fire

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Perspective

A Framework for Burnt Area Mapping and Evacuation Problem Using Aerial Imagery Analysis

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Abstract: The study aims to develop a holistic framework for maximum area coverage of a disaster region during a bushfire event. The monitoring and detection of bushfires are essential to assess the extent of damage, its direction of spread, and action to be taken for its containment. Bushfires limit human's access to gather data to understand the ground situation. Therefore, the application of Unmanned Aerial Vehicles (UAVs) could be a suitable and technically advanced approach to grasp the dynamics of fires and take measures to mitigate them. The study proposes an optimization model for a maximal area coverage of the fire-affected region. The advanced Artificial Bee Colony (ABC) algorithm will be applied to the swarm of drones to capture images and gather data vital for enhancing disaster response. The captured images will facilitate the development of burnt area maps, locating access points to the region, estimating damages, and preventing the further spread of fire. The proposed algorithm showed optimum responses for exploration, exploitation, and estimation of the maximum height of the drones for the coverage of wildfires and it outperformed the benchmarking algorithm. The results showed that area coverage of the affected region was directly proportional to drone height. At a maximum drone height of 121 m, the area coverage was improved by 30%. These results further led to a proposed framework for bushfire relief and rescue missions. The framework is grounded on the ABC algorithm and requires the coordination of the State Emergency Services (SES) for quick and efficient disaster response.

Keywords: bushfires; burnt area; damage detection; UAVs; ABC algorithm; evacuation

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1. Introduction

Australia has suffered from the consequences of bushfires for decades, losing its vegetated landscape and thereby being forced to initiate rehabilitation. Over the years, there have been various efforts towards analyzing the cases of bushfires and trying to mitigate the ill effects of the disaster. However, the recent bushfires from 2019–2020 proved to be among the worst disasters hitting Australia. The Australian summers with prolonged drought, low humidity, and high winds greatly increase the risk of bushfires and thereby worsen the consequences [1]. Australia has consistently lost over 1.5% of its annual GDP to bushfires, with the 2009 bushfires alone causing a loss of $4.4 billion to the Australian economy. The 2019–2020 bushfires surpassed the losses of the previous years by causing a setback of almost $4–5 billion dollars [2]. Along with the economic loss, the country lost around 30 million hectares of its vegetated land and 3 billion of its animal population [2]. The increasing losses faced by Australia are greatly attributed to the increasing rate of climate change. The prolonged summers and increased drought in the country over the years have led to increased damages caused by bushfires [3]. An overview of the bushfires occurring in Australia from the devasting 2009 incidence onwards has been summarized in Table 1. While forest fires continue to occur in Australia almost every year, the highest impact fires have occurred in 2009 and 2019–2020, relatively smaller-scale fires were recorded between the years 2011–2012 and 2015–2016, as shown in Table 1. Apart from the economic losses and deaths, bushfires have also led to damage to the forests where certain areas have been burned time and again [4]. The after-effects of bushfires have also been observed in the form of lasting diseases in humans and animals, along with a lingering rate of air pollution. The diversity of the impact caused by bushfires has provoked a scientific focus on identifying how such disasters could be predicted, possibly prevented, and mitigated.

Table 1. Overview of bushfires in Australia in the last decade.

Sr. No.	Year	Number of Deaths	Region	Area (in Hectares)	Total Loss (in USD)
1	2019–2020	75	Victoria and NSW	30 million	5 billion
2	2015–2016	9	Western Australia and NSW	299,000	N/A
3	2011–2012	4	Southern Australia	92,000	N/A
4	2008–2009	173	Victoria, South Australia	4.5 million	942 million

Understanding the risks and potential losses associated with bushfires calls for identifying the reasons behind the occurrence of the disaster. Climate change and lengthy summers increase the rate of drought, leading to a higher chance of forest fires. In addition to the natural causes of forest fires, there are also instances of human involvement, such as fires lit for land conservation, land use, burning down regions over a property dispute, and other such instances [5]. However, the fires caused by human involvement are much lower in number and impact as compared to the ones caused by natural instances. Since forests are present in proximity to vegetative areas and urban settings, the rate of expansion of the area covered by the fires can be quite quick. Moreover, the presence of weather conditions such as high temperatures and high-speed winds further enhance the spread of wildfires. Understanding the causes is only the first step towards identifying the risks associated with bushfires. The loss of human lives, land, and economic damages linger for long and harm the country's livelihood as well as economy [6].

1.1. Queensland Bushfires

While the previous cases of bushfires in Australia have majorly highlighted the Victoria region due to the high impact of the disasters in this region, particularly the 2009 bushfires, it is important to note that with increasing climate change, other regions of Australia are also increasingly becoming prone to disasters [7]. The Queensland region, particularly South Queensland, is prone to ill effects of bushfires due to the increasing urban development in the region. Along with developments, the population in South Queensland has also increased in the last decade, thereby increasing the potential impact of bushfires in the region [8]. Additionally, local area planning for determining road networks and access to different regions is crucial to predict which routes can be used for relief work and evacuations in the case of fires. The Queensland bushfire planning project has developed hazard maps and identified key markers for local area development and for keeping a distance between urban developments and vegetative areas [9].

