determine the scene of the spread
   of fire and the mechanism of self-extinguishing the fire,
      FirspotFound = FirspotFound +1
      tick = tick + 1;
 while(FirspotFound <TotalFirspot)
   or(tick = maxSearchTime);
| return{tick, FirspotFound };
```

parameters was calculated by averaging the time required for 20 different simulations. Figure 9 illustrates a simulation snapshot with instances of a swarm of drones, fire spots, and pheromones and depicts some important samples of a coordination mechanism strategy.

IV. SIMULATION AND RESULT ANALYSIS

This study uses NetLogo simulation [117], the best simulation tool for swarm intelligence, and agent-based modelling languages. This provides a simple but powerful programming environment to describe different emergent paradigms and design agent-oriented simulation programs by building a model of a forest fire and drone swarm coordination mechanism for autonomous firefighting. It is possible to create intricate models using NetLogo with hundreds of agents in each network. The experiment simulation process of the proposed model was performed using a laptop of Dell Latitude 5590, Intel(R) Core i5-8350U CPU @1.90 GHz with 8GB RAM, Graphic Processor Unit (GPU) Nvidia Geforce GTX 1050 4GB and under the Windows 10 Home operating system with SSD M.2 M9280 256GB.

The search area in NetLogo is a two-dimensional environment (X $\times$ Y) divided into equal-sized patches. The number of patches defined by the maximum and minimum X/Y coordinate values determines the search area size. As the main objective of this study is to cover multiple fire spots, we used a relatively large search area. Thus, the search area size is 401 $\times$ 401, with 160,801 patches. In addition, the fuel used for the fire is evenly distributed. According to the tree density indicated in Section (4.2) throughout the search area (the fuel is short grass), except for a small area of the docking station where a swarm of drones is placed to refuel and reload the extinguishing payloads, no combustion occurs near it. In our study, it should be noted that we refer to "tree density" as the common term for "fuel density". Table 3 lists the parameters maintained by the drone model. The fuel parameter tracked the amount of fuel onboard the drone. A payload parameter is used to track the amount of fire extinguisher payload onboard at a given time. The payload value indicates when the drone must land and refuel its tanks because the *drone StepRange* is limited to 600 steps with a payload of 40, as assumed in the previous section. Therefore, the mission duration is used as a performance measure. It should be noted that the features of the drones mentioned in Table 3 were not chosen arbitrarily but considered the similar features of some of the drones used in [80] and [118], which are capable of performing flights with a payload of 20–30 kg and a flight time of 10 min (e.g., Vulcan D8 and GD-40x, respectively).

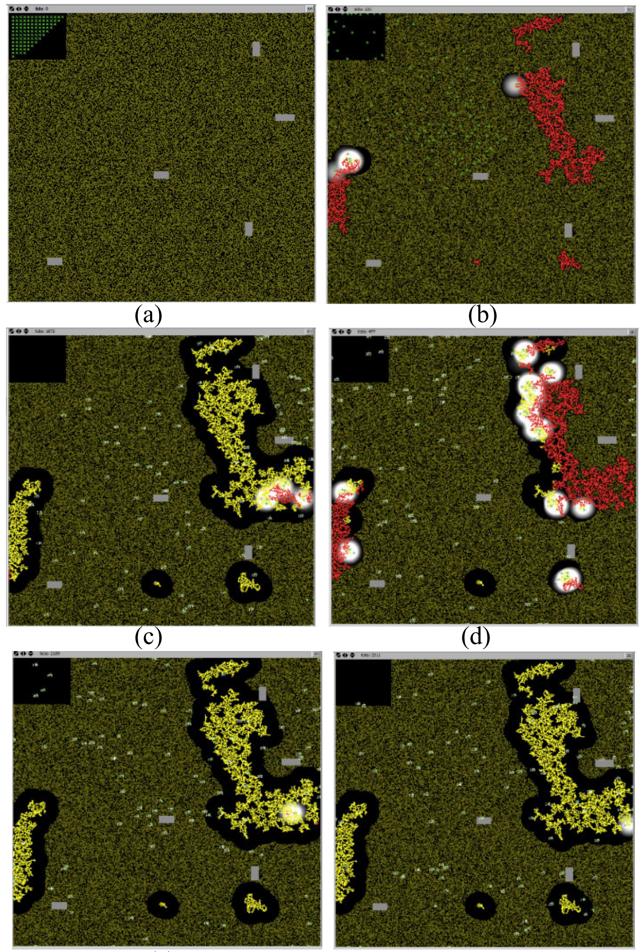
A. CONSIDERED SCENARIOS AND QUALITY MEASURES

Let us consider the following scenario for the self-firefighting model: The proposed model consisted of several hotspots scattered randomly in a forest. Drones are placed at the docking station at the beginning of the mission. These autonomous drones have simple local rules and interact with each other and with the environment. These interactions lead to the collective behaviour of the swarm, covering the area to search for hotspots in the field and then extinguishing them cooperatively. A drone consumes a certain amount of energy or extinguishing fluid at each simulation step in different states. These drones exhibit different behaviours depending on their