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Joint location and assignment optimization of multi-type fire vehicles

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Abstract
Fire service quality relies on fast response and cooperation of various types of responders to maintain efficient operations and reliable rescue services. This paper investigates a joint location and assignment optimization (JLAO) problem, where fire vehicles from different fire stations can be dispatched jointly as a cooperative unit in a fire rescue operation. We first propose a mixed integer non-linear program to optimize the station location and vehicle assignment decisions, aiming to minimize the total system cost including facility construction, operations cost, and fire damage losses. We proposed a Stingy-Interchange (SI) algorithm to efficiently solve this problem to a near-optimal solution. The JLAO model and the proposed solution method are then applied to hypothetical instances with different sizes and parameter settings to compare the performance of the SI algorithm with a commercial solver (Gurobi). An empirical case study on a major city is conducted to reveal insights on how cost measures are affected by key parameters.

1 | INTRODUCTION

Among various types of man-made disasters in the urban environment, urban fires are arguably the most hazardous ones. An estimated number of 1,342,000 fires, responded by the US fire departments in 2016, have resulted in 3390 civilian fatalities, 14,650 civilian injuries, and around $10.6 billion in direct property loss (Haynes, 2017). In China, a total of 1407 civilians suffered fatalities in 2018, increasing by 1%, compared with 2017 (Fire & Rescue Department of Emergency Management Bureau, 2019).

One main goal of the fire service is to protect people's lives and properties to the greatest extent possible. If the fire team arrives at the scene at the initial stage of a fire, the fire loss can be contained efficiently. However, delay in fire response may cause serious loss to people's lives and properties since the loss in a fire increases rapidly as responding time elapses, especially at the middle stage of fire combustion (OFM, 2010). In a fire incident at a large scale, a great loss can occur if some necessary types of fire vehicles are not available or are located at a fire station too far from the fire incident. For instance, in the fire incident of Beijing Television Cultural Tower, the process of rescuing people and fighting fire required several necessary types of vehicles (such as fire tanks, fire trucks, powerful jet engines, helicopters, ambulances, etc.). More than 50 fire vehicles of different types responded from 16 fire stations. However, due to the late response caused by traffic congestion and the long distance between the distributed fire stations and the fire incident, the tower was completely engulfed in flames within less than 13 min, which resulted in heavy losses of life and property (Jacobs, 2009). As another example, in the 2005 wine storage fire in Sichuan Province, China, nine fire vehicles from another city were long-distance dispatched to back up the first response of 13 fire vehicles to form a complete fire vehicle fleet sufficient for completing the fire service (Yang & Liang, 2012).

Therefore, the response time of rescue resources (e.g., fire vehicles) plays an important role in fire rescue operations, especially in a cooperative operation that often requires a combination of multiple fire vehicles. One might address this delay issue by locating many fire vehicles in each fire station to ensure a short response time. This way, however, some of the located fire vehicles might not be used frequently and will be redundant most of the time. Also, locating many fire vehicles at each station is very costly and not always feasible due to other resources and spatial constraints from governments. To strike a reasonable balance between limited resources and fast response time, optimizing the service facility locations and\or service assignment (i.e., assigning a given service to a given demand) has been a common practice in fire rescue operations.

Location planning problems have been well investigated in the literature. Early studies focused on location decisions for a single type of service or resource. Two fundamental mathematical programing models are the location set covering problem (LSCP; Toregas et al., 1971) and maximal covering location problem (MCLP; Church, 1974) models. The former aims to locate a minimal number of single-type facilities to cover given demands, while the latter maximizes the coverage provided by a limited number of single-type facilities. Bao et al. (2015) optimized the watchtower locations using the classical LSCP and MCLP models. ReVelle and Hogan (1989) proposed a maximum availability location problem to incorporate single-type facility availability probability. Daskin and Jones (1993) developed a new location/allocation algorithmic approach to address the difficulty of large-scale problems. Ng et al. (2010) presented a bi-level optimization model to optimally assign evacuees to shelters in natural and man-made disasters. Smith et al. (2014) proposed a location and assignment optimization model that determines fixed staging areas and mobile processing unit locations and optimal material shipment assignment strategies for sustainable highway reconstruction. Xie et al. (2016) proposed a mixed integer linear programing model and a Lagrangian-relaxation-based heuristic algorithm for the location and capacity planning of locomotive maintenance shops. Further, to address the relationships between multiple entities, multiple coverage models have been developed in the emergency facility location context. A double coverage model, called the double standard model, was developed by considering two distance standards from identifiable facilities (Gendreau et al., 1997). Larson introduced the hypercube queuing model (Larson, 1974) and an approximation method (Larson, 1975) to estimate the system performance provided by distinguishable facilities under a predetermined dispatching list. Daskin (1983) extended the classic MCLP model to the maximum expected covering location problem under the assumption of independent and identically distributed busy probabilities of different facilities. Badri et al. (1998) determined fire-station facility locations by considering multiple tangible and intangible criteria. Jiang and Adeli (2003) presented an optimization model for user delay, accident, and maintenance costs in freeway work zones. A method based on Boltzmann-simulated annealing and neural networks is developed to find global optimal solutions. An object-oriented model was then presented for freeway work zone capacity and queue delay estimation (Jiang & Adeli, 2004).

