Digital Twins: A Simulation-Based and Multi-Objective Realtime Stochastic Approach for Fighting Wildfires

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Abstract

Worldwide, ecosystems, communities, and economies are under increased threat from wildfires. Micro Aerial Vehicles (MAVs) and agent-based modeling offer a dynamic method for detecting, preventing, and responding to wildfires. We investigate the potential collaboration between agent-based simulation and MAVs in addressing the dynamic challenges of wildfire management. Simulation considers weather, geography, and vegetation, agent-based simulation augments real-time data by the inclusion of wildfire-prone locations. The spread of the fire and locating high-risk regions, to shifting wildfire conditions and help with resource allocation and decision-making. MAVs and agent-based simulation work together to provide a comprehensive strategy to managing and detecting wildfires. The model's situational awareness is improved by including real-world MAV data, which also helps to identify ignition sources and forecast the direction and rate of a fire. We highlight the ability to lessen the effects of wildfires by providing information on how to allocate resources, make evacuation plans, and prepare communities.

Keywords: MAVs, CVRP, Agent Based Simulation, Discrete Simulation, Wildfires

1. Introduction

Wildfires are one of the most expensive and deadly natural catastrophes in the world, particularly in the western United States. In 2018, a catastrophic wildfire known as the Camp Fire was recorded as one of the worst wildfires in the history of California. Yet these catastrophic fires are expected increase by the year 2050 **?** if preventive actions are not taken nor improvement of response services are studied. These fire events are responsible of large-scale evacuation, homes being set on fire, infrastructure being destroyed, millions of hectares of forest resources damaged, and most critically, human lives being in danger. Fire detection and monitoring technologies have evidenced an rapid increase such as ground sensors, unmaned aerial vehicle (UAVs), and satellite imagery have been deployed. Current systems have drawbacks that include delayed fire detection due to missing minor fires in the early stages, relatively high time lag for satellites to overhead the field and inability to deploy sensors with restricted detecting distance ranges. For instance, a prompt response and resource allocation is desirable as they are likely to conent the fire events on the early stages. It is demmed reponse times and proper resource allocation are key components for an adequated response. On the basis of these we center our research effort on a prompt and proper allocation of resources and simulation of fire events during its curse of action.

Optimization based agent based simulation and deep reinforcement. This study aims to capitalize the use of the listed techniques to propose a practical framework for fire events hadling and resource allocaiton in the context of wildfires using a set of heterogeneous agents drones to provide adequate responses when human controllers are not available to initiate and guide the mission.

2. Literature Review

Authors in **?** present a multi-autonomous UAV disaster monitoring approach for remote areas. These UAVs are either on standby or positioned in observation towers. They automatically establish leader-follower coalitions with competent UAVs as leaders when a fire is detected in order to efficiently monitor the fire zone. According to simulation studies, this fully distributed strategy is scalable for large coverage areas, such as forest fires, and performs comparably to centralized approaches. This system runs independently and doesn't need leaders to communicate with one another. The importance of this approach relies in the use of UAVs and non-communicated this resemble conditions in which certain type of heterogeneous agent may not be employed in certain fire event conditions they may not properly interact. Whereas, in **?** analyze a drone-truck system using the BD algorithm and the AEC technique, presenting a multi-objective mathematical programming model. The findings indicate a trade-off between patrolling time and cost, with higher expenses associated with quicker patrolling during some seasons. It is determined that the coordinated system saves money and saves time. When dealing with large-scale issues, the BD method works well. Environmental conditions, drone overheating, wildlife interference, and lost remote control contact are some of the limitations. Although it should take into account practical limitations, this approach can supplement satellite-based forest observation. We aim at a joint utilization of agents only in certain conditions where fire event conditions are suitable for such job. On top of this we prpose a new CVRP formulation for adressed the problem. Lastly, we employ real data by the use of AirNow API information this addresses the problem on a realtime basis. The research in **?** introduces the Mesh Reliance Architecture, a method for arranging agents swarms. This novel architecture keeps all of the UAVs in the swarm connected and allows different swarm formations. The study used neural network and genetic algorithm simulations to assess the design. With every additional drone, the computational time rose linearly. Subsequent research endeavors to refine the evolutionary algorithms, investigate diverse approaches, and contemplate parallel processing as a means of diminishing runtime. Making the Mesh Reliance Architecture dynamic to adjust to shifting configurations is the primary difficulty. We investigate further investigate these interactions by the use of clustered agents yet implement the model on an agent-based simulation basis. Finally, in **?** a aerial swarms are used in this study to effectively map offshore oil spills. They provide a decentralized method for mission-state-adaptive waypoint planning that draws inspiration from dynamic occupancy grids for oil finding and particle swarm dynamics. It outperformed random walk and spiral search techniques, showed good mapping accuracy, and took less time than exhaustive search. The resilience of the system varied according on the complexity of oil spills. Among other authors, **?** present a cooperation between UAVs and UGVs.

