

## EXPLORATION OF AERIAL FIREFIGHTING FLEET EFFECTIVENESS AND COST BY SYSTEM OF SYSTEMS SIMULATIONS

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### Abstract

Wildfires are becoming a more frequent and devastating phenomena across the globe. The suppression of these wildfires is a dangerous and complex activity considering the vast systems that need to operate together to monitor, mitigate, and suppress the fire. In addition, the required cooperation spans multiple institutes in different capacities. Thus, the recognition of the wildfire suppression scenario as a System of Systems (SoS) is valid. Due to the dangers associated with firefighting and the increased occurrence, there is scope for the design of unmanned aerial vehicles for wildfire suppression. In this work, a SoS driven aircraft design, cost, and fleet assessment methodology is utilized together with a wildfire simulation to investigate several sensitivities relating to design and operational parameters. Further, this paper investigates their impacts on the measures of effectiveness, i.e. burnt area and operating cost. These two parameters enable the identification of optimal fleet size for wildfire suppression for a given scenario and aircraft definition.

**Keywords:** Wildfire Suppression, eVTOL, Aircraft Design, System of Systems, Agent-Based Simulation

### 1. Introduction

The size and number of severe wildfires have been increasing in the northern hemisphere with the impact of its rapid warming rate combined with drought and extreme fire-conducive weather. Fire-prone areas are expected to increase by 200% in Europe by the end of the 21st century [1] with the exacerbating anthropogenic climate change increasing the hazard of wildfires [2]. Even though the developments in wildfire protection plans are accelerated, the wildfires get larger and fire seasons get longer with more uncertainties in ecosystem responses. Every single fire incident causes an increase in the greenhouse effect, air pollution, and fire suppression expenditures. Furthermore, it reduces the capacity of forest regeneration with coupling impacts of drought and temperature increase. Therefore, it is required to have evolved fire suppression tactics including use of various systems in different geographical locations to fight wildfires and prevent the resulting damages. The evolved fire suppression tactics can be comprised of various systems by making use of ground, air, and space vehicles such as bulldozers, helicopters, and satellites. Developing such a system provides a more effective fire suppression method by combining and managing independent agencies. The need of such a system can be disposed of using a System of Systems (SoS) approach according to the Maier criteria [3]. Therefore, the optimal firefighting mission effectiveness is not guaranteed by solely focusing on a single constituent system or aircraft, but requires a SoS driven aircraft design approach.

The ground-based systems face several limitations and do not offer an optimal solution while fighting with large wildfires and they require assistance of air-based systems. During firefighting, the collaborative work done by air and ground-based systems have a substantial effect on obtaining optimal coverage of wildfire [4] by increasing the efficiency of reducing fire intensity and fire spread rate and the effectiveness by providing safe fire-line construction [5]. The assistance can be through detecting, monitoring, and suppressing the fire.

While Unmanned Aerial Vehicles (UAVs) are commonly considered for monitoring and detecting fires in the literature, the available research is very limited with fire suppression by UAVs [6]. According to [7], there is a vast exploration need in the literature to determine the viability of UAVs in fire suppression and its expenditures. However, the on-going development of electric Vertical Take-Off

and Landing (eVTOL) aircraft might also benefit the deployment of such aircraft for firefighting [8]. The developments regarding artificial intelligence and autonomous operations will enable quick deployment of aerial firefighting fleets in harsh unsafe environments. Currently, no such advanced aircraft are utilized for aerial firefighting.

This research aims to fill the abovementioned gap in the literature by providing a large-scale SoS simulation framework to execute suppression of wildfires using eVTOL UAVs. We have presented the general framework at a previous conference [9], where initial investigations on the aerial firefighting effectiveness have been conducted. In this paper, the framework is extended by a cost model in order to find not only effective, but also cost efficient aircraft architectures and fleets for wildfire suppression. For this purpose, an initial Measure of Effectiveness (MoE) that involves aerial firefighting effectiveness and cost is established and investigated.

## 2. Literature Review on Fire Models

There have been many attempts to model and simulate the complex phenomenon of fire propagation in natural environments. The fire spread can be expressed in myriad ways and categorized using different approaches. The classification of fire propagation can be done considering deterministic and stochastic modeling approaches and/or, a vector-based approach with an adaption of Huygens' wave principle and grid-based (raster-based) approach with cell automata or bond percolation [10]. However, there is no strict distinction between models with the existing fire modeling systems and hybrid fire modeling systems include multi-fire models for different cases. For an instance, a commonly used software for wildfire, FARSITE [11] uses different mathematical models for surface fire spread, spotting fires, or fuel moisture modeling and uses a vector-based approach for portraying fire front. Similarly, a deterministic fire simulator, Prometheus [12] is a vector-based simulator that uses physics-based differential equations with Huygens' wave principle.

Even though there are various ways to classify fire propagation simulators, it is possible to combine the available simulators under three main categories as empirical-semi empirical, physical-semi physical, and simulation and mathematical models based on the comprehensive study done by Sullivan [10,13,14]. The physics-based models use physics and/or chemical-based differential equations with numerical solutions for expressing fire spread. These models consider limited areas with laboratory scales and they are computationally expensive due to their complex nature. In addition, even though they are proven to give more accurate results than empirical models for some studies [15,16]; once the complexity increases, the prediction accuracy becomes questionable due to the non-linear nature of fire spread. Empirical-semi empirical models rely on experimental statistics based on observation to model fire behavior. Semi-empirical models follow the physical laws while obtaining the statistical correlation. Due to their nature, they can be easily implemented and require lower computational power compared to the physics-based models. However, they are limited with experimental data and they are not flexible to extend for different fire behaviors and they include substantial approximations. Lastly, the simulation and mathematical analogous model rely on mathematical concepts that express the fire spread based on coincidental similarities.

For simulation models, there are two common approaches as grid-based and vector-based for modeling a fire spread as shown in Figure 1. While the grid-based approach uses square or hexagonal cell interactions to represent fire spread, the vector-based approach uses continuous moving with polygonal expanding in time and space to approximate the fire front. The raster-based approaches are relatively easy to implement and computationally less expensive. In addition, the raster-based models are more adaptable to heterogeneity in vegetation, topography, and weather conditions. Cell Automata (CA) models are one of the most widespread uses of the raster-based approach in recent years. CA models do have not only simple structure and low computational complexity, but also are flexible with coupling other models. For example, the fire spread time accuracy is easily improved by implementing the time correction model to the CA model in Rui et al. [17]. Similarly, the CA model is improved for detecting fire spotting by implementing a relation considering wind and fire interaction to allow a fire to spread to nonadjacent cells [18]. Even though

