

Optimal Resource Allocation for Multiple Wildfires Considering Critical Infrastructure Interdependencies

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Abstract

Due to climate change, prolonged droughts, and extreme weather, wildfires are becoming more frequent and are reaching the level of natural disasters. Under these new conditions, it is critical to develop rapid and effective fire containment strategies. This paper presents an online optimization framework for wildfire containment during concurrent multiple wildfire incidents. The method integrates wildfire damage prediction with a mixed-integer linear programming (MILP) model to optimize the allocation and scheduling of firefighting resources to minimize total losses. Within the optimization framework, operational limits such as resource availability, travel time, and containment effectiveness are incorporated into the decision-making process as the wildfire evolves. The proposed method reduced total losses by as much as 45.1% in some cases compared with a traditional priority-based resource dispatching method. Computational tests on various wildfire scenarios also show that adding additional resources may not linearly translate into loss reduction. Overall, the framework offers an effective and computationally feasible method for planning dynamic wildfire containment, allowing for optimized resource allocation under changing fire conditions. The findings emphasize the value of using predictive simulation and optimization techniques to support effective wildfire emergency management.

Keywords: Critical Infrastructure Interdependencies; Mixed-Integer Scheduling Model; Multiple Simultaneous Wildfires; Wildfire damage assessment; Online decision support; Fire suppression planning.

1 Introduction

Wildfires are complex natural-human phenomena that, over recent years, have increased in frequency and severity due to rising global temperatures and the expansion of human activity in

fire-prone areas, changing the fire landscape [1]. Dryness from higher summer temperatures makes new fires much more likely. Lightning is responsible for approximately 45% of all fires but accounts for nearly 81% of the total area burned annually [2]. The increase in lightning strikes is directly related to rising global temperatures [3]. In 2025, two simultaneous wildfires in Los Angeles cost over US\$140 billion and killed over 30 people. The extreme heat triggered large-scale wildfires across Europe, with over 500,000 Ha burned in Portugal and Spain alone. By the end of the year, almost 500,000 people worldwide had been displaced due to the wildfires [4][5]. According to the Canadian National Forestry Database [2], over 7,000 forest fires occur annually in Canada, burning an average of over 2.1 million hectares. In the last three years, Canadian forest fires have emitted almost 4 billion tonnes of CO_2 from the burning of the boreal forests [4].

It is essential to detect wildfires as early as possible and to rapidly deploy containment resources once a fire has been identified. In general, the response time to a wildfire should not exceed 30 minutes [6]. When adequate firefighting resources are available, allocating them to a single wildfire can be relatively manageable, provided that relevant factors, such as operational costs, infrastructure damage, service disruption costs, and the efficiency and operational readiness of the resources, are properly considered. However, the allocation problem becomes significantly more complex when multiple wildfires with different propagation speeds and paths are reported simultaneously from different locations. Now, decision-makers must distribute the available resources across multiple fires, considering complex interdependent constraints, including operational constraints (e.g., the number of resources and their capabilities), human constraints (e.g., the crew’s working hours and technical experience), and each fire’s behaviour (e.g., how fast the fire is moving and in what direction). The number of constraints and their interdependencies considerably complicate the optimization problem [7].

This paper proposes an optimization–simulation framework to minimize both resource allocation costs and the impact on surrounding [Critical Infrastructure \(CI\)](#) during simultaneous wildfires. The optimization model, formulated as a [Mixed Integer Linear Programming \(MILP\)](#), is integrated with the [Infrastructure Interdependencies Simulator \(i2SIM\)](#), a simulation framework that captures interdependencies among multiple systems, to show how response actions across [CI](#) affect the operation of other Infrastructures. Considering these interdependencies within the cost analysis of wildfire impact provides a more thorough socioeconomic analysis, as it accounts not only for operational costs but also for the social cost to communities affected by the wildfires.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the multiple simultaneous wildfire containment problem. Section 4 introduces the *i2SIM* tool, which quantifies the financial impact of the wildfires. Section 5 presents the mathematical model for the optimal wildfire resource allocation problem. Sections 6 and 7 present computational experiments and discuss the results.

Finally, Section 8 concludes the paper and outlines directions for future research.

2 Literature review

Wildfire containment management involves not only responding to active fires but also planning, acquiring, and organizing the resources required before a wildfire occurs. Over the years, multiple researchers have proposed optimization strategies to allocate limited resources. Granda et al. [8] proposed a mathematical programming model that supports wildfire suppression decisions, optimizing limited ground resources (a brigade) during the dispatch stage of wildfire suppression. However, their research is limited because it does not consider fire intensity as a decision parameter; instead, it is treated as a consequence of actions, and the model uses only one brigade, which moves across fires. Jeon et al. [9] also present an integer linear programming-based decision support framework for helicopter dispatch during multiple wildfires. However, they focus solely on dispatching aerial resources and treat fire intensity as a fixed input parameter that does not change over time.

Hsu [10] developed an AI-based optimization framework to allocate firefighting resources more effectively, but it does not account for real-time changes during a wildfire or for coordination among multiple resources. Zhou et al. [11] formulated an optimization model with a hybrid algorithm for wildfire task scheduling and emergency resource delivery under uncertainty, but it does not consider real-time fire dynamics. Lawton et al. [12] developed a robust optimization framework for allocating fire management resources for species conservation, but it focuses on long-term conservation planning rather than operational wildfire suppression. Dasdemir et al. [13] formulated an integrated scheduling and routing problem for wildfire response using a mixed-integer programming model with dynamic constraint generation, capturing degrading demand and fire spread effects, but the model relies on simplified fire dynamics and ignores operational constraints.

Orphanoudakis et al. [14] developed a decision support system that integrates optimization for resource allocation during wildfires, but it lacks explicit time estimation and remains partially validated, requiring further development for full operational deployment. Zhou and Zhang [15]

proposed an event-response tree-based model for intuitive scheduling of firefighting resources using a fire suppression index, but the approach may involve subjectivity. Mendes and e Alvelos [16] employed the Minimum Travel Time (MTT) methodology to integrate wildfire behaviour into optimization models, yielding a more realistic framework in which suppression strategies directly influence fire dynamics, but the economic impacts of wildfires are ignored.

When accounting for the economic cost of the decision, the theoretical framework commonly used to determine the most economically efficient level of fire management expenditure is the Cost (C) plus Net Value Change (NVC) model, introduced by Gorte and Gorte [17] and widely applied in the literature [18][19]. Our approach follows the same principle by minimizing the combined cost of fire impacts and suppression operations to determine an economically efficient resource-allocation strategy.

Similar to our work, Rodríguez-Veiga et al. [20] propose an integer linear programming model for wildfire resource allocation over multiple time periods, incorporating several operational constraints. However, their formulation assumes deterministic wildfire and resource parameters and is limited to a single wildfire scenario, resulting in high solution times for larger instances. Later, Rodríguez-Veiga et al. [19] applied decomposition techniques to reduce computational complexity, but other limitations remain unchanged. Matos et al. [21] proposed a constructive heuristic for dispatching and routing firefighting resources among multiple fires to minimize burned area, but they assume fixed refill and suppression times and do not fully address dynamic fire uncertainties. Although the heuristic method provides fast decisions, it may not guarantee the best possible resource allocation compared with exact optimization approaches.

