

An Efficient Approach with Dynamic Multi-Swarm of UAVs for Forest Firefighting

Josy John, K. Harikumar, J. Senthilnath, *Senior Member, IEEE*, Suresh Sundaram, *Senior Member, IEEE*

Abstract—This paper proposes the Multi-Swarm Cooperative Information-driven search and Divide and Conquer mitigation control (MSCIDC) approach for faster detection and mitigation of forest fires by reducing the loss of biodiversity, nutrients, soil moisture, and other intangible benefits. A swarm is a cooperative group of Unmanned Aerial Vehicles (UAVs) flying together to search and quench the fire areas effectively. The multi-swarm cooperative information-driven search uses a two-stage search comprising cooperative information-driven exploration and exploitation for quick/accurate detection of fire locations. The search level is selected based on the thermal sensor information about the potential fire area. The dynamic nature of swarms acquired from global regulative repulsion and merging between swarms reduces the detection and mitigation time compared to the existing methods. The local attraction among the swarm members helps the non-detector members reach the fire location faster, and divide-and-conquer mitigation control ensures a non-overlapping fire sector allocation for all members quenching the fire. The performance of the MSCIDC has been compared with different multi-UAV methods using a simulated pine forest environment. The Monte-Carlo simulation results indicate that the MSCIDC reduces the average forest area burnt by 65% and mission time by 60% compared to the best case of the multi-UAV approaches, guaranteeing a faster and more successful mission.

Index Terms—Swarm search, forest firefighting, cooperative information-driven search, divide and conquer mitigation control

I. INTRODUCTION

FOREST fires are extremely destructive, causing significant loss of flora, fauna, wildlife habitats, and other resources. The detection and mitigation of nascent forest fires are imperative to curtail the damage. The existing forest firefighting techniques engaging human firefighters are dangerous and unreliable. UAV systems have been used to monitor, detect, and mitigate forest fires to reduce human interaction in unsafe circumstances. Single UAV systems are inadequate for large and multiple wildfire suppression measures. Multi-task missions like forest firefighting include search, detection, monitoring, and neutralization of the targets. Thus, team-based multi-UAV systems are promising for multi-task missions and increased area coverage [1]. Multi-UAV systems performing multi-task missions need coordination strategies to manage communication and task allocation. The

centralized, distributed, and decentralized control systems with global and local communication have been used in different fire assistance systems [2], [3]. Forest firefighting involves addressing unknown targets in an extensive search area, where uneven fire spread can occur due to the direction and speed of the wind, vegetation type, and other environmental conditions. The large search area with uncertain and challenging conditions makes it difficult for UAVs to manage centralized or distributed communication. A decentralized control with local communication between UAVs is preferred for achieving scalability and robustness in forest fire search missions [4].

This paper presents a Multi-Swarm Cooperative Information-driven search and Divide and Conquer mitigation control (MSCIDC) for the search and mitigation of forest fire. Multi-swarm missions are efficient in quenching the spreading fires as multiple UAVs are likely to detect the same target. A multi-swarm cooperative information-driven search is used in the target search phase to drive the swarm in the direction of the maximum temperature gradient sensed by the swarm. The search phase uses cooperative information-driven exploration and exploitation depending on the sensor information of members in the swarm. The swarm member detecting the fire locally attracts other members in that group to reach the fire front faster. The swarm members reaching the fire front start quenching the fire using divide and conquer mitigation control. The quenching members are assigned to non-overlapping sectors of fire, and the sector division assures a non-overlapped quenching even with a shrinking fire area. The global regulative repulsion and merging between the cooperative swarms, balance target detection and quench time reduction. The performance of the MSCIDC is compared with existing multi-UAV search methods using Monte-Carlo simulations. The results of the MSCIDC are superior to the best case of multi-UAV missions with a 60% reduction in total mission time and a 65% reduction in the burnt area of the forest. Extensive simulations have been conducted to analyze the effect of temperature threshold, number of UAVs, swarms, and fires. The main contributions of MSCIDC are summarized as follows:

- 1) A dynamic multi-swarm configuration with regulative merging and repulsion, based on resource requirements, is proposed to detect multiple forest fires effectively.
- 2) A novel divide and conquer mitigation control is formulated to reduce the quench time by ensuring the quenching of equal non-overlapped fire areas by UAVs.
- 3) Monte-Carlo simulation and ablation studies show that MSCIDC outperforms existing multi-UAV methods with

Josy John and Suresh Sundaram are with the Department of Aerospace Engineering, Indian Institute of Science, Bengaluru, India. josyjohn@iisc.ac.in; vssuresh@iisc.ac.in

K. Harikumar is with the Robotics Research Center, International Institute of Information Technology, Hyderabad, India, harikumar.k@iiit.ac.in

J. Senthilnath is with the Department of Machine Intelligence, Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), Singapore, J_Senthilnath@i2r.a-star.edu.sg

a 60% reduction in total mission time and a 65% reduction in the burnt area of the forest.

The rest of this paper is organized as follows. Section II provides a review of existing forest firefighting approaches. In Section III, the problem definition and different models of subsystems are presented. Section IV explains the MSCIDC for forest firefighting. Numerical simulation results are given in Section V to verify the performance of the MSCIDC over the multi-UAV methods, and Section VI concludes the paper.

II. RELATED WORKS

Fire monitoring is the most researched area in firefighting, and satisfactory perimeter tracking relies on the accuracy of fire models. Simple models use elliptical fire profiles with constant fire spread rate, influenced by fuel energy, fire intensity, speed, and direction of wind [5], [6]. Multi-UAV systems with conventional optimization approaches are used to cooperatively monitor the dynamic fire perimeter and share real-time fire images with base stations or firefighters [7]. A robust reconfigurable perimeter tracking algorithm with minimum information latency of data exchange is proposed in [8]. In a cooperative team of UAVs, detector agents search for hotspots and use an auction-based decision-making algorithm to assign service agents to monitor multiple forest fires using a splay state controller [9]. A leader-follower formation control of a multi-UAV system using a sliding mode controller [10] and a fault-tolerant cooperative control to achieve a reconfigurable formation control [11] are employed for fire monitoring. A collaborative system of UAVs uses a potential field-based algorithm to optimally cover the fire area and monitor the area by capturing multiple sub-pictures in [12]. A fault-tolerant elliptical formation control scheme using the fractional-order sliding-mode control to cooperatively monitor the fire front at safe distances is proposed in [13]. A task allocation-based fire monitoring to manage the actuator faults in multiple UAVs is proposed in [14]. A situation assessment and observation planning system to plan and optimize the fire observation trajectories of UAVs using a variable neighborhood search algorithm is proposed in [15]. Unmanned ground vehicles have also been used to overcome the limitations of UAVs related to communication, fuel, and payload capabilities [16].

In recent years, artificial intelligence methods have been widely used to detect forest fires using image or video analytics. The information gathered by UAVs equipped with onboard infrared or visual cameras has been used to predict the evolution of the fire front by means of image analysis [17]. The wildfire detection from image sequences of the smoke cloud employing different classification algorithms is addressed in [18]. A video-based forest fire smoke recognition using an attention-enhanced bidirectional long short-term memory network optimizes the classification method by measuring the importance of different frames [19]. A convolutional neural network model-based wildfire alert system using images from unmanned aerial vehicles or video surveillance systems is proposed in [20]. The existing monitoring methods require computationally expensive image/video analysis, a priori information on the number and location of forest fires for planning

the search and coverage path. The UAVs for the mission are launched closer to the fire location, assuming that all UAVs are within a specific range of each other, and the base station for uninterrupted communication.

