SOScheduler: Toward Proactive and Adaptive Wildfire Suppression via Multi-UAV Collaborative Scheduling

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***Abstract*—Multiunmanned aerial vehicle (UAV) systems have shown immense potential in handling complex tasks in large-scale, dynamic, and cold-start (i.e., limited prior knowledge) scenarios, such as wildfire suppression. Due to the dynamic and stochastic environmental conditions, the scheduling for sensing tasks (i.e., fire monitoring) and operation tasks (i.e., fire suppression) should be executed concurrently to enable real-time information collection and timely intervention of the environment. However, the planning inclinations of sensing and operation tasks are typically inconsistent and evolve over time, complicating the task of identifying the optimal strategy for each UAV. To solve this problem, this article proposes *SOScheduler*, a collaborative multi-UAV scheduling framework for integrated sensing and operation in large-scale and dynamic wildfire environments. We introduce a spatiotemporal confidence-aware assessment model to dynamically and directly pinpoint locations that can optimally enhance the understanding of environmental dynamics and operational effectiveness, as well as a priority graph-instructed scalable scheduler to coordinate multi-UAV in an efficient manner. Experiments on real multi-UAV testbeds and large-scale physical feature-based simulations show that our *SOScheduler* reduces the fire expansion ratio by 59% and enhances the fire coverage ratio by 190% compared to state-of-the-art (SOTA) solutions.**

***Index Terms*—Autonomous aerial vehicles, multirobot systems, robot sensing systems.**

I. Introduction

WILDFIRES pose a significant threat to human life and cause devastating destruction of homes, infrastructure, and wildlife habitats [1], [2], [3], [4]. For example, the 2020 wildfires in California burned over 4 million acres of land and destroyed thousands of homes, causing billions of dollars in damages [5], [6], [7]. What is even worse, wildfires also release large amounts of carbon dioxide and other pollutants into the atmosphere, leading to climate change and air quality deterioration [8], [9]. The long-term effects of wildfires can lead to soil erosion, loss of biodiversity, and water pollution [10]. Therefore, quick and effective wildfire suppression is crucial to protect the health and safety of human beings and preserve natural ecosystems.

However, conventional fire-fighting methods are not able to provide quick and effective wildfire suppression to *large-scale* and *dynamic* wildfires due to the following reasons. First, the mobility of firefighters is insufficient for expansive areas, especially when hindered by heavy equipment, resulting in a slower pace than the advancing fire [11], [12]. Second, challenging terrain often impedes ground access to fire sites, hindering real-time assessment for effective suppression strategies [13]. Finally, while manned aircraft offer speed, they are labor-intensive and high cost which constrain dense deployment for large-scale firefighting [1].

Fortunately, unmanned aerial vehicle (UAV) shows immense potential in the complex wildfire scenario [12], [14], [15]. First, UAVs are highly mobile and agile, allowing them timely access to different areas of large spaces, especially areas that may be difficult or dangerous for firefighters to reach [16], [17]. Second, equipped with various sensors, such as high-resolution cameras and thermal imaging equipment, UAV swarm can capture real-time information, such as fire location, size, shape, and intensity, supporting the identification of potential hotspots and the allocation of firefighting resources [18], [19]. Third, UAVs are cost-effective compared to traditional manned aircraft, which allows the deployment of multi-UAV systems for the increasing area and complex tasks.

By fully embracing the new advantages brought by UAVs, current innovations explore the collaborative scheduling of multi-UAV for enhancing wildfire management in challenging scenarios [4], [20], [21], [22], [23], [24], [25], [26], [27]. These works mainly treat wildfire monitoring and suppression as two independent entities for scheduling.

1) Most research efforts are dedicated solely to scheduling for wildfire detection or monitoring and mainly aim at maximizing fire coverage [23], [24], [25]. These

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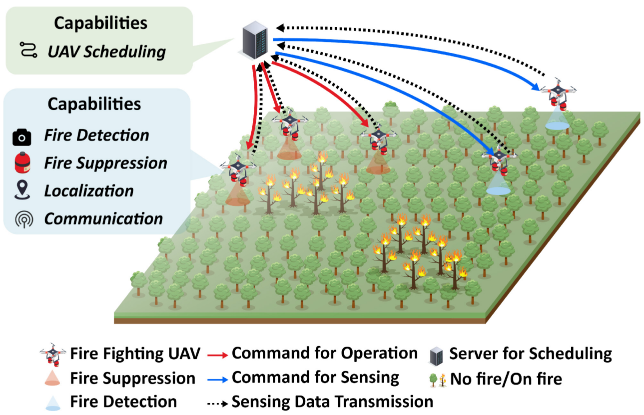


Fig. 1. Illustration of scheduling multi-UAV for wildfire suppression. The server integrates data from all UAVs and sends scheduling commands to UAVs for fire monitoring and suppression simultaneously.

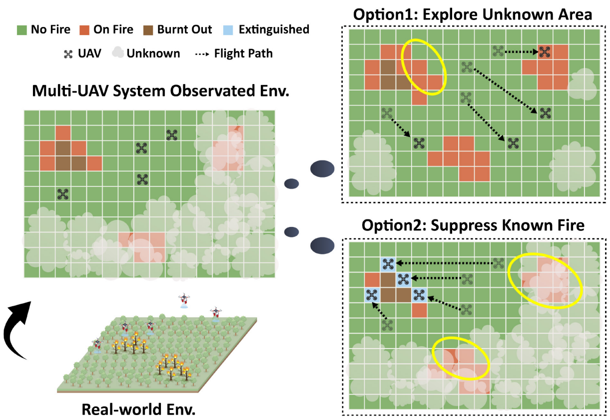


Fig. 2. Illustration for inconsistent goals and different results of scheduling for monitoring and suppression. The yellow circle highlights the fire expansion.

approaches generally necessitate a follow-up fire suppression operation based on gathered information, which often leads to a delayed response in dynamic situations.

2) A few studies explore planning for wildfire suppression (e.g., dispersing fire retardant) with multiple robots [21], [26], [27]. These studies, however, typically rely on an accurate, deterministic environmental model (e.g., an enlarging elliptical perimeter) or they assume complete observation of the environment. Unfortunately, such ideal conditions are seldom present in large-scale situations.

3) The advanced data-driven methods, such as reinforcement learning (RL) [22] could serve as an all-in-one scheduling solution. However, these learning-based methods are prone to major drawbacks, such as scalability and domain shift problems, which hinder the real application in safety-critical firefighting scenarios [23].

As dynamic environmental conditions, like wind, could shift the size, position, and shape of the fire unpredictably, certain areas within the operational environment exhibit unpredictability during specific periods, necessitating reobservation of these regions when their status is uncertain. Therefore, the scheduling for wildfire monitoring and suppression tasks should be executed concurrently – If monitoring is not sufficiently comprehensive, the operation may not be optimally positioned for effective fire-extinguishing actions. In contrast, a lack of adequate suppression could potentially cause the fire dynamics to escalate.

Our Work aims to devise an effective strategy for the collaborative scheduling of multiple UAVs to concurrently execute wildfire monitoring and suppression within *large-scale* and *dynamic* wildfire environments, as shown in Fig. 1. Particularly, we focus on *cold-start* situations where a limited number of UAVs, deployed for emergency tasks, typically possess minimal prior knowledge about the environment. However, realizing the idea is nontrivial and faces two grand challenges.

1) *Divergent Goals of Monitoring and Suppression Scheduling (C1):* Monitoring-oriented scheduling seeks to obtain comprehensive data to enhance the accuracy of environmental dynamics prediction. In contrast, suppression-oriented scheduling aims to optimize resource utilization based on current information. However, the number of UAVs is limited and their sensing and suppression resources are constrained, this gives rise to a decision-making challenge. As illustrated in Fig. 2, sensing-oriented scheduling necessitates the UAV to explore uncertain regions and gather fresh data about fires, while suppression-oriented scheduling urges it to move toward the currently estimated fire boundary to dispense fire extinguishing balls. These divergent planning inclinations also evolve over time, complicating the task of identifying the optimal strategy for each UAV. Achieving a good tradeoff demands a meticulous analysis of their relationship and the quantification of potential gains, a task that poses significant challenges.