3 Problem Formulation

When there are multiple wildfires, both operational and human constraints must be considered during dynamic resource allocation. Firefighting units might be based at stations far from the fire site, the crew might be resting after completing their previous duties, or they might be currently involved in operations at other wildfires.

The time required to travel between fire locations and bases, the limited number of available crew members, and the maximum allowable working periods for ground personnel all act as constraints. Moreover, the effectiveness of resource allocation is influenced by factors such as fire intensity, weather conditions, terrain accessibility, and the proximity of CIs. In our framework,

we consider a set of assumptions and operational conditions that reflect realistic wildfire scenarios. These assumptions and conditions are designed to closely replicate actual multiple-wildfire scenarios and capture the operational complexity of firefighting environments. We assume:

- In the presence of multiple simultaneous wildfires, a heterogeneous set of containment and recovery resources must be allocated from bases distributed across geographic locations. The primary objective is to determine an optimal allocation and deployment strategy that minimizes the total system cost, which includes both the operational costs of resource use and the expected costs of repairing and addressing service disruptions to affected infrastructure.
- Different wildfires may spread in different directions and at different rates, depending on local environmental conditions.
- There may be cases where several wildfires combine to form one large fire, even when firefighters are already involved in containment operations. Such situations can considerably alter the behaviour of the fire and its resource requirements, which in turn means that there is a need for a dynamic reorganization of resource distribution and the suppression strategies employed.
- Some characteristics of firefighting resources are predefined. These include the number of available resources, their containment capacities or rates, current base locations, associated operating and deployment costs, and their status (in use or not).
- Each resource is assigned the maximum permissible work periods based on a rest-efficiency factor that reflects the level of rest in the past 24-hour cycle (the resource rest level) and the training level of human resources [22].
- The fire spread dynamics and containment rates for the different resources are modeled using a discrete-time framework with a 10-minute time step.
- Accurately estimating the travel times for resources to different wildfire locations from a base, as well as travel times between locations, is critical. These travel times are subject to significant variability due to factors such as road closures, congestion, terrain conditions, and damage to transportation infrastructure caused by the wildfire.

The assumed conditions are designed to closely mirror real-world multiple-wildfire scenarios, capturing the operational complexity of firefighting environments.

4 The i2SIM Simulator

Understanding how interdependent infrastructure systems respond to external events, such as wildfires, is a significant challenge for emergency responders. Effective response planning must account for interactions across multiple layers: decision, damage, financial, and production. These complex interdependencies can be analyzed with simulation models.

i2SIM is a simulation framework designed to capture and analyse interactions among multiple infrastructure systems during emergencies. i2SIM has been successfully applied across a wide range of emergency response and infrastructure resilience studies, demonstrating its flexibility and robustness in modelling complex, interdependent systems [23][24][25].

i2SIM integrates multiple factors of different physical natures through a transfer function, described by an input-output table. This table, called the **Human Readable Table (HRT)**, shows how much of each input is required for a specific level of infrastructure operation. At each timestep of the simulation, the availability of input resources varies, and the resource whose output is at the lowest operating level determines the infrastructure’s operating level.

Table 1: HRT for a hospital emergency unit.

management	engineering	engineering	management	management	engineering	management
$y(t)$	$x_1(t)$	$x_2(t)$	$m_1(t)$	$m_2(t)$	$m_3(t)$	$m_4(t)$
Patients per hour	Electricity (kW)	Water (L/h)	Doctors	Nurses	Physical Integrity (%)	Doctors Shift Factor (%)
20	100	2000	4	8	100	100
15	75	1000	3	6	80	75
10	50	600	2	4	50	50
7	25	400	2	3	20	25
0	0	0	0	0	0	0

For example, the hourly number of patients accepted to a hospital emergency unit cannot be adequately captured by physical equations; however, it is well known to the hospital manager and can be systematically documented in an input–output table, commonly referred to as an **HRT**.

Table 1 presents an example of an **HRT** for a hospital emergency unit [26] [27]. In this scenario, the hospital operates at its full capacity of 20 patients per hour when all required resources are available, namely 100 kW of electricity, 2000 L/h of water, four doctors, eight nurses, no physical damage to the hospital, and doctors working at full efficiency. In the illustrated scenario (circled

values), there is no lack of electricity or doctors; however, the hospital experiences shortages of nurses, some degree of physical damage, moderate doctor fatigue, and mostly lack of water. Among these factors, the limited water supply and the number of nurses are the most restrictive, reducing the hospital's treatment capacity to 10 patients per hour.

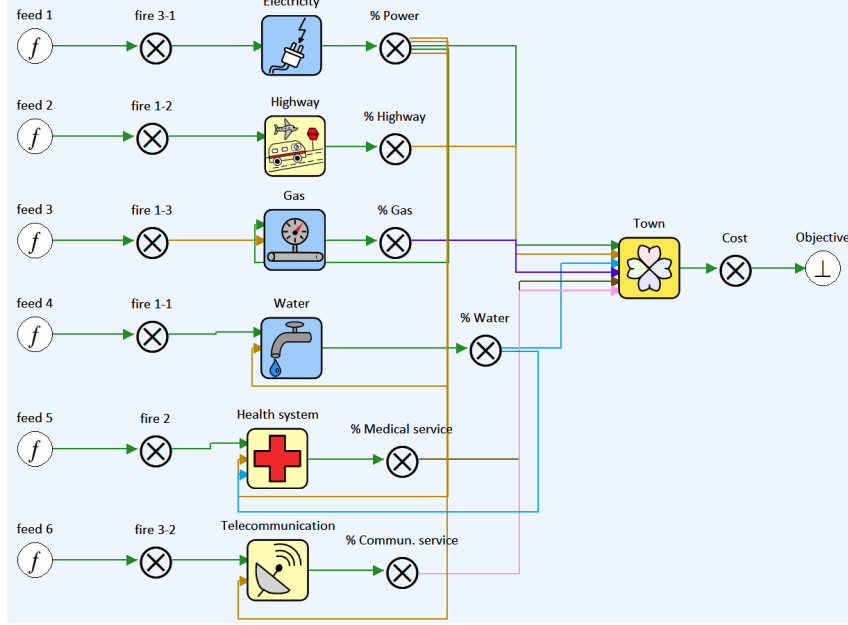


Fig. 1: i2SIM framework to capture interdependencies between CI.

In our i2SIM framework, we focus on six key infrastructures that are critical to the community's operation. They include the electrical network, gas pump, the transportation route (highway/roads), the water distribution plant, the telecommunication towers, and healthcare. These components are closely linked, and a disruption in one can spread through the system, affecting other infrastructures and the communities that depend on them. Figure 1 shows the connections among these infrastructures, and Tables 2 to 8 present the HRT relationship tables for each infrastructure, including the HRT that describes the impact on the community in terms of costs directly affected by the disruption to the other CI.