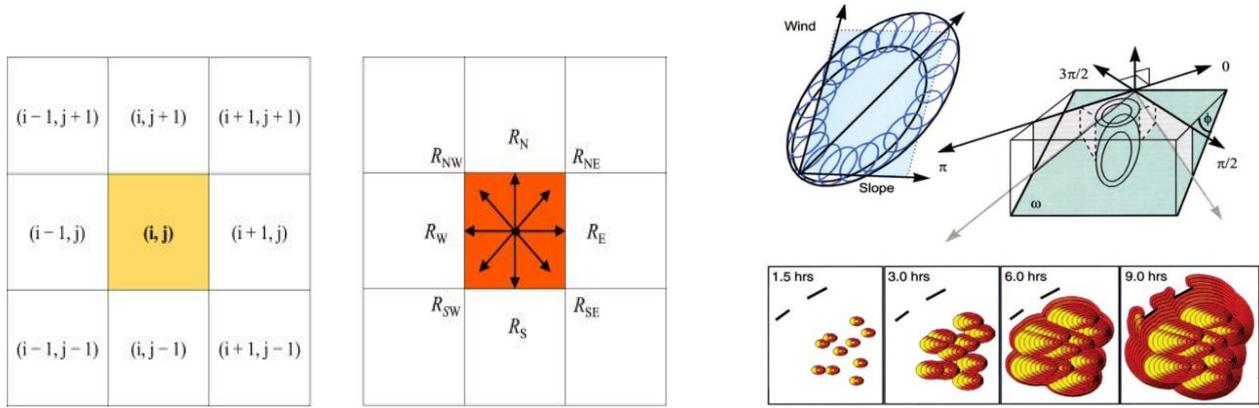


Figure 1 – Grid-based model using equally sized cells with Moore neighbor directions (left) [19] and vector-based fire spread model expanding both space and time (right) [11].

most of the recent studies include vegetation type, topography, and weather conditions for characterizing the cells, the relations between adjacent cells may slightly differ while estimating the rate of spread. The rate of spread is can be calculated stochastically by assigning the fire spread probability factor to each cell as described in [18,20] by using an elliptical distribution scheme to generate new ellipses each time step in each new cell as in [21] or by formulating the relationship between physical, statistical, and empirical data mentioned as in [17,19].

Even though raster-based and vector-based are commonly used in fire spread models, there exist different approaches in the literature. FireCast [22] uses a deep learning approach to predict future fire growth provided by topography and weather conditions data. The method is computationally less expensive and easy to implement and offers fire spread predictions in high-risk areas. Another use of machine learning to predict the fire spread is shown by implementing a deep reinforcement learning algorithm to an online wildfire simulator presented in [23]. The study shows that reinforcement learning methods can outperform physics-based models as long as enough data is provided to the algorithm. WIFIRE [24] introduces a different approach by providing a software infrastructure real-time simulation driven by satellite and sensor data to predict the fire spread. Even though the high accuracy and near real-time response availability are great advantages for predicting the fire spread, the complexity of structure and computational cost bring disadvantages to the model.

### 3. System of Systems Aerial Firefighting Framework

The design of the SoS framework and its components, namely aircraft design, simulation, and cost, are expanded upon in this chapter.

#### 3.1 Framework Definition

In order to structure the SoS design, a framework is developed to establish the key variables of the design, construct the SoS model, execute the simulations, and analyze the output data to constrain the design space (see Figure 2).

The concept of operations of current firefighting and tactics, as described by firefighting handbooks, is implemented in the Multi-Agent-Based Simulation (MABS) with an approach where properties of the fire-model trigger predefined containment and suppression actions. Figure 2 depicts the vision of the fire fighting vehicle design and fleeting where the simulation drives the process. For various scenarios spanning multiple regions, environmental conditions and infrastructure distributions, simulations can be performed to identify the most efficient and robust fleet, aircraft design, and the SoS and System of Interest (Sol) level parameters that respectively constitute them. SoS parameters such as the fleet size, combinations, and distribution and their impact on the wildfire suppression can be investigated by this framework. The wildfire spread model is a medium fidelity model which considers the vegetation index, wind speed & direction, humidity and terrain.

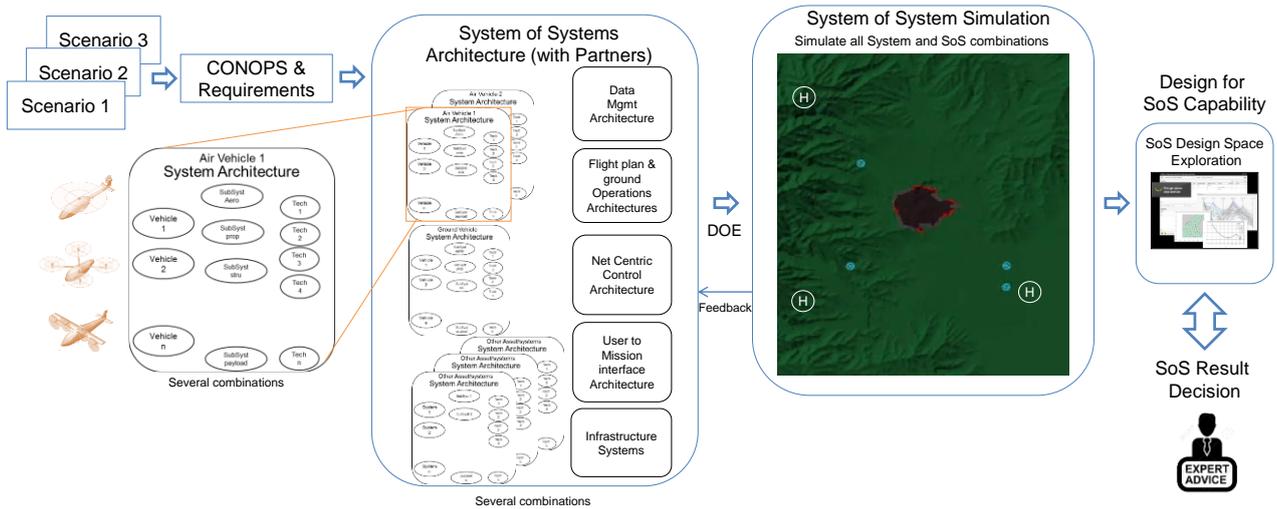


Figure 2 – Framework for system of systems driven wildfire fighting aircraft design.

At the Sol/aircraft level, parameters such as velocity, payload capacity, range, and configuration architecture can be varied and their impacts on the MoE analyzed. Furthermore, the framework can also be used to investigate at the sub system level varying battery parameters and water retrieval and dropping system parameters. For wildfire suppression, multiple heterogeneous fleet of vehicles need to be designed for optimal combined operations. The simulation acts as the testbed on which different homogenous and heterogenous fleets can be analyzed and evaluated. As a simple example of what the simulation could help answer: the question of whether a large fleet of small agile aircraft or a small fleet of large aircraft would perform better at wildfire suppression. Moreover, simulations can help find the ideal balance between the multiple architectures within a fleet and help in driving the design of the vehicle or fleet.

### 3.2 Aircraft Design

Generally, the aircraft design methodology and operational considerations for wildfire suppression have been presented in [9] and are summarized in this section.