2) *Spatiotemporal High-Dimensional Decision Space Impair Scheduling Efficiency (C2):* The large-scale property of environments intensifies spatial complexity in scheduling decision space while the dynamic nature, on the other hand, expands the temporal complexity. Specifically, large-scale environments necessitate high-resolution spatial data for informed decision making. Additionally, the swiftly changing conditions demand forward-thinking planning, which expands the search space along the temporal dimension. The involvement of multiple UAVs further exacerbates this issue, leading to exponential growth in the already high-dimensional search space. Collectively, these elements create a spatiotemporal, high-dimensional combinatorial search space. Given these complexities, finding an optimal policy within a limited time slot becomes unfeasible.

To tackle the above challenges, we design *SOScheduler*, a collaborative multi-UAV scheduling framework for integrated wildfire monitoring and suppression by proactively evaluating the wildfire state and adaptively adjusting the collaboration strategy to track the fire front and perform fire suppression simultaneously. *SOScheduler* can integrate existing probabilistic modeling of dynamic environments for other disaster events and further provide efficient and effective emergency response.

To address **C1**, we introduce a *Spatiotemporal Confidence-Aware Assessment* method, which incorporates the potential information decay and quantifies the expected gain of both sensing and suppression action for each location. Subsequently, both measures are integrated to derive a dual-criteria utility function to guide the follow-up scheduling. This method not only breaks away from the assumption of complete observation of the environment but also equips UAV with a quantitative basis that enables them to dynamically and directly pinpoint locations that can best improve fire estimation quality and fire suppression performance.

To address **C2**, we convert the problem of optimal allocation into maximal coverage scheduling problem. Consequently, we devise an efficient *Priority Graph-Instructed Scalable Scheduling* algorithm, which predicts the environment state in the near future to enable nonmyopic planning. We further introduce the sequential allocation scheme to coordinate multi-UAV operations, which effectively reduces the planning complexity from an exponential to a linear scale, while providing a theoretical guarantee for performance. This method ensures that the algorithm is computationally lightweight and can run on resource-constrained edge platforms.

We implement *SOScheduler* and deploy it on a multi-UAV prototype system for evaluation. Extensive experiments were conducted, including a scaled-down (at a ratio of 1:30) lab-based testbed (15 h) and large-scale physical feature-based simulations under varying environmental conditions (500 runs). Evaluation results reveal that our approach reduces the fire expansion ratio (FER) by an impressive 59% while enhancing coverage ratio by 190% when compared with the latest RL-based solutions. Our main contributions are summarized as follows.

1) We design *SOScheduler*, a multi-UAV collaborative scheduling framework that integrates wildfire monitoring and suppression, specifically designed to handle tasks in large-scale and dynamic environments with limited prior information.
2) We develop a spatiotemporal assessment model that contributes to improving understanding of environmental dynamics and enhancing fire suppression effectiveness simultaneously.
3) We devise a scalable, nonmyopic algorithm that significantly reduces the complexity associated with coordinating multiple UAVs in expansive environments while offering a performance guarantee.
4) We validate *SOScheduler* with comprehensive evaluations involving a real-world multi-UAV system and large-scale physical features-based simulations.

The remainder of this article is organized as follows. We first present the related work in Section II, followed by the overview of *SOScheduler* in Section III. The detailed descriptions of the key components and algorithms are shown in Section IV. We further demonstrate the implementation and evaluation of our framework in Section V. Finally, we discuss and conclude *SOScheduler* in Section VI.

II. Background and Related Work

A. Remote Sensing in Wildfire

Remote sensing has been extensively researched in the wildfire assistance field as it allows the observation of wildfires without unnecessarily exposing humans to dangerous activities. Traditional remote sensing tools consist of two methods: 1) satellite and 2) wireless sensor networks (WSNs).

Satellite imagery has long been employed for Earth surface monitoring [28], [29], [30], offering a broad coverage that aids in identifying fire risks and detecting active fires across regions. Despite its utility, this method is hindered by three prominent limitations. First, the spatial resolution of satellite imagery poses a constraint. For instance, a single image from a moderate-resolution satellite, like Landsat, covers an expansive area (approximately 185 km $\times$ 185 km) but with a spatial resolution of only 30 m per pixel. This limitation becomes apparent when attempting to detect small objects or subtle environmental changes. Second, satellites are unable to provide real-time information. This limitation holds significance because the time required for a satellite to revisit the same region introduces instability in continuous monitoring efforts. Real-time responsiveness is crucial in swiftly changing wildfire events, where timely information is paramount for effective response and intervention. Additionally, the ground coverage provided by satellites is inherently limited. Due to their fixed orbits, satellites lack maneuverability and flexibility, making it challenging to monitor rapidly changing wildfire events in a dynamic and responsive manner. As a result, the reliance on satellite imagery for timely and detailed environmental monitoring becomes compromised.

WSNs are proposed for wildfire monitoring but face significant challenges [31], [32], [33]. First, WSN nodes operate on limited battery power, posing sustainability issues in remote areas, where battery replacement or recharging is challenging. This limitation threatens the operational lifespan of sensors, impacting their reliability in wildfire-prone regions. Second, scalability is a major concern. The static installation of sensors in forests results in coverage and resolution directly tied to investment, making deployment costly. Coordinating a large number of sensors also strains the network, affecting the feasibility of comprehensive wildfire monitoring across expansive areas. Additionally, the overall cost of WSN deployment and maintenance is substantial, encompassing sensor acquisition and network establishment. Moreover, during a fire event, the vulnerability of sensors to destruction raises reliability concerns at critical moments.

In summary, the limitations of traditional methods emphasize the need for innovative, real time, and scalable wildfire monitoring solutions. The rising consideration of UAVs for wildfire assistance is explored in the next section.

B. UAV-Based Scheduling System in Wildfire Assistance

1) Goals of UAV-Based Scheduling System: Mitigating the impact of wildfires involves considering various interconnected factors, such as meteorology, drought monitoring, and ongoing forest status assessment. Research in these areas contributes to proactive wildfire prevention and preparedness. For UAV-based systems, two critical elements emerge during a wildfire. The first goal involves real-time monitoring and surveillance of the wildfire's status. This timely information empowers firefighters to anticipate fire behavior and make informed decisions on resource allocation. The second goal is suppressing the wildfire before the arrival of firefighters. Due to the rapid and large-scale nature of wildfires, swift firefighter response is challenging. Implementing immediate suppression measures, like dropping firefighting retardant from UAVs, becomes pivotal. This early intervention can effectively slow or halt the fire's spread until firefighters arrive, preventing further escalation, conserving resources, and reducing the risk to lives.

2) UAV-Based Scheduling System for Wildfire Monitoring: The most common mission in wildfire assistance is wildfire monitoring. The UAV-based system for wildfire monitoring in the existing works could be classified into three types: 1) a single agent for independent planning; 2) a fully distributed method; and 3) a cooperative method. In [34], a planning algorithm based on RL for a single agent is proposed to achieve efficient information collection. Casbeer et al. [25] proposed a distributed system where each agent independently performs its path planning, but this can result in the underutilization of the information collected by multiagent systems. Therefore, cooperative systems have attracted more attention. The system proposed by Haksar et al. [35] involved two UAVs working as a group to exchange information as well as path planning at regular intervals, but this work has limitations as the two interacting UAVs are determined in advance. Our work differs from the previous work in that we have constructed a cooperative system in which multiple UAVs ensemble information periodically to provide real-time fire status prediction, aiming at supporting the autonomous suppression mission which is performed concurrently.

