Highlights

Conceptual design of a wildfire emergency response system empowered by swarms of unmanned aerial vehicles

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- Identification of wildfire emergency response stages and tasks for which the use of aerial swarms is beneficial.
- Analysis of regulations limiting aerial swarms' adoption and integration into wildfire emergency response systems.
- Conceptual framework proposed for human-centred response systems integrating aerial swarms across tasks and stages.
- Interactions between software, hardware, and human components described following systems engineering approach.

Conceptual design of a wildfire emergency response system empowered by swarms of unmanned aerial vehicles

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ABSTRACT

The frequency and extent of wildfire emergencies have increased globally during the past few decades. Consequently, a large amount of resources are regularly spent on these events in order to protect people, their homes, and the environment. Underpinned by software and hardware technology advancements, particularly concerning sensors, navigation, and artificial intelligence, Unmanned Aerial Vehicles (UAVs) have proven valuable in supporting different aspects of a wildfire emergency response. However, their use is ad-hoc and task-specific within already established systems rather than forming an integral part of their design. Furthermore, while UAV swarms are aimed at exploiting the power of self-organisation and collective intelligence to collaboratively solve tasks that would be impossible to solve otherwise, they add complexity to the design. Additionally, regulations are still remarkably restrictive in terms of operations beyond visual line of sight, autonomy, and self-organisation. This paper identifies the tasks for which the use of UAV swarms is deemed beneficial for a wildfire emergency response system, and regulations that hinder their acceptance, adoption, and integration. A systems engineering approach is then adopted to propose a conceptual design of a human-centred wildfire emergency response system empowered by UAV swarms—including software, hardware, human components, their interactions, and their interfaces. Such a system offers real-time high-resolution monitoring and situational awareness of the fire front, burned area, and evacuation process; support for propagation forecasts and decision-making; and participation in fire suppression activities. Therefore, it protects wildlife, the lives of wildfire responders, and those of residents in the affected areas and beyond.

1. Introduction

Wildfires, forest fires, bushfires, or wildland fires are fires that start in rural areas and spread via combustible vegetation [1]. Because of fire exclusion and changes in population, land use, and climate, wildfire behaviour has significantly changed for the worse, and therefore global concern about their risk and damages is growing. The length of the wildfire season has increased across many regions, and the frequency of long periods of dry, windy weather has soared across more than half of the world's vegetation from 1979 to 2013 [2].

While regions of the world historically accustomed to wildfires are now seeing them of even larger sizes, areas that traditionally have not experienced many wildfires are noticing an unprecedented frequency increase [3]. Many countries are now considering investing in much larger firefighting capabilities in preparation for the future.

The raison d'être of the emergency response is to protect people, their homes, and the environment, in that order. Large wildfires cause a disproportionate fraction of the destruction and burned area, even though they are much less frequent than small and medium wildfires [4]. For example, 3% of wildfires in Canada are responsible for 97% of the burned area [4]. They are also responsible for most of the annual wildfire suppression costs [5]. In addition to homes and residential areas, wildfires can damage critical community infrastructure such as schools, hospitals, power lines, and water supplies. And their smoke results in acute toxicity in communities [6] and chronic toxicity in firefighters [3].

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In the context of Wildfire Emergency Response (WER), the use of Unmanned Aerial Vehicles (UAVs) has increased in recent years underpinned by software and hardware technology advancements, particularly concerning sensors, operational range, navigation, and Artificial Intelligence (AI). They offer inexpensive and safe solutions, adaptability to dynamic environments, and the capability to provide high-resolution remote sensing data, therefore allowing for a better understanding of the evolution of the hazard and its impacts [7]. The use of UAVs has been proposed in the literature for a range of applications in WER [8] such as vegetation mapping [9], fire detection and monitoring [10], and wildfire suppression [11, 12]. Compared to conventional aircrafts, UAVs are much less expensive, safer, and more flexible. The harsh wind, smoke, and heat conditions caused by wildfires hamper airplanes and helicopters operations, and put pilots and land crews at risk. For instance, airplane and helicopter crashes in the United States of America (USA) were responsible for 24% of wildland firefighter fatalities between 2006 and 2016 [13]. As a result, fire departments are using UAVs more frequently. By December 2022, the state of Oregon had already deployed UAVs to fight wildfires in 340 incidents [13]. Evidently, the capabilities of individual UAVs are limited, and therefore the use of UAV fleets controlled by a single operator is highly desirable [14, 15]. Furthermore, such fleets may be designed to self-organise for a collective intelligence to emerge. These fleets are called *swarms*, and their emergent collective intelligence is called *swarm intelligence*. In the foreseeable future, the use of individual UAVs may be extended to UAV swarms that can be monitored Beyond Visual Line of Sight (BVLOS) from a control centre [16].

Thus, a *UAV swarm* (a.k.a. *drone swarm* or *aerial swarm*) is a collection of several similar UAVs that work collaboratively to perform a task, achieve an objective, or solve a problem well beyond the capability of a single UAV—and beyond the added individual capabilities of the fleet (i.e., the whole is more than the sum of its parts). However, designing UAV swarm systems able to self-organise, sense their environment, coordinate their movements, and cooperate to perform collective tasks in real-world situations is a major challenge in swarm robotics [17]. Restrictive regulations in terms of BVLOS operations, autonomy, and self-organisation further hinder the acceptance and adoption of UAVs and UAV swarms in WER.

Hence the use of UAVs in wildfires is still limited and reduced to specific and isolated tasks rather than being an integral part of the response system. Some countries still need to be convinced to adopt UAVs due to safety concerns. Nonetheless, they have the potential to become invaluable assets within a WER system given their unrivaled capabilities, especially if they are empowered by AI and self-organise as a swarm. Specifically, we hold the hypothesis that when a quick and resolute response is needed during a specific time window (e.g. before weather changes), a swarm of cooperative UAVs would be better suited to support the task than a single UAV or than several UAVs operating uncoordinatedly [18]. Boroujeni et al. [19] provide a comprehensive survey of research towards AI-enabled UAVs in wildfire management, with a focus on actual and potential use of UAV technology for specific tasks in pre-fire, active-fire, and post-fire management, leveraging machine, deep, and reinforcement learning techniques. Swarms are only briefly referenced. Particular attention is paid to modelling, prediction, detection, and monitoring. To the best of our knowledge, Innocente et al. [20, 21, 22] were the first to propose self-organising swarms of firefighting UAVs. Aiming towards integration of the UAV swarm into a WER system (refer to Fig. 8 in [23]), Tavakol Sadrabadi and Innocente [23] proposed that the UAV swarm also be used to take wind measurements to support the estimation of the near-surface windfield, which is then to be fed into a wildfire model to enhance its predictions. Roldán-Gómez et al. [24] review attempts and proposals by academia and industry to use different types of robots in wildfire management. Then, they propose a Concept of Operations (ConOps) for the application of UAV swarms to carry out fire prevention and surveillance, and to support fire suppression. They propose three core human roles: (1) *mission commander* (access to all information, providing high-level commands to the swarms and to team leaders), (2) *team leader* (coordinates field operations, providing low-level commands to a firefighting team), and (3) *team members* (execute prevention, surveillance, and extinguishing tasks, with access to limited local information). They also propose the use of virtual and augmented reality interfaces to assist these human roles. Karvonen et al. [16] recently published early developments of a human factors-oriented ConOps for future semi-autonomous UAV swarms to support the management of wildfires, with a focus on fire detection and monitoring—i.e., excluding suppression. While it has the potential to be used at all stages of the system's lifecycle, they view their ConOps as a transitional design artefact playing a critical role in the requirements specification process.

Although the use of remotely controlled UAVs to support specific tasks in wildfire management is fast becoming popular, the use of autonomous UAVs, and especially swarms, is still in its infancy. While most of previous work on the use of UAVs in WER focus on how their capabilities may be used given constraints and requirements of specific tasks, this paper takes a more holistic approach and proposes a conceptual design of a WER system empowered by UAV swarms at the onset. The aim is for the UAV swarm to be an integral part of the system considered at the design stage rather than added *a posteriori* to handle specific tasks, and then having to adapt its operations to an existing system that was not designed for it. A visualisation of the envisioned system in operation is shown in Fig. 1. Thus, we identify tasks for which the use of UAV swarms is deemed beneficial (including suppression), and relevant regulations that hinder their acceptance, adoption, and integration. We then propose a framework for their conceptual design using a systems engineering approach. Whilst such a system will perform some tasks autonomously, it aims to support firefighters and decision-makers. It is, therefore, human-centred. UAV swarms can be used, for example, to detect fire outbreaks, provide real-time monitoring of fire propagation and evacuations, support accurate forecasts of wildfire behaviour, support search and rescue operations, deliver essential supplies, and both support and perform suppression activities.

Figure 1: Envisioned wildfire emergency response system empowered by UAV swarms (generated with OpenArt AI)

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The remainder of this paper is organised as follows: Section 2 provides an overview of the wildfire emergency response during the pre-fire, amidst-fire, and post-fire stages; Section 3 proposes, using a systems engineering approach, a framework for the conceptual design of a wildfire emergency response system empowered by UAV swarms; finally, some concluding remarks are provided in Section 4.

2. Wildfire emergency response

The World Meteorological Organization (WMO) defines natural hazards as severe and extreme weather and climatic events. When a natural phenomenon destroys people's lives and livelihoods, it becomes a disaster [25]. In this context, a wildfire is considered a natural disaster that needs to be managed and controlled. The four integrated phases of *wildfire emergency management* are: (*i*) prevention, (*ii*) preparedness, (*iii*) response, and (*iv*) recovery [26]. Prevention and preparedness are both pre-fire phases which entail all necessary steps and actions to be carried out to reduce the risk of ignition and limit the extent of probable wildfires. Most prevention strategies focus on long-term plans for (*i*) risk mitigation and (*ii*) ignition mitigation [3], which typically includes actions such as reducing the vegetative fuels and increasing the fire resistance of structures and infrastructures [27]. Conversely, preparedness comprises those activities that must be carried out within a short timeframe before the fire breaks (or is detected). The prevention phase will not be considered further in this paper. Instead, the more limited context of *Wildfire Emergency Response* (WER) is defined as composed of three phases: (*i*) *pre-fire response* (preparedness), (*ii*) *amidst-fire response* (suppression, monitoring, predictions, evacuations), and (*iii*) *post-fire response* (loss evaluations, emergency stabilisation, recovery efforts). Fig. 2 presents an overview of the phases and actions that may be considered to comprise a WER.