The 2019–2020 wildfires in Australia were widespread and majorly impacted Victoria and NSW, later covering several areas in Queensland. As per the data from the Australian National Recovery and Resilience Agency, there were around 60 different fires in different regions across Queensland during the summer in 2019. The areas majorly affected by the fires included the Peregian Spring, Stanthorpe, and Numinbah Valley. A total of over 6 million hectares of land was covered by the fires, leading to the destruction of 49 houses. In total, the 2019–2020 disaster affected Queensland leading to a total of 3% insurance loss in the region, as compared to the overall economic hit taken by the rest of the country. Prior to these recent fires, Queensland has faced bushfire-related damages in the past, although these instances have been less severe as compared to fires in the rest of Australia. It is important to note that the risk is increasing with time and each subsequent fire poses a larger risk than before [10].

1.2. Government Policies and Frameworks

Adapting to measures of reducing disaster risks is a major challenge faced by Australia. Opting for international frameworks of disaster risk reduction (DRR) and climate action policies holds great potential for all stakeholders. At present, the Australian government's climate action and risk reduction policies are quite scattered due to the division of jurisdictions across the different states. There is a need to develop cross-region measures for the integration of climate changes policies [11,12]. Moreover, these preventive measures should be interdisciplinary and should involve hazard analysis by experts of different fields to truly include a holistic analysis of the overall loss caused by disasters.

The government needs to adopt a holistic approach which involves local and federal bodies to strengthen the policy and decision-making processes in times of disasters. The National Climate Change Adaptation Framework is a good example of the government's approach to develop a collaborative approach for combating climate change [13]. The national policies thus developed have recognized the long-term impact of climate change as well as the urgency of dealing with the issue. While this approach is a good initiative towards instigating a dialogue and call for action, there is a need to further improve upon the existing risk reduction strategies and develop a sustainable approach towards DRR. Ideally, there should be set policies and strategies in place or that clearly outline the objectives of DRR along with clear directions regarding the actions to be taken when faced with a disaster [14]. The government organizations and NGOs working towards DRR should together develop a visionary plan for dealing with future disasters by identifying the roles and responsibilities that different sectors can assume for combating climate change and responding to disasters efficiently [15]. Collaboration being put in place prior to the occurrence of disasters is extremely important to ensure a prompt response and efficient relief work during and after disasters. Moreover, involving the public sector in the policy development and identifying the stakeholders who can play a role in developing resilience within their communities are crucial tasks [16].

1.3. Advanced Approaches for Disaster Risk Management

The mitigation of disaster risks and post-disaster risk management highly depends on technology in the current era. The Australian government has long since relied on the use of the internet for disaster risk communication and relief work. One of the biggest barriers in achieving efficient online communication is the involvement of different regional governing bodies and agencies. Communication barriers and poorly planned disaster alerts have led to significant losses in the past [17]. Preparing the community for safe evacuations and providing them directions to safe places are huge tasks, and communication inefficiencies render the use of online communications quite pointless [18]. Apart from developing an efficient framework for public awareness and disaster mitigation, technology use has been explored quite widely in the last two decades.

Remote sensing and Geographic Information System (GIS) technology have been at the top of the list of technologies being explored for planning bushfire risk management [19]. Fire risk mapping through the analysis of different regions is a rewarding approach as it provides valuable insights r areas that are prone to fires. As identified in the previous sections, fire risk is associated with weather conditions and regional climate data. Having the climate data and risk patterns from different regions has made it possible to map bushfire risk. In addition to disaster area mapping, the use of Unmanned Aerial Vehicles (UAVs) has been suggested in several studies. The key idea is that areas covered by bushfires generally have low accessibility, a lack of safe routes, and low visibility due to the rising smoke. The use of UAVs potentially lowers the need for human intervention as the safe access routes can be analyzed remotely and communication costs with individuals involved in rescue operations can be reduced [20]. The key to achieve optimum usage of the UAVs is identifying the best possible algorithm for optimizing the path of the UAV. Table 2 provides an overview of different algorithms that are commonly used with UAVs for path planning and for achieving an optimized functionality. The four most commonly reported algorithms are the Ant Colony Optimization (ACO), Genetic Algorithm (GA), the Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) [21,22]. While the purpose of each of these algorithms is slightly different and depends on the task at hand, the overall aim is to achieve the best path for reaching a target in the shortest possible time [23–25]. Each of these algorithms has different advantages and disadvantages and is optimized differently to achieve the end goal.

Table 2. Comparison of different algorithms.