current state (Figure 9). When a single drone detects a fire source, a coalition of other drones is formed to extinguish the fire. Due to the limited payload and flight range, it would be either impossible or too costly to do this individually. The coalition can fight a fire cooperatively if the drone is in the vicinity of the fire. It is also assumed that there is no prior knowledge of the hotspots, such as the size of the affected area and their positions. Therefore, a drone team must survey the entire area to ensure that all fire hotspots are detected. Recall that the focus is on the intelligent coordination mechanisms of swarms. Therefore, drones self-organize to develop the ability to fight fires autonomously and together, avoiding collisions with each other and other obstacles. In the proposed decentralized and collaborative firefighting system, it is important to establish a general quality measure for the characteristics of a swarm robot-based system. Thus, the performance of a swarm can be evaluated based on various factors, including the effectiveness of meeting the requirements of an autonomous firefighting system. For this reason, we propose some quality measures to ensure the effectiveness and characteristics of the approach:

i) Scalability: Increasing the number of drones should minimize the deployment time. However, the number of changes in the flight direction caused by collision avoidance between drones could have a detrimental effect on mission time. Therefore, scalability is measured by averaging the mission time calculated over several trials for each increase in swarm size.

ii) Efficiency: An efficient swarm performs a rapid survey of the search area and detects fire sources in the working environment. One of the objectives of the proposed system is to reduce the time required for firefighting. Formally, the proposed system is considered efficient if it covers all fire sources within the shortest possible time. This is determined by calculating the average time ratio and coordinates of the nearest drone to the coordinates of the visited fire sources and for all multiple fire sources in the environment during the task.

iii) Effectiveness: Given that the flight range of drones is one of the most important features, thus, must evaluate the effectiveness of a mission in terms of firefighting time, i.e., the time it takes to detect 100% of fire spots.



(a) (b) (c) (d) (e) (f)

FIGURE 9. **The initial swarm of 100 drones fighting fire with 10.02% affected area from total area = 14.964 Km2, Total time to fight all fire spots =2311 tick; The rate of return of the swarm of drones to the docking station =3.6 times.**

To confirm this, several experiments have been carried out in this section in which the performance of the UAV-based system is evaluated during firefighting operations.

B. FIRE MODEL EXPERIMENTS WITH DIFFERENT DENSITIES OF TREES

To make the simulation as realistic as possible, two scenarios are run to observe fire propagation in the area of interest.

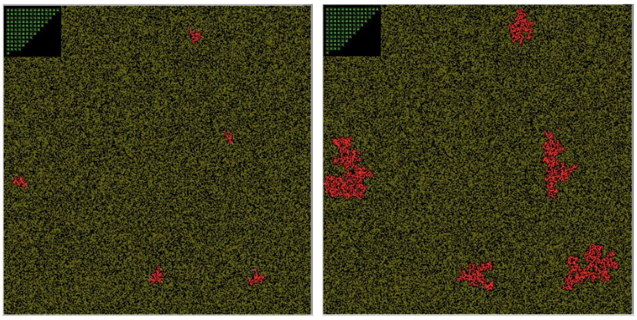


FIGURE 10. **The run scenario of the fire model started when tree density = 50%. The figures are snapshots of the total fire area affected (Fa) at tick = 20 (left) and tick = 500 (right).**

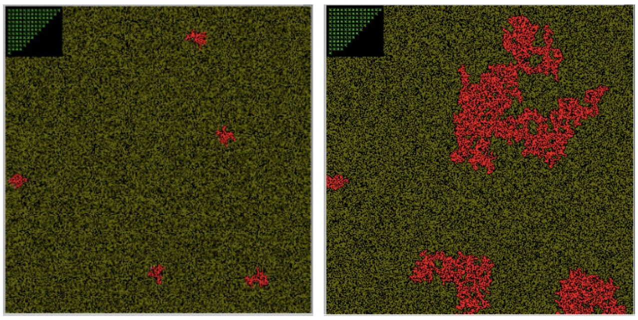


FIGURE 11. **The run scenario of the fire model started when tree density = 60%. The figures are snapshots of the total fire area affected (Fa) at tick = 20 (left) and tick = 500 (right).**

Figure 10 and Figure 11 show the behaviour of the fire propagation and the total fire area affected when a fire is started from five locations with a tree density set to 50% and 60% according to the proposed fire model.