Despite these elegant solution methods, most of these studies focus on a single service and do not consider the interaction between different services. Therefore, these solution methods are not capable of addressing many real-world operational problems. In the fire rescue content, for instance, fire damage might not be controlled completely unless all required fire vehicles arrive at the fire scene in time. Therefore, considering the interaction between multiple fire vehicles in the fire rescue operations is essential.

This need has motivated many researchers and transportation practitioners to focus on the cooperation between multiple agencies, services, and fire vehicles from different perspectives. For instance, a collaboration of responders and stakeholders in emergency scenarios has been investigated in a number of qualitative and quantitative studies. Berman et al. (2009) proposed a discrete cooperative covering problem by introducing single type coverage signals that decay by the distance. Later, a continuous covering and cooperative covering model was developed by Berman et al. (2013). In their model, each facility emits a signal that decays by the distance along the arcs of the network and each node observes the total signal emitted by all facilities. A node is covered if its cumulative signal exceeds a given threshold. Xie et al. (2013) presented a colocation optimization model with multi-type facilities and expansive capacities for the complementary production process of agricultural crops. Lu et al. (2018) presented a multilayer infrastructure network optimization model to investigate the vulnerability impact of unreliable infrastructures on city disasters. These studies highlighted the importance of collaboration between different parties in emergency response, yet they cannot be directly applied to cooperation between multiple resources in fire operations. While collaboration between responders often focuses on policy, regulatory, or institutional issues, emergency resource cooperation usually requires careful location planning for spatial distributions of various types of resources (e.g., how multiple types of fire vehicles are distributed across different fire stations) and reliable assignment mechanisms for fire vehicle dispatching operations.

To address this requirement, another class of studies aimed to optimize the facility location and\or vehicle assignment decisions considering multiple fire vehicles and services. Batta and Mannur (1990) examined the set covering location problem and the MCLP under emergency situations that require multiple response units. An et al. (2015) developed an emergency facility location model under multiple facility reliability, queuing, and en route congestion. Wang et al. (2016) proposed a multi-type fire facility location and allocation model under partial coverage and cooperative operation. Zockaie et al. (2016) presented a discretionary service facility location model to minimize the extra cost spent in refueling detours. Their proposed simulated annealing algorithm outperformed commercial solver CPLEX in solving models with large-scale compact formulations. Park et al. (2016) proposed a stochastic location and allocation model for emergency units by incorporating primary and secondary incident probabilities. Pérez et al. (2016) proposed a location and allocation model for a number of fire stations and the corresponding vehicle fleet to improve the coverage within the standard response in the city of Santiago. Li et al. (2018) proposed a cooperative maximal covering model with the consideration of financial efficiency and uncertainty for multiple humanitarian relief chain management. Wang et al. (2019) proposed a multi-objective mixed integer linear model to optimize temporary debris management sites after large-scale natural disaster. To mitigate congestion caused by uncertain demands, Hajibabai and Saha (2019) presented a station location and patrol route planning model for first responders. While these studies provided impactful insights into the facility location and allocation problems, most of them only aimed to improve a single objective measure. However, to efficiently provide a given service, multiple factors and objectives might need to be considered simultaneously. Although Smith et al. (2014) and Xie et al. (2016) proposed optimization models with more than three objective measures, their algorithm's effectiveness may be challenged in dealing with large-scale problems. In the fire service content, for instance, one might need to determine the fire station locations, the number of fire vehicles with different types to be located at each fire station, and efficiently assign fire vehicles to fire incidents such that the construction cost of fire stations, maintenance and travel costs of fire vehicles, and the damage cost caused by fire at fire incidents be minimized simultaneously. Considering all these objective measures, however, results in a complicated problem structure that requires substantial computational resources to obtain an efficient solution. To the best of our knowledge, there are no studies focusing on such a complicated, yet important, problem that considers multiple objective measures and multi-vehicle types in the fire service content.

The contributions of this study can be summarized as follows.