Forest firefighting relies on efficient search methods to locate spreading fires in large unknown areas. Several deterministic and stochastic strategies have been proposed for multi-UAV search and destroy missions [21]. Stochastic methods are effective for missions involving large, unknown areas with limited or no communication, while Markovian strategies are more effective for dynamic targets [22]. The optimal animal foraging behavior is modeled by random walks, where predators optimize their search for prey or food. Brownian and Levy flight are the major random walk strategies found in the searching behavior of various animal classes, including marine predators [23], [24]. A multi-level search strategy inspired by the foraging behavior of the marine predator, *Oxyrrhis Marina*, is used for a multi-UAV mission to search for forest fire locations [25]. A combination of Levy, Brownian, and directionally driven Brownian search is used to detect the fire locations. A grid-based sand-clock pattern search with a shorter search path and a monitoring strategy to discover the boundary points of the fire, considering a safe hovering time for the UAVs is proposed in [26].

The monitoring and mitigation tasks of forest firefighting with multiple UAVs are addressed in [27]. An artificial potential field-based control law coordinates the motion of UAVs to track and quench the fire. The UAVs distributed uniformly over the fire boundary extinguish a circular fire area directly beneath the UAVs. The efficiency of fire extinguishing balls for firefighting is experimentally verified in [28], and results indicate that fire extinguishing balls might be effective in quenching short grass fires if a swarm of UAVs drops at an optimal location in optimal numbers. A conceptual framework for a UAV-assisted fire mitigation system with a platform for replacing batteries and payloads is explained in [29]. The linear meters of the fire front quenched are computed based on the payload capacity of the UAV, capacity of the platform, time for reaching the fire front, and critical flow rate. In [25], UAVs mitigate the fire by spraying water on the fire areas using Dynamic Formation Control (DFC), maintaining an equal non-overlapping fire area between all UAVs acting on the same fire. However, the cumulative area quenched by all the UAVs should be less than the active fire area to maintain a non-overlapping area. The UAVs mitigate overlapped areas when the area shrinks below a value, which should be accounted as a buffer time in total mission time. Distributed multi-UAV methods have longer detection and mitigation times, resulting in larger area damage due to the independent actions of UAVs.

III. PROBLEM DEFINITION AND MODELLING

A typical forest fire scenario in a pine forest is shown in Fig. 1. Multiple swarms of UAVs are employed to detect and mitigate multiple unknown fire locations. The swarm marked in black is searching the area, and the other marked in red is quenching a fire area by flying along the fire front. Let $\Omega \subset \mathbb{R}^2$ be the search area and the boundary of the search area

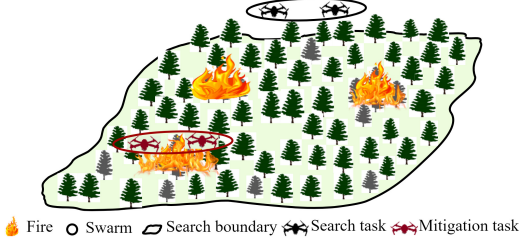


Fig. 1. A forest firefighting scenario where multiple swarms of UAVs perform search and mitigation of forest fire.

is marked in black color, as shown in Fig. 1. Here, multiple swarms of UAVs search the area for multiple forest fire locations. Let n_s be the number of swarms, and the search area boundary is known to all the swarms. Let $S = s_1, s_2, \dots, s_{n_s}$ be the set of multiple swarms of UAVs deployed in the search area to detect and mitigate fire locations. Let swarm $s_i \in S$ has n_{s_i} number of UAVs, where $i = 1, 2, \dots, n_s$. Let the number of unknown fire locations in the search area be n_f . The fire profile is approximated as a circle or ellipse in this work. The coordinates of the j th fire profile are denoted as $p_{f_j} \in \mathbb{R}^2$, with fire center locations, $C_{f_j} \in \mathbb{R}^2$, where $j = 1, 2, \dots, n_f$. Let the major and minor axis lengths of j th fire be $a_j(t)$ and $b_j(t)$, respectively. The location and spread area of fire points are unknown to the searching agents. The fire spread rate depends on the affected area's topography, fuel content, terrain, wind speed, etc. It is necessary to detect the fires at a nascent stage to reduce the quench time and destruction of biodiversity. The objective of the multi-swarm mission is to detect the maximum number of fires and quench the fires early with minimum area damage. The objective of forest firefighting is formulated mathematically, using different models of associated subsystems, given in the following subsections.

A. Fire Spread Model

The circular or elliptical approximation is the most commonly used fire spread model. The fire size grows depending on the rate of fire spread, and the dynamic spread of the fire can be expressed as a function of fireline intensity, I_l [5], [30]. The fireline intensity is defined as the heat release rate per unit length of the fire front and I_l in (kW/m) is given by,

$$I_l = \alpha * (L_f)^\beta, \quad (1)$$

where L_f is the flame length in m, α and β are coefficients that depends on the available fuel content. The fire spread rate (R) in (m/s) is given by,

$$R = \frac{I_l}{H_c F_m}, \quad (2)$$

where H_c is the heat of combustion in kJ/kg, and F_m is the mass of the available fuel per unit area in kg/m². The fire spread rate is assumed to be constant and is calculated assuming uniform fuel availability, terrain, and wind conditions in the search area. The values $\alpha = 259.833$, $\beta = 2.174$, $L_f = 4$ m, $H_c = 18600$ kJ/kg, and $F_m = 4$ kg/m² are considered for a typical pine forest scenario [30], [31].

B. Swarm Model

A swarm is a set of UAVs flying together cooperatively, keeping the swarm intact. The swarm members are free to move independently within the swarm boundary. UAVs in each swarm have an attractive force to the center of the swarm to keep the swarm intact. The schematic diagram of a typical swarm with four members is shown in Fig. 2. A circular swarm

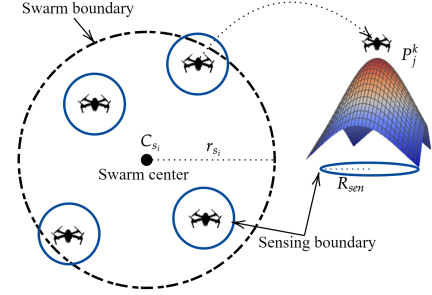


Fig. 2. Illustration of the swarm model showing sensing boundaries.

boundary with a constant swarm radius, r_{s_i} , is assumed for all the swarms. The swarm center, $C_{s_i} \in \mathbb{R}^2$, is defined as the mean of the positions of all UAVs in the s_i th swarm.