5 A MILP Model for Wildfire Resource Allocation

This section presents the optimization model for allocating firefighting resources during multiple simultaneous wildfires. The objective of the proposed model is to minimize the total cost associated with all wildfires throughout the planning horizon, thereby reducing the overall economic impact of the wildfire events.

Table 2: Electricity [HRT](#)

Output Available Power(%)	Input Fire Intensity(level)
100	0
80	1
60	2
40	3
20	4
0	5

Table 3: Highway [HRT](#)

Output Highway Integrity(%)	Input Fire Intensity(level)
100	0
80	1
60	2
40	3
20	4
0	5

Table 4: Gas plant [HRT](#)

Output Gas Availability(%)	Input Available Power (%)	Input Fire Intensity(level)
100	100	0
80	80	1
60	60	2
40	40	3
20	20	4
0	0	5

Table 5: Water distribution plant [HRT](#)

Output Water Availability(%)	Input Available Power (%)	Input Fire Intensity(level)
100	100	0
80	80	1
60	60	2
40	40	3
20	20	4
0	0	5

Table 6: Medical Service [HRT](#)

Output Medical service(%)	Input Fire Intensity(level)
100	0
80	1
60	2
40	3
20	4
0	5

Table 7: Communication Service [HRT](#)

Output Communication Service(%)	Input Fire Intensity(level)
100	0
80	1
60	2
40	3
20	4
0	5

We are given

- $\mathcal{I}$, the set of all resources (aerial, machinery, ground personnel, etc.).
- a set $\mathcal{F} = \{F_1, F_2, \dots, F_n\}$, denote the set of all wildfires. Since any resource assigned to a firefighting operation must first travel from its base to the corresponding fire location, we augment the set of fire locations by including a dummy node representing the base. Thus, we

Table 8: Functionality [HRT](#) which later provides financial impact.

Output	% Power	% Highway	% Water	% Gas	% Medical	% Comm.
Functionality (%)	Power Available	Highway Integrity	Water Available	Gas Available	Medical Service Available	Comm. Service Available
100	100	100	100	100	100	100
80	80	80	80	80	80	80
70	70	70	70	70	70	70
60	60	60	60	60	60	60
50	50	50	50	50	50	50
40	40	40	40	40	40	40
30	30	30	30	30	30	30
20	20	20	20	20	20	20
10	10	10	10	10	10	10
0	0	0	0	0	0	0

define the extended location set as $\mathcal{F}' = \mathcal{F} \cup \{0\}$, where node 0 denotes the resource base and the remaining elements correspond to wildfire locations.

- the set of time periods $\mathcal{T} = \{0, 1, 2, \dots, m\}$, in the planning horizon, where $0 \in \mathcal{T}$ represents the initial state of the system before any firefighting operations are undertaken. A subset $\mathcal{T}^w = \{0, 1, 2, \dots, m-1\}$, is the set of decision periods during which actions can be taken.
- the rate of perimeter change g_{ft} of the fire f at the time period $t \in \mathcal{T} \setminus \{0\}$.
- the ability of the resource i , denoted by CPR_i , is the length of the wildfire perimeter that is contained in a time period by each of the resources.
- the estimated travel time periods τ_{ihf} , taken by the resource i to move from the location of the fire h to f .
- the effective working period WP_i , which represents the maximum number of time periods that resource i can operate during a day. This parameter is applied only to ground personnel, who are more directly exposed to wildfire conditions, whereas aerial resources and machinery are assumed to be available throughout the entire planning horizon. Although several factors may influence crew performance, rest levels and training levels as the two most significant determinants of operational effectiveness. Accordingly, the effective working period (WP_i) for each

ground brigade i is estimated using the concept as follows:

$$WP \approx \text{Time horizon} \times \text{Rest Efficiency Factor} \times \text{Training Multiplier} \text{ [22]}.$$

The decision variables are:

- $z_{ift} \in \{0, 1\}$ for each $i \in \mathcal{I}$, $f \in \mathcal{F}'$, $t \in \mathcal{T}$

$$z_{ift} = \begin{cases} 1 & \text{if resource } i \text{ is at location } f \text{ at the start of period } t \\ 0 & \text{otherwise} \end{cases}$$

- $s_{ift} \in \{0, 1\}$ for each $i \in \mathcal{I}$, $f \in \mathcal{F}'$, $t \in \mathcal{T}^w$

$$s_{ift} = \begin{cases} 1 & \text{if resource } i \text{ stays at location } f \text{ at the start of period } t \\ 0 & \text{otherwise} \end{cases}$$

- $m_{ihft} \in \{0, 1\}$ for each $i \in \mathcal{I}$, $h, f \in \mathcal{F}'$, $t \in \mathcal{T}^w$

$$m_{ihft} = \begin{cases} 1 & \text{if resource } i \text{ leaves location } h \text{ at period } t \text{ toward fire } f \\ 0 & \text{otherwise} \end{cases}$$

- $x_{ift} \in \{0, 1\}$ for each $i \in \mathcal{I}$, $f \in \mathcal{F}$, $t \in \mathcal{T}$

$$x_{ift} = \begin{cases} 1 & \text{if resource } i \text{ contains fire } f \text{ during period } t \\ 0 & \text{otherwise} \end{cases}$$

- $y_{ft} \in \{0, 1\}$ for each $f \in \mathcal{F}$, $t \in \mathcal{T}$

$$y_{ft} = \begin{cases} 1 & \text{if the fire } f \text{ is not contained in period } t \\ 0 & \text{otherwise} \end{cases}$$

It is certain that the wildfire is not contained in the initial period, so $y_{f0} = 1$, $f \in \mathcal{F}$.

- $P_{ft} \geq 0$ is the remaining perimeter of fire f at time t , where P_{f0} is the initial perimeter of fire f when it was reported.

The objective is to minimize both the damage costs incurred by CIs and the operational costs associated with deploying firefighting resources. Thus, the standard wildfire resource allocation problem can be formulated as a MILP model as follows:

$$\begin{aligned}
\min \quad & \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} NV C_{ft} y_{f,t-1} + \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{I}} C_i x_{ift} \\
\text{s.t.} \quad & P_{f,t+1} \geq P_{ft} + g_{ft} y_{ft} - \sum_{i \in \mathcal{I}} CPR_i x_{ift}, & \forall f \in \mathcal{F}, t \in \mathcal{T}^w, & (1a) \\
& P_{ft} \leq M y_{ft}, & \forall f \in \mathcal{F}, t \in \mathcal{T}, & (1b) \\
& P_{fm} = 0, & \forall f \in \mathcal{F}, & (1c) \\
& z_{i,0,0} = 1, & \forall i \in \mathcal{I}, & (1d) \\
& z_{if0} = 0, & \forall i \in \mathcal{I}, f \in \mathcal{F}, & (1e) \\
& m_{ihft} = 0, \quad \text{if } (h = f) \text{ or } (t + \tau_{ihf} > m), \forall i \in \mathcal{I}, h \in \mathcal{F}', f \in \mathcal{F}, t \in \mathcal{T}^w, & (1f) \\
& z_{int} = s_{int} + \sum_{\substack{f \in \mathcal{F} \\ f \neq n \\ t + \tau_{inf} \leq m}} m_{inf}, & \forall i \in \mathcal{I}, n \in \mathcal{F}', t \in \mathcal{T}^w, & (1g) \\
& z_{int} = s_{in,t-1} + \sum_{\substack{h \in \mathcal{F}' \\ h \neq n}} \sum_{\substack{t' \in \mathcal{T}^w \\ t' + \tau_{ihn} = t}} m_{ihnt'}, & \forall i \in \mathcal{I}, n \in \mathcal{F}', t \in \mathcal{T} \setminus \{0\}, & (1h) \\
& x_{ift} \leq s_{ift}, & \forall i \in \mathcal{I}, f \in \mathcal{F}, t \in \mathcal{T}^w, & (1i) \\
& x_{ift} \leq y_{ft}, & \forall i \in \mathcal{I}, f \in \mathcal{F}, t \in \mathcal{T}^w, & (1j) \\
& \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} x_{ift} \leq W P_i, & \forall i \in \mathcal{I}, & (1k) \\
& \sum_{f \in \mathcal{F}} x_{ift} \leq 1, & \forall i \in \mathcal{I}, t \in \mathcal{T}, & (1l) \\
& P_{ft} \geq 0, & \forall f \in \mathcal{F}, t \in \mathcal{T}, & (1m) \\
& z_{iht}, s_{iht}, m_{ihft}, x_{ift}, y_{ft} \in \{0, 1\}, & \forall i \in \mathcal{I}, h \in \mathcal{F}', f \in \mathcal{F}, t \in \mathcal{T}, & (1n)
\end{aligned}$$

where a suitable parameter $M = \sum_{f \in \mathcal{F}} P_{f0} + m \sum_{i \in \mathcal{I}} CPR_i$, called *Big-M*, is a large positive constant which allows certain constraints to be activated or relaxed depending on the value of associated binary decision variables.

Constraint 1a measures the remaining perimeters of each fire in each of the time periods. Constraint 1b ensures that there is no perimeter of a fire remaining in the contained period. Constraint 1c forces the model to include all fires within the given time horizon. Constraints 1d and 1e ensure that all resources are at their base stations at the initial planning stage. Constraint 1f indicates that movement of resources is not possible to the same fire or when the time step exceeds the permissible range. Constraint 1g ensures that if a resource is at a location, it must either stay there or start exactly one feasible move to a fire. Constraint 1h determines a resource’s location in any time period based on its location in the previous time period and any possible movement. Constraint 1i ensures that a resource can contain a fire only when it is at that location. Constraint 1j ensures that a resource contains a fire only if it has not already been contained. Constraint 1k ensures that each resource can work only up to a permissible limit each day. Constraint 1l guarantees that every resource is allocated to exactly one wildfire during each time period. Finally, constraints 1m and 1n define the domain of the variables.

6 Computational Experiments and Simulation Study

This section evaluates the performance and reliability of our proposed simulation-optimization framework across different wildfire scenarios and resource-allocation simulation experiments using realistic test cases. We assess how effectively the model allocates limited resources, responds to changing fire conditions, and reduces overall damage costs, comparing it with a priority-based heuristic.

6.1 Experimental Settings

This section outlines the experimental framework used to evaluate the proposed approach. It details the wildfire scenario generation process, followed by the configuration of available firefighting resources and their operational parameters. Finally, a cost analysis is conducted to assess the impact of different wildfires on CI.

6.1.1 Wildfire Scenario Setup

The wildfire scenarios include three medium-sized starting fires that propagate over 6 hours, from 12 pm to 6 pm, and reach different infrastructure at different times. For the experiments, we assume that the wildfires are detected and reported 30 minutes (three time periods) after ignition.

Consequently, decision-makers begin allocating firefighting resources at the start of time period 4. The three fires progressively merge over time.

Figure 2 presents the wildfire propagation scenario together with the locations of the infrastructures, which are the ones described in Section 4. The scenario is a synthetic scenario modelled after the real wildfire scenario that occurred in Jasper City, Canada in 2024 [28]. In the real wildfire scenario, two fires merged into one large fire. This merging of fires is analyzed in our base test case in subsection 6.2. In Figure 2, each dashed curve shows the location of the fire perimeter at 1-hour time steps. To estimate the rate of perimeter changes, we employ a simplified elliptical fire propagation model for each fire. The perimeters are assumed to grow linearly over time until fire merging occurs. The base setting for their initial perimeters and rate of spread is given by Table 9 which further determines the perimeter growth of 0.545 km, 0.454 km and 0.363 km respectively. For the base setting, we assume that Fires 1, 2, and 3 originate at coordinates (0km,0km), (4km,2km), and (2km,6km), and their directions are 45° , 60° , and 30° , respectively.

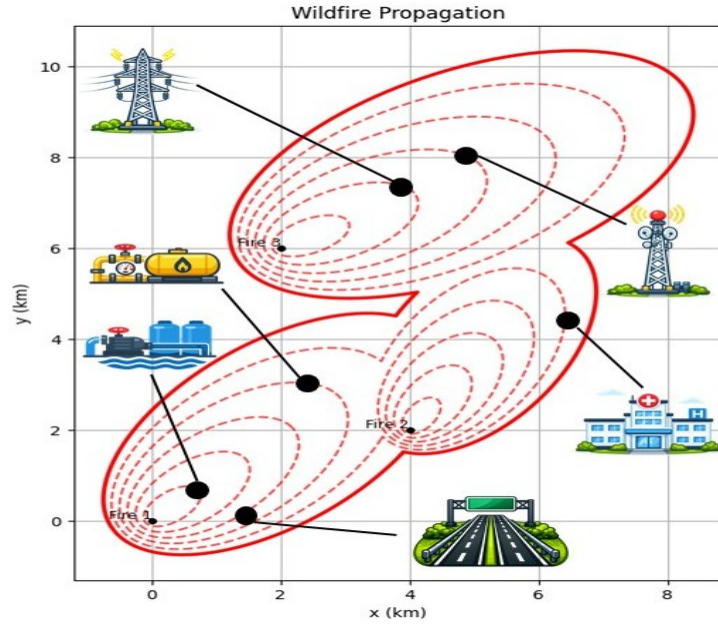


Fig. 2: Wildfire propagation and its impact on CIs under increasing fire intensity

Fire intensity is considered in five levels and encoded with integer numbers from 0, indicating no fire, to 5, indicating the most extreme level. It is assumed that Level 1 causes 20% damage to each infrastructure, and each increase in level adds an additional 20% damage. Figure 2 shows how the impacts of the wildfires on different infrastructures evolve over time, with each infrastructure experiencing varying levels of disruption depending on the intensity and progression of the fires.

Table 9: Initial perimeter(Km) and rate of spread(Km/h) of each fire in each time period .

Fires	Initial Perimeter	Rate of Spread
F1	1.362	1.0
F2	1.089	0.8
F3	1.635	1.2

6.1.2 Resource Setup

The baseline resource configuration consists of four helicopters and four airplanes, categorized as aerial resources, four motor pumps classified as machinery resources, and five brigades of size seven and six brigades of size twelve categorized as ground personnel. These resources are distributed across different bases, resulting in varying travel times to the fire locations.