3) UAV-Based Scheduling System for Wildfire Suppression: In contrast to the wildfire monitoring task, little work has been done on UAV-based systems for wildfire suppression. Saikin et al. [36] presented an approach for accurately dropping fire retardant onto a wildfire from UAVs in close proximity to the epicenter of the fire, which validates the effectiveness of autonomous fire suppression. Haksar and Schwager [22] proposed an RL-based algorithm for fire suppression, but these learning-based methods are prone to major drawbacks, such as scalability and domain shift problems, which hinder the real application in safety-critical firefighting scenarios. Thul and Powell [37], Phan and Liu [20], and John et al. [13] proposed multi-UAV solutions for faster detection and mitigation of forest fires, but they assume the UAV has complete information about the environment or adopt over-simplified elliptical wildfire models.

In summary, our work uniquely focuses on scheduling multi-UAV to conduct wildfire monitoring and suppression simultaneously, particularly in cold-start situations where a limited number of UAVs, deployed for emergency tasks, typically possess minimal prior knowledge about the environment. This work can be viewed as a variant of a wireless sensor and actor network (WSAN) [4], [38], contributing to the growing paradigm of the Internet of Things (IoT).

III. Overview

In this work, we seek to schedule a group of UAVs to concurrently execute wildfire monitoring and suppression in large scale and dynamic wildfire environments. In order to facilitate understanding of the process, we first describe our modeling and problem formulation, then we detail *SOScheduler's* architecture.

A. Modeling

1) Environment Model: In order to represent the dynamics and stochastic characteristics of wildfires, we model it by a graph-coupled hidden Markov model (GHMM) with the probabilistic transition functions [27], in which fire state transition is expressed by a stochastic process to capture the uncertainty of fire evolution. Specifically, we consider an environment as a 2-D terrain $\mathbb{Z}^2$ that is discretized into a collection of congruent n_c cells, as shown in Fig. 2. The position of each cell i is represented by p_i. Each cell $i \in \mathbb{Z}^2$ corresponds to a standard HMM with latent state $x_i^t \in \mathcal{X}$ and observation $y_i^t \in \mathcal{Y}$ at time t. In the wildfire scenario, according to [27], the cell state x_i^t is described by one of three discrete values, $\mathcal{X} = \{\textit{healthy/no fire, on fire, burnt}\}$. Note that, this abstraction covers the core characteristic of the wildfire, which is also widely adopted in other works [26], [39]. For simplicity, we denoted the cell state as $x_i^t \in \{H, F, B\}$ in the following sections.

Consider the propagation of fire, the transition probabilities of each cell i are influenced by its neighbor set $\mathcal{N}(i)$, which is defined as a collection of cells that are one unit away in the Manhattan distance

$$\mathcal{N}(i) = \left\{j \mid \left\|p_i - p_j\right\|_1 = 1\right\}. \tag{1}$$

Therefore, the latent state transition distribution for each cell can be expressed as

$$p_i\left(x_i^t \mid x_i^{t-1}, x_{N(i)}^{t-1}\right) \tag{2}$$

where $x_{N(i)}^t = \{x_j^t \mid j \in N(i)\}$ represents the latent state for the neighbors of cell i. Note that, the objective of this article is not to develop a realistic fire wildfire model but to incorporate the stochastic variability of the fire growth. Any probabilistic wildfire models that allow for stochastic variability of the output can be incorporated into our frameworks.

2) UAV Model: We consider a team of UAVs $R = \{r_1, \dots, r_{n_r}\}$ engaged in the mission. Each UAV has two kinds of actions: 1) moving action $\mu_r^t \in \mathcal{U}$ and 2) operation action $a_r^t \in \{0, 1\}$, indicating where to go and whether to conduct fire suppression at time t, respectively. The UAV moves in the environment and obeys the following dynamic:

$$p_r^t = f\left(p_r^{t-1}, \mu_r^t\right) \tag{3}$$

where p_r^t and μ_r^t are the position of UAV r and the control input to the UAV r at time t, respectively.

In the fire suppression scenario, to allow for performing vision observation and active suppression, we assume the UAVs are equipped with the following capabilities.

1) *Fire Detection*: UAVs are equipped with downward-facing vision sensors, such as thermal imaging cameras to provide visual information about the fire status.
2) *Fire Suppression*: UAVs are equipped with a limited number of fire extinguishing balls, and they will drop the balls autonomously (i.e., $a_r^t = 1$) to extinguish the fire area directly beneath it when they locate at fire front.
3) *Localization*: UAVs use GPS receivers and inertial measurement units (IMUs) to localize themselves and navigate to destinations.
4) *Communication*: UAVs transmit data to the edge server and receive action control from it by radio.

Based on these capabilities, UAVs are able to collaboratively localize and navigate themselves above the terrain to search and suppress the fire area.

B. Problem Formulation

The primary goal of *SOScheduler* is to minimize the affected area as much as possible. Therefore, the objective function could be represented as minimizing a desired suppression criterion $U^T(\cdot)$ over a period of mission time T

$$\max_{\mu_{1:n_r}^{1:T}, a_{1:n_r}^{1:T}} \quad U^T\left(x_{1:n_c}^T\right) \tag{4}$$

$$\text{s.t.} \quad b^{t+1} = h\left(b^t, p_{1:n_r}^t, y_{1:n_r}^t, a_{1:n_r}^t\right) \tag{5}$$

$$a_{1:n_r}^t, \mu_{1:n_r}^t = g\left(b^t, p_{1:n_r}^t\right) \tag{6}$$

$$p_r^t = f\left(p_r^{t-1}, \mu_r^t\right) \quad \forall r \in \mathcal{R} \tag{7}$$

$$a_r^t \in \{0, 1\}, \mu_r^t \in \mathcal{U}, x_i^t \in \mathcal{X}, y_i^t \in \mathcal{Y} \tag{8}$$

where $a_{1:n_r}^{1:T}$ and $\mu_{1:n_r}^{1:T}$ represent the actions and moving control for all UAVs from time 1 to T. The detailed form of $U^T(\cdot)$ for fire suppression is shown in (20). Equation (5) represents that the estimation of the environment state b^{t+1} at time $t+1$ is based on the UAVs' historical trajectories and actions from time 1 to t. Equation (6) states that the action strategy $g(\cdot)$ at time t is based on the environment state estimation b^t and the UAVs' position $p_{1:n_r}^t$. Equation (7) states the dynamics of UAVs. Notably, $h(\cdot)$ can be implemented based on the various existing environment models. In this article, we focus on designing the scheduling strategy $g(\cdot)$ based on the environment state estimation, which in turn contributes to improving fire estimation quality and fire suppression performance concurrently.

C. System Architecture

SOScheduler is a collaborative multi-UAV scheduling framework that aims at proactive and adaptive suppressing wildfire in a timely manner. As shown in Fig. 3, we detail its three main modules.

Collaborative Perception & Prediction Model: This component takes the measurement of the environment from multiple collaborative UAVs as input, and then leverages the Bayes Filter to fuse sensing data and estimate the environment state.

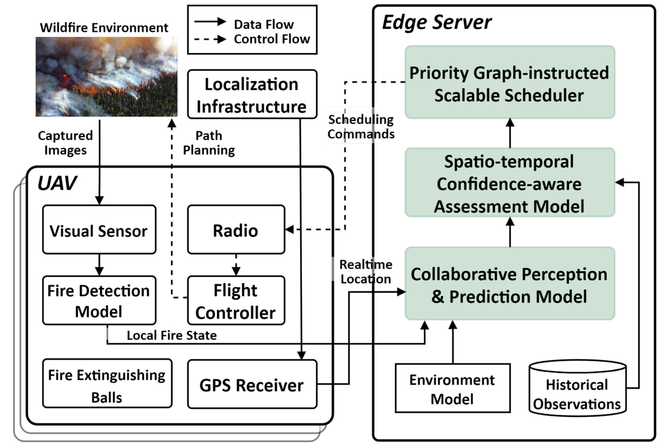


Fig. 3. System architecture of *SOScheduler*.

This module also allows a prediction step to support the nonmyopic planning of UAVs.

Spatiotemporal Confidence-Aware Assessment Model: This component is the core of *SOScheduler*, which introduces a novel utility function to assess the utility of locations based on the predicted environment state. It begins by estimating the sensing gain and operation gain for each location using the predicted environment state. Next, it constructs a confidence map to integrate the sensing gain and operation gain measures into an unified utility function.