$$C_{s_i} = \frac{1}{n_{s_i}} \sum_{k=1}^{n_{s_i}} p_{s_i}^k, \quad (3)$$

where $p_{s_i}^k = [x_{s_i}^k \ y_{s_i}^k]$ is the position of k th swarm member of the s_i th swarm. Each member of a swarm satisfies the condition given below,

$$\|p_{s_i}^k - C_{s_i}\| < r_{s_i}. \quad (4)$$

C. UAV Kinematic Model

Let $v_{s_i}^k \in \mathbb{R}^2$ and $v_{r_{s_i}}^k \in \mathbb{R}^2$ be the velocity and reference velocity vector of k th swarm member of the s_i th swarm at a time, t . All UAVs are homogeneous and belong to the multi-rotor category. The mathematical model governing the motion of UAVs is given by a first-order system as,

$$\begin{aligned} \dot{p}_{s_i}^k(t) &= v_{s_i}^k(t), \\ \dot{v}_{s_i}^k(t) &= -\lambda_{s_i}^k v_{s_i}^k(t) + \lambda_{s_i}^k v_{r_{s_i}}^k(t), \end{aligned} \quad (5)$$

where $\lambda_{s_i}^k$ is the pole of the first-order approximation of the mathematical model of the UAV. The heading angle of the UAV is indirectly controlled by the x and y components of the velocity of the UAV. The reference velocity inputs for the position to velocity reference feedback are given by,

$$v_{r_{s_i}}^k(t) = \frac{V_0(p_{r_{s_i}}^k(t) - p_{s_i}^k(t))}{\tau + \|e_{s_i}^k(t)\|_2} + \dot{p}_{r_{s_i}}^k, \quad (6)$$

$$e_{s_i}^k(t) = p_{r_{s_i}}^k(t) - p_{s_i}^k(t), \quad (7)$$

where $p_{r_{s_i}}^k(t)$ and $\dot{p}_{r_{s_i}}^k$ are the position and velocity of reference trajectory. $p_{r_{s_i}}^k = 0$ during the search phase as the waypoints are generated sequentially. $V_0 > 0$ is the cruise speed in m/s, $\tau > 0$ is a small positive quantity, and $e_{s_i}^k(t)$ is the tracking error vector.

D. Fire Detection Model

A temperature detector and a thermal imaging sensor are mounted in each UAV for the detection of fire areas. The temperature detector measures the temperature and rate of change of temperature. The thermal imaging sensor gives an accurate fire profile and location. The potential fire area identified by the UAV is confirmed using a Gaussian probability model,

$$P_j^k = \exp\left(-\frac{d_{jk}^2}{2\sigma^2}\right), \quad (8)$$

where P_j^k is the probability of detection of the j th fire front by the k th UAV, $d_{jk} = \|p_{s_i}^k - p_{f_j}\|$ is the distance between k th UAV and j th fire front, and σ is the standard deviation of the sensor range. Fig. 2 shows the probability distribution as a function of the distance between the UAV and the fire location. Let $T_{s_i}^k$ be the temperature sensed by k th UAV, and R_{sen} be the sensing radius within which fire detection is possible. The fire location is detected if the probability of detection exceeds the detection threshold (γ). After the fire detection, the swarm members start quenching the fire, according to the sensed fire profile and quench model.

E. Quench Model

The critical flow rate (f_c) is the water flow rate required to quench the fire with infinite time. UAVs can quench the fire by spraying water at a higher rate than f_c . The critical flow rate is proportional to the flame length, and f_c in kg/m²s is

$$f_c = c * L_f^\nu, \quad (9)$$

where c and ν are constants. The quench time is the time

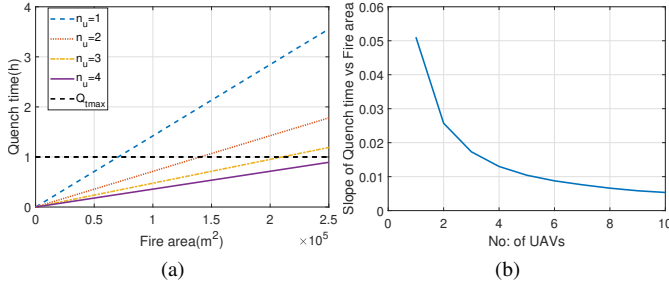


Fig. 3. Plots showing (a) Variation of quench time with fire area for different numbers of UAVs. (b) Variation of slope for different numbers of UAVs.

taken to quench the fire completely after the detection of fire by any number of UAVs. The quench time for the j th fire, $Q_t^j = f(r_q, A_f^j, N_{qu}^j, T_m^j)$, is a function of the quench area rate (r_q), the fire area to be extinguished (A_f^j), the number of UAVs detecting the fire (N_{qu}^j), and the time of joining of UAVs acting on the fire (T_m^j). If the UAVs spray water at a flow rate, W_r in kg/s, then the quench area rate (r_q) in (m²/s) is given by $r_q = W_r/f_c$. Let $u(\cdot)$ be a shifted uniform step function then the fire area quenched, $A_f^j(t)$ at time, t from the start of the mission is

$$A_f^j(t) = \sum_{m=1}^{N_{qu}^j} r_q u(t - T_m^j). \quad (10)$$

Let Q_t^j (s) be the time to quench the fire area A_f^j (m²) assuming same time of joining for N_{qu}^j UAVs,

$$Q_t^j = \frac{A_f^j}{N_{qu}^j r_q}. \quad (11)$$

The variation of quench time with fire area for different numbers of UAVs with the same joining time is shown in Fig. 3a. If multiple UAVs act on the same target, the fire area reduction multiplies with the number of UAVs, thus reducing the quench time. The slope variation of the Q_t vs. A_f graph with different numbers of UAVs is shown in Fig. 3b. The slope reduces with increased UAVs, but the reduction is minimal after a point. This explains the importance of multi-swarm missions with regulated merging and repulsion of swarms for dynamic target scenarios.

F. Performance Model

The goal behind forest firefighting is to minimize the destruction of biodiversity in minimal mission time. The mission time is the total time needed to detect and quench all fire locations in a search area. The search objective of the mission is to maximize the number of targets detected in a given time or, equivalently, minimize the detection time. The mitigation objective is to minimize the quench time of detected targets. The active fire area increases with the increase in detection time. The minimization of detection time results in UAVs quenching the smallest fire areas. Thus, the minimization of the detected fire areas acts as the alternate representation of the search objective. If the number of swarms acting on the same fire increases, quench time reduces and achieves the mitigation objective, but the effect diminishes after a certain point. Furthermore, more swarms quenching the same fire reduce the detectability of undetected fires, increasing the detection time of undetected fire locations. The fire will spread, resulting in crown fires and a longer quench time. It is vital to balance the number of searching and quenching swarms for a successful mission. The search objective is split into minimization of the area of detected and undetected targets to achieve this goal.

Let $A_d(t)$ be the sum of detected fire areas, $A'_d(t)$ be the sum of undetected fire areas, $Q_d(t)$ be the sum of the quench times of all detected fires, and $D(t)$ be the index set of detected fire locations at time t .

$$\begin{aligned} A_d(t) &= \sum_j A_f^j(t) \quad \forall j \in D(t), \\ A'_d(t) &= \sum_j A_f^j(t) \quad \forall j \notin D(t), \\ Q_d(t) &= \sum_j Q_t^j(t) \quad \forall j \in D(t). \end{aligned} \quad (12)$$

The multi-objective performance model can be represented using a weighted sum model as given below,

$$\begin{aligned} \min \quad & w_1 A_d(t) + w_2 A'_d(t) + w_3 Q_d(t), \\ \text{s.t.} \quad & Q_t^j(t) < Q_{tmax} \quad \forall j \in D(t), \end{aligned} \quad (13)$$

where w_1 , w_2 , and w_3 are the weights of the objective functions and $\sum_{i=1}^3 w_i = 1$. The upper limit on the quench

time of a fire location is Q_{tmax} . The choice of weights determines the condition for the repulsion and merging of swarms, which helps to maintain the balance between searching and quenching swarms.