Table 10: Description of resources and some associated parameters.

Resource (i)	Name	Group	C_i	τ_{i0f}			CPR_i	τ_{ihf}				WP_i
				F1	F2	F3						
Helicopter	H1	Aerial	710	1	1	2	0.087					
	H2			1	1	2						
	H3			1	1	2						
	H4			1	1	2		F1	0	1	2	
Airplane	A1		1020	2	2	1	0.08	F2	1	0	1	36
	A2			2	2	1		F3	2	1	0	
	A3			2	2	1						
	A4			2	2	1						
Motor Pump	M1	Machinery	32	3	1	1	0.067					
	M2			3	1	1		F1	0	2	3	
	M3			3	1	1		F2	2	0	2	
	M4			3	1	1		F3	3	2	0	
Brigade of size 7	7B1	Ground Personnel	44	2	3	3	0.023					30
	7B2			2	3	3						
	7B3			2	3	3						
	7B4			2	3	3						
	7B5			2	3	3		F1	0	2	3	
Brigade of size 12	12B1		75	2	3	4	0.040	F2	2	0	2	32
	12B2			2	3	4		F3	3	2	0	
	12B3			2	3	4						
	12B4			2	3	4						
	12B5			2	3	4						
	12B6			2	3	4						

Different resources exhibit different fire containment efficiencies, and they can work for a limited period of time in a day based on their rest efficiency factor and the level of their training (see

Section 5). In this study, the baseline containment capabilities of the firefighting resources are assumed to be 0.087 km, 0.080 km, 0.067 km, 0.023 km, and 0.040 km of fire perimeter per 10-minute time period for helicopters, airplanes, motor pumps, brigades of size seven, and brigades of size twelve, respectively.

Table 10 summarizes the main operational parameters of the available resources i , including the operating cost (C_i) per usage period (in CAD), travel times (τ_{i0f}) from different resource bases to the fires f , the length of the wildfire perimeter that is contained in a time period by resource (CPR_i) and the maximum permissible working time periods (WP_i) of each resource. Resources belonging to the same group (aerial, machinery, ground personnel) are assumed to require identical travel times (τ_{ihf}) when moving from fire h to fire f . It should be noted that the values reported in the τ_{ihf} column has been assumed for the base test case in section 6.2. In the simulation experiments, these travel times vary across scenarios to reflect different spatial configurations of the wildfires.

6.1.3 Wildfire Cost Analysis

In this section, we consider economic losses from both infrastructure rebuilding costs and service disruption costs during the wildfire, while damaged infrastructure is being rebuilt. These values can be calculated using the dynamic outputs from i2SIM and the base costs for different infrastructures and services. Mathematically, the service disruption cost C_i^{svc} and infrastructure rebuild cost C_i^{infra} for the i -th infrastructure are calculated as follows:

$$C_i^{svc} = d_i \times r_i \times (T_i \times 720),$$

$$C_i^{infra} = d_i \times C_i^{rebuild}.$$

where r_i is the hourly service loss, T_i is the rebuilding time, and d_i is the damage fraction for integrity level of P_i calculated as

$$d_i = (100 - P_i)/100,$$

The system-wide total cost is given by

$$C_i^{total} = \sum_{i=1}^n (C_i^{svc} + C_i^{infra}).$$

The rebuilding cost, time and hourly service loss values are calculated and applied according to Table 11.

Table 11: Hourly service lost rate and the rebuilding cost of the interdependent infrastructures.

Infrastructure	Hourly Service Lost Rate (CAD/h)	Rebuilding Cost (CAD)	Rebuilding Time (Months)
Electricity Station	165.38	1000000	1
Gas Station	76.38	1000000	12
Hospital	1166.67	180000000	36
Highway	1654.70	4000000	6
Telecommunication Station	633.84	1000000	6
Water Station	695.45	10000000	12

Table 12: *NVC* of each fire in each of the time period (in thousand CAD).

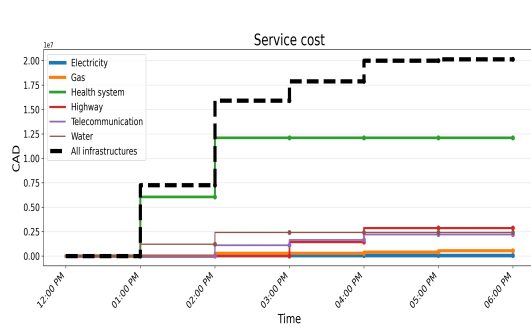
Fires	Time Period	1-6	7-12	13-18	19-24	25-30	31-36
F1		0	533.6	577.6	371.6	493.6	553.3
F2		0	1008	1008	0	0	0
F3		0	0	257.1	191.2	124.6	0

Based on the condition of the different infrastructures over time and the interdependencies among them, the *i2SIM* tool estimates the financial impacts of the wildfires. The resulting cost evolution over time is presented in Figure 3, which shows that the total damage reaches approximately 63.7 million dollars by the end of the simulated period. Table 12 represents the *NVC* of each of the fire in each time period. Those rate of changes are usually constant until the fire reaches to another infrastructure. To be noted, in this study, the costs linked to forest loss are not explicitly considered because all wildfire scenarios are assumed to happen with similar ecological and economic values. As a result, the effect of forest burning is treated the same in each scenario.

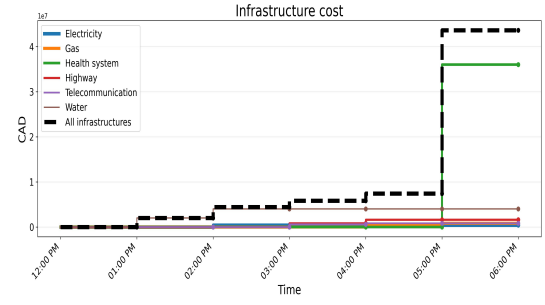
6.2 Base test case

We conducted a test case to illustrate how the proposed optimization model allocates resources to wildfires to minimize the total cost, which includes the cost of damage to infrastructure and the operating costs of resources. For this test case, we consider a special scenario in which the fires progressively merge over time, requiring adaptive re-optimization to capture the evolving wildfire dynamics.