2.1. Pre-fire phase

The actions to be taken during this phase are those related to the *preparedness* of the system to respond to wildfire outbreaks and their consequences [28]. This refers to actions to be carried out right before and during a wildfire season, including (*i*) *pre-suppression and suppression plans*, (*ii*) *wildfire danger/risk forecasting*, and (*iii*) setting of *early warning systems and fire detection* [3]. Identifying endangered critical infrastructure and assets such as hospitals and

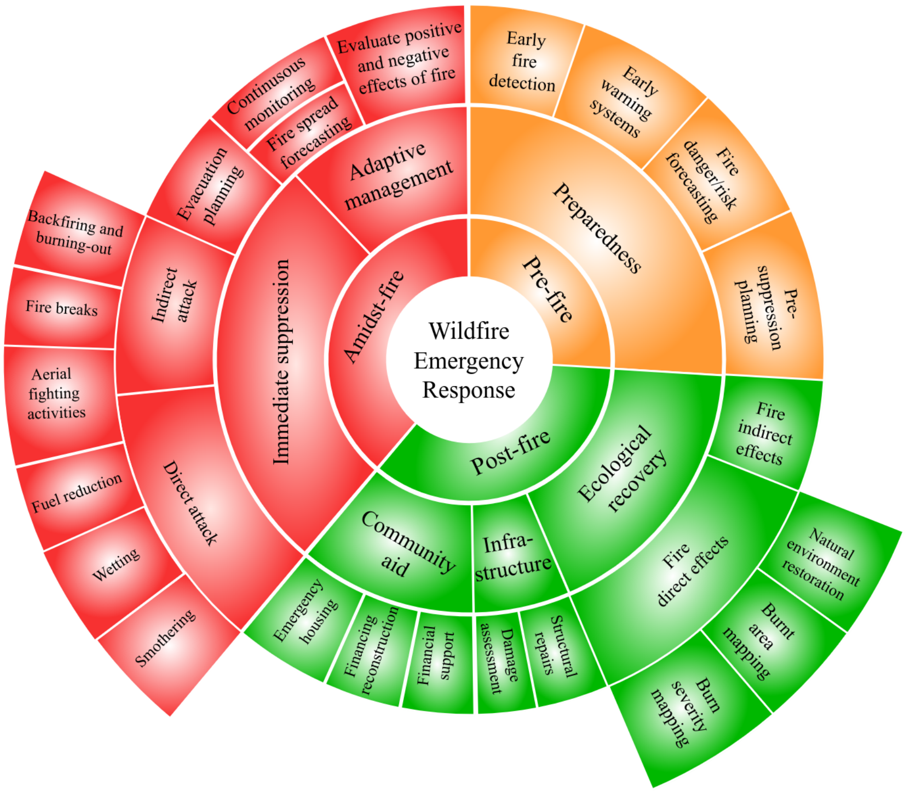


Figure 2: Overview of Wildfire Emergency Response (WER) phases and actions.

transport systems and routes, preparing alternative plans and facilities in case of their probable exposure to the fire, and determining evacuation routes and safe shelter points [3] may also be considered preparedness actions.

Rapid and accurate fire detection is paramount for a fast and successful response. Different monitoring and detection systems have been used worldwide in order to facilitate early fire detection, which may be classified into: (*a*) land-based, (*b*) satellite-based, and (*c*) aerial systems [29]. The advantages of aerial monitoring and detection systems are mainly associated to their unrivalled maneuverability and design flexibility, which make them well suited to a range of tasks in the context of WER [30]. They can carry different sensors, fly autonomously, integrate with other systems, and adapt to different requirements and tasks. Typically, UAVs are used in the pre-fire emergency response phase to carry out monitoring flights aimed at geographical terrain data collection, vegetation detection and classification, fuel load estimations, and fire risk assessment. Different types of UAVs and sensors, such as multispectral cameras and light detection and ranging (LiDAR) sensors, are used for these purposes [7]. Machine learning (ML) or deep learning (DL) techniques are used to classify the vegetation from UAV-acquired multi-spectral images or data points. For example, DL models are used in [31] for detailed classification of plant communities and species based on high-resolution red-green-blue (RGB) imagery collected from UAVs. In turn, the use of UAV-based LiDAR and photogrammetric techniques for characterising forest structure is investigated in [32]. Their results show that UAV-mounted LiDARs are able to successfully acquire information about the canopy cover and sub-canopy layers, providing estimates comparable to those obtained from terrestrial LiDARs (TLS).

2.2. Amidst-fire phase

The actions to be taken during this phase comprise responses to erupted wildfires. Hence this phase is sometimes referred to as *the response phase* [28], even if there are pre- and post-fire responses within the WER framework in

Fig. 2. Once a wildfire has broken out, two main responses may be attempted: (*i*) *direct suppression*, and (*ii*) *adaptive management*—especially in areas where wildfires are likely to have positive ecological effects [3].

Wildfire suppression is typically carried out in stages. In an effort to extinguish a fire as soon as possible after detection, the closest fire management authority often launches the so-called *initial attack*. If this fails to contain the fire, an *extended attack* is launched, which requires fire management teams to deploy increasingly more manpower and resources [33]. While approximately 95% of wildfires are contained during the initial attack [34], understanding the ecosystem adaptability or vulnerability to fire, fuel distribution, infrastructure and lives at risk, and the probability of an uncontrolled fire to develop from the outbreak is crucial to carry out a successful initial attack [3].

Wildfires in different areas of the world present varying characteristics due to differences in fuels, geography, weather, and fire regime. Therefore, and given differences in the nations and individuals involved, firefighting strategies and tactics also differ [35]. One of the most widely used strategies is building fire lines, which are barriers between the fire and unburned vegetation to control its spread. They are strategically located taking into account the predicted direction of propagation and trying to take advantage of natural barriers to minimise the length of the fire line to be constructed. Another strategy is to fight fire with fire, either via *burn out* or *backfiring* techniques [36]. The *burn out* technique consists of pre-burning the fuel with a controlled fire, which may be used to create a fire line. *Backfiring* consists of starting a fire downstream that propagates towards the main wildfire, eventually being sucked in. In addition, firefighters may apply water, retardants, and/or class A foams directly to the fire, depending on their availability and the specifics of the situation [36]. Tactical air operations may be used to deploy significant amounts of water and/or retardants, although their suitability is limited by the features of the vehicles (dimensions, payload, heat/weather resistance), characteristics of the terrain, wind speeds, and fire-induced turbulence [36]. Furthermore, the purchasing and operational costs of firefighting aircrafts are both high. Roughly, having an air tanker with a flight crew available at a base could cost around $30,000 per day, whilst flying it may add around $7,600 per hour [37]. If undertaking fire extinguishing operations, the costs associated to the suppressant must also be added.

Once a wildfire starts to threaten structures and assets, a series of actions are taken to mitigate its impact—including asset protection and population evacuation [3]. Early evacuation of at-risk populations is widely suggested to be the safest course of action in order to prioritise resident safety and reduce the complexity of wildfire management [38]. Modelling evacuation is an important tool for evacuation planning during a WER. Important aspects to consider include population size, time before evacuation, variables impacting movement, judgments on routes and destinations, flow restrictions, events affected by policy decisions, wildfire propagation speed, and designated safety zones [39]. Serious negative consequences may result from inadequately planning an evacuation procedure or inaccurately forecasting the wildfire's advance rate [40]. Consequently, different studies have focused on the development of reliable evacuation modelling platforms integrating pedestrians, traffic, and wildfire propagation models (e.g. [41, 42]).

The current use of UAVs in the amidst-fire phase mainly focuses on fire detection and monitoring, with much more limited use for fire suppression. Various spectral and atmospheric measurement sensors are used onboard UAVs for fire detection and propagation monitoring, although they can be inaccurate due to external disturbances [7]. Atmospheric sensors offer numerical data on environmental variables such as temperature and humidity, and enable straightforward analysis using statistical and AI techniques. Spectral sensors such as RGB, thermal, and infrared (IR) cameras mounted on UAVs are also extensively used for fire detection and monitoring purposes [7, 30]. Data may be processed onboard without a constant wireless connection to a central system. For example, Georgiev et al. [43] introduced an autonomous early fire detection system using a convolutional neural network (CNN). It employs live video feed from a UAV patrolling high-risk areas, incorporating optical and thermal cameras to improve fire probability predictions. The software platform autonomously processes data from both cameras, filters false positives, maintains a gallery of patrol images, and provides real-time UAV location on a map. However, it should be noted that implementing DL algorithms on board UAVs is far from straightforward due to the limited computational capacity of onboard processors. Consequently, some studies have proposed lightweight models for wildfire detection which may be executed in real time onboard UAVs (see [44]). Studies have also proposed using UAV swarms for wildfire detection and monitoring. Comparing the performance of four algorithms, namely random walk (RW), random walk with dispersion (RWDP), pheromone avoidance (PHA), and dynamic space partition (DSP), Tzoumas et al. [45] explored the use of UAV swarms with long endurance for early wildfire detection in large areas. Considering an area as large as California, DSP proves to be the most effective, detecting 82% of fires with just 20 UAVs and achieving 100% coverage with 40 or more UAVs. The system also exhibits resilience and robustness in the face of agent failures and new fire outbreaks. Roldán-Gómez et al. [24] and Karvonen et al. [16] propose a ConOps for a swarm of UAVs to support WER during the amidst-fire phase by providing real-time fire surveillance, detection, and monitoring.

With regards to fire suppression, firefighting UAV systems with different levels of autonomy and functionalities have been proposed. Peña et al. [12] developed a heavy-duty UAV for day and night firefighting operations called WILD HOPPER, with a payload of up to 600 liters. Bhat et al. [11] proposed a hexacopter framework capable of carrying and dropping fire extinguishing balls on the fire front. Instead of designing specific firefighting UAVs, some studies have focused on the concept of UAV swarms. Innocente and Grasso [20, 21, 22] proposed a swarm of collaborative UAVs self-organised to carry out autonomous wildfire suppression using swarm intelligence. Ausonio et al. [14] proposed a swarm of hundreds of UAVs producing a rain effect on the fire front, with uninterrupted delivery ensured through automatic battery replacement and suppressant refill. The system's performance is estimated by calculating the critical water flow rate based on various factors influencing fire behavior and the number of meters of active fire front that can be extinguished with the available UAVs and fire suppressant. Another strategy for fighting fires with UAVs is dropping fireballs to ignite prescribed fires. Lawrence et al. [46] studied the incorporation of UAVs for aerial ignition in prescribed fire and wildfire programs, comparing UAV versus non-UAV burns. Analysing data from 2012 to 2021 (including 58 UAV burns conducted from 2019 to 2021) with a focus on post-burn assessment data, it was found that UAV burns were 129% more efficient than non-UAV burns.

2.3. Post-fire phase

Wildfires directly impact the natural environment (vegetation cover, wildlife, water quality, soil quality), infrastructures (transportation, water supply, communication), and human communities (socio-economical impact, human lives). The actions to be taken during this phase are those related to recovery, including (*i*) *community aid* (emergency housing, financial support), (*ii*) *infrastructure* damage assessment and repairs, and (*iii*) *ecological recovery* (burned area mapping, environment restoration) [3]. For example, the burned area emergency response (BAER) program established by the United States Department of Agriculture (USDA) Forest Service is designed to address and stabilise emergency situations after a fire by determining, recommending, and implementing emergency actions that prioritise the protection of life, property, and natural resources [47].

Wildfires at the wildland-urban interface (WUI) pose a great risk to buildings and infrastructures, which may be ignited either directly as they are reached by the fire front or indirectly via firebrands. The latter mode of propagation poses a threat to buildings which are farther away from the fire front yet still close enough for the firebrands to reach them [48]. For example, the Lahaina fire in the island of Maui (Hawaii, USA) in 2023 burned an area of approximately 900 ha, burned nearly $2,200$ buildings, destroyed the historic town of Lahaina, and left more than 115 people killed. Initial estimations indicated that the costs of re-building would be around 5.52 billion dollars [49].

The ultimate goal of a forest and landscape restoration plan is to restore ecological functionality and improve human wellbeing throughout damaged environments [50]. A variety of strategies may be used for this purpose such as unassisted recovery, removal of succession obstacles, restoration of plant species, and creation of commercial plantations or agro-forestry systems [50, 51]. Adopting strategies and post-fire recovery planning requires accurate and timely information on the amount and severity of losses caused by the fire incident, as well as information regarding the natural potential of the environment to recover. For example, despite burning less frequently, humid tropical forests are more susceptible to the impacts of fire and recover more slowly than dry forests with a longer fire history [51]. When deciding what immediate actions should be taken after a fire, burn severity (BS) maps—which represent changes in plant and forest soil properties—and burned area (BA) maps are essential [52].