Priority Graph-Instructed Scalable Scheduler: This component first constructs a priority graph based on the utility assessment results to facilitate the path search. Next, it provides a sequential allocation scheme to generate collaborative paths for multiple UAVs, which efficiently reduces the computation complexity from exponential to linear.

We describe the workflow of *SOScheduler* as follows. For each communication cycle, our algorithm begins with UAVs receiving the visual sensing data as inputs. After employing existing fire detection processes (e.g., YOLOX [40]), the identified fire states are transmitted to the edge server. Following this, *Collaborative Perception and Prediction Model* integrates all the collected information to predict the global wildfire status in the operational environment at the next time step. This prediction guides *Spatiotemporal Confidence-Aware Assessment Model* in deriving an utility estimation for each location to prioritize the regions. Finally, *Priority Graph-instructed Scalable Scheduling* generates collaborative scheduling commands for multiple UAVs, which are dispatched to the UAVs and executed by their onboard controllers. Notably, the communication content between UAVs and the edge server consists of scheduling commands and abstracted fire states (rather than raw visual sensing data), thus the algorithm only requires low bandwidth and the optimization of communication latency falls outside the scope of this work. A summary of the key procedures at the edge server for the UAVs is presented in Algorithm 1, and the algorithm workflow is illustrated in Fig. 4.

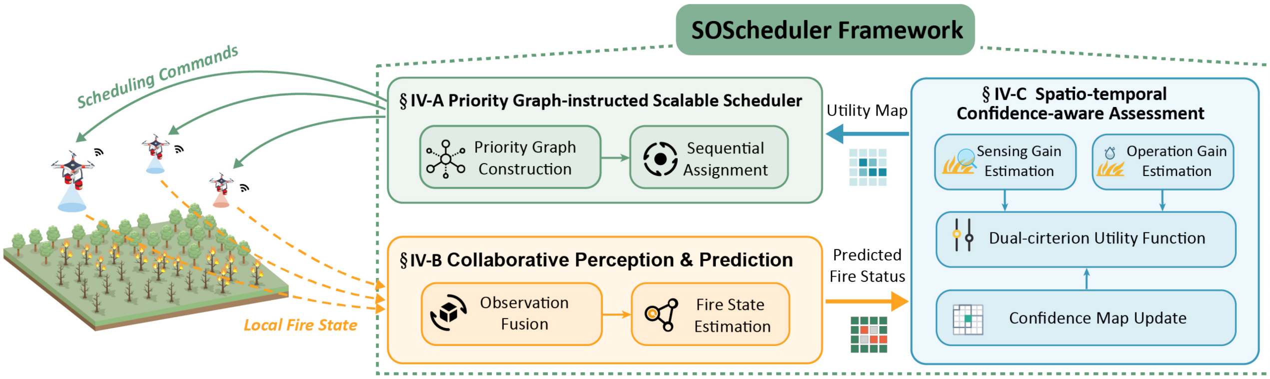


Fig. 4. Algorithm workflow of *SOScheduler*.

Algorithm 1 *SOScheduler* Algorithm

Input: UAV positions $\{p_r^t\}$, belief of fire status $b(x^t)$

Output: Joint action-moving path $\hat{\mathcal{P}^{t+\mathcal{T}}}$ for next time period $\{t : t + \mathcal{T}\}$

Collaborative Perception & Prediction: predict the global fire status $b(x^{t+\mathcal{T}})$ after $\mathcal{T}$ steps based on the gathered local information from all UAVs

Spatio-temporal Confidence-aware Assessment: estimate the utility $u(x_i^t)$ for each cell i based on the predicted fire status

//Priority Graph-instructed Scalable Scheduler

for each UAV in the team **do**

  Path planning: find the collaborative paths $\hat{\mathcal{P}^{t+\mathcal{T}}}$ for all UAVs based on the estimated utility map

end for

IV. System Design

A. Collaborative Perception and Prediction Model

The perception module of *SOScheduler* considers all the information collected by UAVs and uses data fusion technologies to estimate the evolution of the wildfire environment. For each communication cycle, each UAV processes the sensing data and provides the extracted information to the edge server, where the joint estimation takes place.

1) Observation Fusion: Due to various factors, such as occlusion and imperfect detection models, noise and errors are inevitable in measuring the environment status. We consider the overall measurement accuracy with a parameter $0 \leq P_m \leq 1$, which indicates the probability of detection results matching the ground truth state of the cells. The specific value of this parameter hinges on the accuracy of the adopted fire detection model. Consequently, the measurement model of cell i observed by UAV r can be mathematically expressed as

$$p^{[r]}(y_i^t \mid x_i^t) = \begin{cases} P_m, & y_i^t = x_i^t \\ \frac{1}{2}(1 - P_m), & y_i^t \neq x_i^t. \end{cases} \tag{9}$$

We assume each observation is dependent only on the state of the corresponding cell, and noise on the observations is uncorrelated between UAVs. The joint measurement probabilities of the environment are then

$$p(y^t \mid x^t) = \prod_{r=1}^{n_r} \prod_{i=1}^{n_c} p^{[r]}(y_i^t \mid x_i^t). \tag{10}$$

We note that the fusion of multiple observations has been studied extensively [41], and is not the focus of our contribution in this work.

2) Fire State Estimation: For the integration of new information, we update the environment state estimation according to the Bayes' Rule based on the state transition model and the joint measurement model in (10). Let $b(x^t)$ be the belief that represents the environment state estimation conditioned on all historical measurements [i.e., b^t in (5)], then this process can be mathematically expressed as

$$b(x^t) \propto \prod_{i=1}^{n} p(y_i^t \mid x_i^t) \sum_{x^{t-1}} b\left(x^{t-1}\right) \prod_{i=1}^{n} p\left(x_i^t \mid x_i^{t-1}, x_{N(i)}^{t-1}\right). \tag{11}$$

Typically, we have a priori about the coarse position of the initial fire (e.g., satellite remote sensing and residents' alarm), thus $b(x^1)$ can be initialized by setting part of the cells' state with higher probabilities on fire.

B. Spatiotemporal Confidence-Aware Assessment Model

The wildfire's stochastic variation across space and time leads to the fact that UAVs' collected information about the environment becomes partially outdated, thus some locations need to be reobserved when their states become uncertain —a perpetual spatiotemporal task. Given the limitation in the number of available UAVs and the expanding nature of the fire, prioritizing regions that significantly contribute to understanding the environment's dynamics and reducing the time required to suppress the spreading fire becomes imperative. Therefore, our assessment model seeks to answer two critical questions.

1) How to quantify the potential impact of sensing and operation at each location?
2) How to mitigate over-reliance on the employed environment model that typically may not be entirely accurate?

To answer these questions, we first leverage the fire status estimation and the mutual information (MI) tool to quantify the potential contribution of each cell to both objectives, denoted as sensing gain S and operation gain O. We then craft a location-wise confidence map based on UAVs' historical measurements, accounting for the information decay due to a lack of measurement and breaking down over-dependence on the environment model. Finally, we combine the gain estimations with the confidence map into a dual-criterion utility function, more directly determining the locations where they can best improve the model quality and operation performance. Overall, this assessment model not only enables the simultaneous optimization of both sensing and operation but also facilitates policy adjustments at each decision interval according to the environment dynamics.

1) Sensing Gain Measure: Since we aim to infer the environment state from the measurements, we are motivated to schedule the UAVs to locations that maximize the information collected from the environment. This information can be quantified by MI, which is an information-theoretic tool that enables measuring the reduction in expected uncertainty about the environment given the observations.

As such, the sensing gain by moving to each cell in the environment can be represented as the information gain

$$\begin{aligned} S\left(x_i^t\right) &= I\left(x_i^t, y_i^t\right) = H\left(x_i^t\right) - H\left(x_i^t \mid y_i^t\right) \\ &= \sum_{x_i^t}\sum_{y_i^t} p\left(y_i^t \mid x_i^t\right) b\left(x_i^t\right) \log \frac{p\left(x_i^t \mid y_i^t\right)}{b\left(x_i^t\right)} \end{aligned} \tag{12}$$

where $H(x_i^t)$ is the entropy of the environment state and $H(x_i^t \mid y_i^t)$ is the conditional entropy given the new observation.