The evolution of the affected fire area (Fa) for each fire in the two experiments is shown in Figure 12, with the final values of the total fire area affected for each of the two scenarios. The total fire area affected in the first experiment was approximately 2.6% of the total area (equivalent to 2994 m^2), whereas the total fire area affected in the second experiment was approximately 4.8% of the total area (equivalent to 7824 m^2), which is calculated using the following formula:

$$Fa = \frac{Area\ Affected}{160000} \tag{7}$$

where Area Affected refers to the total burnt trees

C. SCALABILITY ANALYSIS OF THE FIREFIGHTING MODEL

To investigate the impact of the number of drones (scalability) on the proposed self-extinguishing model, we tested it by increasing the number of drones from 30 to 100 at two different densities of forest trees. It is important to note that fire can permanently be extinguished if there is a sufficient number of firefighting drones and enough time, even if the number is unreasonably high. Therefore, all experiments start with insufficient swarm size. Thus, the impact of adding more drones to the swarm size (Sn) on the success rate is analyzed

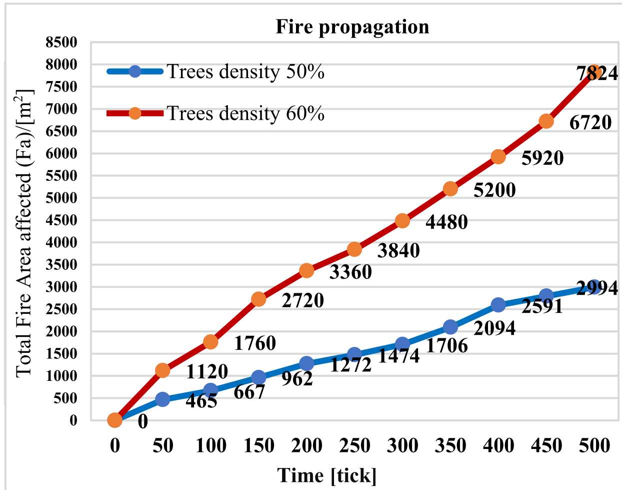


FIGURE 12. **Total affected fire area (Fa) for different tree densities (50, 60) % respectively after running the model.**

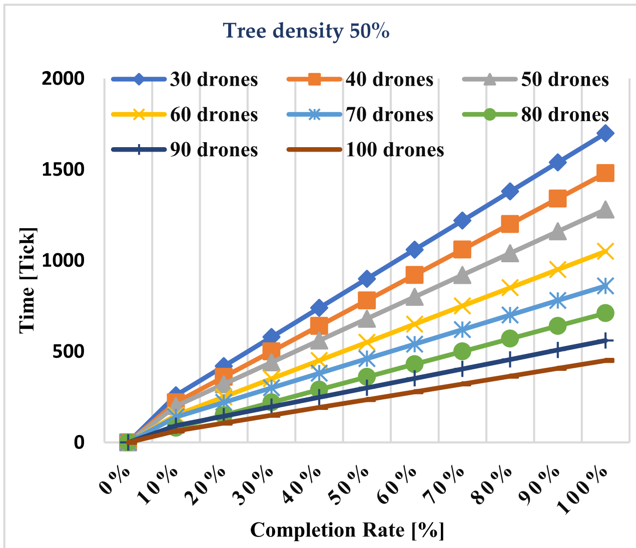


FIGURE 13. **The scalability analysis of the different swarm sizes experiments with a tree density of 50%.**

and investigated by calculating the total time (Td) and total area of fire affected (Fa). In addition, the number of times the drone returned to the docking station to refuel or fire suppressant ball (Nr) over 20 repeated trials was recorded.

One of the most important features of the fire spread model and the proposed fire suppression system is a randomness to achieve maximum realism in an uncertain environment. Therefore, it is important to perform several experiments to calculate the basic statistics required to draw reliable conclusions from the results. Table 4, Figure 13, and Figure 14 show the experimental results for fires that occurred at 50% and 60% of forest tree density, respectively, and at swarm sizes of 30 to 100 drones, to give a little insight.