Algorithms	Ant Colony Optimization (ACO)	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Artificial Bee Colony (ABC)
Purpose	Finding the shortest path	Locating the best path (or any item) among a selection	Approaching target in the shortest time	Numerical problem optimization. The purpose of the algorithm is to look for the best possible solution to a problem.
Advantages	Can work in diverse environment; quick in selecting suitable solutions	Faster than most other exhaustive searches; efficient in solving complex problems	Applicable in a number of engineering research; no overlap or mutation calculation.	Wide problem-solving range, can be applied to combinatorial and complex problems; has high flexibility and fast convergence
Disadvantages	Stagnation, low convergence speed, and local optimum	Time consuming and expensive	Low convergence speed and local optimum	Can have premature convergence in secondary search stages
Optimization	Metaheuristic Optimization	Discrete Optimization	Stochastic Optimization	Metaheuristic Optimization

This study considers the case study of the South Queensland region which is prone to fires. The rest of the paper is organized as follows: Section 2 briefly outlines the problem statement, proposed approach, and the drone coverage of the area. Section 3 gives details on the proposed framework for emergency response. Section 4 summarizes the benefit of the ABC optimization method to overcome the existing barriers of UAVs.

2. Problem Statement

While drones provide an ease in that they can be optimized for coordinates and allow for the remote observation of the target area, there are also certain limitations with the use of UAVs. The main limitations to the use of UAVs include path deviation due to wind, air pressure, and the possibility of collision with other drones. The region covered by different UAVs can overlap, leading to an increased chance of collision. These limitations make it crucial to optimize the algorithm operating on the UAVs to ensure that the target region is covered appropriately and the limitations can be overcome. At present, there are several existing algorithms which are being used for optimizing UAVs, as have been described in the previous section.

3. Methodology

3.1. Case Study

The South Queensland region is selected for the case study, as seen in Figure 1. This region is frequently affected by bushfires. Planned urban development is a key towards ensuring that the vegetative areas and forests have a clear distinction and distance from housings.

Figure 1. South Queensland region was selected for the study.

3.2. Proposed Approach

The aim of this study is to optimize path planning and drone routing through the application of the ABC algorithm. The reason for choosing the ABC algorithm over others is its high functionality in solving numerical problems. The algorithm was first proposed by Karaboga as a solution to complex numerical problems [25]. Various applications of the algorithm have been developed for optimizing constrained and unconstrained problems. The algorithm relies on three parameters, including maximum cycle repeats, population size, and adjustable limits. There are three components involved in the model: food sources, foraging bees, and unemployed foraging bees. The flowchart of the algorithm is shown in Figure 2. The ABC algorithm uses metaheuristic optimization for achieving optimal solutions, as described in the previous sections. Each of the ABC optimization phases (initialization, employed bee phase, onlooker bee phase, and storage of resources) has been described in the following sub-sections. At the end of all the iterations and analyses, the optimal output is selected by the bees (UAVs or drones in this case).

In the ABC algorithm, the agents (bees—or a colony of bees) look for a solution to the suggested problem (identifying food source). The application of the ABC algorithm converts the numerical problem, such as looking for an optimum vector, thereby reducing the objective function. The fitness function of the artificial bee colony algorithm is applied to solve the facility location problem and refers to the quality of the solution for a given problem. The alpha scores relate to the measure of internal consistency, that is how closely related a set of objects is in a group. The pseudo code of the algorithm is given below, and the algorithm is explained in the following section along with an overview of the proposed model.

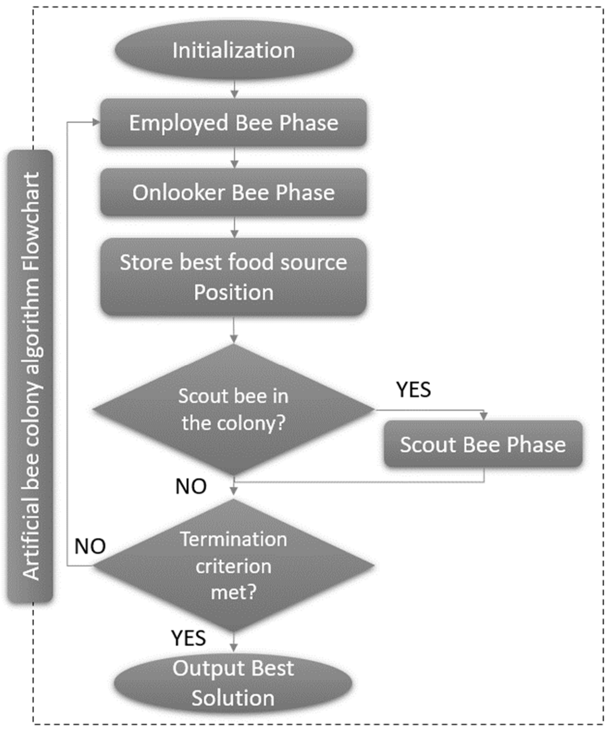

Figure 2. Proposed ABC algorithm-based framework for UAV optimization.