2) Operation Gain Measure: Given that the ultimate goal is to intervene in the dynamic environment process as soon as possible but the operation resource (i.e., fire extinguishing balls) is limited, it is required to assess the operation gain of each location by leveraging the environment state estimation. In the wildfire scenario, efficient fire suppression necessitates applying fire retardant directly to the time-varying fire front. Therefore, areas with estimated fire front positions are assigned higher operation gains.

The locations of fire front should be in the estimated boundary of the burning area. Let $\kappa(x_i^t) = \operatorname{argmax} b(x_i^t)$ be the maximum likelihood state of cell x_i^t, then we define the boundary of the fire as

$$B\left(x^t\right) = \left\{i \mid \kappa\left(x_i^t\right) = F \wedge \kappa\left(x_j^t\right) = H, \exists j \in \mathcal{N}(i)\right\}. \tag{13}$$

From these boundary positions, the final fire front $\sigma(x^t)$ is obtained by considering the cells of the boundary with high fire probabilities $b(x_i^t = H)$ over a given threshold δ. As such, the operation gain of moving to each cell in the environment can be denoted as

$$O\left(x_i^t\right) = \mathbf{1}\left(i \in \sigma\left(x^t\right)\right). \tag{14}$$

3) Confidence Map Update: When we estimate the sensing and operation gain, some locations are incorporated with infield observation in close proximity, while others rely solely on the environment model's prediction. Intuitively, the former one should have a stronger "confidence" in the predicted gains. Therefore, we provide a confidence value $\lambda(i, t)$ for each target cell i based on two aspects: 1) the spatial distances of historical observations to cell i and 2) the temporal distances of historical observations to cell i. These two aspects can be formally combined and defined as

$$\Omega(i, t) = \sum_{j=1}^{n} \mathcal{N}\left(\left(t_{\text{now}} - t_j\right)\left|p_j - p_i\right|; 0, \sigma\right) \tag{15}$$

where t_{now} is the current time and t_j is the time cell j was final observed. $|p_j - p_i|$ is the Chebyshev distance between x_i^t, (the cell being updated) and x_j^t, (the cell which has been observed). n indicates the recent w observations and $\mathcal{N}(\cdot)$ is an univariate Gaussian function to represent the importance of observation obtained at p_j to estimate the state of the cell at p_i. The kernel size σ is a hyperparameter.

We introduces a confidence map $\lambda(i, t)$ by normalizing $\Omega(i, t)$ to the interval [0, 1)

$$\lambda(i, t) = 1 - e^{-(\Omega(i,t))^2}. \tag{16}$$

The confidence map depends on the historical trajectories of UAVs and the final observed time of each cell. A high confidence value for a cell means that the estimated gain is derived from a large number of recent observations in close proximity to this cell. On the contrary, a low confidence value suggests that there are few historical observations near this cell, or this cell was final observed long time ago.

4) Dual-Criterion Utility Function: Finally, the overall utility assessment is calculated by integrating the confidence map, sensing gain, and operation gain into a dual-criterion utility function as follows:

$$u\left(x_i^t\right) = \sum_{j \in R_S(x_i^t)} \lambda(j, t) O\left(x_j^t\right) + (1 - \alpha) \sum_{k \in R_O(x_i^t)} \lambda(k, t) S\left(x_k^t\right) \tag{17}$$

where $R_S(x_i^t)$ and $R_O(x_i^t)$ are the cells in the range of sensing and suppression when an UAV is located above cell i, respectively. α is a parameter to adjust the relative influence of the component objectives.

In this way, when the estimated sensing and suppression gains of a cell are rooted in a low confidence value $\lambda(i, t)$, the overall utility of that cell decreases. The confidence map can be viewed as a dynamic weight coefficient to adjust the estimated gains, which mitigates the reliance solely on the estimation result based on the employed environment model.

C. Priority Graph-Instructed Scalable Scheduling

This module aims to generate paths for multiple UAVs based on the spatiotemporal confidence-aware assessment model. To address the challenge of spatiotemporal high-dimensional decision space mentioned in Section I, we proposed a scalable, heuristic-based algorithm to find an approximate solution with a performance guarantee. Its core ideas are as follows.

1) Construct a priority graph based on the utility assessment and utilize a graph search algorithm to plan the path for each UAV.
2) Utilize a sequential allocation scheme, where UAVs make decisions sequentially conditioned on all the paths that have been selected, to coordinate multiple UAVs. This approach reduces the planning complexity from

exponential to linear, enabling efficient and nonmyopic path planning for multiple UAVs in dynamic environments.

1) Prioriy Graph Construction: The optimal scheduling requires the perfect knowledge of the future environment state. However, the multi-UAV system has only partial information and an imperfect environment model, the environment state prediction can not be entirely accurate. To adapt to the uncertainty in real time, we leverage the principle of model predictive control (MPC) approach, which requires optimizing an UAV's path for the predicted environment state at $t + \mathcal{T}$, but only executing the first action from the optimized path.

Specifically, we use the collaborative perception component to predict the environment states for future time step $t + \mathcal{T}$ based on the recursive Bayesian function, and then the priority score for each location can be obtained by (17). Our objective is to find a $\mathcal{T}$-step path for each UAV such that the score sum of visiting the locations in the paths is maximized. We then construct a priority graph for the cells by directed acyclic graph (DAG) to facilitate the path calculation. Specifically, we characterize a priority graph $\mathcal{G}$ as (V, E, W), where V, E, and W are the set of nodes, edges, and edge weights, respectively. Each node v_i represents a cell i in the environment, while each edge e_{ij} connects node v_i and node v_j whose Chebyshev distance is less than two (i.e., $\|v_i - v_j\|_\infty \leq 2$). For each edge e_{ij} with its tail on node v_j, the weight is assigned denoting the predicted priority score.

2) Multi-UAV Sequential Allocation: Even if we only consider one-step planning, finding optimal paths for multiple UAVs in a DAG is known to be an NP-hard team orienteering problem [42]. Given the limited decision time in real-world deployment in a dynamic environment, we do not expect to find the optimal solution (OPT) efficiently. Instead, our goal is to efficiently find near-OPTs, where the performance is close to the optimal value.

Inspired by [43], we adopt a sequential allocation scheme to coordinate multiple UAVs. To simplify notation, let $\mathcal{P}_r = \{a_r^{t\,:\,t+\mathcal{T}}, \mu_r^{t\,:\,t+\mathcal{T}}\}$ indicate the joint action-moving path for UAV r, and $U^{t+\mathcal{T}}(\mathcal{P}_r)$ indicate the sum of score for path $\mathcal{P}$ over the constructed priority graph. Thus, the solution for a single UAV is denoted as

$$\hat{\mathcal{P}}_1 = \arg\max_{\mathcal{P}} U^{t+\mathcal{T}}(\mathcal{P}) \tag{18}$$

which can be efficiently solved by the *Bellman–Ford* algorithm [44] with an $\mathcal{O}(\mathcal{T}^4)$ complexity. The sequential allocation algorithm then optimizes the path $\mathcal{P}_r$ for UAV r conditioned on all paths $\mathcal{P}_1, \ldots, \mathcal{P}_{r-1}$ that have been selected such that

$$\begin{aligned} \mathcal{P}_r &= \operatorname{argmax}_{\mathcal{P}} U_{\mathcal{P}^{(1:r-1)}}(\mathcal{P}) \\ U_{\mathcal{P}}(\mathcal{P}') &= U(\mathcal{P} \cup \mathcal{P}') - U(\mathcal{P}) \\ \mathcal{P}^{(1:r-1)} &= \mathcal{P}_1 \cup \cdots \cup \mathcal{P}_{r-1}. \end{aligned} \tag{19}$$

It is noticed that this approach reduces computation complexity from exponential to linear, i.e., from $\mathcal{O}(|\mathcal{U}_1 \times \cdots \times \mathcal{U}_{n_r}|^{\mathcal{T}})$ to $\mathcal{O}(\sum_{i=1}^{n_r} \mathcal{T}^4)$. Since the constructed priority graph satisfies modularity, the obtained solution $\hat{\mathcal{P}}$ by sequential allocation can achieve least 50% of the optimal values as proven in [45], i.e., $U(\hat{\mathcal{P}}) \geq 1/2U(\mathcal{P}^*)$, where $\mathcal{P}^*$ denotes the OPTs.