3. Model Formulation

3.1. Data Inputs

3.1.1. Landsat

Latency - defined as time since satellite observation and the data being available in FIRMS: within 30-60 minutes for the continental US (CONUS), southern Canada and northern Mexico.

The Landsat 8 and 9 Active Fire and Thermal Anomalies product, generated from the Landsat Operational Land Imager (OLI) shows active fire detections and thermal anomalies, such as volcanoes, and gas flares. The fire layer is useful for studying the spatial and temporal distribution of fire, to locate persistent hot spots such as volcanoes and gas flares, and to locate the source of air pollution from smoke that may have adverse human health impacts.

3.1.2. VIIRS

3.1.3. MODIS

3.2. Problem Modeling

The problem relies on establishing waypoints for firefighting incidents by applying the principles of a capacitated vehicle routing problem. This optimization aims to enhance the efficiency of the water dumping process while considering the attributes of the agents involved. On a C-VRP foundation, it is expected that agents may go to the waypoints while do not overuse their designed capacity. The challenge is to create the waypoints in a way that can successfully stop the spread of the fire and slow down the fire evolution. Dynamic development model of forest fire is represented through agent based modeling. The formulation for the vehicle routing problem is presented lines below. The proposed set of POIs is generated randomly and combined with the manually selected POIs for experimentation process yet it relies on real information provided by AirNow ©. Each node is calculated following a eclidian distance. Calculated intensities are ordered maintaining adjacency. A for loop is designed to iterate over the ordered set of points I. Each of the i points receives the parameters containing the POIs and agents. The algorithm will return a minimized path routing upon fulfillment of the capcity of the agents.

Table 1: Model notations

Variables	**Definition**
i	Index of initial node
j	Index of ending node
depot	Index of deport
$x_{i,j}$	Binary variable selection from point i to j
u_i	MTZ variable for node i
u_j	MTZ variable for node j
Parameters	
dempoints	List of nodes enumeration
k	Number of agents
Q	Agent's capacity
q	Fire intensity demand for fire nodes
lengths	Fire intensity required