1. This study proposes a mixed integer joint location and assignment optimization (JLAO) model to optimally select the fire station locations, determine the number of each type of fire vehicles to be located at each fire station, and assign multiple types of fire vehicles to fire incidents with the objective of simultaneously minimizing the facility construction cost, maintenance and travel costs, and fire damage losses. Although the joint facility location and vehicle assignment problem has been well studied, to the best of our knowledge, there are no studies focusing on such a complicated and necessary problem considering multiple vehicle types and objective measures, especially in the fire rescue context.
2. This study proposes an efficient Stingy-Interchange (SI) algorithm that can solve the investigated JLAO problem much more efficiently and obtain smaller solution gaps than the existing commercial solvers (e.g., Gurobi). This study evaluates the effectiveness of the proposed model and the performance of the proposed optimization algorithm through a set of numerical tests and an empirical case study with fire incident data from the Fire Department of Harbin in 2018. This study also investigates how different parameter settings can affect the optimal design of the joint location and assignment problem.

The remainder of this paper is organized as follows. Section 2 presents the JLAO model and illustrates the proposed SI algorithm. In Section 3, we test the effectiveness of the proposed algorithm and the state-of-the-art commercial solver, Gurobi, under different scenarios and parameter settings with a set of hypothetical examples. Section 4 applies the model to an empirical case and presents the sensitivity analyses results. Finally, Section 5 provides concluding remarks and future research directions.

2 | JLAO PROBLEM

This section describes the investigated multi-type fire vehicle location and assignment problem. We first introduce the investigated problem and its parameters, variables, and assumptions. Then, we formulate the JLAO problem as a mixed integer programing (MIP) model that integrates location and assignment decisions for multi-type fire vehicles to minimize an objective function representing the total system cost. At last, we present the proposed SI algorithm to solve the problem to a near-optimum solution.

TABLE 1 Notation list of the joint location and assignment optimization problem

Parameters	
$\mathcal{I} := \{1, \ldots, I\}$	Set of fire stations' locations
$\mathcal{J} := \{1, \ldots, J\}$	Set of incidents' locations
$\mathcal{K} := \{1, \ldots, K\}$	Set of all fire vehicle types
$\mathcal{Z} := \{0, 1, \ldots, Z\}$	Set of different number of fire vehicle
$L := \{1, \ldots, L\}$	Set of incident types
$W := \{1, \ldots, W\}$	Weight level of incident
S_i	Capacity of fire station $i \in \mathcal{I}$
l_j	Type of incident $j \in \mathcal{J}$
w_j	Weight level of incident $j \in \mathcal{J}$
f_j	Occurrence probability of incident $j \in \mathcal{J}$
$t_{i,j}$	Response time for a fire vehicle located at station $i \in \mathcal{I}$ to serve incident $j \in \mathcal{J}$
$T := \{1, \ldots, T\} = \cup_{i\in\mathcal{I}, j\in\mathcal{J}} \{t_{i,j}\}$	Set of all possible response times
$\pi_{j,t}$	Fire damage cost of incident $j \in \mathcal{J}$ with response time $t \in \mathcal{T}$
$r_{l_j,w_j,k}$	Required number of type-k fire vehicle to serve incident $j \in \mathcal{J}$ with type l_j and weight level w_j
$c_{i,k,z}$	Cost of locating zk-type fire vehicle at fire station $i \in \mathcal{I}$
$d_{i,j,k}$	Travel cost of k-type fire vehicle travels from station $i \in \mathcal{I}$ to incident $j \in \mathcal{J}$
Decision variables	
$p_{i,k,z} \in \{0, 1\}$	$p_{i,k,z} =$ 1 if zk-type fire vehicles are located at station $i \in \mathcal{I}$ and 0 otherwise
$y_{j,t} \in \{0,1\}$	$y_{j,t}=1$ if incident $j \in \mathcal{J}$ is served with response time $t \in \mathcal{T}$ and 0 otherwise
$x_{i,j,k} \in \mathbb{N}^+$	Integer variable that denotes the number of k-type fire vehicle at station $i \in \mathcal{J}$ that have been allocated to incident $j \in \mathcal{J}$

2.1 | Problem statement

In this problem, each discrete location has a certain type of potential fire incident with a certain frequency and a fixed weight reflecting the corresponding damage severity. The types and corresponding numbers of fire vehicles required for each incident are predetermined (e.g., by the local fire department). If an incident requires the cooperation of multiple vehicles, we assume that it is served only after the last required vehicle arrives at the scene. In other words, an incident requiring multiple fire vehicles will not be served until all required vehicles arrive. The system decisions include locating fire vehicles of different types across candidate fire stations and allocating them properly to each potential incident so as to minimize the long-term cost including both facility investment and fire losses. For the convenience of the readers, we list the key notation in Table 1.