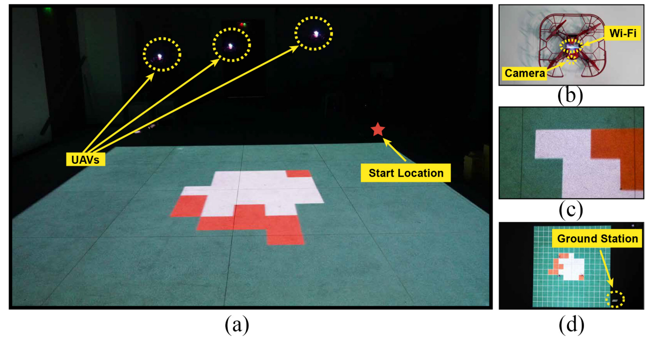


Fig. 5. Testbed experimental setup and scenarios of *SOScheduler*. (a) and (d) Side view and top view of the experimental scenario with dynamic wildfire animation. (b) UAV platform DJI Tello EDU. (c) Example view of an UAV.

V. Evaluation

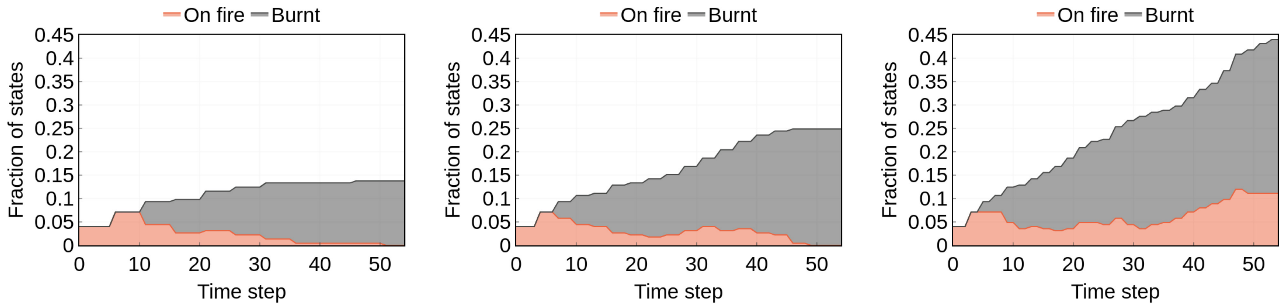
In this section, we evaluate the performance of our *SOScheduler* and baselines for fire suppression scenarios. Experiments are conducted on both real multi-UAV systems and physical feature-based simulations.

A. Implementation and Methodology

1) Testbed Implementation: To validate our *SOScheduler* in the fire suppression scenario, we run experiments on a real-time multi-UAV testbed in the 8 m×10 m indoor environment, as shown in Fig. 5. Most parts of the testbed adopt the same setup as the real scenario, including the sensing, motion, communication, and computation of the multi-UAV system. The UAVs take off randomly at a corner of the area to emulate the entry of UAVs into a real-world wildfire scenario.

To eliminate safety concern and increase repeatability, we mimic fire spread and suppression through projected lights, which has been validated by [46]. The testbed consists of three major components.

1) *Multi-UAV Platform:* Three commercial UAVs DJI Tello EDUs, which is equipped with an onboard camera for visual information and a 2.4 GHz 802.11n Wi-Fi for wireless communication. Fire state classification is performed using the imagery from the onboard camera through the *OpenCV*. At each time unit of the experiment, UAVs derive commands from the ground station for sensing and operation.
2) *Ground Station:* A laptop equipped with an Intel i5 2.60 GHz CPU is used as the ground station (i.e., edge server), where we merge the information from multiple UAVs and plan their paths at each decision interval.
3) *Fire Environment:* We project the dynamic fire environment animations to the ground, which is discretized into cells representing an area of 250 m×250 m in real world with an 1:1000 scaled-down ratio. Environment states (x_i^t) are illustrated with different colors (e.g., red for on fire). When an UAV conducts fire suppression operation on one cell, its color (state) changes with a probability to mimic the uncertainty of fire suppression effect. The



(a) (b) (c)

Fig. 6. Fractions of cells in different states change with time under different wildfire scenarios. (a) Slow-moving fire condition. (b) Moderate-paced fire condition. (c) Fast-evolving fire condition.

TABLE I
DEFAULT PARAMETERS FOR TESTBED EXPERIMENT AND SIMULATION

Parameter	**Symbol**	**Value**
UAV velocity (testbed)	v_t	3m/s
UAV velocity (simulation)	v_s	15m/s
Measurement accuracy	P_m	0.95
Successful fire suppression probability	P_s	0.80
Sample period	r_t	5s
Planning horizon	$\mathcal{T}$	16
Communication frequency	T_c	8
Initial Fire Size	n_i	4×4
Fire extinguishing ball number	n_b	16
Fire update rate (slow-moving fire)	ρ_1	3
Fire update rate (Moderate-paced fire)	ρ_2	2
Fire update rate (Fast-evolving fire)	ρ_3	1
Range of sensing	R_s	3×3
Range of operation	R_o	1×1

wildfire animation updates according to fire suppression operation of UAVs and a stochastic fire spread model [27]. Note that based on our experiences and previous experiments, different wildfire models adopted do not change the effectiveness of our experiment. In the experiment, we consider three typical scenarios: 1) slow-moving wildfire; 2) moderate-paced wildfire; and 3) fast-evolving wildfire in the experiments. The major default settings are summarized in Table I.

2) Simulation Setup: To validate the performance of *SOScheduler* under various environmental conditions in a large-scale terrain with more UAVs, we conduct evaluations with respect to the two most significant environmental factors [23]: 1) fire propagation velocity and 2) number of initial fires. To mimic real-world wildfire fighting scenarios with more UAVs, we simulated a terrain of 10 km × 10 km and discretized it into 50 × 50 cells. The measurement accuracy is set as 95.7% according to the testbed detection results on average. The default number of UAVs is set as 15, other default settings are consistent with the testbed experiments and summarized in Table I.

3) Evaluation Metrics: Our collaborative framework aims to prevent the spread of the fire and minimize the damage to the surrounding environment. Besides, the effectiveness of our method is based on the coverage of real-time observations of fire. Therefore, we use the following two metrics.

1) *FER:* It evaluates the operation performance by measuring the average ratio of the increase in fire and burnt out area after the mission to the initial fire area

$$\mathrm{FER} = \frac{\sum_i^n \left(1 - \mathbb{I}_H(x_i^T)\right)}{\sum_i^n \left(1 - \mathbb{I}_H(x_i^0)\right)} - 1 \tag{20}$$

where $\mathbb{I}_H(x_i^0)$ and $\mathbb{I}_H(x_i^T)$ are indicator functions that denote whether cell i remains healthy at the beginning and end of the mission, respectively. FER is the specific form of $U^T(\cdot)$ in (4) for wildfire suppression scenarios. The metric is typically far more than one due to the fast expansion of fire thus the smaller value indicates better performance.

2) *Fire Coverage Ratio (FCR):* It evaluates the sensing performance by measuring the average fraction of ground truth fires covered by the UAVs over the full mission period

$$\mathrm{FCR} = \frac{1}{T} \sum_{t=1}^{T} \frac{\left|\bigcup_{r\in R}\left\{i \in R_S(p_r^t) \mid x_i^t = F\right\}\right|}{\left|\left\{i \in \mathbb{Z}^2 \mid x_i^t = F\right\}\right|} \tag{21}$$

where T is the total number of simulation time steps. The metric is typically less than one due to the limited number of UAVs and their constrained sensing capabilities. The larger value represents better performance.