UAVs may be used to carry out or assist with a range of actions in the post-fire phase, including community aid, infrastructure surveillance and assessment, and ecological recovery. They are frequently used to deliver critical humanitarian aid to the communities affected by disasters, even though they are unlikely to fully replace conventional vehicles. Examples are the delivery of critical supplies (food, water, lighting devices, communication devices, vaccines, medical aid), and attempting to establish a network for emergency communications [53, 54]. Various heavy lift or cargo delivery platforms have been developed by different companies, which may be used during post-fire actions. For example, the coaxial multi-rotor FB3 has a flight time of nine minutes while carrying a payload of 75 kg at a cruise speed of 124 m/s [55], which makes it a candidate to carry out post-fire delivery of critical supplies (and even to participate in firefighting activities). Furthermore, UAV-based sensing of the site may be used for mapping damages at landscape scale [56]. In addition to the BS and BA mapping, UAVs may be used for plant health assessment, water resources quality monitoring and sampling, and wildlife tracking and census during restoration planning [57]. Environment recovery by tree planting may target different objectives such as reducing soil erosion and runoff, reducing the likelihood of zoonotic disease outbreaks, offering ecosystem services to indigenous people, or conserving carbon dioxide [58]. This can be achieved by UAVs scattering seeds (i.e. drone planting [59]) in predetermined areas where the likelihood of seedling establishment is higher. This is considerably less expensive, quicker, and more efficient than manual planting, and may cover larger areas—even more so if used in swarms.

Fig. 3 provides an overview of UAV utilisation in the three phases of WER. It is important to note that the majority of these uses are not yet firmly established but being proposed, researched, or undergoing early trials.

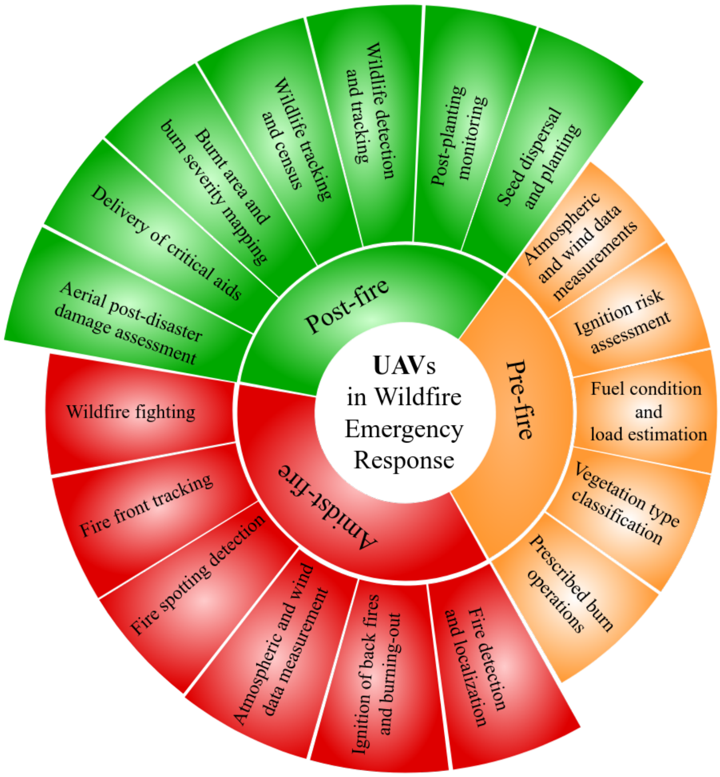


Figure 3: Applications of UAVs in different phases of WER, including uses not yet firmly established.

3. Swarm-based wildfire emergency response system

Ideally, WER systems should be systematically designed. In practice, they typically rely on ad-hoc designs of some parts, and on ad-hoc dynamic adaptations due to budgetary constraints, changing environment, evolving threats, or any other unplanned situation. Using a systems engineering framework [60, 61], we propose here a conceptual design of a WER system explicitly leveraging self-organising UAV swarms. The main motivation is that the use of UAVs has the potential to cut costs, boost efficiency, and improve safety in various existing forest service programs, including risky operations in which piloted aircrafts are not actively employed [62]. This is reinforced by the use of autonomous AI-enabled UAV swarms. Although the presence of firefighters on the ground is indispensable in a WER system, UAV swarms can significantly improve its functionality and performance while reducing economic and human losses.

Following systems engineering ideas, we view the WER as a system in which a collection of interconnected human, hardware, and software components function together to achieve common goals. Such WER system may be defined in *functional* or in *physical* terms. A functional description is concerned with what the system will do and how (intended objective, achievement conditions, partner systems) during its life cycle, whereas a physical description is concerned with the physical characteristics of its components, their interactions, manufacturing, and integration. Understanding both descriptions and how they relate is paramount for a deep understanding of the system. [60]

The life cycle of a system can be broadly divided into two phases: *acquisition* and *utilisation*. The acquisition phase comprises four main stages, illustrated in Fig. 4: (i) *conceptual design*, (ii) preliminary design, (iii) detailed design and development, and (iv) construction and/or implementation. This paper is concerned with the *conceptual design*, which aims to define the system in functional terms.

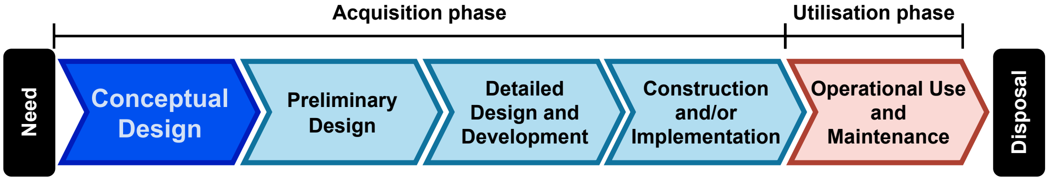


Figure 4: Life cycle of a system, which starts with the statement of a need and ends with the system disposal. The focus here is on the *conceptual design*, which is aimed at defining the system in functional terms. (modified from [60])

While ConOps like those in [24, 16] describe how the system is intended to be used from the end-user or stakeholder perspective, the *conceptual design* defines the high-level architecture, components, and interactions needed to realise the ConOps. It is crucial to unambiguously define the functional requirements of the system to avoid future problems during the system development and operational stages. The main steps comprising a *conceptual design* are [60]:

1. Stakeholder requirements identification.
2. System feasibility analysis.
3. System requirements analysis.
4. System-level synthesis.
5. System design review.

3.1. Stakeholder requirements identification

The first step in the conceptual design of a system is to identify stakeholders and their requirements, which involves defining the system's functions, objectives, constraints, operational features, interactions with third-party systems, and operational environment. These requirements are specified in layman's terms rather than technical language [60].

3.1.1. Stakeholders

A stakeholder is any party that has a stake or an interest in the system [63]. The UK Forestry Commission identifies the following stakeholders when planning for wildfires [64]: (*i*) fire and rescue services, (*ii*) local authorities and resilience forums, (*iii*) local wildfire groups, (*iv*) local and adjacent tenants and property owners, and (*v*) managers and owners of national infrastructures. In addition, public law authorities such as police forces [3, 16], public health agencies, meteorological organisations, aerial flight crews, and telecommunication operators and companies may be added to the list. At a broader scale, governmental organisations and departments such as agricultural departments, forest and rangeland management services, water management services, municipalities, insurance companies, and the military may also be considered stakeholders. Finally, the natural environment comprises an external stakeholder, as it is highly affected by a wildfire and the strategies adopted during the emergency response. For example, the effects of fire suppression activities on the environment are so high that they could surpass the impacts of the fire itself [65].

With specific regard to the swarm-related components of the response system, their users and operators also comprise internal stakeholders. Examples are *(i)* swarm operators, *(ii)* data analysts, and *(iii)* U-space operators. *Swarm operators* communicate with operators of other components of the response system, whilst commanding, monitoring and controlling the mission—including launch and return of the swarm (i.e. command, control, and communication). *Data analysts* make use of sensor data and AI-based analytics to monitor and assess the situation, make recommendations to the incident commander, and inform external stakeholders. *U-space operators* establish U-space areas and provide traffic control, maintaining communications with pilots of manned and unmanned aerial vehicles [16]. Table 1 summarises the requirements of some important stakeholders related to the UAV swarm within the WER system, including internal stakeholders, nature, and regulatory authorities.

3.1.2. Objectives and constraints

Since the *need* in Fig. 4 is typically loosely stated, system-level objectives must be clearly articulated at the beginning of the conceptual design. Common *objectives* of a WER system are:

1. Reduce the risk of a fire.
2. Limit the consequences of a fire should one break out.

Table 1
Overview of some important stakeholders of the WER system empowered by aerial UAV swarms and their requirements.

Type of stakeholder	Stakeholder	Requirements
External	Governmental organisations	The swarm-based WER system must be safe, economically viable, adaptable to regulations, and publicly acceptable.
	Aviation and regulatory organisations	The system must function within the specific aerial domain to maintain safety for other aerial vehicles.
	Insurance companies	The system must be able to protect human crew, valuable property, businesses, heritage sites, and infrastructure to reduce exerted damage and reconstruction/repair costs.
	Local authorities, landowners, tenants, etc.	Minimising damage to local property, lands, tenants, and environment.
	Nature	1- minimising the damage to all components of the ecosystem either caused by the fire or firefighting activities. 2- accelerating rehabilitation of the environment through performing timely and large scale recovery missions.
Internal	Forest management services	The UAV swarm is to be capable of carrying out Inspection missions, fire and environment monitoring and sensing, fire propagation estimations, fire fighting activities, damage assessment missions and recovery actions efficiently and economically to reduce the costs compared to current approaches.
	Fire and rescue services	The UAV swarm should be reliable, accessible, maintainable, and operable for the mission's duration. It must be capable of carrying out fighting activities, logistic and support missions, and continuous monitoring
	UAV system operators and maintainers	The UAV swarm must be (1) maintainable in a timely and cost-efficient manner, (2) energy efficient, (3) operable for the duration of the mission, and so on.
	Data analysts	The UAV swarm must be capable of providing reliable and accurate data throughout the entire mission time from desirable locations and with desirable resolutions.

3. Monitor area of interest (surveillance).
4. Detect and localise fire outbreaks.
5. Alert firefighters, incident commander, and other decision-makers.
6. Gather and assess fire data.
7. Forecast fire propagation.
8. Identify natural resources and map roads.
9. Monitor and assist evacuations (assets, people).
10. Suppress the fire.
11. Map burned area.

Project *constraints* include organisational policies, procedures, standards, resource allocations, and time frames guiding and restricting the system development. External *constraints* include compliance with laws, regulations, and industry standards, and capabilities to interface to other systems.

Currently, there are no UAV regulations that directly address forest firefighting activities, as the majority of UAV regulations are focused on operations over populated and urban areas (see [66]). However, most of these regulations are still generally applicable and valid in WER situations. Even though a comprehensive review of regulations is beyond the scope of this paper, the aim here is to discuss limitations imposed by some countries and modifications required to take advantage of UAV capabilities such as autonomous flights beyond the visual line of sight (BVLOS).

The U.S. Federal Aviation Administration (FAA) passed regulations in 2014–2015 stating that every UAV with a mass of at least 0.25 kg and a maximum speed higher than 100 mph is permitted to fly only during daytime and controlled by certified operators no younger than 17 years old. Furthermore, UAVs may not be used for deliveries or fly BVLOS [67, 66]. In 2021, the FAA published a new set of rules permitting operations over people and moving vehicles, and night operations as long as UAVs are equipped with anti-collision lights [68]. In August 2023, the FAA authorised the "Phoenix Air Unmanned" company to perform BVLOS operations for aerial work, aerial photography, survey, as well as powerline and pipeline patrol and inspection [69]. In September 2023, two other companies were granted BVLOS mission authorisations for small package delivery, and for testing detect-and-avoid technologies [70].