Algorithm 1: ABC algorithm for UAV path planning

```
Initialization:
Initialize the population and evaluate the fitness function;
Calculate the value for initial cost function;
Set best solution, Solbest ← Sol;
Set the maximum number of iterations;
Set population size = PS;
PS = Onlookerbee = EmployeedBee;
Iteration ← 0;
Improvement:
while iteration < NumOflte do
    for i = 1: EmployeedBee do
    Select a random solution and apply random neighborhood structure;
    Sort solutions in ascending order based on penalty;
    Determine probability for each solution using:
```

$$P_i = \frac{\sum\left[\frac{1}{fit_i}\right]^{-1}}{fit_i}$$

```
    end for
    for i = 1: OnlookerBee do
    Sol* ← Apply random number on Sol*;
        Sol* ← select the solution who has the higher probability;
    if Sol ∗ ∗ S olbest then
    Solbest = Sol**;
        end if
    end for
        Scoutbee determines the abandoned patient's location and replace it with the new patient's location;
        Iteration + +
end while.
```

3.2.1. Global Optimization Problem

In the case of the global optimization problem, the vector is defined as x, which minimizes the function (f) ($\rightarrow-x$) which is described as:

$$\min f\left(\vec{x}\right),\ \vec{x}=(x_1,x_2,\ldots,x_i,\ldots x_n)\in\ R^n \tag{1}$$

with the following constraints:

$$l_i\ \le\ x_i\ \le\ u_i,\ i=\{1,\ldots,n\}, \tag{2}$$

$$h_j\left(\vec{x}\right)=0,\ j=\{p+1,\ldots,q\}. \tag{3}$$

In this case, the $f\left(\vec{x}\right)$ is described in the space S (a n- dimensional rectangle in R^n (SR^n). Here, the upper and lower limits of the variable (2) are known as the constrained optimization problem, considering that both p and q are 0 for the unconstrained problem. h_j is a name of the function. As this is a constrained problem. h_j puts the upper bound on the solution and l_i puts the lower bound on the solution of the $f\left(\vec{x}\right)$.

3.2.2. Initiation Phase

The first phase is the initiation, where the food sources are generated for every individual bee. The generation of sources (x_{mi}) depends on the problem which is being considered. For our study, x_{mi} are the affected locations to be visited. This can be defined as follows:

$$x_{mi}=l_i+rand(0,1)*(u_i-l_i) \tag{4}$$

where l_i is the upper limit and u_i- s the lower limit of the parameter.

3.2.3. Employed Bees

This phase is concerned with the search for the food sources by the bees. The food sources can be alternated such that the bees determine the neighboring food source (u_{mi}) to be fit for use. For our study, u_{mi} are the affected neighboring locations to be visited, as shown in (6).

$$u_{mi}=x_{mi}+\phi_{mi}\ (x_{mi}-x_{ki}) \tag{5}$$

Each of these parameters is selected randomly, where $\underset{x_k}{\rightarrow}\ |$ is a food source, i is a parameter index, and $\underset{v_m}{\rightarrow}\ |$ is a number within the range $[-a,a]$. The food fitness is determined through the application of a greedy fitness between $\underset{v_m}{\rightarrow}\ |$ and $\underset{x_m}{\rightarrow}\ |$.

$$fit_m\left(\vec{x_m}\right)=\left\{\begin{matrix}\frac{1}{1+f_m\left(\vec{x_m}\right)} & if\ f_m\left(\vec{x_m}\right)\ge0\\ 1+abs\left(f_m\left(\vec{x_m}\right)\right) & if\ f_m\left(\vec{x_m}\right)<0\end{matrix}\right\} \tag{6}$$

u_m represents the neighboring food source for bees. ϕ_{mi} is a random number within the range [−a,a] which randomly decides how much distance bees cover towards the calculated direction towards the food source.

3.2.4. Onlooker Bees Phase

The employed bees provide information to the onlooker bees depending on the food source. The probability (p_m) selected by the onlooker bee is determined by the following equation:

$$p_m=\frac{fit_m\left(\vec{x_m}\right)}{\sum_{m=1}^{SN}fit_m\left(\vec{x_m}\right)} \tag{7}$$

3.2.5. Scout Bees Phase

Once the food sources of the neighbors are explored at length and its fitness value does not improve for a certain number of cycles, they are then abandoned after which the scout bees look for random food. This step is similar to the initiation phase. For example, the food source, $\vec{x_m}$ is now abandoned and the scout bee now looks for a new solution, as shown by (4).

The proposed algorithm has been tested and benchmarked against Augerat et al. [24]. The benchmarks were applied using python on a machine having a core i7 processor and a 16 GB RAM. In this approach, the number of bees applied as employed and onlookers is equal to that of the number of available food sources. The evaluation sources in this case are Karaboga and Basturk [25].

3.3. Drone Coverage

In terms of using drones for disaster region coverage, the key parameters include wind pressure, possibility of collision, appropriate drone height, and maximum area coverage by a single drone. A critical analysis of these parameters contributes to the determination of the optimal path and height attained by a drone during the coverage of a target area. In the case of using drones at the time of bushfires, it is crucial to account for the rapid speed at which bushfires can spread in the vegetated areas and the nearby locations. Therefore, identifying the correct number of drones to be used and their coordinates with respect to the distance between different drones and the area to cover are the most important parameters. Figure 6 provides an overview of the relation between drone height and the corresponding area coverage. As can be seen in the figure, height and area coverage have a proportional relation whereby attaining an optimal height is crucial for covering the maximum possible region of the target area. The key idea is to determine a drone height at which the camera mounted on the drone can provide good area coverage and thereby obtain clear images of the desired region for directing relief work. Since the images and videos obtained through UAVs, deployed at a region where bushfires are ongoing, help in directing the relief workers and identifying safe evacuation routes, it is important to carry out the calculations and determine the optimal drone height.