4) Baselines: Two baselines are adopted to validate the advantages of our *SOScheduler*.

1) *DDRL [22]:* A state-of-the-art (SOTA) RL-based framework for dynamic wildfire control. During the wildfire, each UAV receives an uncertainty map as the input of the policy network, and outputs a direction to move for the next time step.

2) *Heuristic (HEUR) [47]:* A two-stage complex heuristic algorithm, which schedules the agents to find the fire centers at first and then move counterclockwise along the fire fronts.

B. Overall Performance

1) Testbed Experiment Results: To analyze how the fire changes with suppression efforts, we plot the percentages of cells in different states over time under various fire speeds in Fig. 6. As seen in Fig. 6(a) and (b), the fractions of on fire and burnt cells increase initially as time steps change from 1 to 10, indicating rapid wildfire spreading while UAVs explore the area. However, as time steps increase, UAVs find the fire front

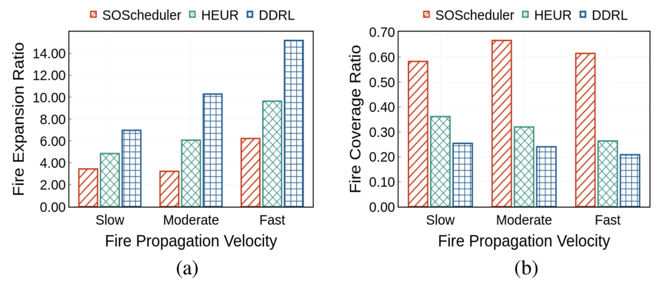


Fig. 7. Overall performance in testbed experiments under various wildfire speeds. (a) Impact of fire propagation velocity on FER. (b) Impact of fire propagation velocity on FCR.

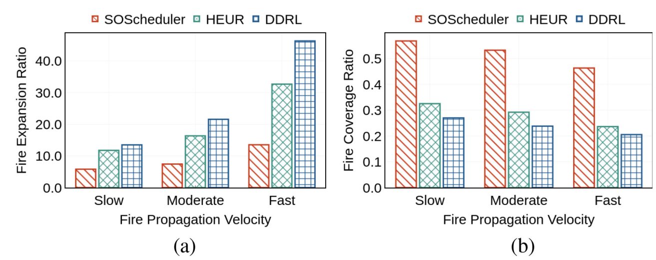


Fig. 8. Overall performance in simulation experiments under various wildfire speeds. (a) FER comparison. (b) FCR comparison.

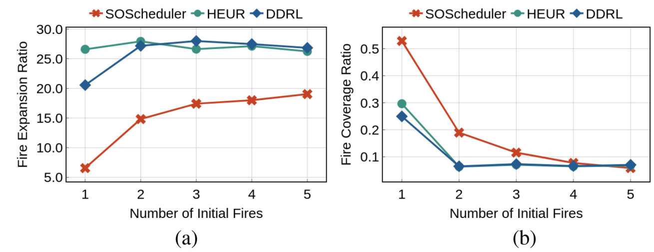


Fig. 9. Overall performance in simulation experiments under different numbers of initial fires. (a) FER comparison. (b) FCR comparison.

and start to suppress the fire, leading to a downtrend in terms of the fraction of burning cells. Finally, the fraction of burning cells in both scenarios turns to zero, signifying a successful fire suppression. As for the most challenging fast-evolving scenario in Fig. 6(c), the fraction of on fire cells first increases again after an initial decrease. This is because UAVs reach the fire front and mitigate the spreading to some extent initially. However, the aggressive propagation and exponential growth of the firefront make suppression highly complex, rendering it impossible to extinguish the wildfire completely for three UAVs.

Fig. 7(a) measures the average FER for all scenarios after experiments, comparing with two baselines. The results show that the *SOScheduler* outperforms HEUR and DDRL under all scenarios. As seen, the FER increases with the growth of fire propagation velocity, which indicates an increasing difficulty in timely fire suppression. As for the performance in the most challenging fast-evolving scenario, the FER of *SOScheduler* is 6.22, which outperforms DDRL by 59.1% and exceeds HEUR by more than 35.4%.

We also evaluate the average FCR for all scenarios, as shown in Fig. 7(b). With the increase of the fire propagation velocity, the FCR of two baseline methods decrease. In contrast, our *SOScheduler* remains an FCR of more than 0.55 under all fire velocities, outperforming baselines. This is because our algorithm actively evaluates the information gain throughout the mission, enabling the UAVs to revisit the uncertain areas and thus discover more regions that just transited from healthy into burning.

In summary, *SOScheduler* can successfully contain wildfires in general with a small group of UAVs due to its adaptive action strategy and effective cooperation. Further evaluation of the influence of the number of UAVs will be conducted in Section V-C.

2) Simulation Experiment Results (Fire Propagation Velocity): We evaluate the FER and FCR of *SOScheduler* on three wildfire scenarios mentioned in Section V-A, as shown in Fig. 8. Fig. 8(a) shows that the *SOScheduler* has consistent advantages over two baselines under all wildfire conditions. Especially, in fast-evolving fires, *SOScheduler* outperforms the DDRL and HEUR flight by 70.8% and 58.7% on FER, respectively. This superior performance can be attributed to the system's ability to actively estimate the confidence values of each location, leading to a timely and dynamic adjustment of the scheduling strategy. Furthermore, Fig. 8(b) shows the average FCR under all scenarios. We can see that the FCR of all methods decrease with the growth of fire velocity, since the area size of fire increases exponentially. However, *SOScheduler* achieves an average FCR greater than 0.5 in the fast-evolving scenario whereas for the best baseline HEUR, the maximum achievable FCR is only 0.2. In summary, these results validate that the *SOScheduler* has the ability to adapt the planning policy in a manner that is commensurate with the propagation velocities of the fire, contributing to effective and efficient fire suppression.

Number of Initial Fires: To evaluate the efficacy of our *SOScheduler* for various initial fire conditions, we consider scenarios, including one to five initial fires in the terrain. Each initial fire occupies 3×3 cells and is randomly placed in the terrain without overlap at the beginning. From Fig. 9(a), we can see that FER increases with the number of initial fires in general. *SOScheduler* outperforms baselines under variant initial fire conditions, because it explicitly models the uncertainty in the environment model and reason about the fire status. This can also be verified in Fig. 9(b), where *SOScheduler* maintains higher FCR for most of the scenarios, indicating more exploration to collect the new information. Fig. 10 illustrates an example snapshot of scenarios during experiments under three initial fires. In summary, *SOScheduler* enables the UAVs to efficiently cooperate with each other and provides an empirically better solution when there are multiple initial fires.

C. System Robustness

We further evaluate *SOScheduler* with respect to the number of UAVs and model accuracy. Since the system performance has been verified under varying wildfire speeds, we do not

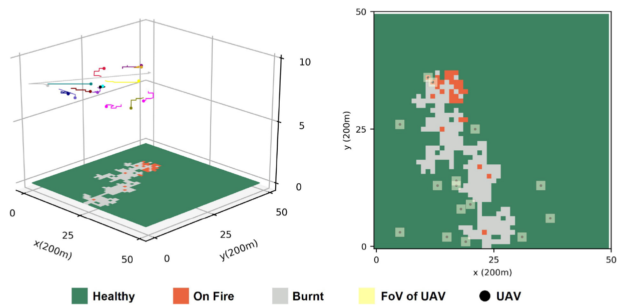


Fig. 10. Example snapshot of the simulation experiment under three initial fires. *Left:* 3-D view. Dots and lines in various colors denote distinct UAVs and their trajectories, respectively. *Right:* 2-D view. Translucent rectangles around the UAVs indicate their Field of View (FoV).