Applying the aircraft design methodology by Brown and Harris [25] allows for fast first order conceptual eVTOL aircraft design. Here, different eVTOL aircraft configurations or architectures, namely multirotor, compound helicopter, lift + cruise, and tiltrotor, are sized and evaluated for their performance in hover and cruise flight state. The underlying methods consist of momentum theory for hover and steady level flight equations for cruise segments. The Maximum Takeoff Mass (MTOM) of the electric aircraft simply consists of payload mass, battery mass, and empty mass. At that, the payload is a mission requirement, the battery is sized according to the mission performance, and the empty mass is determined by an assumed empty mass fraction for each eVTOL aircraft architecture. For aerodynamics and performance computations, the maximum disk loading and lift-to-drag ratio of the respective architecture are assumed. The aforementioned eVTOL aircraft architectures are modeled with their respective performance characteristics as utilized by [25]. This is a simple approach to conceptually design eVTOL UAVs for wildfire suppression and to propagate the design performance of one vehicle to the fleet level. The design process will be updated in future work. In fact, we have presented an extended approach in [26], where the eVTOL aircraft design methodology was refined.

The sizing mission requirements are based on the underlying wildfire suppression scenario. Accordingly, a short-range cruise mission of 30 km and a mid-range cruise mission of 60 km are considered. Regarding the battery technology level, an advanced battery pack specific energy of 300 Wh/kg is assumed, where the maximum depth of discharge is limited to 80%. Even though it might not be required for non-urban operations of UAVs, the sizing mission also contains a 20-minute loiter for battery energy reserves. Regarding the payload requirement, two payload masses, 250 kg and 500 kg, are taken into consideration. Finally, the UAVs are expected to operate fully automated or autonomously and are monitored by a remote pilot.

### 3.3 Multi-Agent-Based Simulation

While the MABS for the wildfire fighting case study will be explained in the following, the detailed work on the underlying simulation toolkit has been extensively described in [27].

The simulation model has four major components, which will be explained in the following. The components are namely:

- 1) Wildfire model
- 2) Agent model
- 3) Wildfire suppressant drop model
- 4) Aircraft performance and energy model

#### 3.3.1 Wildfire and Suppression Drop Model

In the Agent-Based Simulation, a medium-fidelity CA wildfire spread model of Rui et al. [17] is incorporated [9,27]. This CA-based fire model was chosen because of its ability to model the influence of combustibles, temperature, humidity, wind and terrain in physical time steps. The use of physical time steps is necessary in order to allow coupling with the firefighting agents. Moreover, the ability to model the temperature, humidity, and wind enables the representation of the reduced intensities of wildfires at night. The agent's attack the wildfire by suppressant drops of which the dimensions are governed by the suppression drop model. The Suppression drop model was developed using a regression based on data generated by USDA Forest Service during real-scale water drop tests [28] relating the suppressant patch dimensions to payload and suppressant flow rate. Further details on the implementation is given in [9].

#### 3.3.2 Agent Model

The agent model is composed of the fire fighting vehicles which actively fight the fire using the logic in Figure 3 as also implemented in previous studies [9].

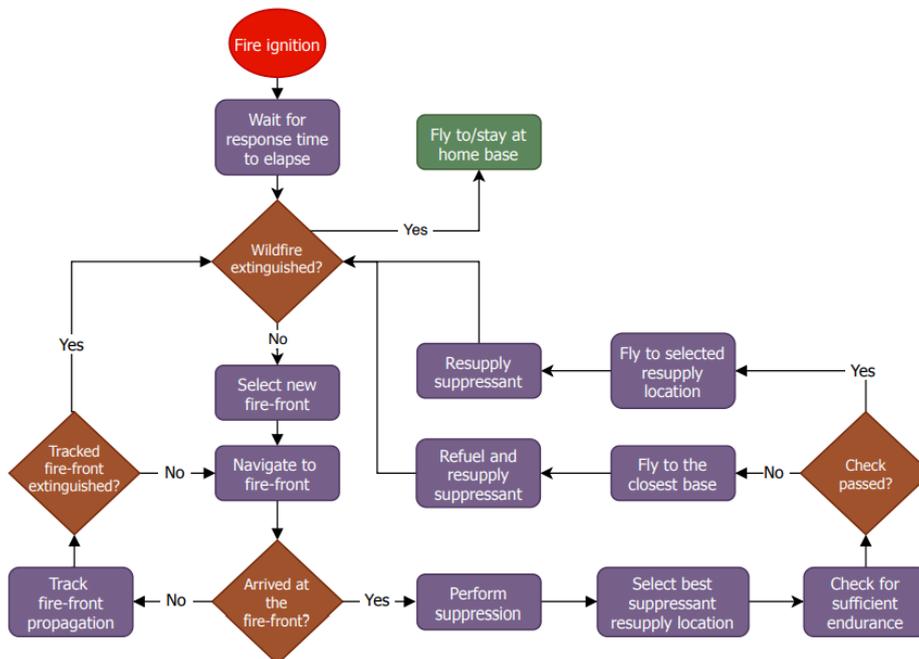


Figure 3 – Firefighting agent logic.

At the current stage, fire detection is only modelled through an imposed time delay termed as the response time. Once the fire is ignited in the simulation, the agents are made to hold until the response time has elapsed. Afterwards, the agents select an initial fire position based on proximity. After the initial fire front is selected, the agents begin their approach to the chosen fire front while tracking the fire front. The fire front is tracked in each step of the agent by considering a neighborhood around the chosen fire front and updating the chosen fire front to the point of maximum value within that neighborhood considering the fire spread rate and the proximity to priority locations.

By this way, the agents attempt to suppress the wildfire at the points of highest important or the simply the highest spread if the priority locations are disabled. In the case that the targeted fire position is suppressed by a different agent or is burnt out, the agent selects a new fire front based on the aforementioned criteria. After a successful attack on the fire front, each agent then evaluates whether or not it has sufficient endurance to perform another suppression attack. If possible, the agent selects the closest point to resupply either at a base or a water source, if not possible the agent returns to the base to refuel.

### 3.3.3 Aircraft Performance and Energy Model

The Agent-Based Simulation employs an energy model to track and update the energy available to the aircraft considering its flight state and payload in each iteration of the simulation. The maximum battery energy is reduced by the usable energy fraction and the reserve energy where the remainder is made available to the agent. The power consumption data for each state of flight and payload configuration is provided to the MABS through the aircraft sizing tool. In the simulation, the agents can recharge for subsequent missions at the bases.

## 3.4 Cost Model

The total operating cost is calculated on a mission basis combining both operating and capital expenses. The operating expenses consist of direct and indirect operating costs. The direct operating cost is divided into remote pilot cost, maintenance cost, and energy cost while the indirect operating cost is estimated as a fixed fraction of direct operating cost. The capital expenses only consider the aircraft depreciation cost per mission. To calculate the depreciation cost, the acquisition cost of aircraft is included as an intermediate step in the cost model. The acquisition cost includes airframe, avionics, and battery costs.