The European Aviation Safety Agency (EASA) and the Civil Aviation Authority (CAA) in the UK classify UAV flights into three categories, namely (*i*) *open category* (low risk), (*ii*) *specific category* (medium risk), and (*iii*) *certified category* (high risk) [66, 71]. The *open category* is sub-divided into three sub-categories: A1 (UAVs mass below 0.25 kg, which may be flown over people but not crowds), A2 (UAV mass under 4 kg according to EASA, and under 2 kg according to CAA), and A3 (general operations, including UAV mass up to 25 kg). *Open category* flights do not require authorisation from the National Aviation Authority (NAA), although Operator ID registration and some certification of competency may be required for sub-categories A2 and A3. The CAA requires a Flyer ID from anyone piloting a UAV. The *specific category* is for flights posing higher risks which may nonetheless be mitigated, requiring risk assessment and authorisation from the NAA. The *certified category* applies to complex operations, typically with larger and/or more sophisticated UAVs, requiring the highest levels of safety assurance. The levels of risk are determined with respect to cargo, population density, UAV dimensions, and whether the flight is within visual line of sight (VLOS) or BVLOS [71]. UAVs must fly lower than 122 m in the open category, may fly higher in the specific category, whilst special permission is required in the certified category. For all UAVs with a mass of 0.25 kg or above, operators must have some level of training [66, 71].

BVLOS flights are typically prohibited in the USA, the UK, and the EU, unless prior authorisation is obtained from the NAA and within well-defined geo-fenced zones [66, 72]. The CAA has provisions that allow emergency services to operate drones with certain exemptions during situations that present an immediate risk to human life or major incidents. Regulatory bodies anticipate a variety of parties that will benefit from autonomous UAV missions [72], and hence are striving to adapt and define regulatory frameworks to allow for this. For example, the UK has established the airspace modernisation strategy (AMS) program, which aims to examine how Remotely Piloted Aircraft Systems (RPAS) flying BVLOS will be incorporated into the UK airspace system by 2040 [73]. EASA has developed the concept of *U-space*, which consists of a set of services and procedures to facilitate safe and efficient airspace access for multi-UAV missions. The aim is to allow for automated UAV management and integration, coexisting safely with the current air traffic management system [74, 75]. The NASA Ames research centre is developing a so-called *UAV traffic management* (UTM) platform to safely integrate large numbers of UAVs operating at low-altitude airspace into existing air traffic [76].

WER missions are carried out largely under uncontrolled and uncertain situations. For instance, aircrafts and land crew mostly operate within smoky, windy, and highly turbulent environments. Consequently, a UAV swarm system must be adaptive, and able to operate autonomously and BVLOS [72]. These are precisely defining features of a swarm intelligent, self-organising, multi-UAV system. However, regulations—especially in the context of wildfires—do not yet support such missions. In fact, the FAA states that “drones and wildfires are a toxic mix” as fire response services have to halt their airborne support vehicles to avoid midair accidents if unauthorised UAV flights are observed near the wildfire event [77]. Therefore, an autonomous aerial swarm-based system must be designed as an integral component of the WER system rather than incorporated *a posteriori* to enable coordinated and safe operations for both manned and unmanned vehicles in wildfire airspace. As such systems are progressively developed and tested, proving themselves efficient, reliable and safe, it is reasonable to expect that regulations become less restrictive in the near future.

3.1.3. Operational scenarios

Operational scenarios take into account (i) *operational environments* (external factors) and (ii) *modes of operation of the system* (internal factors) so as to meet the stakeholders requirements.

Wildfires can happen in diverse areas, including remote locations and wildland-urban interfaces (WUI). As a result, a WER may unfold within diverse environmental, topographical, and societal contexts. Environmental factors which may affect the system’s operations include difficulty in accessing the terrain, fuel type, availability of natural bodies of water, weather, wildlife, human population, infrastructure, and natural barriers to fire propagation. Missions addressing different objectives such as detection and localisation of fire outbreaks, fire propagation monitoring, fire suppression, and mapping of the burned area (see Section 3.1.2) require different *modes of operations* within each *operational environment*. In order to cope with diverse *operational environments* and meet *stakeholders* requirements, the WER system must exhibit adaptability and flexibility. For example, the detection and localisation of fire outbreaks heavily depends on visibility, which can be affected by day–night status, smoke, and weather [78]. Such conditions can affect the accuracy and detection speed, and limit the use of reconnaissance resources available to the system. In turn, suppression operations are affected by the characteristics of the fire (type, size, intensity, rate of spread), smoke, terrain, vegetation, weather, and day–night status [79]. These conditions inform the intensity and strategy of the response, and constrain operations. Responding to larger, more severe, and faster spreading wildfires evidently requires more resources such as water or fire retardants, larger UAV fleets, higher numbers of firefighters, and more equipment. It is important to highlight here that a swarm of self-organising UAVs comprises a robust, resilient, adaptable, and scalable system.

Whilst leveraging the power of autonomous AI-enabled UAV swarms, the WER system is still human-centred, with human firefighters at its core. The UAV swarm is the WER sub-system that provides (i) real-time aerial monitoring and situational awareness, (ii) precise estimations of fire behaviour and propagation, (iii) decision-making support for fire management, search and rescue, and evacuations, (iv) delivery capabilities (e.g. firefighting tools, first aid kits, food, water), and (v) autonomous fire suppression capabilities.

3.2. System feasibility analysis

Once the stakeholders requirements are stated (including objectives and constraints), feasible alternatives for the WER system must be considered taking into account the operational scenarios, costs, timeliness, and available technologies. For example, a variety of environmental and meteorological factors and conditions such as fog, haze, cloud cover, wind and turbulence, precipitation, temperature and humidity, lightning, tornadoes, and so forth, have the potential to impact UAV operations. Some of these may be defined as severe hazards or conditions, and impose serious risks on the operators and other personnel [80], possibly rendering the system infeasible under such conditions.

During operations aimed at early fire detection and localisation, the size of the area to be monitored, the estimated fire risk, and the estimated severity of the resulting hazard have a great influence on the design of the system and the technology adopted (e.g. static sensors, fixed-wings, multi-rotors, swarm-size, satellites). During fire suppression operations, the heat released from the burning front drives air temperatures to extremes and puts both UAVs and firefighting personnel in dangerous situations facing strong and turbulent wind conditions.

The horizontal wind velocity within a wildfire may vary significantly under different fuel and topographical conditions, e.g. between 1.4 m/s and 26 m/s [81]. In turn, the vertical wind velocity may also be of great importance as it pushes the UAV upwards, with the potential to overturn it. For example, airborne cloud radar measurements [82] indicated that, under extreme conditions of the Pioneer fire, the updraft and downdraft velocities reached maximums of 60 m/s and 30 m/s, respectively. In order to address the wind effect on the UAVs, different approaches and methods are being utilised, such as the design of enhanced controllers [83] and enhancing the structural design of UAVs [12]. Alternatively, smaller off-the-shelf extreme-weather UAVs are available in the market. For example, the Sky Mantis 2 [84] is advertised to be able to operate with winds of 75 km/h and under heavy rain. With a payload of 2 kg, it may be used for dropping swarms of fire suppression balls, though it is limited to a maximum operational temperature of 50 °C. Nonetheless, the UAV temperature resilience issue is also being addressed by different studies (e.g. [85]).

3.3. System requirements analysis

System requirement analysis is a crucial step in conceptual system design, establishing the basis for functional design by prioritising essential needs over implementation details [60]. When it comes to fully autonomous BVLOS firefighting missions, certain requirements and significant shortcomings need to be addressed to ensure these systems are reliable and safe enough to be utilised in such challenging and dangerous missions. This section briefly discusses the most important requirements and limitations of such a system, with Fig. 5 presenting an overview.

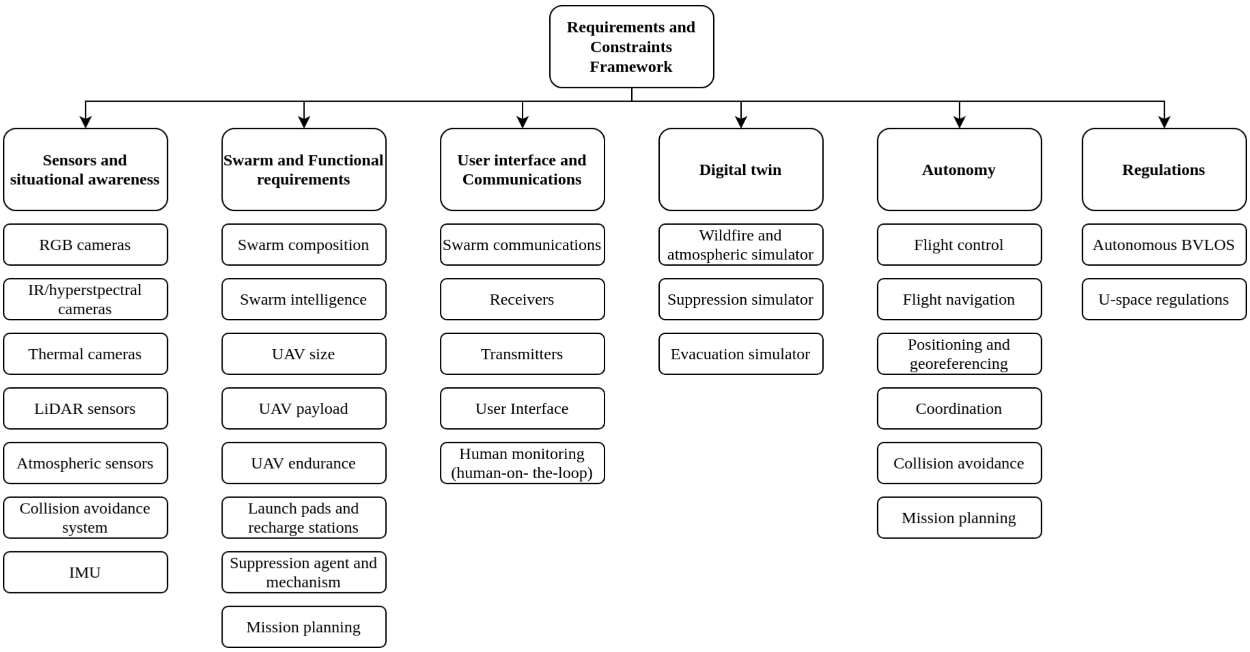


Figure 5: Overview of a UAV swarm system requirements

3.3.1. Mechanical and operational requirements

Safe operation of individual UAVs within the system, and their interactions and cooperation with external elements such as manned aircrafts and human land crew is of high importance to the UAV swarm function. For example, UAVs operating in a wildfire environment should be able to withstand extreme conditions, including high temperatures and turbulent winds. The temperature of the ambient environment during suppression operations could be as high as ≈ 80 °C [86], which can significantly affect the UAV performance. Currently, no commercial off-the-shelf UAV could operate in high temperatures close to the values that take place in a wildfire environment. It should be noted that even temperatures of up to ≈ 60 °C substantially reduce battery lifetime and its capacity, damaging the lithium-ion battery [87], which is detrimental to the system's functionality. Consequently, the UAVs should be temperature agnostic in order to be able to maintain safe operation, especially for those units that participate in direct suppression activities. Apart from the battery performance, temperature variations are also detrimental to the structural integrity of the UAV frame, while lower air density reduces the thrust generated by the motors [80] and therefore the UAV payload capacity.