In a typical multi-objective optimization problem, the objective function remains fixed for a static scenario. The problem formulated in this study is of dynamic nature (fire area varies with time). Hence, the objective function doesn't remain static, which is more challenging to solve. In addition, the number of fires, locations, and size are unknown a priori. Hence, the objective function given in Eq. 13 is not explicitly minimized, and a stochastic search-based solution is proposed in this work. The MSCIDC algorithm is formulated to achieve the search and mitigation objectives of multi-swarm forest firefighting.

IV. MULTI-SWARM COOPERATIVE INFORMATION-DRIVEN SEARCH AND DIVIDE AND CONQUER MITIGATION CONTROL

The MSCIDC uses swarms of UAVs to search and mitigate forest fires. The schematic diagram of the MSCIDC is shown in Fig. 4. The swarms use multi-swarm cooperative information-driven search for faster detection of targets, which combines cooperative information-driven exploration and exploitation. Local intra-swarm cooperation between the mem-

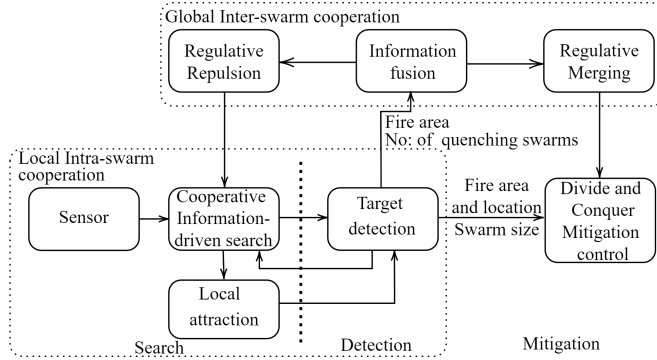


Fig. 4. Schematic diagram of the proposed MSCIDC

bers of the same swarm enables swarm members to search in the direction of maximum information and assists non-detector swarm members in detecting the same fire location. After the fire detection, swarm members use divide and conquer mitigation control to quench the fire by spraying water. The global inter-swarm cooperation between swarms helps in the merging and repulsion between swarms during the mitigation of detected fires. Global inter-swarm cooperation leads to faster mitigation of detected fires and faster detection of undetected fires. The swarm members maintaining the swarm structure during local intra-swarm and global inter-swarm cooperation, indicate the high emergence and self-organizational behavior of swarms [32], [33].

A. Multi-Swarm Cooperative Information-driven Search

The Multi-swarm cooperative information-driven search is a two-stage search process depending on the temperature value sensed by the temperature detector. The two stages of

the MSCIDC are cooperative information-driven exploration and exploitation. The value of the temperature threshold is important to control the exploration and exploitation strategy for the multi-swarm search. The target search missions require initial identification and subsequent detection of targets. A potential fire area is identified if the temperature measurement exceeds the temperature threshold. Cooperative information-driven exploration is performed until a possible fire location is identified. UAV swarm moves to the next stage of the search process once a potential target is identified. In this stage, the swarm uses cooperative information-driven exploitation and switches back to cooperative information-driven exploration if the temperature falls below the threshold value.

The working of cooperative information-driven search is shown in Fig. 5. The swarms are desired to move in the direction of the maximum temperature gradient sensed by UAVs in a swarm. The motion of swarms in the maximum information direction is attributed to the cooperative behavior of swarm members. Communication between swarm members is essential to maintain the swarm structure and to share the information sensed about the fires to ensure the cooperative mission. The swarm members exhibit higher emergence due to the stronger interactions between the swarm members [32].

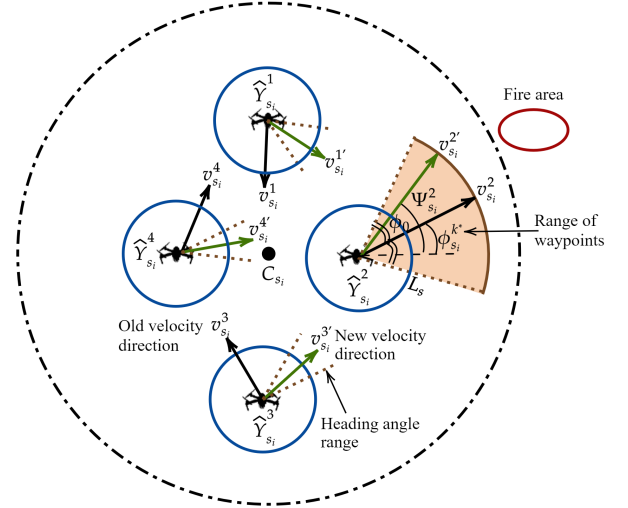


Fig. 5. Working of cooperative information-driven search.

The swarm members broadcast their positions, temperature, rate of temperature, the probability of detection, and the fire location specifications sensed by each member within the swarm. Thus, k th swarm member of the s_i th swarm will have data, $\hat{Y}_{s_i}^k(t) = (p_{s_i}^k, T_{s_i}^k, dT_{s_i}^k/dt, P_j^k)$ from the sensors for the corresponding position of UAV. If $P_j^k > \gamma$, then j th fire is detected and the UAV have the information $\hat{Y}_{s_i}^k(t) = (p_{s_i}^k, T_{s_i}^k, dT_{s_i}^k/dt, P_j^k, C_{f_j}, a_j, b_j, h_j^k)$, where h_j^k is the heading direction towards the j th fire from the k th UAV. Each swarm member broadcasts the sensed information to all the members in the swarm. The information structure available for the s_i th swarm is $\hat{Y}_{s_i}(t) = \hat{Y}_{s_i}^1 \cup \hat{Y}_{s_i}^2 \dots \cup \hat{Y}_{s_i}^{n_{s_i}}$. The information structure is used by the swarm to push the swarm center toward the desired direction. If there is a complete communication failure, the members in the swarm will not be

able to maintain the swarm structure and search independently, as in the case of multi-UAV search [25]. In scenarios involving intermittent communication, if the duration of communication failure is shorter, the self-organizing ability of the swarms will help to regain the swarm structure.