### 3.4.1 Acquisition Cost

Airframe cost depends on the maximum take-off mass, the airframe price per unit mass, and the mass fraction of the airframe, which differs from one aircraft architecture to another [25].

$$\text{Airframe mass} = \text{Maximum takeoff mass} * \text{Empty mass fraction}$$

$$\text{Airframe Price} = \text{Airframe price per mass} \left[ \frac{\$}{kg} \right] * \text{Airframe mass} [kg]$$

The avionics cost is approximated as a fixed value shown in Table 1. The cost of avionics depends on the autonomy and technology readiness level of unmanned aircraft systems. Autonomous aircraft has a higher avionics cost compared to piloted aircraft, however, it doesn't require the installation of passenger entertainment systems.

The battery cost depends on the required number of batteries and battery lifetime for a single aircraft. Since the lifetime of a battery is less or equal to the lifetime of an aircraft, the required number of batteries must be estimated based on the aircraft usage. The required number of batteries can be estimated by relating the number of missions required from an aircraft during its lifetime and the number of missions available per unit battery. Therefore, the battery cost is calculated using the relations in [29].

$$\text{Battery mass} = \text{Maximum takeoff mass} [kg] * \text{Battery Mass Fraction}$$

$$\text{Battery Capacity} = \text{Battery mass} [kg] * \text{Battery Specific Energy} \left[ \frac{kWh}{kg} \right]$$

$$\text{Number of Mission Required per Life} = \text{Number of Missions per Year} * \text{Expected Life Time}$$

$$\text{Number of Missions Available per Battery} = \frac{\text{Life Cycle of Battery}}{\text{Cycle per Mission}}$$

$$\text{Cycle per Mission} = \frac{\text{Network Energy}}{\text{Battery Capacity} * \text{Number of Agents}}$$

$$\text{Number of Batteries Required} = \frac{\text{Number of Mission Required per Life}}{\text{Number of Missions Available per Battery}}$$

$$\text{Battery Price} = \text{Battery Capacity [kWh]} * \text{Number of Batteries Required} * \text{Battery Specific Cost} \left[ \frac{\$}{\text{kWh}} \right]$$

### 3.4.2 Operating Expenses

The operating expenses are calculated as the summation of remote pilot cost, maintenance cost, energy cost, and indirect operating cost. The model does not consider the fees paid to air traffic control and the landing fees for wildfire suppression missions.

$$\text{Operating Cost} = \text{Remote Pilot Cost} + \text{Maintenance Cost} + \text{Energy Cost}$$

The wildfire suppression mission is assumed as an autonomous flight mission. Therefore, the missions are guided by a remote pilot who is responsible for the fleet on the ground. The remote pilot cost is calculated by modifying the relation mentioned in [25] by multiplying by the fleet size to estimate the cost per mission. The number of aircraft assigned to remote pilot is assumed to be equal to the fleet size and the average pilot wrap rate is shown in Table 1.

$$\text{Remote Pilot Cost} = \frac{\text{Pilot Wrap Rate} \left[ \frac{\$}{\text{hour}} \right] * \text{Mission Time [hour]}}{\text{Number of Aircraft per Remote Pilot}} * \text{Number of Agents}$$

The maintenance cost per mission depends on the mechanic wrap rate, the ratio of maintenance man-hours to flight hours, mission time, and the number of agents [25].

$$\text{Maintenance Cost} = \text{Mechanic Wrap Rate} \left[ \frac{\$}{\text{hour}} \right] * \frac{\text{MMH}}{\text{FH}} * \text{Mission Time [hour]} * \text{Number of Agents}$$

For electric aircraft, the ratio of Maintenance Man-Hours (MMH) to Flight Hours (FH) has lower values provided that electric motors require less maintenance and are easily accessible. The energy cost per mission depends on the total amount of energy used in the mission and the electricity price.

$$\text{Energy Cost} = \text{Network Energy per Mission [kWh]} * \text{Electricity Price} \left[ \frac{\$}{\text{kWh}} \right]$$

Indirect operating cost is calculated as a fixed fraction of the direct operating cost. In the wildfire suppression mission, indirect operating cost includes a hangar to store and maintain the vehicles in addition to the necessary infrastructure for take-off and landing.

### 3.4.3 Capital Expenses

The capital expenses only consider the depreciation cost of aircraft in each mission. The depreciation cost refers to the decrease in the value of an aircraft over time. The value of assets after their useful life is not included in the capital expenses. The insurance cost and finance cost are also not included in the capital expenses for the wildfire suppression mission.

$$\text{Capital Expenses} = \text{Airframe Depreciation Cost} + \text{Avionics Depreciation Cost} + \text{Battery Depreciation Cost}$$

Exponential decay over time is assumed for airframe depreciation referring to [30].

$$\text{Airframe Depreciation Cost} \left[ \frac{\$}{\text{mission}} \right] = \frac{\text{Airframe Price} * (1 - \exp(-\text{depreciation rate}))}{\text{Number of missions per year}}$$

The equation used in the model implicitly approximates the lifetime of the aircraft as 10 to 15 years. To find the depreciation cost per mission, the equation is modified by dividing by the number of missions per year.

The avionics depreciation cost per mission is estimated in the same manner as the airframe depreciation following [30].

$$\text{Avionics Depreciation Cost} \left[ \frac{\$}{\text{mission}} \right] = \frac{\text{Avionics Price} * (1 - \exp(-\text{depreciation rate}))}{\text{Number of missions per year}}$$

Battery depreciation cost is assumed as a straight-line approximation. The number of missions provided by the battery is found by dividing the life cycle of the battery by the required battery cycle per mission.

$$\text{Battery Depreciation Cost} \left[ \frac{\$}{\text{mission}} \right] = \frac{\text{Unit Battery Price}[\$]}{\frac{\text{Life of Battery}}{\text{Cycle per Mission}}}$$

3.4.4 Parameters

Finally, the cost model section is concluded by Table 1, which summarizes the underlying cost model parameters, the assumed values, and corresponding references.

Table 1 – Cost model parameters.

Parameter	Value	Reference
Airframe price, USD/kg	1,102	[25]
Avionics price, USD	100,000	[25]
Depreciation rate, %	7.5	[30]
Electricity price, USD/kWh	0.2	[31]
Battery specific cost, USD/kWh	300	[29,31]
Lifetime, years	15	[30]
Number of Missions, missions/year	60	[32]
Mechanic wrap rate, USD/hour	75	[25]
MMH to FH ratio, dimensionless	0.6	[25]
Pilot wrap rate, USD/hour	150	[33]
Indirect operating cost, %	20	Assumed

4. Results and Discussions

The evaluation parameters used in this study for the analysis of results are as follows:

- **Number of Agents [count]**  
Total number of wildfire suppression aircraft deployed
- **Energy [kWh]**  
Represents the total energy used by each fleet and is indicated by marker size
- **Burnt Area [football fields]**  
The total burnt forest area in [football fields], i.e. 5,000 m<sup>2</sup> per football field
- **Operating Cost [USD]**  
The total operating cost per mission (incl. depreciation) of each fleet
- **Measure of Effectiveness (MoE) [nondimensional]**  
Combines firefighting effectiveness and cost with minimum indicating optimality

$$MoE = 0.5 * \frac{\text{Burnt Area}}{\text{Maximum Burnt Area}} + 0.5 * \frac{\text{Operating Cost}}{\text{Maximum Operating Cost}}$$

The parameters investigated in this study and their values are given in Table 2, where the underlined values represent the baseline case. Each sensitivity study is carried out in comparison with the baseline case.