Based on the experimental results for a fire with a tree density of 50%, Table 3 clearly shows that a swarm of 30 drones

TABLE 4. The results were extracted after simulating a fire of two different intensities(50% and 60%, respectively) of the experiment for each swarm size.

Swarm Size Sn	Tree density 50%			Tree density 60%		
	Mean Fa [m^2]	Mean Nr [time] to coverage all grids cell	Mean Td[tick]	Mean Fa [m^2]	Mean Nr [time] to coverage all grids cell	Mean Td[tick]
30	2806	2.2045 ± 0.0354	1699 ± 188	7023	3.6706 ±0.0360	2482 ± 93
40	2894	2.1026 ± 0.0789	1480 ± 162	7321	3.2337 ±0.0865	2366 ± 67
50	2812	1.6607 ± 0.0256	1279 ± 146	7321	2.9427 ±0.0561	2244 ± 68
60	2894	1.2806 ± 0.0325	1050 ± 129	7304	2.708 ± 0.0964	2124 ± 88
70	2806	1.2028 ± 0.0533	860 ± 111	7071	2.6419 ±0.0735	2007 ± 97
80	2920	1.1800 ± 0.0345	710 ± 96	7820	2.4204 ±0.0412	1888 ± 86
90	2890	1.1502 ± 0.0546	560 ± 50	7321	2.2179 ±0.0714	1764 ± 77
100	2829	1.1015 ± 0.0676	450 ± 23	7399	2.1017 ±0.0564	1648 ± 42

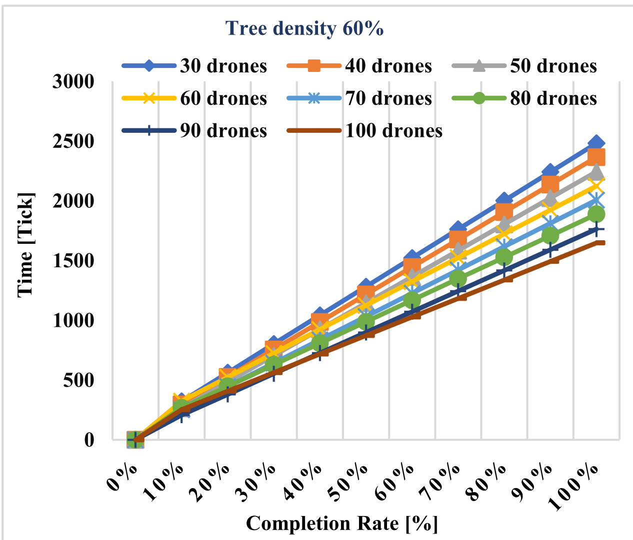


FIGURE 14. The scalability analysis of the different swarm sizes experiments with a tree density of 60%.

spends more time on coverage and fighting fire spots, with the affected fire area being up to 2806 $m^{2.}$ Incidentally, this can also be deduced from the curves in Figure 14 for 30 drones, which increase more than the others. On the other hand, when the swarm size was increased to 40 drones, the time of coverage and fighting a fire spot decreased by 87%. As a result, further increasing the swarm size to 50, 60, 70, 80, 90, and 100 drones improved to 75%, 62%, 51%, 42%, 33%, and 26%, respectively.

A fire with a tree density of 60% is more challenging than a tree density of 50%, and a swarm of 30 drones spent more time covering and fighting a fire spot with an affected area of 7,321 m^2 (see Table 4). On the other hand, when the swarm size was increased to 40 drones, the total time needed to cover and fight a fire spot decreased by 95%. As a result, further increasing the swarm size to 50, 60, 70, 80, 90, and 100 drones improved to 90%,86%, 81%, 76%, 71%, and 66%, respectively. Although there is a different degree of improvement in reducing the mean Td[tick] time for each increase in swarm size, this difference is not very significant for each increase of 10 drones. However, this difference is greater across all experiences. There was no significant difference in the Mean Td[tick] for each interval of increase in the drone swarm size.

Incidentally, from the curves in Figures 13 and 14, it can be deduced that an increase in swarm size significantly affects deployment time as it substantially reduces the time for firefighting. Interestingly, increasing the number of swarm members significantly affected the time required for firefighting, while decreasing the number of return flights of the swarm to the docking station. In addition, the curves show that when the area is affected by fire triples, the difference in the time required for the swarm to extinguish the fire is not very large for each increase in swarm size. This is because the swarm spends most of its time returning to the docking station to refuel because of the flight range and payload of drones.