In this study, we carried out a series of experiments using drones for area coverage in the Queensland region. Table 3 shows the parameters explored in determining optimal drone height, drone numbers, and area coverage. As can be seen in Table 3, at a maximum elevation of 121.97 m, drones achieved an area coverage of 145.04 km^2. In this experiment we used a total of 12 drones; the maximum height capacity of each of the drones was 121.97 m (around 400 feet). The field of view X or FoVx refers to the horizontal field of view and the field of view Y or FoVy refers to the vertical field of view.

Table 3. Specifications of drones, their units, and parameters.

Parameters	Symbol	Units	Value
Area Coverage	A	km^2	145.04
Maximum Elevation of drones	h_{max}	m	121.97
Elevation of drones in solution	n	m	120
Drone field of view X	FoV_x	degree	83.97
Drone field of view Y	FoV_y	degree	61.93
Total number of drones	n	-	12

Figure 3 provides an overview of area coverage using different numbers of drones. As can be seen, using more drones increases the total area coverage by drones. Therefore, determining the number of drones is possible in connection with the total area in kilometers that needs to be covered in any given scenario.

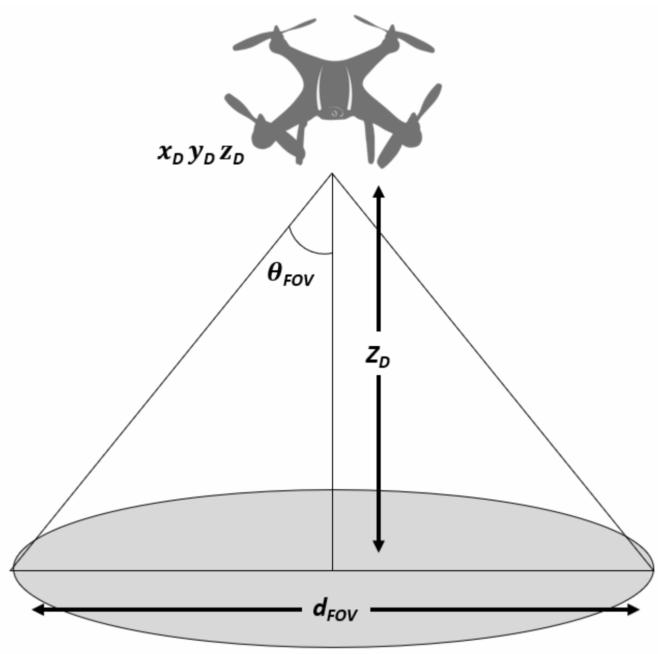

Figure 3. Relation between height and maximum area coverage by a drone.

4. Results

We considered a case study of South Queensland to further evaluate the proposed approach. In the case of bushfires, a reliable approach is required for analyzing safe routes for evacuation. In this approach, we have carried out several experiments for evaluating the ABC algorithm for bushfire disaster in the Queensland region. In order to keep the numerical factors simple, the total number of employed bees was kept equal to that of the onlooker bees. It was found that the optimum speed of convergence was achieved when the colony size was fixed at 50. Figure 4 illustrates the fitness function of the ABC optimization for drones. The fitness function in the ABC algorithm refers to the quality of the solution for a given problem. As can be seen through the figure, the linear fitness value decreases with an increase in the epoch. Up until an epoch value of 50, the fitness value is above or around 900, but as the epoch increases, the fitness score drops linearly.

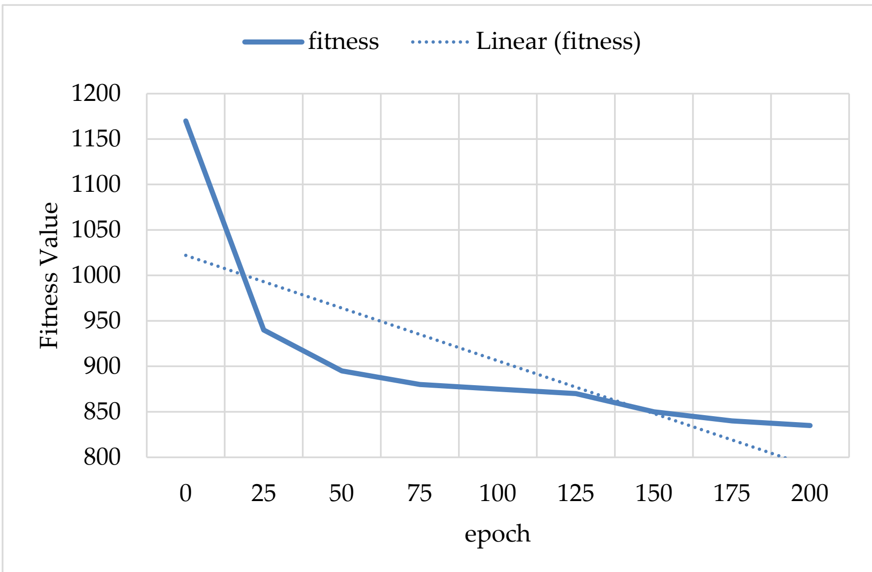

Figure 4. Fitness function of Artificial Bee Colony for path planning of drones.