This study considers a network with a set of candidate fire station locations $\mathcal{I} := \{1, \ldots, I\}$ for locating the planned fire vehicles. Each candidate location $i \in \mathcal{I}$ has a fixed capacity S_i for locating fire vehicles. We assume there are different types of vehicles $\mathcal{K} := \{1, \ldots, K\}$ with different functionality (e.g., high-rise trucks, high-power water supply server, nuclear and biochemical fire engines, etc.). The cost of locating z number of type-k vehicle at a station i is denoted by $c_{i,k,z}$. We consider a set of potential incident locations $\mathcal{J} := \{1, \ldots, J\}$ where l_j denotes the type of incident $j \in \mathcal{J}$. For simplicity, we assume that fire incidents are infrequent events and no two incidents occur at the same time. Further, each incident j has a predetermined level denoted by w_j representing its weight. A type-l incident at weight w must be served with a specific number of type-k vehicles, denoted by $r_{l,w,k}$. In another word, each incident j must be served by $r_{l_j,w_j,k}$ number of type-k fire vehicles. Further, the occurrence probability of incident j is denoted by f_j. An incident's fire damage cost is the damage that the lives and properties at the incident location bear due to the response time from the start of the incident to the completion of the cooperative fire operation with all required fire vehicles. To be conservative, we assume this cost is a function of the response time of the fire vehicle combination, that is, the time duration from an incident's starting time to the time the last fire vehicle in the corresponding combination arrives at the scene. The response time for a fire vehicle located at station i to serve incident j is denoted by $t_{i,j}$. Let $\mathcal{T} = \cup_{i\in\mathcal{I},j\in\mathcal{J}} \{t_{i,j}\}$ denote the set of all possible response times. With this, we denote the fire damage rate of an incident at j with response time t as $\pi_{j,t}$. Further, the location decisions are made with a binary variable $p_{i,k,z}$ that denotes the number of type-k vehicles located at station i:

$$p_{i,k,z} = \begin{cases} 1, & \text{if the number of type -}k\text{ vehicles located at station } i \text{ is } z, \\ 0, & \text{otherwise} \end{cases}$$

$$\forall i \in \mathcal{I}, k \in \mathcal{K}, z \in \mathcal{Z}$$

Then the assignment decisions are incorporated with integer variable $x_{i,j,k}$ that denotes the number of type-k vehicles at station i allocated to incident j. The following auxiliary variable for each incident j is also introduced to determine the corresponding response times:

$$y_{j,t} = \begin{cases} 1, & \text{if incident } j \text{ is served with response time } t, \\ 0, & \text{otherwise} \end{cases} \quad \forall j \in \mathcal{I}, t \in \mathcal{T}$$

For the formulation convenience, we stack the variables $x := \{x_{i,j,k}\}_{i\in\mathcal{I},j\in\mathcal{J},k\in\mathcal{K}}$, $y := \{y_{j,t}\}_{j\in\mathcal{I},t\in\mathcal{T}}$ and $p := \{p_{i,k,z}\}_{\forall i\in\mathcal{I},k\in\mathcal{K},z\in\mathcal{Z}}$

2.2 | Model formulation

This section presents a discrete model for the investigated problem. We formulate the JLAO problem as a MIP model that selects a set of candidate locations to build fire stations, decides the number of each-type vehicles to be located at each station, and allocates the fire vehicles to the fire incidents.

We formulate the JLAO problem as

$$JLAO : \min_{x,y,p} O^{JLAO}\left(x_{i,j,k}, y_{j,t}, p_{i,k,z}\right) :$$
$$= C\left(p_{i,k,z}\right) + F\left(y_{j,t}\right) + D\left(x_{i,j,k}\right) \tag{1}$$

subject to

$$D\left(x_{i,j,k}\right) = \sum_{i\in\mathcal{I},j\in\mathcal{J},k\in\mathcal{K}} \left(f_j . d_{i,j,k} . x_{i,j,k}\right) \tag{2}$$

$$F\left(y_{j,t}\right) = \sum_{j\in\mathcal{J},\, t\in\mathcal{T}} \left(f_j . w_j . \pi_{j,t} . y_{j,t}\right) \tag{3}$$

$$C\left(p_{i,k,z}\right) = \sum_{i\in\mathcal{I},\, k\in\mathcal{K},z\in\mathcal{Z}} \left(c_{i,k,z} . p_{i,k,z}\right) \tag{4}$$