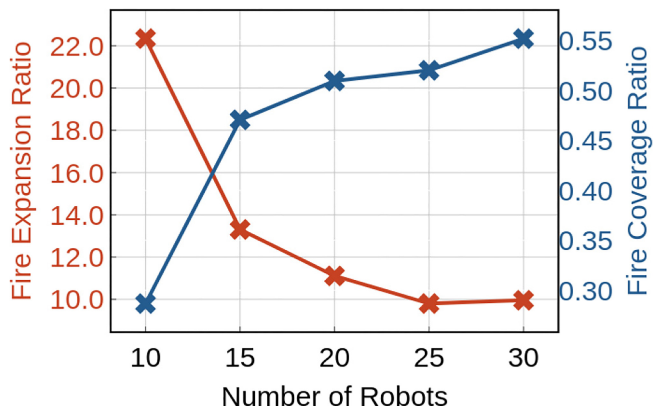


Fig. 11. Impact of number of robots.

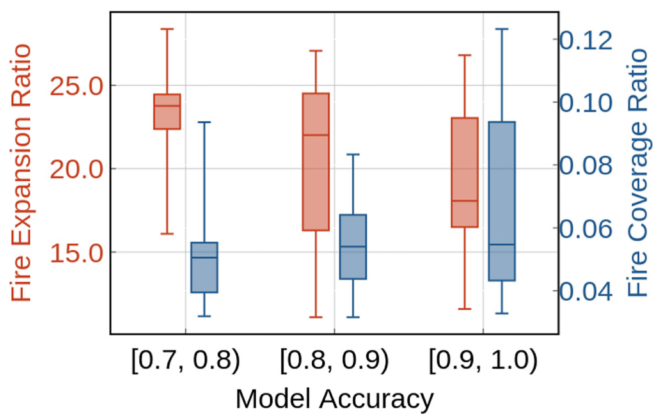


Fig. 12. Impact of model accuracy.

verify the impact of UAV speed, which is equivalent to validating the influence of wildfire speed.

1) Number of UAVs: We examine the impact of the number of UAVs under the challenging fast-evolving scenario with five initial fires, as shown in Fig. 11. The result demonstrates that increasing the number of UAVs leads to a higher FCR and a lower FER in general, as a larger team of UAVs allows for more sensing and operation actions to be applied. Furthermore, the benefit of increasing the number of UAVs diminishes for *SOScheduler* after the number of 25, since 25 UAVs are sufficient to quickly extinguish the wildfire in this scenario. It is noteworthy that the *SOScheduler* still achieves an FER of 22.3 even with 10 UAVs, outperforming the DDRL and HEUR approaches with 15 UAVs that achieve FER of 46.3 and 32.7, respectively, [as shown in Fig. 8(a)].

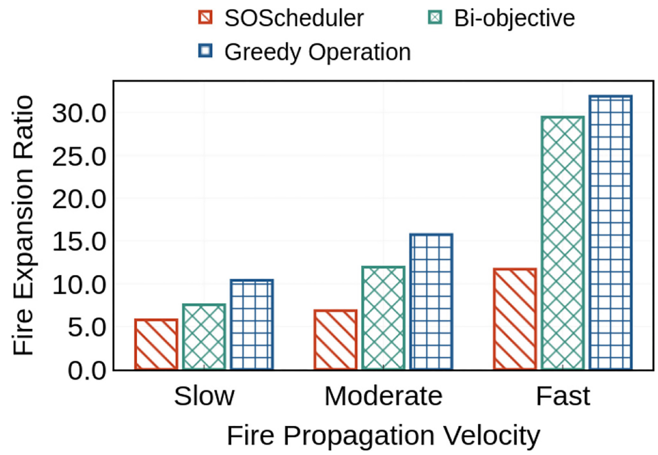


Fig. 13. Comparison of different utility function.

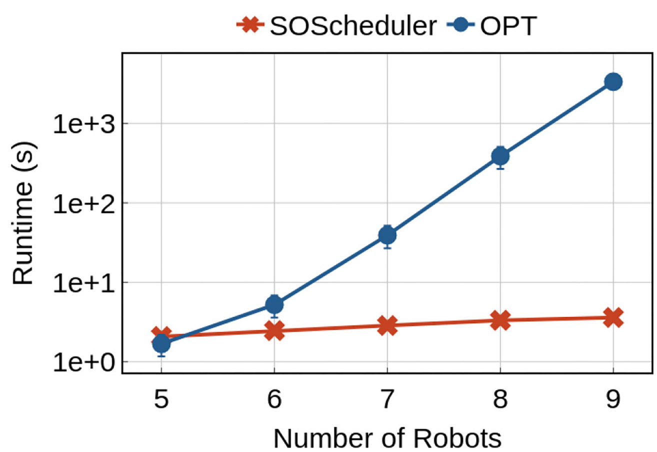


Fig. 14. Comparison of runtime.

2) Model Accuracy: We showed the robustness of *SOScheduler* to the different levels of accuracy of the environment model. The model accuracy is influenced by the accuracy of the measurement model. We take measurement accuracy as a random variable and sample its values from the random uniform distribution in $[0.5, 0.95]$. With different configured parameters, we can obtain multiple spatiotemporal environment models with varying accuracy levels. As Fig. 12 shows, the overall FER under varying model accuracy levels remains robust. This is because our algorithm encourages the system to explore the environment based on the uncertainty in the belief and incorporate the infield measurement to instruct the scheduling strategy, therefore it can tolerate the imperfect model to some extent and maintain high performance.

D. System Micro-Benchmark

1) Effectiveness of Confidence-Aware Assessment: We also compare the FER with different utility function designs in Fig. 13. In the experiment, we compare our spatiotemporal confidence-aware assessment model with another two strategies, greedy operation (i.e., $\lambda(i, t) \equiv 1, \alpha = 1$) and bi-objective with equal weights (i.e., $\lambda(i, t) \equiv 1, \alpha = 0.5$), both widely used in previous works [48]. As seen, when the fire is fast-evolving, *SOScheduler* demonstrates greater advantage with an improvement of FER for 31.5% and 60.3% compared to greedy operation and bi-objective, respectively.

This outstanding performance is due to the design of the confidence map as an efficient knob to dynamically adjust the estimated gains, which mitigates over-reliance on the environment model and enables the adaptive adjustment of scheduling strategy in uncertain dynamic environments.

2) Runtime: We further evaluate the computation efficiency and advantages of the *SOScheduler*'s coordination scheme in a small-scale scenario (i.e., less than 10 UAVs). Fig. 14 illustrates the runtime of our graph-based sequential allocation algorithm, compared with the OPT calculated by brute force methods. As seen, the time cost of OPT grows exponentially with the number of UAVs, while *SOScheduler* has a negligible time cost, e.g., when there are 9 UAVs, the time cost of OPT is up to more than 3000 s, while *SOScheduler* keep a small time cost of less than 4 s. Notably, the runtime of our sequential allocation algorithm grows linearly with the number of UAVs, which echoes the linear computation complexity, as described in Section IV-C.

VI. Conclusion

This article proposes *SOScheduler*, a multi-UAV scheduling framework for integrated wildfire monitoring and suppression. First, UAVs estimate and predict environment state with shared onboard sensing data in a collaborative way. Second, UAVs adaptively identify optimal locations for enhancing environmental understanding and operational effectiveness. Finally, UAVs decide their trajectory and corresponding actions in a nonmyopic way with a scalable planning algorithm. Extensive experiments demonstrate its superior performance, which indicates that the *SOScheduler* can integrate with existing probabilistic modeling of disaster environments and provide autonomous and efficient emergency response in large-scale and dynamic environments.

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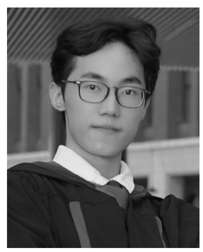

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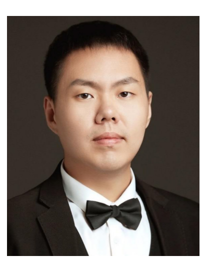

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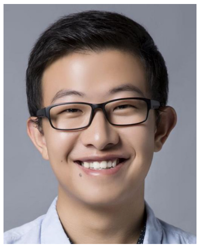

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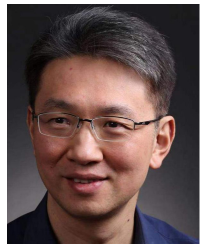

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