The alpha (linear alpha) scores achieved by the ABC algorithm are shown in Figure 5. The alpha refers to the greediness of the search, as explained in Section 3.2.3. The higher the alpha score, the more randomization can occur in the drone pathway, where a score of 1 refers to complete greediness. Moreover, linear approximation is important because determining the value of a function at a certain point can be challenging. Linear approximation is a more simplistic approach than an exponential approximation. In Figure 4, a linear approximation is also more suitable as we are trying to show fitness values decreasing with every iteration.

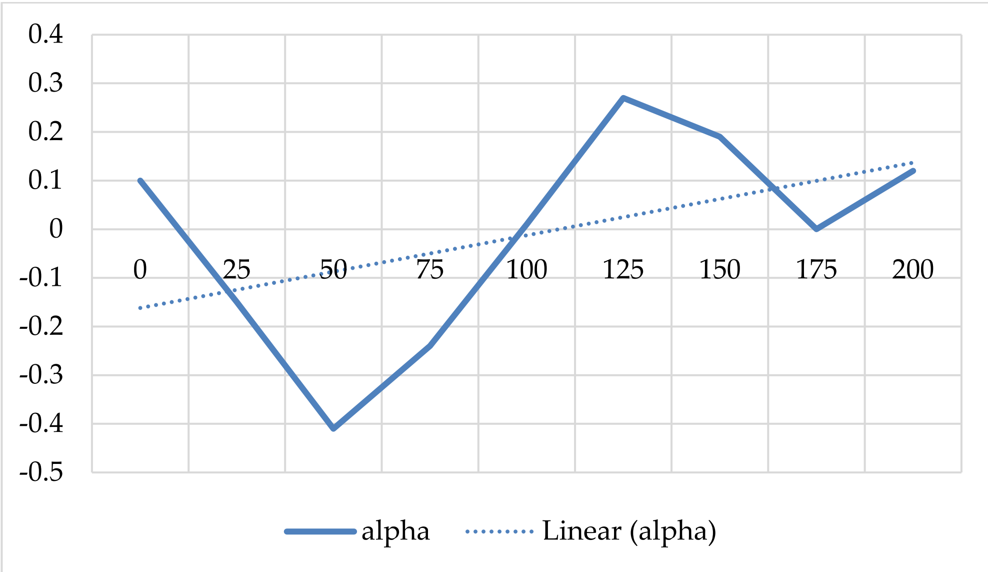

Figure 5. Liner (alpha) scores of Artificial Bee Colony for path planning of drones.

Drone route optimization using ABC algorithm to deliver payload across selected Queensland region Figure 6 shows the paths used by the UAVs for disastrous region. It is notable that the drones follow the ABC algorithm for maximum area coverage and avoid overlaps in the drone paths.

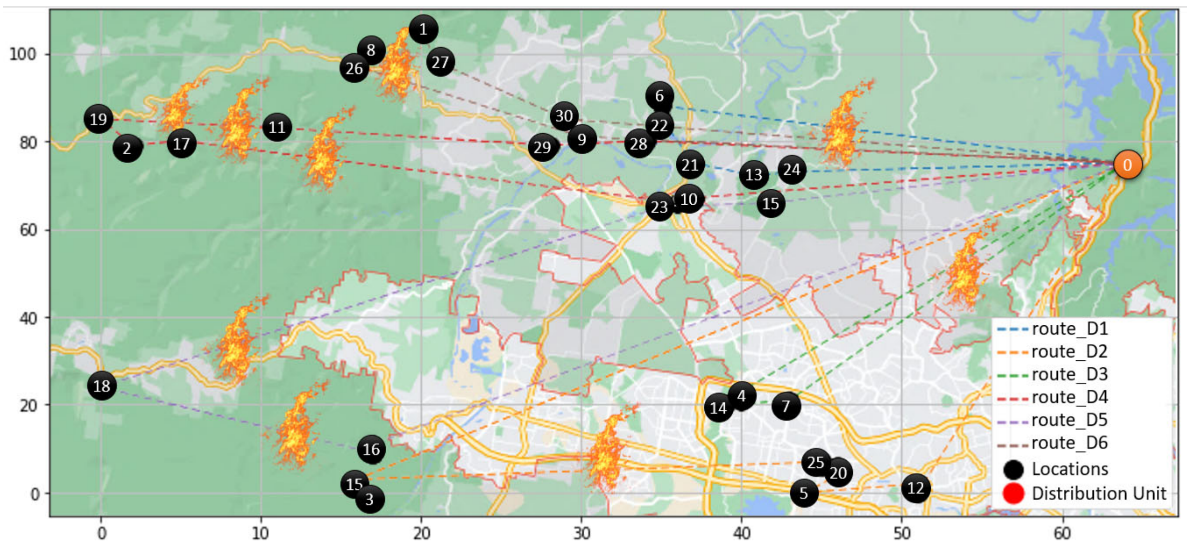

Figure 6. Drone route optimization using ABC algorithm to deliver payload across selected Queensland region. The parameters in this case were: search limit is 50, number of epochs (iterations) is 200, number of onlooker bees is 20, and number of locations to be visited is 30.