In addition to the high temperature, the turbulent wind and smoke in a wildfire environment could increase the probability of aircraft accidents. High wind speeds reduce the endurance time of UAVs and easily divert them from their original trajectory or even turn them upside down [80]. Therefore, the UAV resistance against horizontal and vertical gusts and turbulence is of great importance, and needs to be considered when designing UAVs for wildfire environments. Furthermore, smoke exhaled from the burned vegetation increases the noise in the data acquired by sensors like RGB cameras and LiDARs [88], hence limiting their functionality required for maintaining situational awareness and autonomous operation of the UAV.

Launch pads and recharging stations are essential components of any UAV-based system [14, 16], supporting their continuous operation. A UAV launchpad or docking station is a multi-functional system that supports UAVs in various ways, including safe landing and take off, recharging and replacement of batteries and payloads, and possibly the required space for storing them. This enables the swarm to operate over long periods of time. UAV docking systems could be either mobile or fixed during the mission [89]. A range of fixed and mobile docking systems have been developed, including the DJI dock [90]. A detailed survey of these technologies is beyond the scope of this paper.

Suppression agents and methods encompass a variety of different agents suitable for use in fire suppression activities, including water, surfactants (wetting agents), class A foams (plain or enhanced by nanoparticles [91]), fire retardants, and fire gels [36]. Compared to air tankers, UAVs have a limited payload capacity prompting researchers to propose some innovative solutions to tackle this limitation, including the use of fire extinguishing balls [92], tethered firefighting hose [93], or water spraying systems that mimic rainfall [14] to maximise the evaporation and hence reduce the temperature of the burning fuel facilitating suppession.

Generally, the amount of required suppressant is directly linked with fire intensity. Thus, the primary concerns of using suppression agents like water are using the right amount, with the correct form, and in the right place to increase the chance of success [36]. Apart from the considerably lower costs, one of the main advantages of UAVs over air tankers is that they can be equipped with advanced technologies that facilitate the calculation of the critical amount of suppressant required, and can deliver it in the optimal form and place to maximise the effectiveness of the suppression operation. Therefore, some researchers have tried to calculate the required amount of suppressant liquids, such as water, for different fire conditions (e.g., rate of spread or fire intensity) and fuel types when utilised in UAV systems (see [14]). In addition to the amount, the form of water delivery to the fire affects its effectiveness in absorbing heat and suppressing the flames. For instance, delivering water in a spray or fog form offers higher efficiency than a straight stream of water. [36].

Distance from suppressant resources is also important for the uninterrupted operation of the system. Generally, air tankers and helicopters can access suppressant sources such as lakes and rivers located kilometres away from the main fire scene. Conversely, UAVs have limited endurance, which limits their flight range. Therefore, having access to a nearby water source or other suppression agents is critical for the effective operation of a UAV swarm.

3.3.2. Sensors and situational awareness

Situational awareness may be defined as the ability to perceive elements in the environment within a volume of time and space, understand their meaning, and project their status in the near future [94]. A UAV swarm should be able to maintain its situational awareness, constantly transmit environmental information to the Command and Control Centre (CCC), receive instructions, and carry out the assigned tasks autonomously throughout the operation. For the UAV system to carry out its mission safely within its operation environment, it must be able to evaluate its environment status and make timely decisions. Using data fusion and intelligent system health management can render such status assessments possible [95].

Apart from structural and flight necessary sensors, UAVs are capable of carrying a range of sensors with various applications in environmental remote sensing, including RGB, infrared (IR), thermal, and multi-spectral cameras;

light detection and ranging (LiDAR) sensors; and atmospheric measurement sensors such as temperature sensors, humidity sensors, PM and gas sensors [7, 30], wind probes, and anemometers [96]. Spectral sensors such as RGB, thermal, and IR cameras—e.g. near-IR (NIR), red-edge (RE), and shortwave IR (SWIR)—are the most prevalent types of sensors mounted on UAVs to assist in wildfire monitoring and response tasks. Spectral property analysis is made possible by the cameras' ability to record radiation from the material or object under observation at various wavelengths and frequencies. A spectral image is hence created by recording the intensity of radiation that the camera detects at each frequency band as a value for each pixel [7, 30], which then needs to be localised or geo-referenced to be used as actionable data or as input into the fire predictive models. LiDAR sensors are also extensively used for various applications, such as vegetation mapping [97], fuel and burn severity mapping [98], and sub-canopy forest structure detection. The main drawback is that their performance deteriorates in adverse weather conditions such as snow, fog, or rain [99], potentially affecting UAV operations in smoke-covered environments during wildfires. Unlike LiDAR sensors, the performance of ultrasonic or sonar sensors is not affected by weather conditions. They are ideal for outdoor use because they offer broad coverage as well. However, radars' low output resolution prevents them from providing precise object dimensions [13], which limits their use in wildfire monitoring tasks. Hence, given that a single sensor may not be able to meet all the situational awareness requirements, each UAV in the swarm must be equipped with a specific set of sensors based on its unique operational needs, in addition to the standard sensors essential for autonomous flight and communications.

3.3.3. Autonomy and decision making

The National Institute of Standards and Technology (NIST) defines autonomy as the ability of a drone to operate independently, including sensing, perceiving, analysing, communicating, planning, decision-making, and taking action to achieve its objectives. It may be categorised into four levels: (i) full autonomy, when operation requires no human intervention; (ii) semi-autonomy, when tasks involve different levels of human-robot interaction; (iii) tele-operation, when a human operator uses feedback to control and assign tasks; and (iv) remote control, when the operator directly controls the UAV's actuators [100].

A UAV swarm system requires a high level of autonomy. The system requirements for an individual UAV to fly autonomously can be classified into: (i) *control*, (ii) *flight management*, and (iii) *path planning* [95]. In addition, *perception* is an inherent part of autonomous flight management and planning as the control algorithms of the UAV rely on the data provided by the perception sensors [101]. Flight control and navigation, as well as the UAV positioning system, are also fundamental functions of the autonomous system that enable safe operation [95]. Besides, for the UAV to safely navigate from its current location to the desired destination, a series of functions, including flight planning, mission scheduling, fail-safe protocols, contingency management, conflict resolution, and obstacle detection and avoidance, must be executed. UAV positioning is another important element for autonomous navigation, which may be achieved through technologies like *simultaneous localisation and mapping* (SLAM) or GPS sensors [95].

In a multi-robot or swarm system, decisional autonomy comprises four main capabilities: (i) task allocation, which means dividing tasks among the robots; (ii) mission planning, scheduling, and refinement, which means converting tasks and missions into feasible sequences of actions while taking environmental conditions and UAV capabilities into account; (iii) coordination, which deals with resource conflicts and planning cooperative tasks to guarantee consistent actions among a group of robots; and (iv) supervision and execution control, which manages encountered circumstances and guarantees proper task execution [102].

3.3.4. Swarm communication and coordination strategy

An autonomous UAV swarm allows for a single operator to manage and control a group of UAVs instead of a group of operators controlling individual UAVs. UAVs in the swarm exchange information with one another, and self-coordinate to achieve a common goal. It is virtually impossible for human operators to process the shared information efficiently, reach consensus, and coordinate collective, cooperative actions. This makes autonomous swarms significantly more efficient, responsive, and timely than collections of human-controlled robots in a variety of situations [103].

Swarm communication and coordination can be categorised into centralised (infrastructure-based) and decentralised architectures. Centralised communication involves direct communication between all UAVs and a central command center, making the system semi-autonomous [30, 101]. While it benefits from real-time computation and optimisation, it has drawbacks like susceptibility to attacks and restricted communication range in remote and harsh wildfire environments. Decentralised architecture involves UAVs communicating with each other and planning collectively. They rely on onboard processing power, enhancing redundancy but increasing payload and reducing endurance. In addition, it introduces higher complexity, requiring distributed coordination algorithms for implementation [101]. However, given the typical operational conditions of a UAV swarm suppressing a wildfire, which often involve BVLOS operations, a decentralised architecture would inherently be a superior choice provided that sufficient safety mechanisms are embedded into the system, such as emergency landing, return-to-home (RTH), and alternative communication such as satellite communications (SatCom).

Collective behaviours emerge from local UAV–UAV and UAV–environment interactions via self-organisation. This results in a swarm robotic system that is scalable (up and down), resilient to failure, and flexible in response to changing environmental conditions [18] such as the harsh and highly dynamic environment of a wildfire event. These can be attained through meticulously hand-designed local rules for a desired collective behaviour to emerge often accomplished through a bio-inspired strategy (reproducing baseline behaviours), or via some automatic design method using evolutionary-based techniques (evolutionary swarm robotics) or multi-agent reinforcement learning (MARL) methods. Some baseline behaviours include (i) synchronisation (coordination of actions); (ii) coordinated mobility (coordinated flight to preserve a stable spatial organisation); (iii) aggregation (gathering in a specific area), (iv) collective exploration, and (v) decision-making [18]. Whatever the design method, the swarm robotic system exhibits swarm intelligence (not every group of UAVs makes a swarm).

3.3.5. User interface and human-robot interaction

A user interface (UI) in a human–robot system is a communication platform that makes it feasible for human users to interact with the robot and exchange information [104]. Conventional robotic systems require human decision-making, planning, action approval, and close human–system interaction. Such configurations are generally referred to as Human-in-the-Loop (HiL) systems. However, with the fast-paced development of AI, fully autonomous systems are now at the centre of attention. HiL systems are capable of autonomous decision-making and execution without direct human control. Nonetheless, human operators are still expected to perform monitoring and supervisory roles [105]. The UAV swarm system may be supervised and monitored by fire managers and fire agencies, and therefore the UI should be simple and easy to use. On the other hand, it should be comprehensive enough to facilitate situational awareness for the user or the CCC. A poor UI can be a source of problems and failures in robotic systems [105].

3.3.6. System digital twin

The 2022 NASA workshop highlighted issues in the current firefighting operations, including an overload of unhelpful data, poorly scaled information from predictive services, and communication limitations that lead firefighters to rely on intuition rather than actionable data [61]. In order to estimate wildfire behaviour and make informed decisions, the WER system needs real-time and accurate information about the wildfire's status, and reliable estimations of its future behaviour and extent.

A digital twin may be described as an integrated model that incorporates different discipline-specific models (e.g. architecture, mechanical, electrical, software) and information from many existing technologies to monitor real-time situations and estimate future scenarios [106]. Integrating these partial models is important as it provides the capability to study the multifaceted behaviours that occur from interactions between diverse system components [107]. Different studies have focused on developing digital twin frameworks of UAV swarm monitoring systems [108] and wildfire incidents [109]. However, the digital twin required for a UAV swarm-based WER system interacting with the environment and participating in suppression, evacuation, and monitoring tasks must be able to consider (i) fire propagation, (ii) atmospheric conditions variations, (iii) UAV swarm actions and their effects on the environment, (iv) evacuation behaviour and traffic modelling, and (v) the effect of suppression activities on the fire dynamics. Besides, these simulations should be executed in faster-than-real time to be utilised in response activities. An accurate numerical solution over a large domain is prohibitively computationally expensive [110]; hence, a possible solution is to use faster-than-real-time reduced-order models (e.g. [111]) and improve the estimations through other techniques such as data-assimilation (e.g. [23]).

3.3.7. Performance requirements

In order to provide a basis for evaluating the effectiveness of the proposed system, we need to define measurable quantities to offer insight into how the system is functioning. A Technical Performance Measure (TPM) is a measurable parameter that provides a way to compare the system function to the requirements that it needs to satisfy [112].