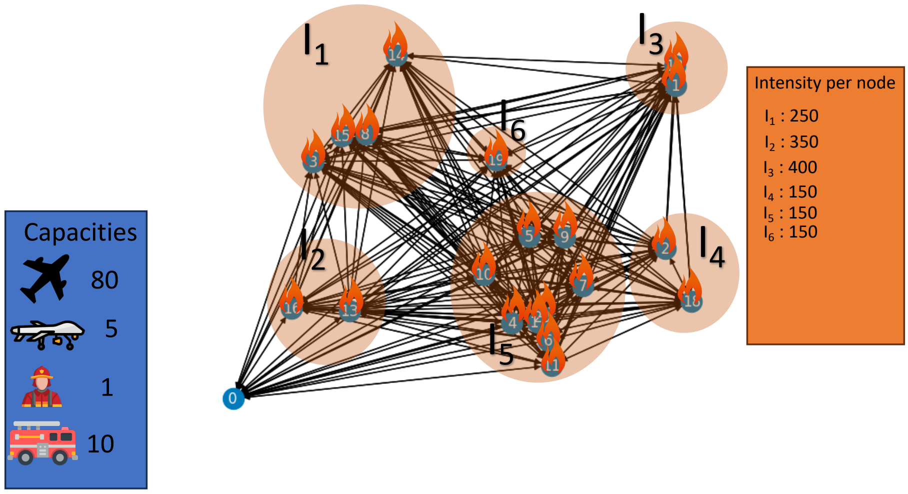

Figure 1: Quantified intenside per node is listed on the right while capacities per agent are listed on the left. Wildfire areas are labeled on a basis of fire intensity and agent fire capacity. Area shown represents 6 intensity zones and 20 nodes. Node 0 represents the operation based centralized location where all fire equipment will be distributed to the wildfire location. Nodes are extrapolated form the Airnow©official API service and serve as the status of the fire event (Agent). This are recalculated on a temporal basis and re considered for capacity routing purposes. Internal caracteristics of the agents are considered within the agent-based simulation interacting with the fire event and other agents. Forecasted caracteristics of the fire event are included.

Model Formulation

Sets:

$$\text{Locations: } \mathcal{L}$$

$$\text{Suppliers: } \mathcal{S}$$

Parameters:

$$\text{Cost matrix: cost\_matrix}_{ij} \quad \forall i, j \in \mathcal{L}$$
$$\text{Average demand: demand\_avg}_i \quad \forall i \in \mathcal{L}$$
$$\text{Demand standard deviation: demand\_std\_dev}_i \quad \forall i \in \mathcal{L}$$
$$M \quad \text{(A big-M constant)}$$
$$\alpha \quad \text{(Weighting factor for cost)}$$
$$\beta \quad \text{(Weighting factor for resource allocation)}$$
$$\text{Confidence level low: confidence\_level\_low}$$
$$\text{Confidence level high: confidence\_level\_high}$$

Decision Variables:

$$x_{ij} \quad \text{(Binary decision variable indicating if a route from location } i \text{ to } j \text{ is selected)} \quad \forall i, j \in \mathcal{L}$$
$$z_{is} \quad \text{(Binary decision variable indicating if supplier } s \text{ serves location } i\text{)} \quad \forall i \in \mathcal{L}, s \in \mathcal{S}$$
$$y_i \quad \text{(Continuous decision variable representing the resource allocation at location } i\text{)} \quad \forall i \in \mathcal{L}$$

Objective Function:

$$\text{Minimize:} \quad \alpha \sum_{i,j \in \mathcal{L}} \text{cost\_matrix}_{ij} \cdot x_{ij} - \beta \sum_{i \in \mathcal{L}} y_i$$

Constraints:

Connectivity constraints: $\sum_{j \in \mathcal{L}} x_{ij} = 1 \quad \forall i \in \mathcal{L}$

$$\sum_{i \in \mathcal{L}} x_{ij} = 1 \quad \forall j \in \mathcal{L}$$

Supplier assignment constraints: $\sum_{s \in \mathcal{S}} z_{is} \leq 1 \quad \forall i \in \mathcal{L}$

Resource allocation constraints: $y_i \geq \text{demand\_avg}_i + M \sum_{j \in \mathcal{L}} x_{ij} \quad \forall i \in \mathcal{L}$

Stochastic demand constraints: $y_i \geq \text{demand\_avg}_i - \text{demand\_std\_dev}_i \cdot \text{ppf}(1 - \text{confidence\_level\_low}) \quad \forall i \in \mathcal{L}$

$$y_i \leq \text{demand\_avg}_i + \text{demand\_std\_dev}_i \cdot \text{ppf}(1 - \text{confidence\_level\_high}) \quad \forall i \in \mathcal{L}$$

Confidence level constraints: $\text{cdf}\left(\frac{y_i - \text{demand\_avg}_i}{\text{demand\_std\_dev}_i}\right) \leq \text{confidence\_level\_low} \quad \forall i \in \mathcal{L}$

$$\text{cdf}\left(\frac{\text{demand\_avg}_i - y_i}{\text{demand\_std\_dev}_i}\right) \leq \text{confidence\_level\_high} \quad \forall i \in \mathcal{L}$$

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