Table 2 – Wildfire suppression case study parameters.

Parameter	Value
<b>Design</b>	
Payload Capacity	<u>250 kg</u> 500 kg
Cruise Speed	20 m/s <u>30 m/s</u> 40 m/s
Range	<u>30 km (short)</u> 60 km (mid)
<b>Operations</b>	
Operational Range	<u>5 km average (short)</u> 10 km average (high)
Response Time	<u>20 min</u> 25 min

#### 4.1 General Cost Model Discussions

The results demonstrate that the total operating cost is substantially dominated by capital expenses. The domination of capital expenses for wildfire suppression missions is expected due to the small number of missions per year. Therefore, the number of missions strongly affects the capital expenses which decrease as the use of aircraft increases. Consequently, changes in the aircraft configuration and maximum take-off mass have substantial effects on the total operating cost as well.

While the airframe depreciation cost is the leading cost component in capital expenses, the battery depreciation cost has a considerably low effect on them. On the other hand, the operating expenses are driven by maintenance cost and energy cost, and the pilot cost is reduced significantly due to autonomy. The total operating cost is hardly sensitive to any changes in the parameters for operating expenses. Overall, both capital and operating expenses are strongly sensitive to the fleet size.

#### 4.2 General System of Systems Simulations Capabilities

Before addressing the SoS simulation results in the following, the authors would like to introduce some qualitative results to demonstrate the capability of the framework. Therefore, Figure 4 shows an active wildfire suppression mission on the left. Here, the active fire front is represented by red cells, whereas the burnt area is shown by brown cells. The firefighting UAVs are shown as blue disks. Furthermore, the completed successful mission can be seen in Figure 4 on the right, where suppressed area is represented by grey cells.

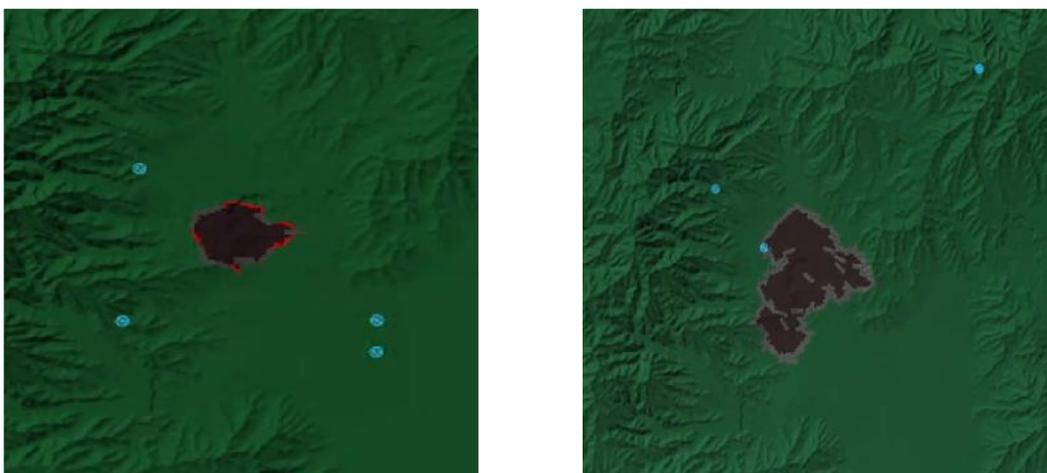


Figure 4 – Active wildfire suppression mission (left) and completed successful wildfire suppression mission (right).

The MABS also provides the capability or feature to prioritize certain locations. While in this study this capability is not utilized, it was generally developed to model the priority protection areas such as housing areas, which would be prioritized in a real-life suppression scenario. Thus, Figure 5 presents the capability for completeness. On the left screenshot in Figure 5, a failed wildfire suppression mission is shown, where the feature is disabled. This can be found, since the protection locations (represented by yellow icons) are fully burnt. Instead, the UAV bases and off-base water sources were protected by the UAVs. However, enabling the feature for priority protection areas shows that these areas can be saved as display on the right screenshot in Figure 5. More detailed discussions on this capability demonstration can be found in [9].

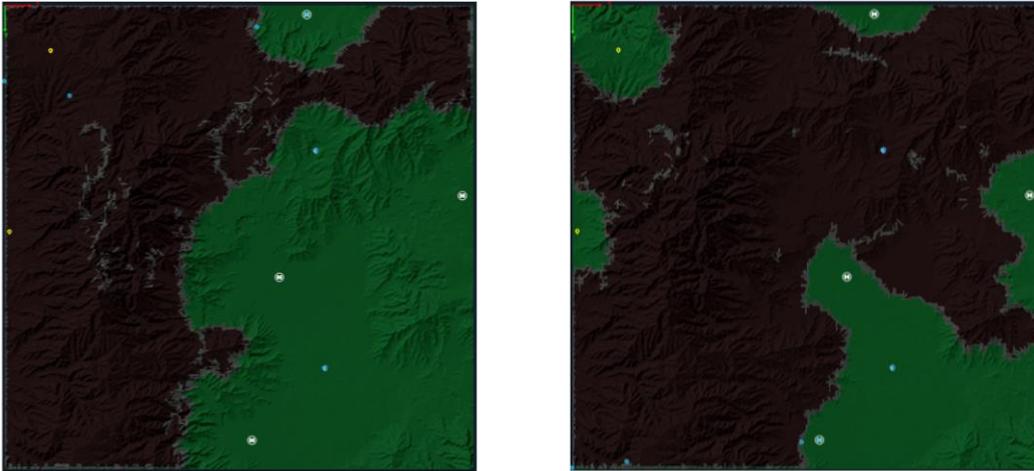


Figure 5 – Failed wildfire suppression missions with protection locations disabled (left) and protection locations enabled (right).

### 4.3 System of Systems Simulations of Design Parameters

In the following sections, the impact of top level aircraft design parameters on the aerial firefighting effectiveness and cost will be presented. Accordingly, the cruise speed, the payload capacity, and the design range are studied.