Even though performing an exhaustive review of performance assessment metrics for such systems is beyond the scope of this paper, it is fair to note that the technical performance measures for a UAV-swarm-based WER system encompass a range of aspects important to different stakeholders at different levels of the system. For example, at the system level and in terms of evaluating the effectiveness of the response system, performance assessment metrics may include parameters such as average response time, suppression costs, burned area, fire detection and alert time, fire and spotting localisation and mapping accuracy, system development, maintenance and operational costs, accuracy of fire behaviour estimations, human crew casualties, and facilities entrapment.

On the other hand, the system can be evaluated based on the functional efficiency of the UAV swarm as a subsystem of the WER system, which may include metrics for assessing the (*i*) system robustness and fault/error tolerance, which may be discussed in terms of the effect of a failed agent on group performance and on other working agents; (*ii*) scalability, which reflects on the system performance against varying swarm sizes; and (*iii*) the system adaptability, which reflects system capacity to adjust and respond to the external circumstances and dynamic environment [113]. In terms of autonomous navigation and motion planning at the UAV level, the performance can be evaluated by utilising metrics for trajectory evaluation such as trajectory corrected distance, maximum curvature, minimum distance from obstacles, etc [114]. From the standpoint of airworthiness and operational capabilities, the UAV system performance may be evaluated utilising metrics like flight endurance, range, collision avoidance, terrain following, energy consumption, portability and deployment time, wind resistance, navigation and autonomy, safety measures, payload capacity, suppression effectiveness, communication range and quality, sensor resolution, scalability, cost-effectiveness, environmental impact, human-robot interaction, system reliability, and redundancy, among others.

3.4. System-level synthesis

System-level synthesis is the step in which the abstract concepts and requirements are turned into a feasible architecture for implementation. It includes establishing relationships among system elements and forming an initial system configuration to satisfy system requirements, even if such a configuration is not final and could be expected to undergo significant changes as the design matures [60]. This section proposes a possible swarm composition and defines the functional relationships among the WER system elements.

3.4.1. Swarm composition

The proposed UAV swarm must be capable of carrying out WER missions autonomously, without direct human intervention other than having a human in the loop. However, a singular UAV type may be inadequate for the varied demands of different WER operations. For instance, heavy-lift UAVs may not be suitable for long-range inspection missions, while fixed-wing UAVs—with higher wind resistance than multi-rotors—prove more reliable for monitoring fire fronts and operations near visible plumes [80]. Although there is research on the use of heterogeneous swarms, the original idea of swarm intelligence and swarm robotics is that agents are quasi-identical so that intelligence emerges from the interactions among similarly capable individuals in a massively redundant system (no single point of failure). Thus, single individuals are disposable with a graceful degradation of system performance. Likewise, UAVs may be incorporated to the swarm to enhance its performance, even during operations (scalability). Therefore, we propose the WER system to have at least one quasi-homogeneous swarm composed of quasi-identical fixed-wing UAVs for tasks such as long-range monitoring, and one quasi-homogeneous swarm composed of quasi-identical multi-rotors for tasks such as fire suppression and precision deliveries. Although the spirit of swarm robotics is to make use of numerous relatively inexpensive robots, certain tasks may require a trade-off between many small and few heavy-lift UAVs. Hence, the multi-rotor swarm could potentially be split into one swarm of light-weight and another of heavy-lift multi-rotors for different tasks. There may—and usually will—be information exchanged between swarms, but they will not self-organise to collaboratively perform a given task (i.e. they will not conform a single heterogeneous swarm). The preliminary proposed composition includes (*i*) swarm of fixed-wing UAVs for long-range and long-endurance reconnaissance and monitoring missions; (*ii*) swarm of small to medium-size multi-rotors for local monitoring tasks as well as for supporting or performing fire suppression (e.g. autonomous suppression or ignition of prescribed fires or backfires); and (*iii*) swarm of heavy-lift multi-rotors for supporting or performing fire suppression and equipment delivery missions (e.g. to support and protect firefighters). Heavy payloads requirements may also be met by means of collaborative transport using only relatively small multi-rotors, thus making use of only two swarms at the expense of adding complexity to the system. Figure 6 shows different tasks to which each of these swarms could be assigned.

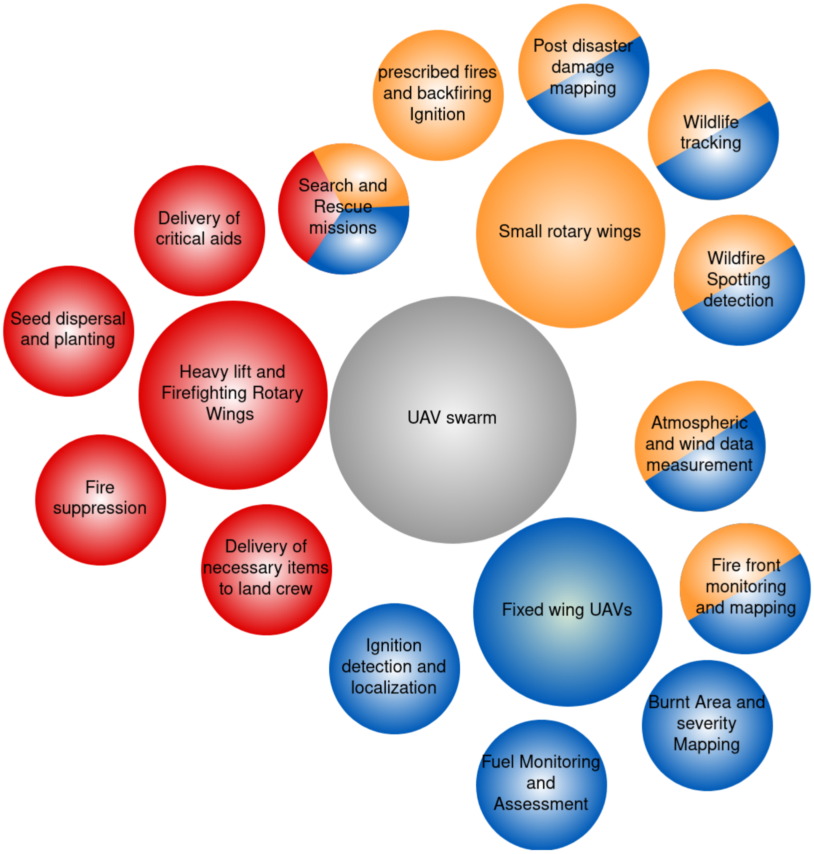


Figure 6: WER missions to which each of the three proposed UAV swarms could be assigned.

3.4.2. Potential UAV selection

A product planning matrix known as the *House of Quality* (HOQ) or the *Quality Function Deployment* (QFD) may be used to relate stakeholders' requirements to lower-level technological specifications that will meet them [115]. QFD is generally a planning process that uses a quality approach to designing, developing, and implementing new products while considering the needs and their importance levels to the customer. It is a widely used method in industry, which numerous companies active in the automotive, ship-building, electronics, aerospace, utilities, leisure and entertainment, financial, software, and other sectors have used with great success [115]. The Voice of the Customer (VOC) is the term used to describe the process of determining customer requirements. The other side of the QFD coin is called the Voice of the Organisation (VOO), which assesses whether the business can meet the customers' needs under the current conditions by conducting a gap analysis of the team and the process to evaluate the company's capabilities. However, this can easily be translated into *how questions* or Technical Performance Measures (TPMs). The first step is to form a planning matrix that outlines the relative importance of every requirement to be met. The next step is to identify the level of relationships between customer requirements and engineering specifications (i.e., TPMs) [115].

Three homogeneous swarms composed of different UAV types will be used to perform different tasks in the WER (see Section 3.4.1). The requirements, their level of importance, and the relationship between different TPMs and those requirements will be different for each swarm. Therefore, three QFD matrices are formed and presented in Tables 2–4. The top row of the QFD matrix consists of potentially relevant TPMs. The middle section provides the relationships between customer requirements and these TPMs, with zero representing no relationship and nine representing a strong relationship in this example. The sum of the product of the customer requirement importance and the relationship value then returns the importance value for each TPM. The relative importance yields the weighting importance matrix for each TPM, which is then used in the UAV ranking. It is worth mentioning that all importance levels and the values

Table 2
Long-range monitoring UAV HOQ.

		TPMs											
Customer requirement	Importance level	Flight time	Cruise speed	Maximum wind resistance	Cost	Payload capacity	Autonomy level	Collision avoidance	Max Temperature	Communication range	Uav mass	UAV volume	Multi sensors
portability	3	0	0	0	0	0	0	0	0	0	9	9	0
Fast Deployment	0	0	0	0	0	0	0	0	0	0	6	6	0
High resolution data	9	0	0	0	6	3	0	0	0	6	0	0	9
Day and Night operation	9	0	0	6	6	6	9	6	3	0	0	0	9
Controllability	9	0	0	3	3	0	6	6	0	3	3	3	6
Safety	6	0	0	6	6	0	6	9	3	0	0	0	6
Cost effectiveness	6	6	0	3	9	3	0	3	3	0	3	3	9
Long time flight	9	9	9	6	0	0	3	3	0	3	0	0	0
name Long range flights	9	9	6	6	0	0	9	6	0	6	0	0	0
Distster monitoring and assessment	6	6	6	3	0	0	0	6	0	0	0	0	6
	Importance weight	234	171	261	225	99	279	297	63	162	72	72	342
	Relative Importance weight	0.103	0.075	0.115	0.099	0.043	0.123	0.130	0.028	0.071	0.032	0.032	0.150

Table 3
Small monitoring and response rotary-wing UAV HOQ.

		TPMs											
Customer requirement	Importance level	Flight time	Cruise speed	Maximum wind resistance	Cost	Payload capacity	Autonomy level	Collision avoidance	Max Temperature	Communication range	Uav mass	UAV volume	Multi sensors
portability	3	0	0	0	0	0	0	0	0	0	9	9	0
Fast Deployment	3	0	0	0	0	0	0	0	0	0	6	6	0
High resolution data	9	0	0	0	6	3	0	0	0	6	0	0	9
Day and Night operation	9	0	0	6	6	6	9	6	6	0	0	0	9
Controllability	9	0	0	3	3	0	6	6	3	3	3	3	6
Safety	6	0	0	6	6	0	6	9	9	6	0	0	6
Cost effectiveness	6	6	0	3	9	3	0	3	6	0	3	3	9
temperature resilience	6	9	9	6	0	0	3	3	9	0	3	3	0
Carrying dragon balls	9	9	6	6	0	6	9	6	6	6	6	6	0
Disaster monitoring and assessment	6	6	6	3	0	9	0	6	6	6	0	0	6
	Importance weight	207	144	243	225	207	270	288	315	207	162	162	342
	Relative Importance weight	0.075	0.052	0.088	0.081	0.075	0.097	0.104	0.114	0.075	0.058	0.058	0.123

Table 4
Heavy-load response rotary-wing UAV HOQ.

		TPMs											
Customer requirement	Importance level	Flight time	Cruise speed	Maximum wind resistance	Cost	Payload capacity	Autonomy level	Collision avoidance	Max Temperature	Communication range	Uav mass	UAV volume	Multi sensors
portability	3	0	0	0	0	0	0	0	0	0	9	9	0
High resolution data	9	0	0	0	3	3	3	3	0	6	0	0	9
Day and Night operation	9	0	0	0	6	6	9	9	9	0	0	0	9
Controllability	9	0	0	6	3	0	3	3	3	3	3	3	6
Safety	6	0	0	6	6	0	9	9	9	6	0	0	6
Cost effectiveness	3	0	0	3	9	3	6	6	0	0	3	3	9
temperature resilience	9	0	0	0	0	0	0	0	9	0	3	3	9
Carrying Heavy payloads	9	9	0	6	9	9	0	0	0	0	6	6	0
Participation in fire Suppression	9	9	6	6	9	9	9	9	9	6	6	3	6
Participation in Emergency Recovery	6	9	6	3	9	9	9	9	0	6	6	3	6
	Importance weight	216	90	225	387	306	342	342	324	207	234	189	450
	Relative Importance weight	0.065	0.027	0.068	0.117	0.092	0.103	0.103	0.098	0.063	0.071	0.057	0.136

that represent the relationship between individual TPMs and customer requirements are estimations, which might not be necessarily accurate.