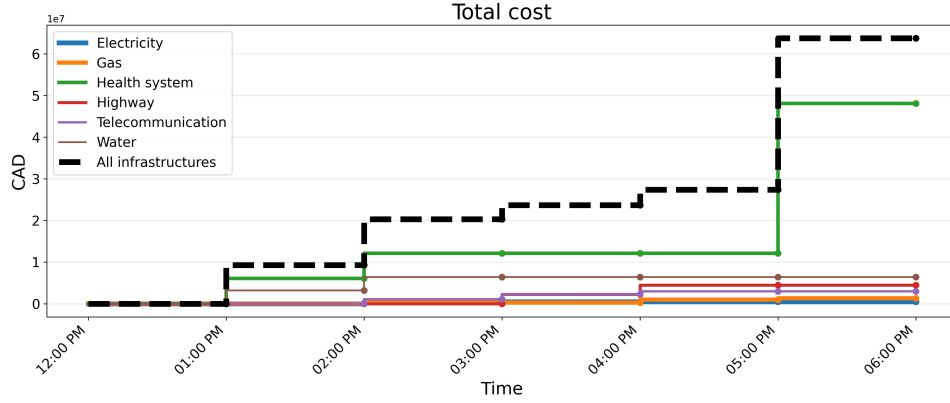
The initial fire perimeters and perimeter growth rates are adopted from the baseline experimental settings. However, when the two fires merge, they are treated as a single wildfire. As a result, the perimeter growth of the merged fire is reduced compared to the sum of the individual fire perimeters, since the original fires share common boundaries that disappear upon merging. At each merging event, the remaining uncontained perimeter of the newly formed fire and its



(a) Service loss values over time



(b) Reconstruction cost of damaged infrastructures over time



(c) Overall financial losses associated with the wildfires

Fig. 3: Overall financial losses associated with the wildfires. Financial impacts are estimated by the *i2SIM* tool based on infrastructure conditions and their interdependencies over time.

growth rate are recalculated, and the travel time of the resources that were already working on the merging fires is set to $\tau_{i0f} = 0$ for the new fire f .

For the base test case, we assume three helicopters, three airplanes, three motor pumps, four brigades of size 7, and six brigades of size 12, and we assign their operational factors from Table 10. Furthermore, because fire merging alters the affected area and the infrastructure exposed to the wildfire, the associated infrastructure damage and service disruption costs are updated accordingly.

Let us assume that Fire 1 and Fire 2 merge to form fire X at time period 11, and subsequently fire X merges with Fire 3 to create fire A at time period 16. Table 13 and Table 14 present the perimeter change and *NVC* for fire X and fire A in each time period, respectively. The negative perimeter changes reported in Table 13 reflect the reduction in the total fire perimeter resulting from wildfire merging, as the shared boundary between the merging fires is eliminated.

This evolving scenario allows us to demonstrate the ability of the proposed framework to dynamically adapt resource allocation decisions in response to changing wildfire conditions.

Table 13: Perimeter growth of merged fires (in Km) in each time period.

Period	Fire X	Fire A	Period	A	Period	A	Period	A	Period	A
11	.514	-	17	-.126	23	.380	29	.445	35	.475
12	-.014	-	18	.132	24	.397	30	.451	36	.457
13	.321	-	19	.235	25	.410	31	.457		
14	.398	-	20	.294	26	.420	32	.462		
15	.434	-	21	.332	27	.430	33	.467		
16	-	-.463	22	.360	28	.438	34	.471		

Table 14: *NVC* of each new fire in each time period (in thousand CAD).

Fires	Time Period	11-12	13-15	16-18	19-24	25-30	31-36
X		1541.6	1585.6	-	-	-	-
A		-	-	1842.7	562.8	618.2	605.5

6.3 Large test case simulations

To evaluate the behaviour of the proposed model under realistic operating conditions, a set of simulation scenarios with varying characteristics was designed. We consider 50 wildfire scenarios, each consisting of three simultaneous fires. These scenarios differ in key characteristics, including initial fire perimeters, rates of spread, and spatial configurations, with fires located at varying distances from one another. The initial fire perimeter and its growth rate are derived from the values provided in Table 9 by applying a random scaling factor uniformly distributed in the range [0.75,1.25]. For simplicity, we assume that the fires will not merge within the 36-time-period (6-hour) time horizon, allowing the analysis to focus exclusively on resource allocation and containment decisions without the added complexity of fire interactions.

Three key factors, resource availability, resource effectiveness, and initial resource arrival times from bases, are examined in the experiments.

First, we analyze the impact of resource availability by varying the number of each resource type simultaneously. Specifically, we increase the number of available resources in each category by up to six units relative to the baseline resource configuration, allowing us to assess how additional resource capacity affects wildfire containment performance and overall costs.

Second, we investigate how resource effectiveness affects wildfire containment. Starting from baseline containment abilities of 0.087 km, 0.080 km, 0.067 km, 0.023 km, and 0.040 km per time period for helicopters, airplanes, motor pumps, brigades of size 7, and brigades of size 12, respectively, the containment capability of each resource type is increased in 0.005 km increments.

We consider four successive increments to assess the sensitivity of the solution to improvements in resource performance.

Finally, we examine the influence of resource accessibility by varying travel times from the resource bases to the wildfire locations. Starting from the baseline travel times, all arrival times are increased by one time period in each experiment, and this process is repeated three times. This analysis provides insight into how delays in resource deployment affect wildfire containment and the resulting damage costs.

6.4 Heuristic approach to resource allocation

To demonstrate the benefits of the proposed optimization framework, we compare its performance against a common operational strategy using a benchmark heuristic. We use a priority-based heuristic in which all available firefighting resources are first sent to the active wildfire with the highest infrastructure damage plus service disruption costs if that fire is unattended. These resources remain at that wildfire until it is fully contained. After containment work is complete, all resources are sent to the next active wildfire with the highest infrastructure damage plus service disruption costs, and we repeat the process until all fires are under control.

This heuristic method uses a focused wildfire containment strategy. At each step, it prioritizes the most critical wildfire based on associated costs and dedicates all available resources to that fire before moving on to others, thereby avoiding resource allocation complications. While this method is easy to apply and may seem appealing from an operational standpoint, it overlooks the changing nature of multiple active wildfires and their costs, as well as the trade-offs of resource distribution.

All computational experiments were conducted on a machine with an Intel(R) Xeon(R) Gold 5218R CPU running at 2.10 GHz, using Gurobi Optimizer version 13.0.0. Each optimization run was subject to a 600-second time limit to reflect the operational requirements of real-world restoration settings, where decisions must be generated within limited computational time.

7 Analysis of the Results

In this section, we analyze the results of the base test case and generalized results to demonstrate the effectiveness of our optimization model integrated with the [i2SIM](#) simulation tool.

7.1 Results of the base test case

With a resource configuration consisting of 3 helicopters, 3 airplanes, 3 motor pumps, 4 brigades of size 7, and 6 brigades of size 12, the optimization model determines an efficient allocation of resources across wildfire incidents. Figure 4 illustrates the operational timeline for the firefighting resources throughout the planning horizon.