#### 4.3.1 Cruise Speed

The sensitivity of three design cruise speeds on the firefighting effectiveness is presented in Figure 6, where the number of agents is plotted against the Measure of Effectiveness and its individual components. The first clear trend is that larger fleet sizes perform better in fire suppression as expected. Considering the fleet size of 8, it is observed that the design cruise speed of 30 m/s results in the most effective fleet for the multirotor and compound helicopter architectures. In comparison, for the same fleet size, the lift + cruise and tiltrotor architectures are the most effective with 40 m/s cruise speed. This shows that the optimal fleet size and speed is dependent on the architecture in consideration. At the high speeds of 40 m/s, the compound helicopter and multirotor architectures suffer in performance due to the energy limitations. This can be seen from the marker sizes as it represents the total energy consumed by each fleet. Considering the operating cost, larger fleets cost more to operate as expected. It is found that depending on the design cruise speed, the cheapest architecture to operate changes between multirotor for the lower speeds and the compound helicopter for the higher speeds. Combining these two factors together into the MoE, an optimal fleet size can be obtained for each architecture and cruise speed. For the lowest cruise speed, the fleet size of 10 is found to be optimal for all architectures, whereas for the middle cruise speed the fleet size of 8 is optimal for multirotor and compound helicopter architectures and a fleet size of 12 is optimal for the others. A fleet size of 10 is found to be optimal for the highest cruise speed in consideration.

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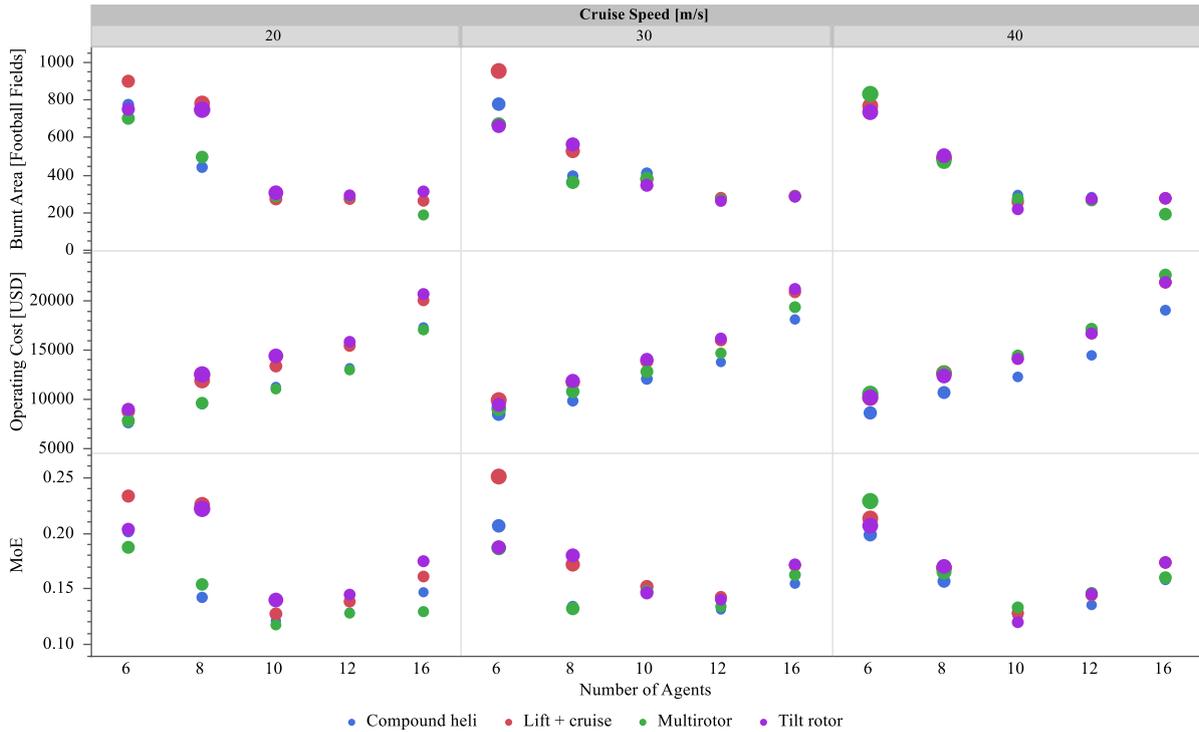


Figure 6 – The sensitivity of cruise speed on the aerial firefighting effectiveness and cost.

4.3.2 Payload Capacity

The effect of payload capacity on the effectiveness of aerial suppression is shown in Figure 7.

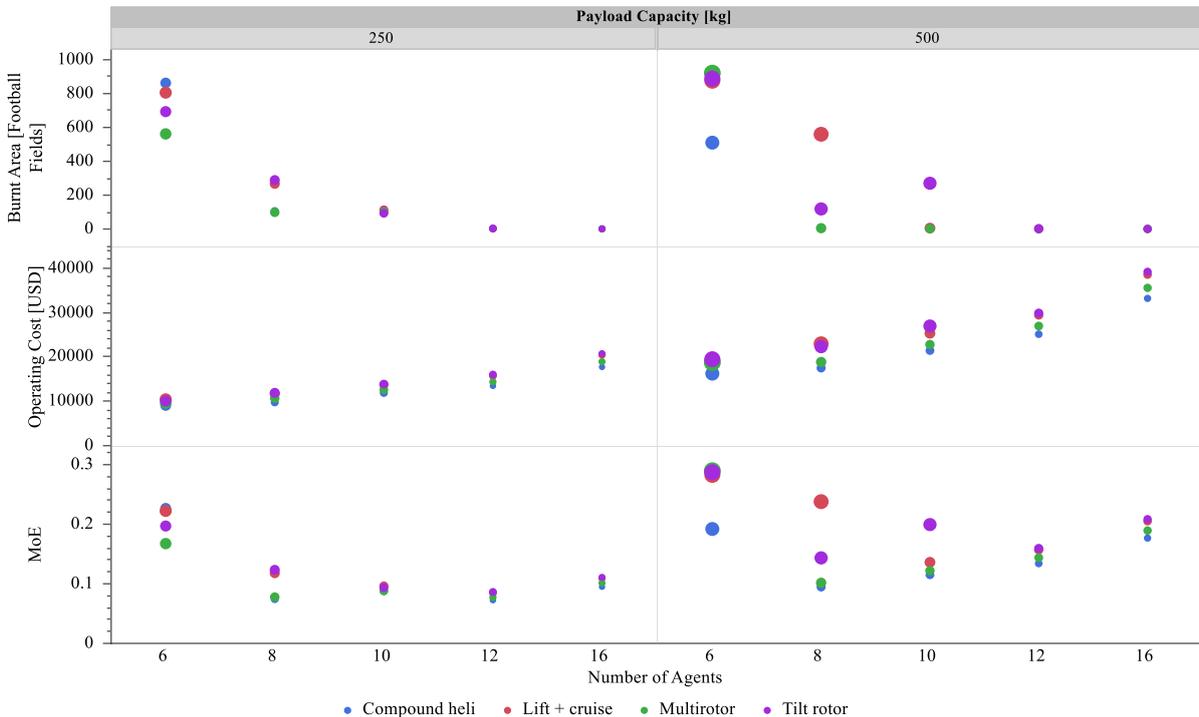


Figure 7 – The impact of payload on the aerial firefighting effectiveness and cost.