The swarm member with maximum information, k^* , is defined as the member having the highest temperature gradient,

$$k^* = \arg \max_{(k \in s_i)} \frac{d}{dt}(T_{s_i}^k). \quad (14)$$

The maximum information direction, $\phi_{s_i}^{k^*}$ is defined as the velocity direction of swarm member having maximum information, and $\hat{Y}^{k^*}(t)$ is used to drive the swarm in maximum information direction. In Fig. 5, UAV 2 has a velocity direction towards the fire and has the highest temperature gradient, hence $k^* = 2$. The range of waypoints generated for swarm members in the search area is shown as a shaded region. The heading angle range of swarm members depends on the range of waypoints. Therefore, the search space of the swarm members is constrained to the heading angle range. The search angle $\Psi_{s_i}^k$ for the k th swarm member to generate a waypoint in the maximum information direction is

$$\Psi_{s_i}^k \sim U(\phi_{s_i}^{k^*} - \phi_0, \phi_{s_i}^{k^*} + \phi_0), \quad (15)$$

where $\Psi_{s_i}^k$ is drawn from a uniform distribution from $\phi_{s_i}^{k^*} - \phi_0$ to $\phi_{s_i}^{k^*} + \phi_0$. The angle ϕ_0 is calculated using

$$\phi_0 = \frac{K_\phi}{1 + \exp(-K_e T_s)}, \quad (16)$$

where T_s is the maximum temperature sensed by the swarm. The constants, K_ϕ and K_e indicate the maximum value of ϕ_0 and gain of the temperature sensor respectively, $K_\phi = \pi/2$ and $K_e = 10$. The waypoint for k th swarm member, $p_{rs_i}^k(t)$ is calculated as,

$$p_{rs_i}^k(t) = p_{s_i}^{k^*}(t) + L_s * l_{s_i}^k [\cos(\Psi_{s_i}^k) \quad \sin(\Psi_{s_i}^k)], \quad (17)$$

where $p_{s_i}^{k^*}(t)$ is the position of swarm member with maximum information, and the second term in Eq.17 corresponds to the movement contributed by the stochastic search. L_s is the search step length, $l_{s_i}^k$ is individual lengths drawn from the probability distribution functions. The waypoints are generated using different probability distribution functions. The appropriate selection of these functions results in effective exploration and exploitation of the search area. The swarm members are navigated toward the generated point, and a new waypoint is generated only after reaching the current waypoint.

1) *Cooperative Information-driven Exploration*: The cooperative information-driven exploration is performed as long as the maximum temperature sensed by the swarm, T_s , is less than the detection threshold of temperature, ξ . In this case, Levy distribution is used to calculate the stochastic search factor. The search step length L_s in Eq.17 is the Levy step length, and $l_{s_i}^k$ is the individual lengths of the Levy flight legs, which are drawn from the Levy distribution. The cooperative information-driven exploration uses higher step lengths, which helps in the exploration of the search area. When $\phi_0 = \pi$, the search becomes a conventional Levy search. The heading angle and randomized leg lengths compose the cooperative information-driven exploration trajectory.

2) *Cooperative Information-driven Exploitation*: The cooperative information-driven exploitation is used for exploiting the search area once the UAV swarm reaches a possible target location and $T_s \geq \xi$. For cooperative information-driven exploitation, Brownian step length is used for better exploitation of the region, and $l_{s_i}^k$ in Eq.17 is drawn from the normal distribution $N(0, 1)$. The step length used in this exploitative search is considerably shorter than the explorative search, and the shorter step length aids in the efficient exploitation of the search area to reach the precise target location.

3) *Local attraction*: The attractive force acting within the swarm is termed local attraction, which preserves the swarm structure in the search and detect phase. The local attraction comes into play either when a swarm member moves outside the swarm boundary or when a swarm member detects a fire. If any UAV in a swarm tends to move outside the swarm boundary, the attractive force of the swarm center pulls the UAV inside. A fire location is detected if the probability of detection determined using Eq. (8) exceeds the detection threshold. The swarm member with maximum information detects the fire and attracts other swarm members toward it, enabling the swarm to reach the fire front faster. After target detection, divide and conquer mitigation control is employed for target mitigation.

B. Divide and Conquer Mitigation Control

Dynamic targets like forest fires need uninterrupted attention to prevent the spread and accelerate mitigation. The mitigation control is designed to cover an equal non-overlapping area by UAVs even when the area is shrinking to avoid the buffer time regarding the overlapped area. Each UAV in the swarm

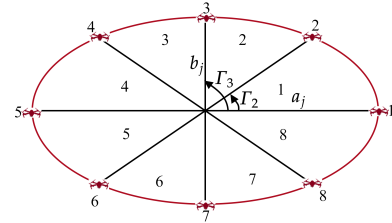


Fig. 6. Divide and conquer mitigation sectors for 8 UAVs for an elliptical fire front.

is restricted to quench an elliptical or circular sector of the equal fire area. Fig. 6 shows the initial alignment of 8 UAVs according to the proposed mitigation control. The UAVs move to and fro in the allotted sector along the fire front.

Let N_{qu}^j be the total number of UAVs in the N_{qu}^j swarms quenching the j th fire. The angular position and reference angular position of the m th UAV quenching j th fire at time, t be $\theta_j^m(t)$ and $\theta_{rj}^m(t)$, where $m = 1, 2, \dots, N_{qu}^j$. The total fire area is divided into N_{qu}^j equal-area sectors. The area of m th sector is

$$A_{m*m+1}(t) = \frac{a_j(t)b_j(t)}{2} \left[\tan^{-1} \left(\frac{a_j(t) \tan \Gamma_{m+1}(t)}{b_j(t)} \right) - \tan^{-1} \left(\frac{a_j(t) \tan \Gamma_m(t)}{b_j(t)} \right) \right]. \quad (18)$$

The sector angle, Γ_m , will be the same for all sectors in the case of a circular profile but different for the elliptical profile.

The sector angle of the first sector, $\Gamma_1 = 0$, and Γ_m for $m \geq 2$ are computed to get equal-area sectors. The control law for the m th UAV is given by,

$$\begin{aligned}\dot{\theta}_j^m(t) &= \omega(t) + K_m(\theta_j^m(t) - \theta_{rj}^m(t)), \\ \dot{\theta}_{rj}^m(t) &= \mu(t)\omega(t),\end{aligned}\quad (19)$$

where $\omega(t)$ is the nominal angular velocity of the UAVs. The control law asymptotically tracks the reference angular displacement for gain values, $K_m < 0$. The direction of motion of the UAV along the fire front is controlled by factor $\mu(t)$ as given by,

$$\mu(t) = \begin{cases} 1, & \text{if } \theta_{rj}^m(t) - \Gamma_{m-1} < \delta_\theta, \text{ and} \\ & \text{sgn}(\theta_{rj}^m(t)) = -1; \\ -1, & \text{if } \Gamma_m - \theta_{rj}^m(t) < \delta_\theta, \text{ and} \\ & \text{sgn}(\theta_{rj}^m(t)) = 1. \end{cases} \quad (20)$$

The waypoint, $p_{rj}^m(t)$ for the m th UAV mitigating j th fire location is generated as,

$$p_{rj}^m(t) = C_{fj} + [a_j(t) \cos \theta_j^m(t) \quad b_j(t) \sin \theta_j^m(t)]^T. \quad (21)$$

1) *Global Regulative Merging and Repulsion:* The regulative merging of swarms helps in reducing the quench time when multiple swarms detect the same fire location. The regulative merging of swarms happens either if the fire area detected is higher than a threshold, δ_A or if the number of remaining active fires, F_r , is substantially lesser. The total number of swarms allowed to merge, N_{qs}^j , is limited to δ_s to minimize the detection time of undetected targets. The condition for regulative merging can be represented as,

$$(A_f^j > \delta_A \text{ or } F_r < \delta_f) \text{ and } N_{qs}^j < \delta_s. \quad (22)$$

The threshold values of area (δ_A), remaining fires (δ_f), and the number of swarms under mitigation (δ_s) are chosen to achieve the performance objectives of forest firefighting in Eq.13. This minimizes the detection and quench times of detected fire based on the total number of swarms and their capacity. It is assumed that the approximate number of fire locations is known towards the end of the mission due to the effective coverage of the search area. The merged swarms split after completely quenching the fire and split swarms search for other potential fire areas.