D. EFFICIENCY ANALYSIS OF THE FIREFIGHTING MODEL

To investigate the efficiency of the proposed model in terms of area coverage with the improved random walk algorithm (*see Section III-A1.a*), we performed a comparative analysis between the traditional Levy Flight algorithm (LF), Particle Swarm Optimization (PSO) algorithm, and improved algorithm.

Figure 15 shows the comparative relationships between the area coverage ratio and the number of iterations for PSO with LF and our improved algorithm, confirming the final results of the current study on the relative strength of interval repetition. To simplify the comparison process and verify the efficiency of the proposed algorithm, we set the parameters listed in Table 5 for the three algorithms.

Figure 15 shows that the iterative process for both the PSO and LF algorithms failed to reach the optimal coverage after 200 iterations. The proposed algorithm achieved optimal

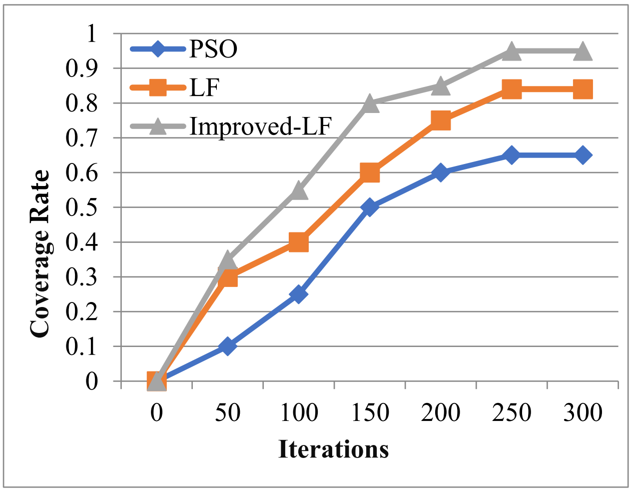


FIGURE 15. Comparative relation between coverage ratio vs no. of iterations.

TABLE 5. General Simulation parameters.

Parameter	Values
Search area (X * Y)	100 × 100 patches
Swarm size	100 drones
Flight range	2000 steps
Sensing range	10 patches

coverage after only 150 iterations. This indicates that the proposed algorithm is effective to a certain extent in covering all the fire points with the least number of iterations. In addition, the improved algorithm achieved the highest coverage of 95.3% compared with the algorithms LF and PSO, which reached 84.3% and 65.8% coverage, respectively, with the same initial parameter settings.

Moreover, the proposed model improves the global search capability of the optimized algorithm by increasing both the coverage and diversification in the population. Improved-LF controls whether the drones improve firefighting cooperation in the selected environment. If both the PSO algorithm and the Levy flight algorithm fail to improve self-cooperation, the improved LF redistributes drones to search for distributed fire spots using random walks. The improved LF ensured that the distribution of drones is random and the search space is used effectively. Thanks to this random walk of the proposed algorithm, early convergence between the drones was prevented so that they gathered on single fire spots without searching for other fire spots in multiple locations in the search space.

Based on the experimental results, the improved LF by Levy distribution prevents early convergence fall into the local minimum. It can be observed that the improved LF algorithm achieves better results than the PSO algorithm and the Levy flight algorithm in most experiments. Therefore, the proposed algorithm is more powerful than the PSO algorithm and the Levy flight algorithm.