The importance of TPMs may vary based on the specific function and the corresponding stakeholders' requirements for each task. An example is shown in Table 5 for the three types of UAVs discussed before. The QFD approach is used to determine the relative importance of each TPM, which may be used to design a system tailored to the requirements or to choose from commercially available options.

Even though there is ongoing work on the development of solutions such as UAV-based monitoring systems to support WER, they are still mainly in research and development stages and typically use frameworks tailored to their operational needs. As a result, public access to the specs is limited. Alternatively, a list of commercial off-the-shelf frameworks manufactured by different companies for use in precision farming, land mapping, and/or other activities may be used instead (see Tables 6–8), although they may lack high-temperature resistance.

Table 5
Example of importance level of requirements for three different tasks or UAV types during a WER.

Requirement	Importance level from stakeholders'/customers' point of view: Long-range reconnaissance fixed-wing UAVs	Small multi-rotors for local monitoring and/or fire suppression	Heavy-lift multi-rotors for fire suppression and/or equipment deliveries
Portability	3	3	3
Fast deployment	0	3	0
High resolution data	9	9	9
Day and night operation	9	9	9
Controllability	9	9	9
Safety	6	6	6
Cost effectiveness	6	6	3
Long-time flight	9	0	0
Long-range flight	9	0	0
Disaster monitoring and assessment	6	6	0
Temperature resilience	3	6	9
Carrying dragon balls	0	9	9
Participation in fire suppression	0	6	9
Participation in emergency recovery	0	0	6

Table 6
Potential alternatives for long-range aerial imaging UAVs.

UAV type	Flight Range (km)	Data link range (km)	Max Endurance (hours)	Maximum payload (kg)	Cruise Speed (km/h)	Maximum windspeed (m/s)	Maximum temperature (deg celcius)	Camera resolution (megapixel)	weight (kg)	UAV Length	Wing span	Price (£)
WingtraOne Gen II	60	10	1	0.8	58	18	40	42	3.7	0.68	1.25	25.5k
Atmosuav Marlyn	50	7	0.83	1	65	15	40	61	5.7		1.6	26k
AgEagle eBee X	37	8	1.5		70	12.8		24	1.6		1.16	20k
deltaQuad Pro Map	120	150	2	1.2	65	14	45	42	5	0.9	2.35	17k
Quantum Systems Trinity F90+	100	7.5	1.5	1	61	12	50	42	4.5		2.4	19k
Delair UX11	53	160.934	1.33	0.2	54	12.5	49	21	1.6	0.75	1.2	15k
Boeing-Insitu ScanEagle	1500	100	20	5	148.2		49			3.1	1.7	2.64M
SkyRobot FX450	2500	2500	20	30	125		55		100	4.1	7.2	
Stalker VXE30	432.914	160.934	4	2.5	93		49		20	2.6	4.9	

Table 7
Potential alternatives for small monitoring and response rotary wing UAVs.

UAVs	Max air speed (km/hr)	Max Endurance (mins)	Communication Range (km)	Max Wind speed (m/s)	Max payload (kg)	weight (kg)	MTOW (kg)	Max Temperature	folded volume (m^3)	Price (£)
DJI Mavic 3 Enteprise	75	45	15	12	0.1	0.92	1.05	40	0.0019	4800
Yuneec Typhoon H +	70	25	1.6	15			2.1	40	0.0700	2100
Autel robotics evo ii (Dual 640T)	72	35	15	20			2	40	0.0030	4600
Parrot Anafi USA	53	32	3.99	14.7	0.15	0.5	0.65	50	0.0020	7800
DJI Matrice 30T	83	41	15	12		3.77	4.1	50	0.0150	8500
FreeFly Alta X	95	50	3.2		15	11	34.86	50	0.2977	23000
DJI Matrice 600	65	35	5	8	5.5	9.6	15.1	40	0.2321	5000
Acecore Neo x8	91	25	10	20	9	7.3	16.3	50	0.3651	33000
Vulcan UAV D7	80	40		13.4112	10	14	40	35		

The *Technique for Order Preference by Similarity to the Ideal Solution* (TOPSIS) method is used here to rank M off-the-shelf alternatives $A_i (i = 1, 2, ..., M)$ based on N criteria $C_j (j = 1, 2, ..., N)$. The relative significance of each criterion for ranking alternatives is presented through a weighting vector $W_j (j = 1, 2, ..., N)$. The performance ratings for all alternatives against each attribute form a decision matrix (X) [116]:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2N} \\ \dots & \dots & \dots & \dots \\ x_{M1} & x_{M2} & \dots & x_{MN} \end{bmatrix}. \tag{1}$$

The core idea is that the optimal solution is the one that is farthest from the negative ideal and closest to the positive ideal. An overall index derived from the separations between the ideal solutions and the alternatives is used to rank

Table 8
Currently available UAV platforms potentially suitable for amidst-fire response and post-fire recovery phase.

UAV model	type	Max air speed (km/hr)	Max Endurance time With payload (min)	Communication range (km)	Max Wind speed (m/s)	payload	weight (kg)	MTOW (kg)	Max Temperature	Folded Volume M^3	max speed (km/hr)	price (£)
Aeronavics SkyJib	eight-motor coaxial multi-rotor	90	45			7		24			90	
Aeronavics ICON	eight-motor coaxial multi-rotor	100	20			25		50			100	
DJI Agras T40	eight-motor coaxial multi-rotor	36	6	5	6	51	50	101	50	0.71	36	$26K+
DJI Agras T30	eight-motor coaxial multi-rotor	36	7.8	5	8	40	26	78	45	0.67	36	£23k+
Hylio AG-272	octocopter		10			68						£65k
Hylio AG-230	octocopter		10			30						£37k
DH- S.L. WILD HOPPER	octocopter- thermal engines		30			600						~£220K
DH- S.L-agro hopper	hexacopter	90	10		11	16	24.5				90	
Vulcan UAV D8	eight-motor coaxial multi-rotor	80	40		13.4	25	16	55				

them. The first stage in TOPSIS is to normalise the X matrix using the following equation:

$$y_{ij} = x_{ij} \cdot \left(\sum_{i=1}^{M} x_{ij}^2 \right)^{-1/2}. \tag{2}$$

This is then multiplied by the weighting vector to form the weighted-normalised decision matrix (V) in Eq. (3). That is to say that $v_{ij} = W_j \cdot y_{ij}$, where $i = 1, 2, ..., M$ and $j = 1, 2, ..., N$.

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1N} \\ v_{21} & v_{22} & \dots & v_{2N} \\ \dots & \dots & \dots & \dots \\ v_{M1} & v_{M2} & \dots & v_{MN} \end{bmatrix} \tag{3}$$

The positive and negative ideal solutions are:

$$A^+ = \left[v_1^+, v_2^+, v_3^+, ..., v_N^+ \right] \quad \text{and} \quad A^- = \left[v_1^-, v_2^-, v_3^-, ..., v_N^- \right] \tag{4}$$

where v_j^+ and v_j^- are selected as in Eqs. (5) and (6).

$$v_j^+ = \begin{cases} \max v_{ij} & \text{for benefit type attributes} \\ \min v_{ij} & \text{for cost type attributes} \end{cases} \tag{5}$$

$$v_j^- = \begin{cases} \min v_{ij} & \text{for benefit type attributes} \\ \max v_{ij} & \text{for cost type attributes} \end{cases} \tag{6}$$

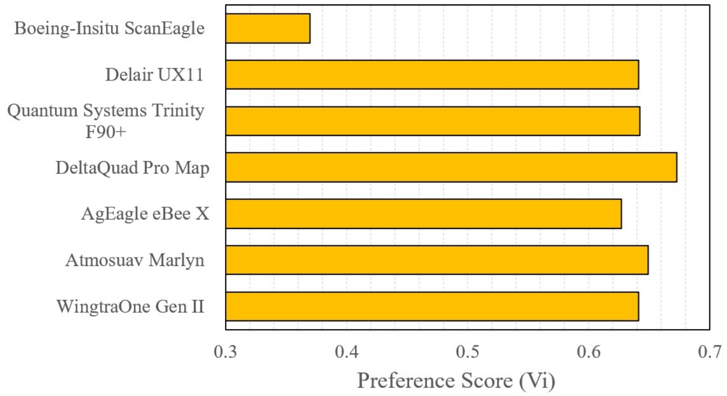
The next step is to calculate the Euclidean distance of each alternative from the positive and negative ideal solutions:

$$S_i^+ = \sqrt{\sum_{j=1}^{N} (v_{ij} - v_j^+)^2} \quad \text{and} \quad S_i^- = \sqrt{\sum_{j=1}^{N} (v_{ij} - v_j^-)^2}. \tag{7}$$

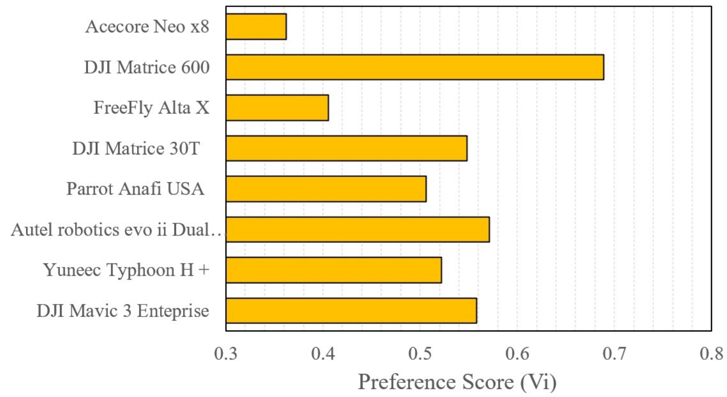
Finally, the overall preference score (V_i) for each alternative A_i is obtained and then used to rank the alternatives:

$$V_i = \frac{S_i^-}{S_i^- + S_i^+}. \tag{8}$$

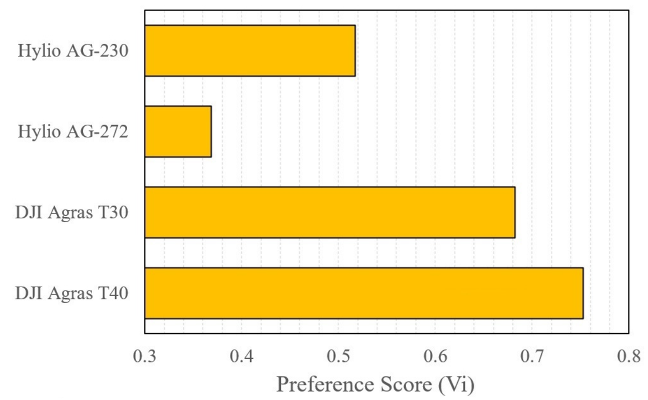
As an example, the TOPSIS method was applied to rank UAVs based on stakeholders' specifications and requirements weights from the QFD method, resulting in the preliminary selection of the DelatQuad Pro-Map for long-endurance/long-range monitoring tasks. DJI Matrice-600 and DJI Agras-T40 are potential selections for small and heavy-lift multi-rotors, respectively (see Fig. 7). All alternatives assume the same autonomy and collision avoidance capabilities, with missing values of TPMs filled with the minimum value of that TPM from other alternatives as a conservative assumption.



(a) Long-range aerial imaging UAVs.