The introduction of regulative repulsion of swarms reduces the mission time for the scenarios that don't satisfy the condition in Eq. 22. If a swarm detects a fire under mitigation, the second swarm gets repelled by the first swarm. The repulsion happens when the probability of detection value of the second swarm is $\gamma_0 < P_j^k < \gamma$. The repelled swarm uses cooperative information-driven exploration in the direction opposite to the maximum information direction. This repulsive action between swarms helps identify unattended fire locations at an earlier stage. The dynamic swarm approach helps to maximize target detection, minimizing the detection and quench time. The algorithm of MSCIDC is summarized in Algorithm 1.

Algorithm 1: MSCIDC Algorithm

```

Initialize with  $n_s$  swarms with  $n_{s_i}$  swarm members
Initialize  $N_{qu}^j = 0, N_{qs}^j = 0 \forall j$ 
for  $i = 1$  to  $n_s$  do
    Each  $i$ th swarm has information  $\hat{Y}_{s_i}(t)$ 
    for  $j = 1$  to  $n_f$  do
        for  $k = 1$  to  $n_{s_i}$  do
            if  $P_j^k < \gamma$  then
                if  $T_s < \xi$  then
                    Cooperative information-driven exploration
                else
                    Cooperative information-driven exploitation
            else
                 $k$ th swarm member detects  $j$ th fire
                 $N_{qu}^j = N_{qu}^j + 1$ 
                Local Attraction of swarm members
                for  $m = 1$  to  $N_{qu}^j$  do
                    Move to initial position of  $N_{qu}^j$ 
                    Quenches  $N_{qu}^j$  sector
                    if  $(A_f^j > \delta_A \text{ or } F_r < \delta_f)$  and  $N_{qs}^j < \delta_s$  then
                         $N_{qs}^j = N_{qs}^j + 1$ 
                        Global regulative merging
                    else if  $k \notin s_i$  and  $\gamma_0 < P_j^k < \gamma$  then
                        Global regulative repulsion

```

V. NUMERICAL SIMULATION RESULTS

The proposed MSCIDC is analyzed for an area of size 10 km x 10 km considering 15 UAVs with varying swarm sizes for the detection and mitigation of 5 fire locations. A circular profile is assumed for 2 fire areas and an elliptical profile for the rest. The fire coordinates and initial lengths of semi-major and semi-minor axes are given in Table I. The members of the swarm fly at a constant speed of 20 m/s during the search. In this study, different swarms are assumed to fly at different altitudes during search and at the same altitude during mitigation. The members in a particular swarm maintain a constant altitude during the mission. Due to information sharing among swarm members and the restriction of UAV operation to the designated sector during the mitigation, explicit collision avoidance is not necessary during the mission. But any collision avoidance scheme, as in [34], can be incorporated into the algorithm. During mitigation, the speed varies according to the size of the fire area. The swarms initiate the search from different locations within the search area under consideration. The simulations are performed in MATLAB R2021a environment with an Intel Core-i7, 3.2-GHz processor, and 16-GB memory. The Monte-Carlo analysis is performed for 100 iterations to evaluate the average performance of the MSCIDC by varying the number of swarms for

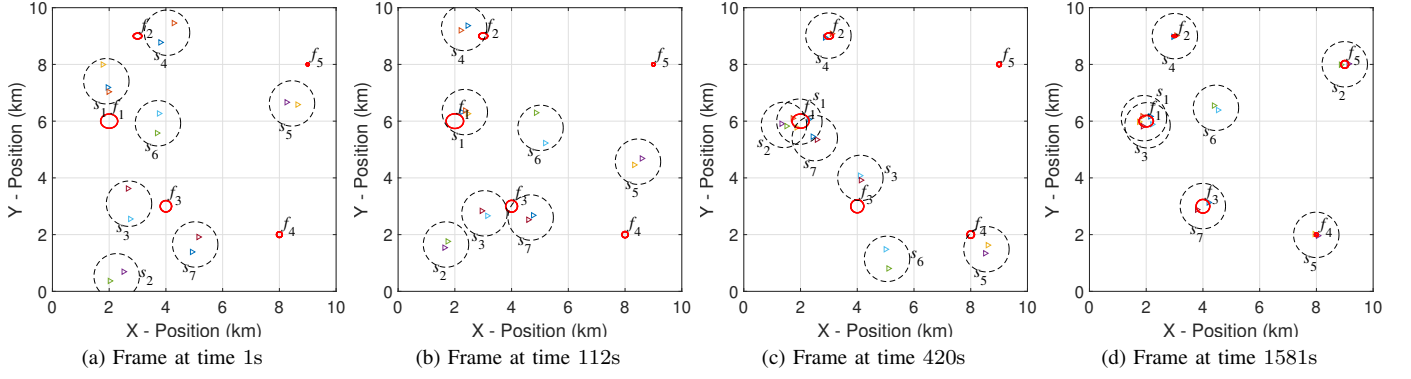


Fig. 7. Working of MSCIDC: (a) All swarms performing cooperative information-driven search task (b) Swarm, s_1 detects a fire, f_1 and UAVs in s_1 have local attraction, (c) s_1 starts quenching f_1 using Divide and Conquer mitigation control and swarms s_2 , and s_7 get repelled due to global regulative repulsion (d) Global regulative merging of s_1 and s_3 to mitigate f_1 .

the same number of UAVs. The results are compared with the Oxyrrhis Marina-inspired Search (OMS) [25] and other random search methods with different probability distributions to analyze the efficiency of the MSCIDC. The results of the MSCIDC are compared with different multi-UAV search methods with Dynamic Formation Control (DFC) used in [25] for fire mitigation.

TABLE I
FIRE LOCATIONS AND INITIAL SIZE

Sl.No	C_{f_j} (m)	a_j (m)	b_j (m)
1	(2000, 6000)	300	250
2	(3000, 9000)	150	100
3	(4000, 3000)	200	200
4	(8000, 2000)	100	100
5	(9000, 8000)	50	50

The performance indices used to analyze the results are detection time, mission time, and Fire Expansion Ratio (FER). Detection time is the time required to detect all the targets, whereas mission time is the time taken to complete the mission, i.e., the total time taken to detect and mitigate all the fires. The FER is an index to evaluate the extent of the burnt area. It is the ratio of the increase in fire area after the commencement of the mission to the initial fire area.

The working of the MSCIDC is explained for a scenario of 15 UAVs searching for the 5 fire locations given in Table I. The 15 UAVs are grouped into 7 swarms with a swarm size of $[3 \ 2 \ 2 \ 2 \ 2 \ 2 \ 2]$. The different features in the MSCIDC can be analyzed from Fig. 7. The swarms are initiated randomly in the search area at the beginning of the mission. In Fig. 7a, the swarms are in the search phase of the mission to detect the fire location using cooperative information-driven search. When the swarms are far from the fire, the members use cooperative information-driven exploration to spot potential fire spots, and when the swarms get closer to the fire, they use cooperative information-driven exploitation. In Fig. 7b, swarm s_1 detects the fire location, f_1 , and the detected swarm member has a probability of detection greater than the detection threshold. The detected swarm member starts moving toward the waypoint above the fire front for mitigation. Subsequently, other swarm members are attracted towards fire location f_1 due to local attraction, leading to the detection of the same fire location. Fig. 7c shows

the divide and conquer mitigation control of fire location, f_1 , by the swarm members. Each member of the swarm mitigates the fire by spraying water in the assigned sector of the fire area. The swarms s_2 and s_7 moving closer to fire f_1 get repelled due to the global regulative repulsion in Fig. 7c. The swarms s_2 and s_7 repelled from fire f_1 detect fires, f_5 and f_3 , respectively. The global regulative repulsion helps in the faster detection of undetected fire locations. All the fire locations are detected due to the search area coverage of the swarms towards the end of the mission, and the condition for global regulative merging is satisfied. In Fig. 7d, two swarms s_1 and s_3 merge to mitigate fire f_1 to reduce the quench time.