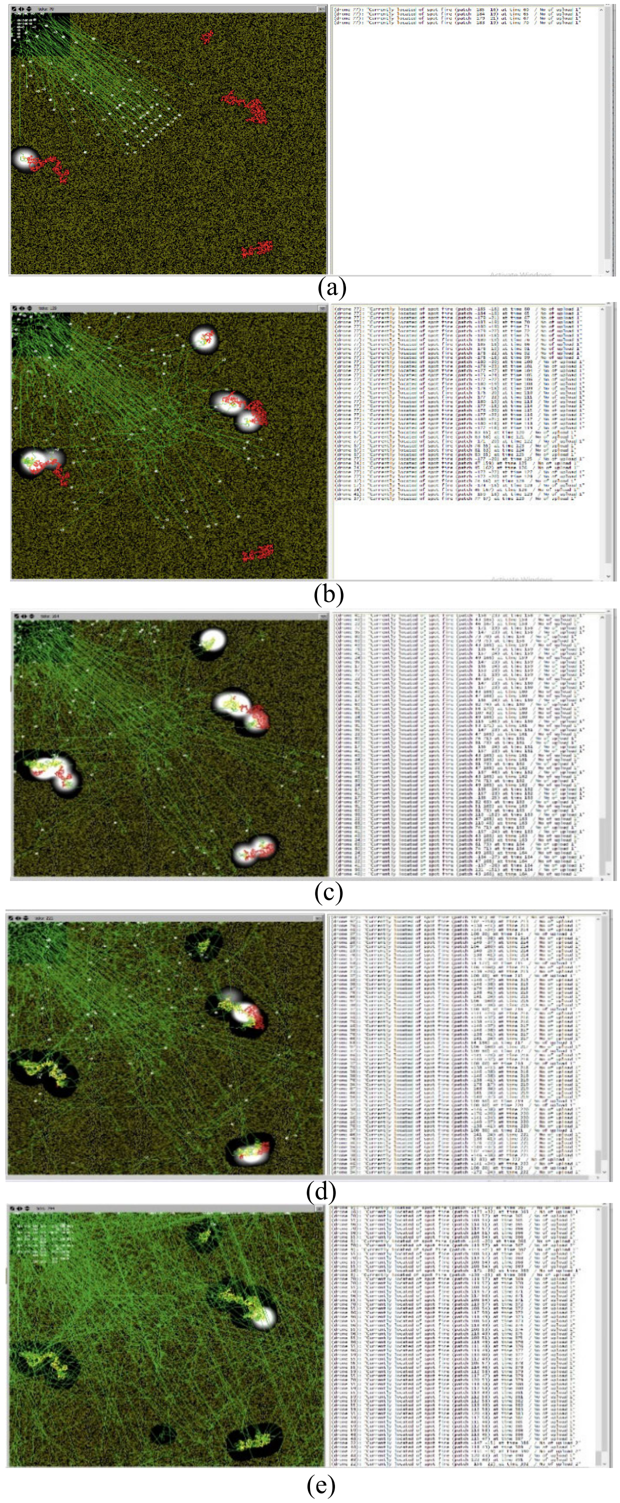


FIGURE 16. Area coverage by 100 drones based on the proposed model and the improved RW algorithm.

This indicates that fewer flight steps are required when a larger number of drones are used to cover this area. These

TABLE 6. The performance effects of various firefighting models are influenced by execution time.

	Swarm Size Sn	Mean Fa [m^2]	PSO Model in Innocente and Grasso [32] Mean Td[tick]	PSO Model in Innocente and Grasso [32] Performance rate	Our Model Mean Td[tick]	Our Model Performance rate
Single-Hot spot	30	61.07+45	236.43	0.258301	173.24	0.352517
	40	52.75±43	255.05	0.206822	159.63	0.330452
	50	43.6±39	203.52	0.21423	126.57	0.344473
	60	34.88±33	143.47	0.243117	98.71	0.353358
	70	33.30±27	100.73	0.330587	74.42	0.44746
Multi-Hot spot	80	278.48±49	357.18	0.779663	270.28	1.030339
	90	247.83±46	335.42	0.738865	245.86	1.008013
	100	214.38±40	263.91	0.812322	196.42	1.091437
	110	191.19±33	232	0.824095	156.34	1.222912

results show that the improved LF algorithm can effectively re-cover the grids and cover the area in a limited number of steps. If we want to cover more area in less time, we need more drones. But the newly covered area becomes larger at the same time.

From the simulation, it appears that all drones perform well in covering the fire spots. From the observation of the persistently large number at this location, it can be inferred that other drones are able to independently fly over the area previously covered by the faulty drone. In addition, the drones are able to change their position to evenly distribute their population.

To illustrate the success of the proposed algorithm, the efficiency of the proposed model of unknown environments was examined here to further evaluate its performance. This section shows how a drone swarm can achieve area coverage based on the proposed random walk algorithm. Figure 16 shows a set of snapshots of a swarm of 100 drones for a cover operation driven by the proposed random walk algorithm. Figure 16 (a) shows 100 drones moving randomly from their positions in the search space. All the areas visited by the drones were identified, and a local coordinate system was created.

Figures 16 (b), (c), and (d) show the swarms of drones covering the area using a random-walk algorithm. The covered areas are indicated by light green lines in the snapshot. Figure 16(e) shows how the drone swarm covers the entire fire area. It can be observed from the snapshots that there are many dark green areas, indicating that the concentration in these areas is still very high. The left side of Figure 16 shows each snapshot of the simulation output. The right-hand side represents the simulation results in terms of the coordinates of each fire area covered by a drone.

It should be noted that the terrain to which the method is applied consists of randomly distributed grass and an area free obstacle, and the number of drones can be increased and decreased.