(b) Small monitoring and response rotary wing UAVs.



(c) Heavy-lift response UAV platforms.

Figure 7: preference scores calculated for potential off-the-shelf alternatives for different types of UAVs in the swarm

It should be noted that the maximum endurance and flight range of the DeltaQuad is limited to 2 h and 120 km in ideal conditions, which exceeds what is achievable in a real wildfire. This suggests that multiple UAVs are required to ensure continuous area coverage, leading to increased expenses in terms of purchase and maintenance. Nonetheless, these costs remain considerably lower than those associated with military UAVs like ScanEagle or SkyRobot. Similar constraints are applicable to alternatives considered for smaller and heavy-lift multi-rotors in the preliminary swarm selection. Consider, for instance, the DJI Agras T40, identified as the top commercially available option for heavy-lift firefighting UAVs. This model offers a mere six-minute flight time when carrying its maximum payload. Furthermore, its maximum safe temperature and wind speed for operational conditions are limited to 50 °C and 6 m/s, respectively, which are significantly lower than those encountered during a wildfire event. Consequently, it can be inferred that existing commercially available alternatives for a heavy-lift response UAV require substantial enhancements in terms of resilience to temperature, endurance, and range before they can effectively contribute to a WER system.

3.4.3. Functional relationships

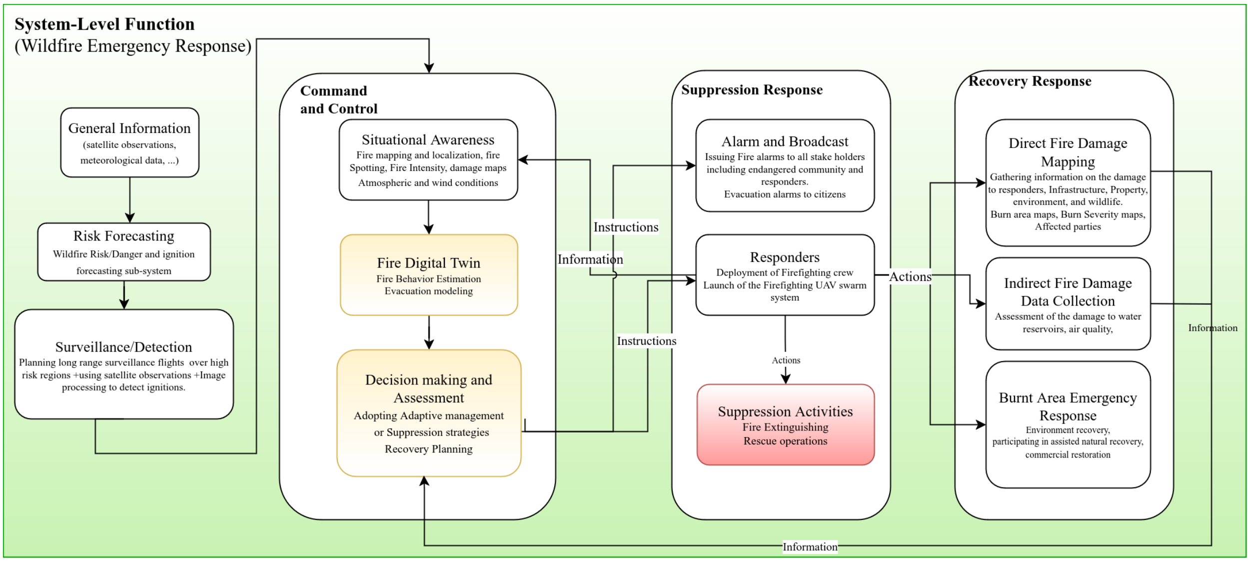
The UAV swarm system will perform various functions to support the safety of human firefighters, shelter seekers, and other stakeholders. These may include reconnaissance, search and rescue, fire front monitoring, environmental data collection, data transmission for analysis and decision-making assistance, fire suppression, and delivery of critical supplies and equipment. Additionally, it may support post-fire damage assessment and emergency environmental recovery efforts. Fig. 8 shows the functional process of the system's operational activities.

The operational process of the system typically commences with the onset of the wildfire season. At this stage, initial wildfire risk and danger estimations are made using satellite data and meteorological information. Next, long-range surveillance flights are planned using fixed-wing UAVs equipped with high-resolution cameras. They aim to identify potential ignition points in high-risk areas early, before the fire spreads. Confirmation flights and observations from other UAVs enhance accuracy, and reports from the public and/or other sources contribute to the reliability of the assessment. A detailed analysis of the fire's extent and conditions follows, considering factors like fire intensity, rate of spread, fuel conditions, and environmental variables. This data is crucial for maintaining situational awareness for the CCC, and for creating a digital twin of the fire to predict its behaviour, plan its suppression (required amount of suppressant, swarm size, suppression strategies), and design potential evacuation plans. While the CCC assigns tasks to the UAV swarm and other response teams, the swarm must operate autonomously (with a human in the loop) exchanging information with the fire digital twin. The latter is continually updated, enabling precise predictions of fire behaviour. The UAV swarm receives instructions from a central hub, minimising human intervention. Management decisions are made in the CCC, ensuring coordinated operation.

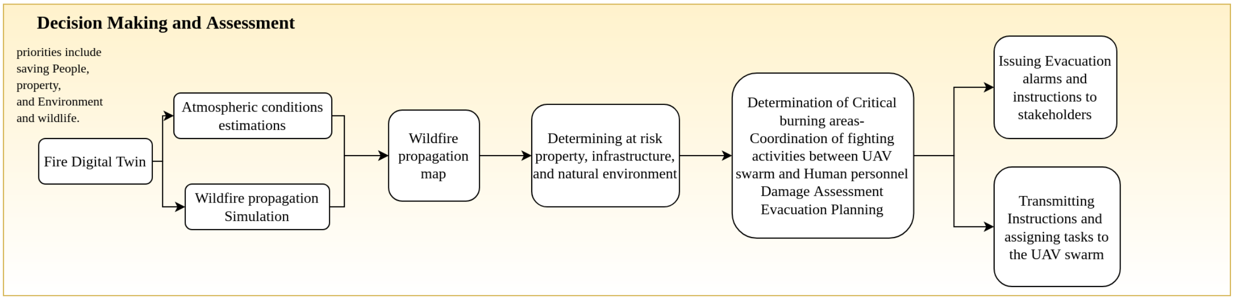
Emergency stabilisation is the top priority following a fire to save individuals, property, or natural resources [47]. The recovery response starts immediately after the fire is suppressed. In this phase, the UAV swarm would normally be responsible for carrying out high-resolution imagery and measurements of the burned area, and for delivering the information gathered to the CCC. This would then be used to provide accurate estimations of damage to infrastructure, property, wildlife, natural environment (e.g. soil and water bodies), and to construct burned area and burn severity maps to aid the design of emergency stabilisation programs and environmental recovery plans. The same swarm may be used for ecological recovery plans by planting seed pods and seedlings in vast areas within a short timeframe.

3.5. System design review

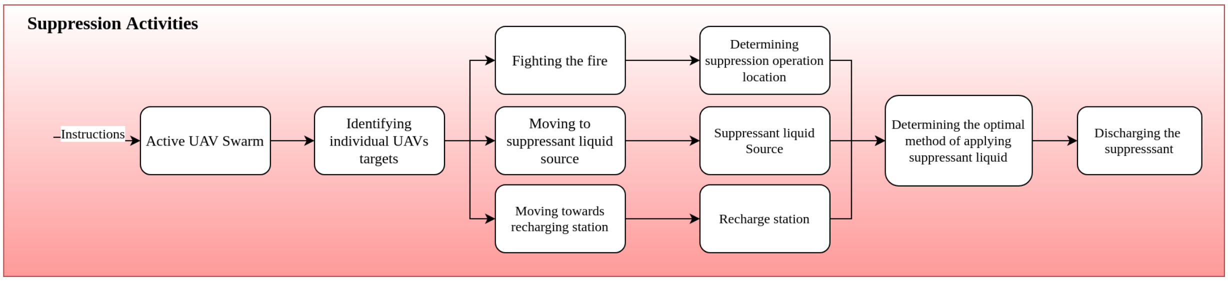
The System Design Review (SDR) aims to (i) provide a formal evaluation of the conceptual design against specified requirements, (ii) communicate the intended design approach to key stakeholders, (iii) offer a platform for addressing and resolving interface issues, and (iv) document design decisions and approvals. Additionally, it aims to examine whether all requirements are fulfilled by the preliminary system architecture established during the system-level synthesis [60]. For example, the SDR should confirm that the system is feasible and would significantly improve the quality and effectiveness of the WER system, reducing the damage caused to the natural habitat, facilities, local properties, and infrastructure, and minimising human casualties. This would fulfil requirements of insurance companies, authorities such as forest management services, land owners, and the natural environment. With regards to the potential selection of UAVs in Section 3.4.2, the cost-effectiveness of UAVs was addressed by means of a multi-criteria decision-making process. A series of requirements such as those involving safety mechanisms, sensor fusion, autonomy units, and high-level swarm control algorithms can be progressively addressed as the design matures.



(a) System level functional description.



(b) Decision-making and assessment component level.



(c) Suppression activities component level.

Figure 8: Functional description of and relationships within the WER system.

4. Conclusions

The upward global trend in the frequency and intensity of wildfires during the past decades results in serious consequences for both natural and built environments, including the degradation of natural habitats, air and water pollution, destruction of cities, and human deaths. Governments have attempted to establish fire suppression strategies and plans to limit the extent and span of these losses. However, prohibitive wildfire suppression costs hinder these efforts. With current technological advancements, UAVs have been progressively adopted in WER due to their relatively low acquisition and operational costs coupled with unrivalled capabilities. Adding to these, the use of swarms instead of individual UAVs not only increases efficiency but also enables them to undertake more complex tasks by way of collaboration, empowered by their emergent swarm intelligence. UAV swarms hold the potential to transform WER by enhancing situational awareness and decision-making through real-time monitoring of wildfire conditions. Additionally, they can provide assistance in—and even autonomously perform—search and rescue and fire suppression operations effectively and efficiently, supporting firefighters, stranded people, and operation managers.

This paper made use of a systems engineering approach for the conceptual design of a WER system empowered by UAV swarms. It first provided a general overview of the current state of WER strategies and actions, including fire detection, danger forecasting, fire suppression, and emergency recovery response, as well as the state of the art in the use of UAVs in different WER phases. It was argued that, despite their evident practical usefulness, the use of UAVs is inconsistent and unstructured—often arbitrary—therefore failing to leverage their full potential, especially with regards to the emergent capabilities of swarm systems.

In order to address the diverse requirements involved in a WER operation, the use of two or three (potentially interacting) homogeneous UAV swarms was recommended, each composed of one type of UAV: (*i*) fixed wings for long-endurance monitoring, (*ii*) small multi-rotors for monitoring, autonomous suppression, and deliveries of essential supplies (e.g. by collaborative transport), and (*iii*) heavy-lift multi-rotors for fire suppression and deliveries of heavy payloads. Additionally, we applied the QFD method to relate system requirements with its technical specifications, and a multi-criteria decision-making method (TOPSIS) for the UAV selection among commercially available ones.

Thus, this paper provided some guidelines and structure for the systematic preliminary design of UAV swarms to enhance WER systems.

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CRediT authorship contribution statement

Mohammad Tavakol Sadrabadi: Conceptualization, Investigation, Methodology, Writing. **Joaquim Peiró:** Conceptualization, Investigation, Methodology, Writing. **Mauro Sebastián Innocente:** Conceptualization, Investigation, Methodology, Writing. **Guillermo Rein:** Conceptualization, Investigation, Methodology, Writing.

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