TABLE II
PERFORMANCE OF THE MSCIDC FOR DIFFERENT SWARM NUMBERS

Number of swarms	Mean detection time (min)	Mean mission time (min)	Mean FER
3	41.82	107.01	1.029
5	31.03	81.19	0.642
6	27.59	83.27	0.550
7	24.13	71.56	0.477

The MSCIDC is evaluated using Monte-Carlo simulations for a different number of swarms with the same number of UAVs and the results are summarized in Table II. The cases with 3 and 5 swarms have equal UAVs in all swarms. The cases with 6 and 7 swarms have a swarm size of $[3 \ 3 \ 3 \ 2 \ 2 \ 2]$ and $[3 \ 2 \ 2 \ 2 \ 2 \ 2 \ 2]$ respectively. The mean detection time decreases with an increase in the number of swarms. As the number of swarms increases, the UAVs will be more distributed in the search space. The regulative repulsion also helps detect unattended fire locations, reducing the mission time and improving performance. The 80% of total fire locations are detected in 15% of the total mission duration for the 7 swarm case. Even though the mean mission time decreases with an increase in the number of swarms, the effect declines beyond a value. The FER also decreases with an increase in the number of swarms as fire locations are detected at an earlier stage. The 7 swarm case has the lowest mean detection time, mission time, and FER.

The number of swarms executing the search (S_s) and quenching (S_q) for a total mission duration in the 7 swarm case is shown in Fig. 8. The number of swarms performing the search decreases as more fire locations are detected and eventually increases when fires are quenched. About 50% of

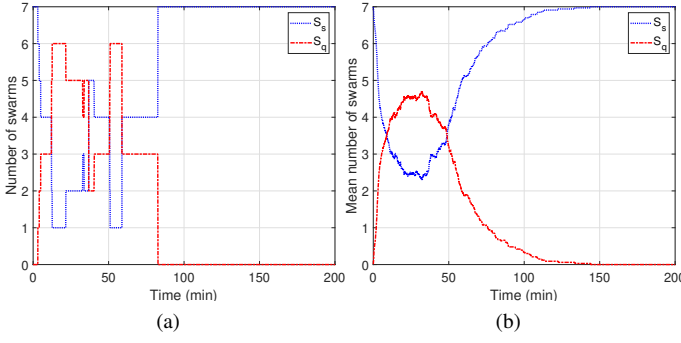


Fig. 8. Number of swarms performing search (S_s) and mitigation (S_q) for (a) single run (b) Monte-Carlo simulation.

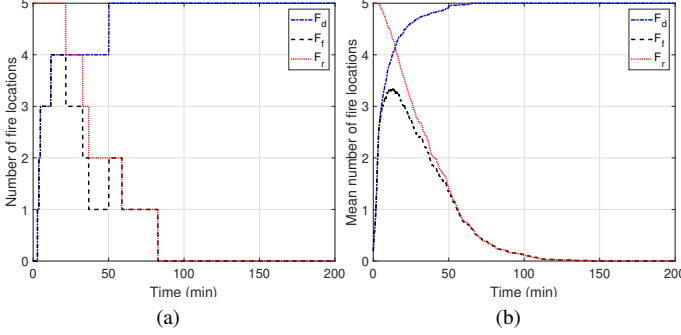


Fig. 9. Number of fire locations detected (F_d), fire locations under mitigation (F_f), and fire locations remaining (F_r) for (a) single run (b) Monte-Carlo simulation.

the total mission time, swarms perform the search operation. The number of fire locations detected (F_d), under mitigation (F_f), and remaining to be quenched (F_r), is shown in Fig. 9. The maintenance of searching swarms to identify unattended fires is essential until all the fire locations are detected. The introduction of global regulative repulsion achieves this feature, and the Monte-Carlo simulation results shown in Fig. 8b and 9b verify the feature.

TABLE III
PERFORMANCE COMPARISON FOR DIFFERENT METHODS

Method of forest firefighting	Mean detection time (min)	Mean mission time (min)	Mean FER
Uniform-DFC	66.10	217.47	1.808
Brownian-DFC	56.63	192.39	1.518
Levy-DFC	52.59	184.14	1.398
OMS-DFC	52.63	180.11	1.319
MSCIDC	24.13	71.56	0.477

The results of MSCIDC are compared with the multi-UAV search with different random search methods such as uniform, Brownian, Levy, and OMS with DFC for fire mitigation. OMS uses a multistage search with Levy and Brownian distributions, and the remaining methods use a single-stage search with corresponding probability distributions for generating the waypoints during the search. The step length used in the single-stage search methods is the same as the step length used for explorative search in multi-stage methods for a fair comparison. The performance of the single-stage search methods depends on the distribution of the fire locations. Explorative Levy search performs better for non-uniformly distributed fire areas, while uniform search performs better

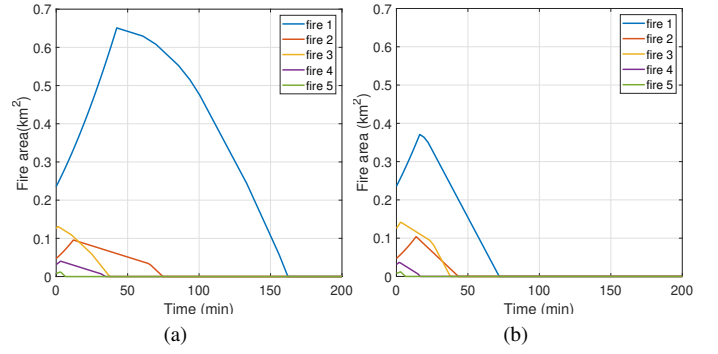


Fig. 10. Variation of fire area with time for a single run between (a) OMS-DFC and (b) MSCIDC.

for uniformly distributed fires, and Brownian search performs better in clustered fire scenarios. Table III summarizes the mean detection time, mission time, and FER for different forest firefighting methods. In this study, the Levy search performs best among the single-stage search methods as the fire locations considered are non-uniformly distributed in a large search area. Uniform search with DFC performs worst with the highest mean detection time, mission time, and FER. The OMS-DFC has the advantage of explorative and exploitative search compared to the single-stage search methods. Among the multi-UAV methods, OMS-DFC is superior, with the lowest mean mission time and FER. All the multi-UAV methods are analyzed with DFC, where the UAVs mitigate overlapped areas as the area shrinks, which should be accounted for with a buffer value in the performance indices. The comparison study based on the Monte-Carlo simulation shows that the MSCIDC performs better with a 65% reduction in the burned area and a 60% reduction in mission time compared to the OMS-DFC method. The faster detection and mitigation of forest fires with minimum damage are the result of the multi-swarm configuration, local attraction among the swarm members, cooperative information-driven search in the maximum temperature gradient direction, global regulative merging, and repulsion incorporated in MSCIDC.