In general, increasing the total number of drones had a positive effect on each situation to varying degrees. However, it should be noted that in scenarios with many obstacles or target cells, nonlinear phenomena may occur due to the complexity of avoidance situations. When the task complexity increases, it can be seen from Figure 16 that there may be more drones in the overlapping region receiving the same orders and heading for the same fire source, leading to unnecessary redundancy. However, in most scenarios, the proposed model shows better performance and distributes the drones better in the coverage area based on the improved random walk algorithm, especially compared to traditional methods.

E. EFFECTIVENESS ANALYSIS OF THE FIREFIGHTING MODEL

The last experiment in this study is to evaluate the energy consumption of the proposed model by applying the strategies at 50% and 60% of the forest tree density and varying the number of drones involved by the number of times the drone returned to the docking station to refuel or reload the extinguishing payloads. A drone's remaining flight range is measured before it needs to be refuelled or fire suppressant fluid by updating the distance that can still be travelled by each drone to ensure that the maximum flight range is not exceeded.

Table 4 and Figure 17 summarize the simulation results, including the total energy consumed by the drones, determined by the mean of many experiments, and the average of the proposed model for each simulation run. The results show that the average energy of the model decreases as the swarm size increases; however, the energy consumption increases as the size of the fire increases. The effectiveness of a drone swarm is likely to increase with the number of drones. Figure 17 shows that the difference in performance is smaller for the two cases (50 and 60) than for the tree density. However, it increases when the complexity of the implementation levels is increased due to the addition of many obstacles

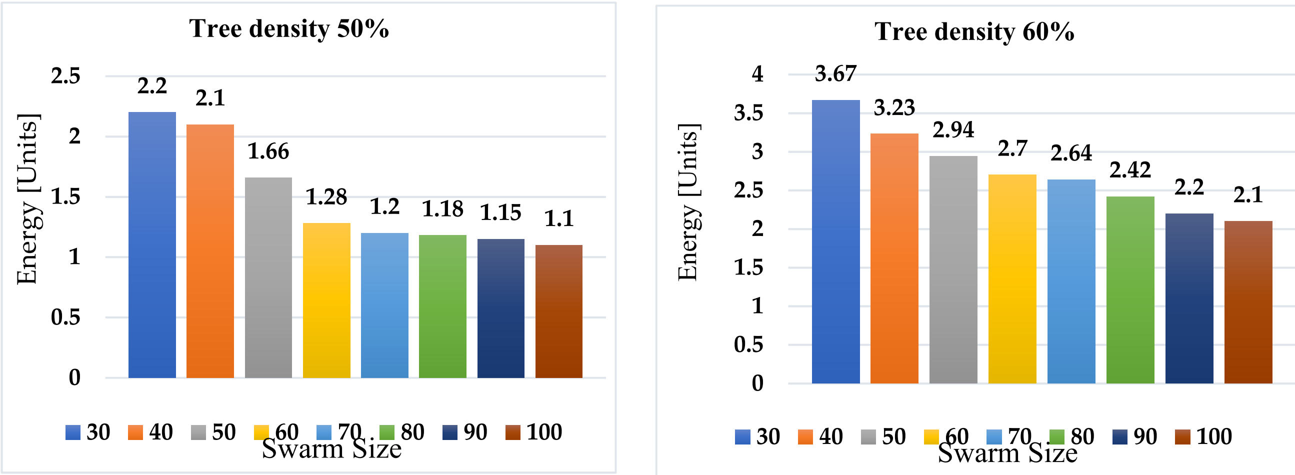


FIGURE 17. Evaluation of Total- Energy-Consumed in terms of units of energy with different swarm sizes of drones and tree density.