In general, the higher payload capacity of 500 kg is shown to improve aerial firefighting effectiveness compared the 250 kg payload capacity. Conversely, the fleet with the higher payload is more expensive to operate. The optimal fleet size is found to be dependent on the payload and architecture. In particular, for the lift + cruise architecture, the smaller payload fleet is found to be optimal with 12 aircraft whereas for the larger payload fleet 10 aircraft is optimal. For the multirotor architecture, for both the payload capacities, a fleet size of 8 is found to be optimal.

### 4.3.3 Design Range

The effect of the design range on the aerial firefighting effectiveness considering short (30 km) and mid (60 km) ranges is given in Figure 8. In terms of the burnt area both design ranges perform similarly. However, for the mid design range the vehicles are oversized which mostly leads to higher energy consumption (indicated by marker size) and operating cost. Consequently, it is observed that the best MoE is slightly worse for the mid design range than the short design range. In addition, some architectures (e.g. multirotor) are very sensitive to higher design range and as such this parameter must be chosen carefully.

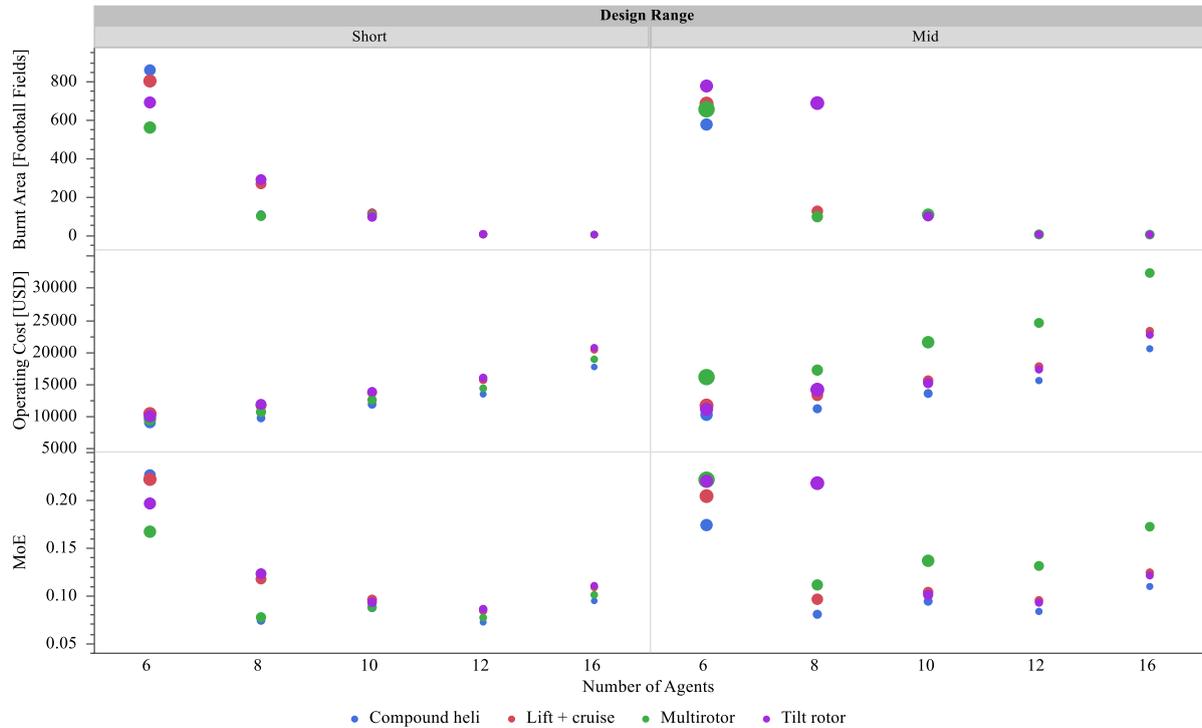


Figure 8 – The impact of design range on the aerial firefighting effectiveness and cost.

### 4.4 System of Systems Simulations of Operational Parameters

In the following sections, the impact of operational parameters on the aerial firefighting effectiveness and cost will be presented. Here, the operational range, which is the distance between the fire ignition center and the aircraft bases, is varied. Furthermore, the impact of the response time until the firefighting aircraft are deployed is studied.

#### 4.4.1 Operational Range

Figure 9 shows the results for a wildfire scenario, in which the operational range is doubled from 5 km (short) to 10 km (high), whereas the aircraft are sized for the low design range of 30 km. It should be noted that both operational ranges are averaged. It is found that the number of successful fleets clearly diminishes for the high operational range. Accordingly, this effects the operating cost, which can be seen by the significant cost increase for the smaller fleet sized. Consequently, the best MoE of the short operational range scenario cannot be reached in the high operational range scenario. This operational scenario results in a fleet size requirement of at least 10 fixed-wing cruise eVTOL aircraft architectures, i.e. lift + cruise or tiltrotor, or 12 eVTOL aircraft of any architecture. Compared to the low operational range, where 8 aircraft are sufficient, an increased fleet size of 25% or even 50% is required.

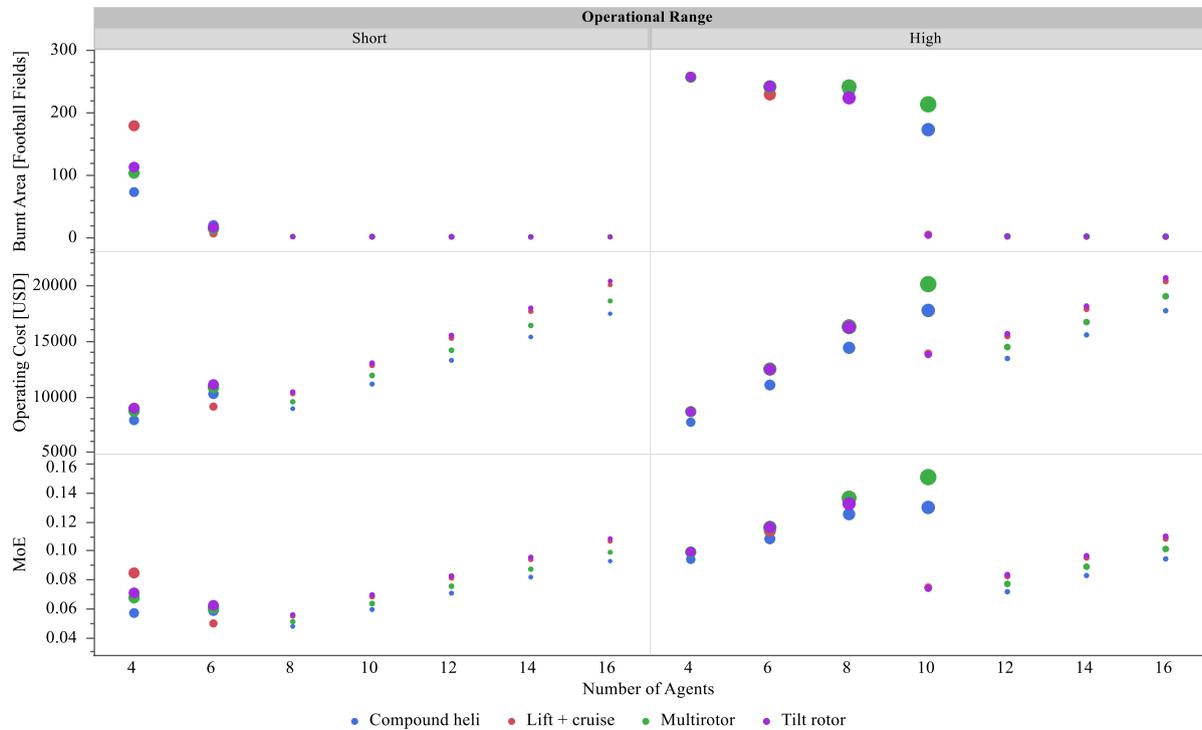


Figure 9 – The impact of operational range on the aerial firefighting effectiveness and cost.