At the beginning, all aerial and mechanical resources, all brigades of 12 men, and two brigades of 7 men are assigned to Fire 2. This allocation enables Fire 2 to be fully contained by the end of time period 9, before its scheduled merger with Fire 1 at time period 11. Additionally, one brigade of 7 men finishes its work earlier and heads towards Fire 1 at the end of time period 8. Once Fire

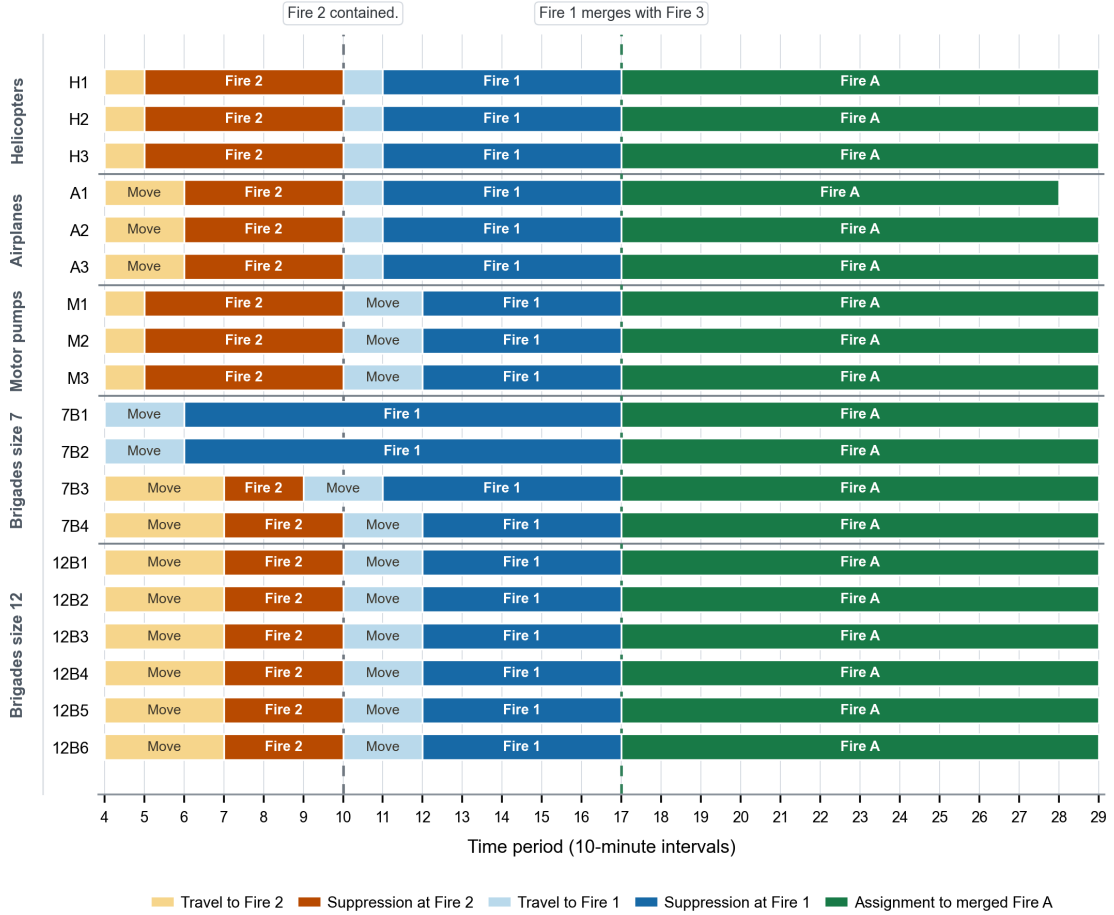


Fig. 4: Operational timeline of firefighting resources, illustrating their deployment over the planning horizon. Fire A is the merged fire of Fire 1 with Fire 3.

2 has been contained, all available resources are redirected to Fire 1. By the end of time period 16, Fire 1 combines with Fire 3 to form a larger wildfire (Fire A). The resources already allocated

to Fire 1 continue their suppression work on the combined fire without any break. If the merger had not taken place, the optimal schedule would likely have transferred some resources from Fire 1 to Fire 3 before Fire 1 was fully contained, and the remaining resources would have completed their suppression tasks at Fire 1 before moving on to participate in operations at Fire 3. This example shows how merging wildfires can have a major impact on resource allocation decisions and underscores the importance of having a system that can dynamically reschedule in changing wildfire situations.

7.2 Results of the simulations

The simulation results provide the total optimal cost, comprising infrastructure damage costs, service disruption costs, and the operational costs of firefighting resources. For each experimental setting, 50 wildfire scenarios were generated, and the reported results represent the average cost (in thousand CAD) across all scenarios.

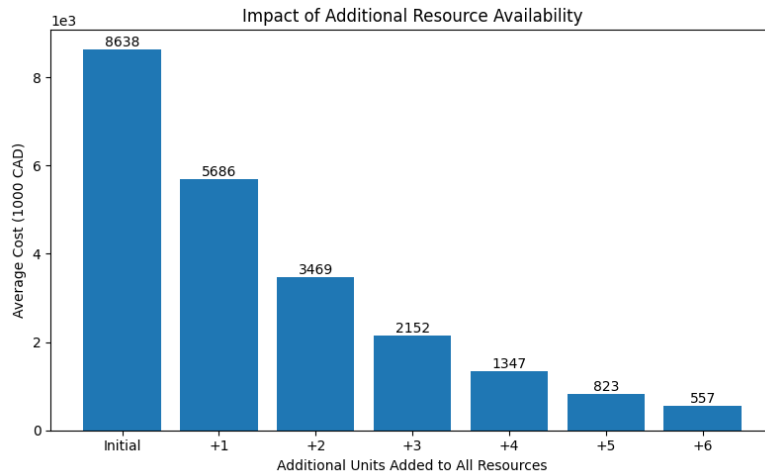


Fig. 5: Average cost comparison for different levels of additional resource availability relative to the baseline resource setup.

Because the proposed optimization model is formulated as an NP-hard [MILP](#) model, obtaining a proven optimal solution within the prescribed time limit is not always possible. Nevertheless, the computational results indicate that only 2.78% of the instances reached the time limit without proving optimality. Even in these cases, the solver produced high-quality near-optimal solutions, with a maximum MIP-Gap [\[29\]](#) of only 0.02%, demonstrating the effectiveness and computational tractability of the proposed approach.

Figure 5 illustrates the impact of increasing resource availability on the average total cost. The reduction in average cost is not linear with the addition of resources. As more resources are introduced, the marginal benefit of additional resources decreases, and the cost reduction becomes less significant than initially expected. In particular, adding one unit of each resource type individually results in a larger cost reduction than adding multiple units simultaneously across all resource categories, indicating diminishing returns from increasing resource availability.

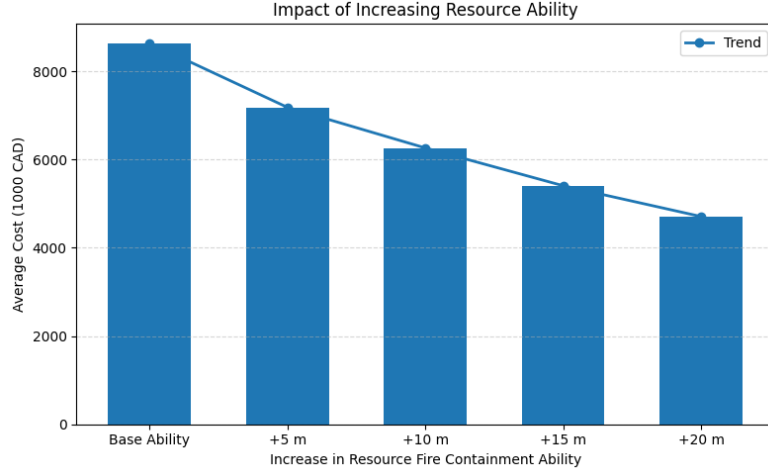


Fig. 6: Average cost comparison under different levels of fire containment efficiency relative to the baseline efficiency setting.