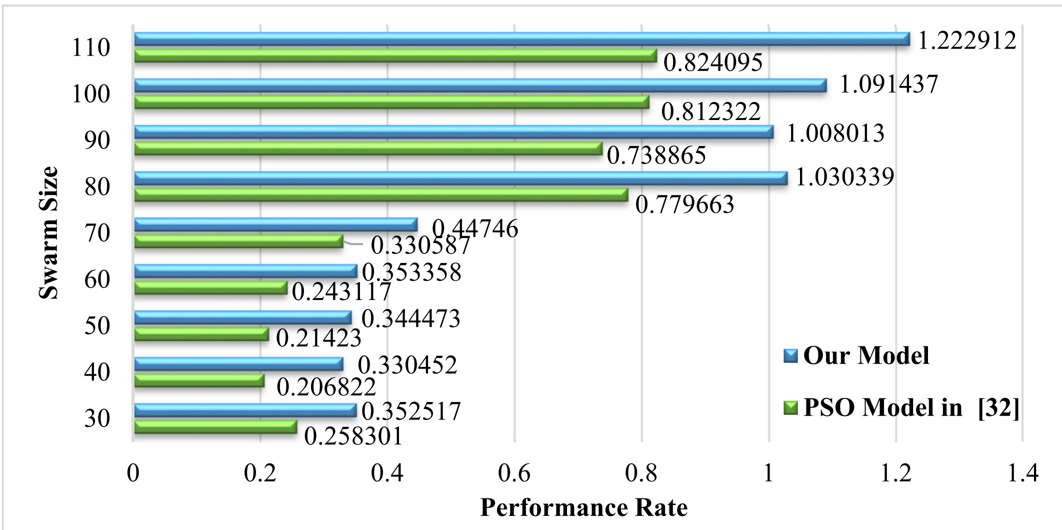


FIGURE 18. Comparison between the performance of the proposed self-firefighting model and the firefighting model in [32].

in the search area. It is reasonable to expect that the swarm energy efficiency will improve by increasing the number of drones. The more fire spots that are introduced, the higher the energy consumption and the number of times the swarm returns to the docking station. However, as the number of fire spots increases, recruitment tasks become more complex and this strategy becomes more critical.

Furthermore, we evaluated the proposed model by comparing its performance with state-of-the-art benchmark studies [32]of wildfire self-suppression based on the time taken to complete the task. In our simulations, we tested the two models using the same parameters, as shown in Table 6, for comparison, as well as on the same size as the area affected by the fire with different swarm sizes. The results of these evaluations are presented in Table 6 and Figure 18, and show that our proposed model performs better in most cases where the swarm size changes, whereas the performance ratio converges with the increase in the swarm size.

Finally, the autonomous firefighting model proposed in this study is scalable, efficient, and effective, as shown in these experiments. This means that increasing the swarm size will lead to an increase in firefighting power. Therefore, larger wildfires are less of a concern because their energy consumption and resulting damage are minimized.

V. CONCLUSION AND FUTURE WORK

Globally, the frequency and severity of forest fires have increased, becoming larger, more dangerous, and more costly to extinguish. However, most studies have focused on drone technology in firefighting systems, which are currently used for wildfire detection and monitoring, post-fire surveillance, fire hazard mapping, and disaster response support. However, research and development on the use of UAV swarms to extinguish wildfiresis still scarce. In this paper, we presented a new self-firefighting model and developed a simulation to test the effectiveness of autonomous and decentralized behaviour for a swarm of drones to fight the propagation of wildfires instead of humans. This model is based on the principles of different bio-inspired metaheuristics that use swarm intelligence to coordinate a swarm of drones to perform tasks cooperatively in an unknown environment. The main features of the proposed model are as follows.

- Scalability: The proposed model works well when changing the swarm size of the drones and the area affected by the fire.
- Adaptability: The proposed model can be used under different environmental conditions by spreading fires to other ecological locations.
- Parallelism: Each drone can perform its tasks autonomously and in parallel, making individual decisions based on local information.
- Efficient: The proposed model is effective because it rapidly detects all fire-spreading spots in the working environment by detecting the area and searching for them.
- Effective: The proposed model is effective because it evaluates the effectiveness of a mission in terms of the time taken to fight the fire and the time taken for the drone to return to the docking station to refuel or fire suppressant fluid, i.e., the time taken to detect 100% of fire spots.

Our simulation experiments showed that the coverage was ineffective, and the energy consumption was higher when the particle swarm optimization algorithm was used, especially when the swarm size was small. Consequently, the affected fire area was large. Our proposed approach using the improved random-walk algorithm is effective when the environment is not complex. However, the difference was more evident when the area of the affected fire to be extinguished was more significant, and the number of drones in the area was small. Therefore, coordination mechanisms have become more concerned with complex dynamic problems, so strategies based on our proposed approach often provide better performance. The simulation results demonstrate the effectiveness of the proposed model in covering multiple fire spots and suppressing wildfires. Future work will investigate more complex problems involving priority fire areas with many simultaneous fire spots and heterogeneous fire conditions, considering other environmental conditions.

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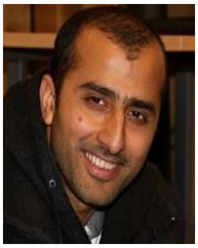

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