#### 4.4.2 Response Time

Eventually, Figure 10 shows the impact of a delayed firefighting response on the effectiveness and cost. If the response time is prolonged from 20 min to 25 min (by 5 min or 25%), most previously successful fleets fail to suppress the fire successfully. As a consequence, the operating cost shows a steeper increase compared to the baseline response time of 20 min. This step increase affects the MoE, which shows a wavy trend. Regarding the fleet design, the fleet size must be increased. This means that the 12 instead of 8 aircraft are required for the delayed response time scenario. For this case study, an only 5 min or 25% longer response time leads to 4 additionally required aircraft or a 50% increased fleet size.

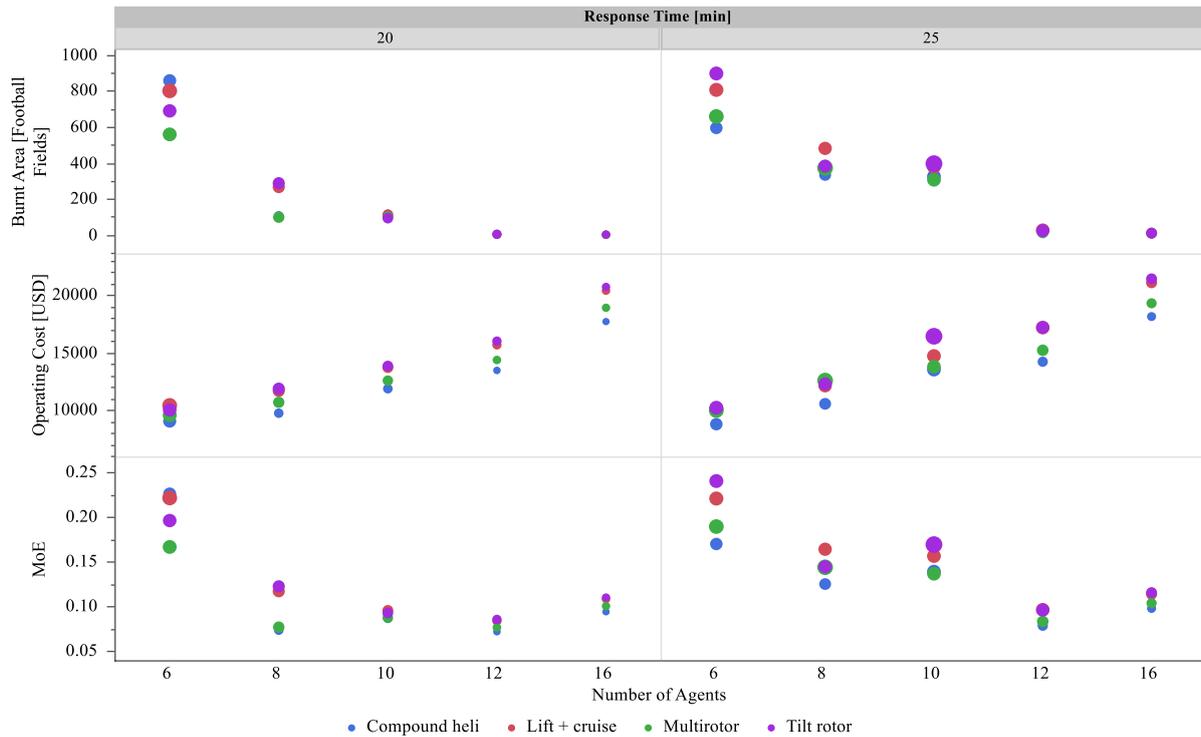


Figure 10 – The impact of response time on the aerial firefighting effectiveness and cost.

### 5. Conclusions and Future Work

The aim of this study was to establish an initial MoE for wildfire suppression that involves aerial firefighting effectiveness and cost. The inclusion of cost estimations allows to identify an optimal fleet for a given wildfire scenario and fleet composition. It was investigated how various design and operational parameters impact the MoE and optimal fleet size.

Generally, the aerial firefighting fleet and its interaction with the fire model is a complex SoS, where analytical methods cannot evaluate the fleet effectiveness based on fire spread and aircraft performance. Hence, a small change in one of the aircraft design or operational parameters will have a snowball effect throughout the mission. Therefore, the investigations carried out in this study and the results highlight the importance of the SoS approach to the design and fleet planning as well as management of wildfire suppression aircraft.

Several sensitive parameters such as cruise speed, payload, and response time were identified and the complex impacts on the effectiveness were highlighted. An ideal combination of these parameters, along with aircraft performance, needs to be identified for a robust fleet that can sustain its effectiveness over various environmental conditions and terrains. Furthermore, this work proved that there is need for simulation embedded SoS approaches for such non-linear complex explorations of emergence.

Future work includes exploring more subsystem, Sol or SoS level parameters and fine-tuning of the MoE to better represent the priorities of the stakeholders in terms of financial and environmental costs. While in this study the terrain and environmental conditions were fixed, the capability exists in the MABS to vary the temperature, wind, and other environmental conditions in addition to the vegetation indices of the terrain and its topography. Various environmental conditions and terrains can be included in the sensitivity investigations to aid in the identification of the parameters that contribute most to a robust aerial firefighting fleet. Moreover, heterogenous fleets can be investigated and compared to homogenous fleets. In addition, the simulation can be expanded to extended attack scenarios with the inclusion of ground agents and parallel as well as indirect attack strategies. In terms of aircraft design, more sophisticated methods will be incorporated in the design process of the wildfire suppression UAVs together with refined modelling of subsystem level performance as performed in other works by the same authors [26]. Moreover, the simulation of historical fires can be attempted together with their suppression using various fleet sizes and aircraft architectures.

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## 7. Contact Author Email Address

The authors would like to invite potential collaborators for this aerial firefighting project with the objective of collaborative simulation driven aircraft design. Access to the existing simulation will be provided. Please contact the corresponding author: Prajwal.Prakasha@dlr.de

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