Table 4 provides a summary of different experiments that were conducted at varying locations and used a different number of drones. The optimal cost calculations have been carried out using the experiments described in [21]. This approach is known to have the best solutions for numerical problems. The limitation of using these linear approaches is that the increase in the number of drones leads to an elevation in the computations involved in the process. In the case of using six drones, the overall simulations can take several hours which is not a real-time solution for emergencies such as bushfires. The use of ABC enables the achievement of optimal solutions within seconds, as can be seen from Table 3.

Table 4. Overall evaluation of ABC for drone's path planning.

Iteration	Critical Points	Drones	Storage Capacity (MB)	Optimal Cost (Using [25])	Cost (Using ABC)	Time (Seconds)	Error
0	31	5	100	672	706.66	21.0367	0.051577
1	34	5	100	788	809.074	23.5703	0.026744
2	35	5	100	955	996.295	24.6331	0.043241
3	38	6	100	805	820.314	28.3691	0.019024
4	39	5	100	549	567.367	26.8919	0.033455
5	41	6	100	829	947.106	30.5565	0.142468
6	43	6	100	742	777.851	33.6116	0.048317
7	44	7	100	909	986.059	36.7406	0.084773
8	45	5	100	751	796.908	32.6524	0.061129
9	45	6	100	678	768.924	37.4266	0.134106
10	50	7	100	741	763.955	41.7246	0.030978
11	50	8	100	1312	1354.94	44.8531	0.032729
12	51	7	100	1032	1124.71	43.0054	0.089835
13	52	7	100	747	818.93	43.3379	0.096292
14	56	7	100	707	792.406	47.5649	0.120801
15	57	7	100	1153	1555.3	66.1008	0.348916
16	57	9	100	1598	1740.75	57.7029	0.08933
17	63	10	100	1496	1776.06	75.7468	0.187206
18	64	9	100	861	1083.07	75.1847	0.257921
19	66	9	100	1316	1611.29	82.6786	0.224384
20	67	10	100	1032	1206.91	86.5646	0.169486

The error in this method is quite small, considering the little time required for computation, as is shown in the following equation:

$$error = \frac{ABC\ Cost - Optimal\ Cost}{Optimal\ Cost} \quad (8)$$

Drone Coverage Outcomes

Analysis of areas covered in bushfires is a critical task and requires careful consideration of all the parameters involved.Table 5. Shows the number of drones required for maximum area coverage in disastrous situation.

Table 5. Number of drones required for maximum area coverage.

Number of Drones	Area Coverage (km^2)
4	57.52
6	69.63
8	59.00
10	112.79
12	146.06

The height of the drones corresponds to the area covered, as shown in Table 6. As can be seen from the results in the table below, increasing the height of the drone has a direct positive effect on the area coverage, in that the area coverage increases. Starting from 5 m, the area coverage is 0.38 km^2. At a maximum height of 121 m, the area coverage reaches 182.62 km^2.

Table 6. Drone height and the corresponding area coverage.

Height (m)	Area Coverage (km^2)
5	0.38
20	6.10
40	20.43
60	38.22
80	78.38
100	119.64
121	182.62

5. Discussion

Proposed Framework for Emergency Response

Building upon the results obtained in this study, we propose a framework for efficient disaster management by the State Emergency Services (SES). The framework is described in detail in Figure 7. Firstly, an operational planning step needs to be carried out in which the recovery and relief work methods are designed, known as the mission design step. The operational planning method depends on the region hit by the bushfires since the local area government policies for disaster management can differ. The key management tasks in the case of bushfires are to analyze the area impacted by the bushfire and determine the equipment, human resources, and costs associated with the management plan. Although the auditing for disaster management occurs prior to a disaster to determine state budgets and national capacity for dealing with a disaster, it is crucial to determine the budgets when faced with a disaster. Once the cost and equipment have been agreed upon and deployed for disaster management, it leads to the mission design phase. The mission design part in the scenario of bushfires involves working on determining the safe routes for evacuations and analyzing the number of drones needed and the overall area that can be covered by the available resources. The flight parameters and drone trajectories are also determined during the mission design stages. The next stage is the UAV take-off which essentially initiates the analysis and rescue process through a series of steps. As per the proposed method, an ABC-based UAV coverage of the bushfire-covered areas is carried out in the first stage of the mission (rescue work). The flight parameters and trajectories are determined depending on the identification of the optimal height of the drones through ABC for determining the desirable area coverage through the UAVs. As explained in the prior sections, the height of a drone directly corresponds to the area it covers. The maximum height attained by most commercial drones is 400 feet (121.97 m), which corresponds to an area coverage of above 182 km^2. These numbers are key to achieving correct resource allocation. After the initial design and preparatory phase, the drones take off and the rescue operation begins. One of the major needs in the disaster management framework is ensuring that the State Emergency Services (SES) are set at the initial stages and that the communication with the rescue workers is straightforward and quick. Since the SES must carry out the monitoring and collaborative teamwork across the different teams involved in post-disaster management, it is important to make sure that everything is in place once the drones have been deployed. The flight of the drones has different phases, including the climb, hovering, and descent. During the climbing stage, the drones must attain their maximum height, which leads to the hovering stage, where the task of the drones is to capture data in the form of images or videos, which can then be used for monitoring the disaster-hit area. The monitoring stage is carried out by data received from different drones covering varying patches of the bushfires, for example, data from UAV 1, 2, 3, and 4. This stage is where the proposed ABC algorithm comes into play for analyzing the drone data and determining the best output, which in this case is the best safety route. The data from individual drones are combined in the form of swarm knowledge, which in turn helps in the development of fire maps. The mapping of bushfires is a critical step and enables the disaster response and risk reduction steps. Once the fire maps have been generated and all the possible information from the UAVs has been streamlined, a report is developed for guiding the rescue services. The report in this case is in the form of result analysis provided by the ABC algorithm. The optimized and automated functions of the algorithm ensure that the analysis and result derivation phase is quick and accurate. Information such as the safe routes, road networks, and accessibility to the bushfire areas for rescue purposes can be extracted from the data gathered by the UAVs. This report is then sent to the ground station where the relief workers and the SES assume charge for carrying out the necessary relief work. Thus, a highly optimized and streamlined approach can be put into practice for reducing and mitigating the risks associated with bushfires.