We conducted experiments to evaluate how increasing the availability of individual resource types affects outcomes, while keeping all other resources at their baseline levels. The results show that when resource operational costs are not considered a limiting factor, increasing aerial resources, especially helicopters, significantly reduces wildfire damage costs. This is due to their high containment efficiency and fast deployment. For airplanes, even though they help reduce fire impacts, their use can be limited by practical constraints, such as movement and deployment issues. These factors are incorporated into resource settings by accounting for the time it takes to move resources between fire locations, leading to a more accurate picture of aerial resource operations.

Figure 6 shows how increasing the containment efficiency of firefighting resources affects the average total cost. As with the resource availability analysis, the relationship between resource efficiency and cost reduction is not straightforward. While improved containment ability lowers overall costs by minimizing wildfire impacts, the additional benefit diminishes as efficiency rises. This occurs because, beyond a certain point, further gains in resource capability yield fewer extra benefits due to other wildfire factors.

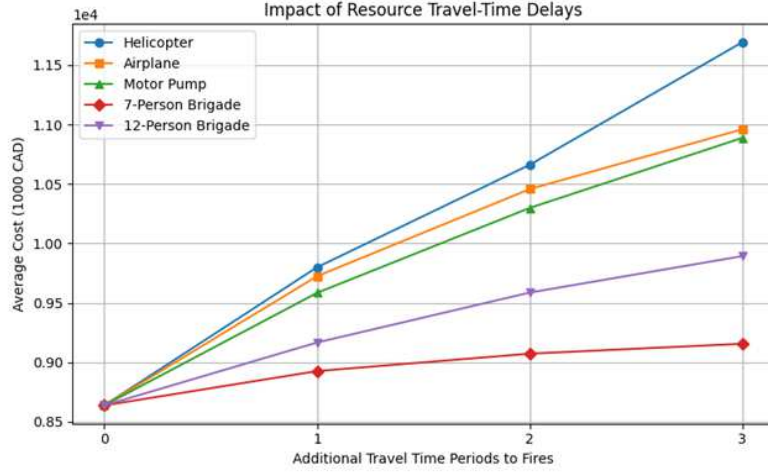


Fig. 7: Sensitivity analysis of the average total cost with respect to resource travel times from bases to wildfire locations.

Figure 7 illustrates how resource travel times from their bases to wildfire locations affect overall cost. The experimental results show that early deployment of aerial and machinery resources plays a crucial role in reducing wildfire-related damage and total costs. Because these resources generally have higher containment capabilities, delays in their arrival can significantly increase fire spread and associated impacts. Therefore, when dispatching decisions are required, prioritizing the early release of aerial and machinery resources can yield greater benefits, even if ground brigades experience relatively longer delays in reaching the fire locations.

7.3 Comparison with heuristic

Figure 8 compares the total costs from the proposed optimization model with those from the benchmark heuristic under the baseline resource configuration. The results show that the proposed optimization method consistently outperforms the heuristic, yielding considerable reductions in total cost. This better performance stems from the model’s ability to allocate firefighting resources optimally by considering multiple operational factors simultaneously, such as each resource’s suppression capabilities, travel times, the cost associated with each wildfire, the maximum number of consecutive working periods, and other operational constraints. By contrast, the heuristic depends only on the current infrastructure damage and the service disruption cost ranking of the fires and thus cannot incorporate other decision-making factors. Across the 50 wildfire scenarios, the proposed optimization model reduces total cost by 6.6% to 45.1% compared with the heuristic, illustrating the effectiveness of the integrated optimization framework.

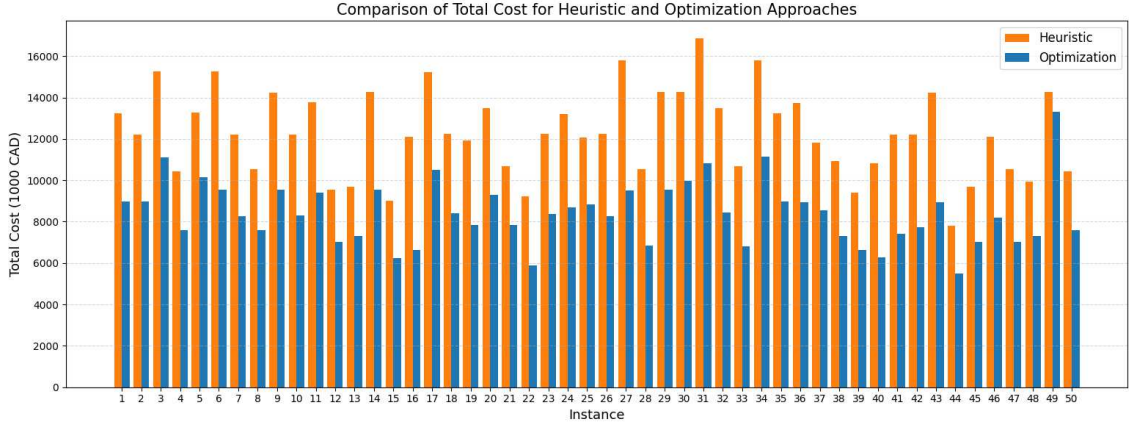


Fig. 8: Comparison of the total cost between the Heuristic approach and the Optimization approach over 50 instances.

8 Conclusion

This paper presents a simulation-based optimization framework for online wildfire containment planning under changing fire conditions. The framework combines a wildfire impact simulation model for infrastructure systems with a MILP optimization model. This helps determine the optimal allocation and scheduling of firefighting resources. It accounts for practical operational constraints, such as resource availability, travel times, maximum working hours, and varying resource effectiveness. This enables more flexible decision-making as wildfire conditions change. The computational results show that this approach can efficiently generate effective containment strategies.

Nearly all cases were solved within the specified computational limit. The numerical analysis shows that increasing resource availability or improving containment capabilities reduces wildfire-related costs. However, the benefits diminish as additional resources or efficiency gains yield smaller returns. The results also underscore the need for strategic resource prioritization. Aerial resources, especially helicopters, offer considerable advantages because of their rapid deployment and high containment effectiveness.

Additionally, deploying high-capacity resources early can significantly reduce wildfire impacts. The travel-time analysis indicates that accessibility and response delays are crucial factors in planning for emergency resources. In summary, this framework serves as an effective decision-support tool for flexible wildfire containment by combining predictive simulation with optimization-based resource management.

As the future direction of this study, the authors intend to extend the framework by incorporating social impacts, including evacuation needs and risks to vulnerable communities, while calibrating assumptions and validating the results using data from recent Canadian wildfires. Next research can also integrate advanced fire propagation simulations that account for uncertainties in vegetation type, temperature and wind forecasts, as well as slope steepness. Furthermore, expert firefighting knowledge and machine-learning methods can be used to generate warm-start solutions to enhance the optimization process.

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