The variation in the fire area of all fire locations versus time for a single run with the OMS-DFC and MSCIDC is shown in Fig. 10. The fire area increases until the swarms detect and start quenching the fire. For a single run shown in Fig. 10, the burnt area accounts for 0.9295 km² with a FER of 1.07 and 0.6654 km² with a FER of 0.48 for the OMS-DFC and MSCIDC, respectively. The fire spread area increases in the OMS method due to a higher detection time than the MSCIDC. Fig. 10 also shows faster mitigation as all swarm members detect the same fire location. The global regulative merging also accounts for reduced quench time.

Fig. 11 shows the box plot of detection time, mission time, and FER. The box plots depict that the spread of the interquartile range of the MSCIDC is smaller than all the other existing methods. This indicates that existing multi-UAV methods have greater variability for performance indices compared to the MSCIDC. Even though the UAVs are distributed and search independently in multi-UAV methods, the MSCIDC has a lower search and mitigation time. The cooperative information sharing within the swarm helps to detect the target faster, and

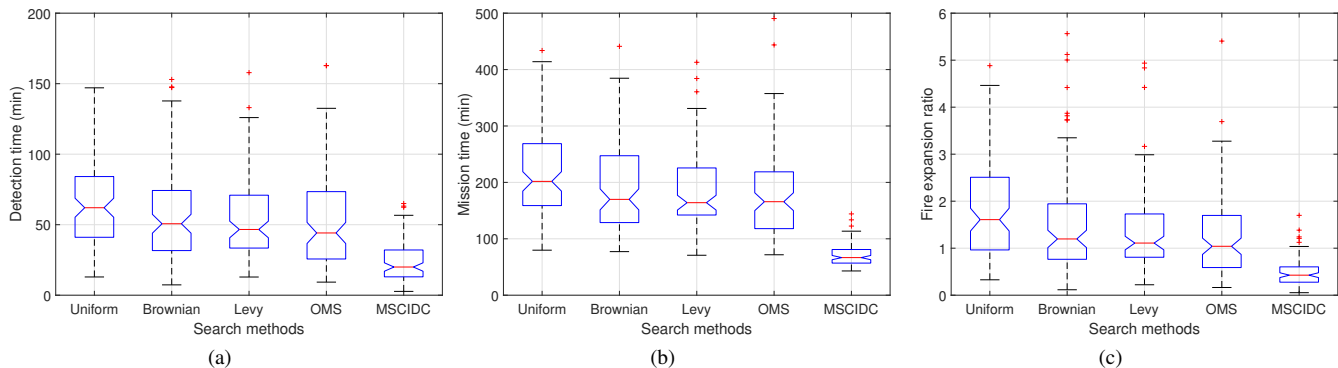


Fig. 11. Box plots showing performance indices for different methods. (a) detection time, (b) mission time, and (c) fire expansion ratio

the swarm behavior leads to the detection of the same target by swarm members, reducing the mitigation time compared to the multi-UAV cases. Even though there are outliers in plots of the MSCIDC, the outlier values are smaller than the 75th percentile of the OMS method in all plots. The box plots of the MSCIDC show a higher agreement to the median value of performance indices compared to multi-UAV methods.

TABLE IV
PERFORMANCE COMPARISON FOR DIFFERENT THRESHOLD VALUES

Temperature Threshold	Mean detection time (min)	Mean mission time (min)	Mean FER
0.01	28.46	76.17	0.596
0.1	25.57	71.70	0.501
0.2	25.92	71.69	0.506
0.3	25.40	71.16	0.504
0.4	27.74	74.31	0.559

The effect of temperature threshold value has been analyzed, and the results are tabulated in Table IV. The study is performed on the fire location similar to the one mentioned in Table I, considering the 7 swarm case. The performance indices increase, when the threshold value of the sensor is decreased below 0.01 and increased beyond 0.3. If the fire locations are clustered, a lower temperature threshold value gives better results as the cooperative information-driven exploitation happens for a wider range of temperature values. A higher temperature threshold value performs better if the fire locations are distributed and spread over the search region, where more cooperative information-driven exploration is required. The performance is better in the 0.1 to 0.3 range, and the threshold value is chosen as 0.1 to accommodate the different distribution of fire locations. The MSCIDC has also been analyzed for the different numbers of UAVs, swarms, and fires to evaluate the variation in performance, and the details of the analysis are provided in the supplementary material.

VI. CONCLUSIONS

This paper presents multi-swarm cooperative information-driven search and divide and conquer mitigation control for forest firefighting. The swarm members communicate the information sensed and cooperate in searching faster and more efficiently. The members of the swarms are free to operate within the swarm boundary, and the information sensed is used to decide the search direction and detect the fire locations. The local attraction between the swarm members maintains

the swarm structure and helps swarm members reach the fire front faster. The divide and conquer mitigation control ensures that the areas quenched by UAVs are non-overlapped for effective and faster mitigation. The MSCIDC has no communication between the swarms during target search, and the global regulative repulsion between swarms detecting the same targets benefits the detection of unattended targets. The quenching time for higher capacity fires is effectively reduced with the global regulative merging of swarms. The Monte-Carlo analysis shows that the total time to detect all targets in the search area is less than 35% of the mission time. The MSCIDC is more efficient than the OMS method, with a reduction of more than 55% in detection time and 60% mission time. The MSCIDC limits the destruction of forest land area by 65% compared to the OMS method. The results establish that the MSCIDC is more competent in diminishing the destruction of forests by faster detection and mitigation of the fire areas.

The MSCIDC approach has limitations due to the assumptions of infinite resource availability, uniform terrain, and wind conditions. The future work focuses on missions involving heterogeneous systems where UGVs carry resources for the swarms acting on the fire and the allocation of firefighting tasks considering resource availability and target capacity.

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Josy John is working toward the Ph.D. degree with the Department of Aerospace Engineering, Indian Institute of Science, Bengaluru, India. Her current research interests include dynamics and control of autonomous systems, task allocation in multiagent systems, search and optimization.



K. Harikumar received the Ph.D. degree in aerospace engineering from the Indian Institute of Science, Bengaluru, India, in 2015. He is working as an Assistant Professor with the Robotics Research Centre, International Institute of Information Technology, Hyderabad, India. His research interests are applications of control theory to unmanned systems and flight dynamics



J. Senthilnath (Senior Member, IEEE) received the Ph.D. degree in aerospace engineering from the Indian Institute of Science, Bengaluru, India, in 2014. He is a Scientist with the Institute for Infocomm Research, Agency for Science, Technology, and Research (A*STAR), Singapore. His research interests include reinforcement learning, online learning, and optimization in multiagent systems, materials informatics, and remote sensing.



Suresh Sundaram (Senior Member, IEEE) received the Ph.D. degree in aerospace engineering from the Indian Institute of Science, Bengaluru, India, in 2005. He is currently an Associate Professor with the Department of Aerospace Engineering, Indian Institute of Science. From 2010 to 2018, he has been an Associate Professor with the School of Computer Science and Engineering, Nanyang Technological University. His research interests include flight control, unmanned aerial vehicle design, machine learning, optimization, and computer vision.