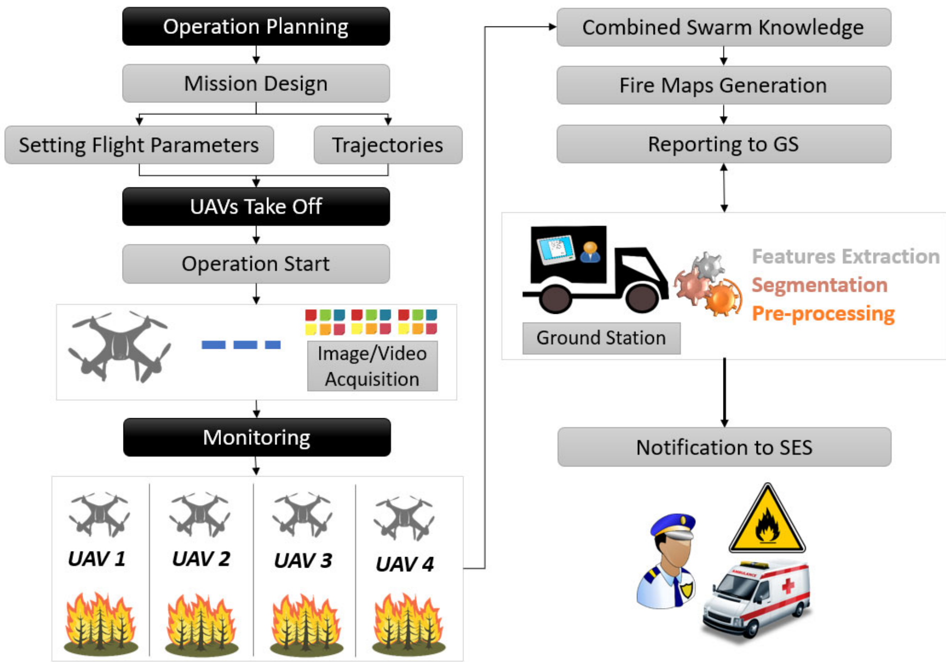

Figure 7. Proposed framework for emergency response by the State Emergency Services.

6. Conclusions

This study proposes an Artificial Bee Colony (ABC) optimization method for overcoming the barriers that exist with the use of UAVs. The limitations at present include the determination of an optimized framework for achieving efficient post-disaster response by monitoring the effected regions. Some of the main concerns addressed in this study include: (a) identifying the best algorithm for utilizing the full potential of UAVs; (b) achieving a balance between the numbers of drones used, the area covered by individual drones, and the maximum height that a drone can function upon.

The framework developed and proposed in this study suggests that a flight height of 100 m provides a near-optimal area coverage. Increasing the height to 120 m can lead to an improvement of about 30% in terms of area coverage. A series of experiments and repeated simulations were run to determine the velocity, height, area coverage, and energy requirements by the drones for optimal functioning. It was found that the best coverage was achieved when the drones were in the hovering stage, at a flight altitude of 120 m. This helped in determining the optimal velocity and battery usage by the drones. In the case of bushfires, using drones at the parameters determined through the simulations can enable quick responses and recovery tasks can be underway in an efficient manner. The disaster recovery framework for enabling an optimal response by the SES depends on the use of the proposed ABC model for the optimization of the UAVs and their subsequent deployment in the regions covered by bushfires. We have proposed a framework based on our results which includes the use of the ABC algorithm for data analysis and a subsequent correspondence with the SES for taking the appropriate actions for dealing with the disaster. Future research in UAV pathways, energy consumption, and the type of UAVs can provide more insight into the selection of the UAVs that can be used for data acquisition and disaster management. Moreover, as per the proposed framework, identifying the key parameters for quick response by the SES should also be explored in more depth to truly achieve appropriate disaster responses.

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