$$\sum_{z\in\mathcal{Z}} \left(z . p_{i,k,z}\right) \geq x_{i,j,k}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K} \tag{5}$$

$$\sum_{k\in\mathcal{K},z\in\mathcal{Z}} \left(z . p_{i,k,z}\right) \leq S_i, \quad \forall i \in \mathcal{I} \tag{6}$$

$$\sum_{i\in\mathcal{I}} \left(x_{i,j,k}\right) = r_{l_j,w_j,k}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K} \tag{7}$$

$$\sum_{t\in\mathcal{T},\, t\geq t_{i,j}} \left(y_{j,t}\right) \geq \frac{x_{i,j,k}}{\max_{j\in\mathcal{J},k\in\mathcal{K}}\left\{r_{l_j,w_j,k}\right\}}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K} \tag{8}$$

$$\sum_{t\in\mathcal{T}} \left(y_{j,t}\right) = 1, \quad \forall j \in \mathcal{J} \tag{9}$$

$$\sum_{k\in\mathcal{K}} \left(x_{i,j,k}\right) \leq S_i, \quad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{10}$$

$$\sum_{i\in\mathcal{I},\, z\in\mathcal{Z}} \left(z . p_{i,k,z}\right) \geq r_{l_j,w_j,k}, \quad \forall j \in \mathcal{J}, k \in \mathcal{K} \tag{11}$$

$$\sum_{z\in\mathcal{Z}} \left(p_{i,k,z}\right) = 1, \quad \forall i \in \mathcal{I}, k \in \mathcal{K} \tag{12}$$

$$y_{j,t} = \{0,1\}, \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \tag{13}$$

$$p_{i,k,z} = \{0,1\}, \quad \forall i \in \mathcal{I}, k \in \mathcal{K}, z \in \mathcal{Z} \tag{14}$$

$$x_{i,j,k} \in \text{Integer}, \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K} \tag{15}$$

Objective function (1) minimizes the summation of three operational costs of the system. To avoid requiring a set of cost coefficients for different objective measures, a set of realistic cost values are drawn from the literature (e.g., Wang et al., 2016) and used in numerical tests. However, to investigate how prioritizing the objective measures affects the solution quality, one can simply add a set of cost coefficients to different objective measures without requiring any changes in the proposed algorithm. Constraints (2), (3), and (4) define the travel cost, fire damage cost, and installation cost, respectively. The travel cost is the total distance traveled by all fire vehicles. The fire damage cost is the damage cost caused by fire before the arrival of all required fire vehicles. The installation cost is the cost of allocating and maintaining fire vehicles at candidate stations. Constraint (5) ensures that the number of type-k fire vehicles from station i assigned to incident j does not exceed the number of available type-k fire vehicles located at station i. Constraint (6) ensures that the total number of fire vehicles located at station i does not exceed the capacity of the station. Constraint (7) enforces that the total number of type-k fire vehicles assigned to incident j from all the stations must be equal to the required number of type-k vehicle for incident j. Constraint (8) imposes that the response time of incident j must be at least $t_{i,j}$, if at least one fire vehicle is assigned to incident j from station i. Constraint (9) enforces that the response time of incident j should only have one value. Constraint (10) ensures that the total number of type-k fire vehicles from station i to incident j does not exceed the capacity of station i. Constraint (11) ensures that the total number of type-k vehicles at all stations must be greater than the required number of type-k vehicles at each incident. Further, constraint (12) enforces that only one number in $\mathcal{Z}$ must denote the total number of each type-k vehicles located at each station i. Finally, constraints (13) to (15) define the binary and integer variables.

2.3 | SI algorithm

We first attempted the Lagrangian relaxation (LR) approach for this problem due to its efficiency in solving classic location problems (Daskin, 2011). Constraints (5) were relaxed and a branch and bound algorithm was applied for solving subproblems in the LR framework. However, the bound obtained from LR was poor, and only a small number of branches could be eliminated. Without a tight bound, the performance of LR was much compromised. Alternatively, we proposed an SI algorithm that combines the classic Stingy and Interchange algorithms to solve the JLAO problem to a near-optimal solution (Nemhauser et al., 1978). The Stingy algorithm is a heuristic algorithm that starts with a (possibly infeasible) solution with maximal variable values (e.g., maxing out all types of fire vehicles at all fire stations) and iteratively reduces variable values (e.g., removing vehicles) until reaching certain stopping criterium. The Interchange algorithm starts with a feasible solution and iteratively changes the variable values within a feasible neighborhood from the current solution until reaching a certain stopping criterium. By integrating these two algorithms, the proposed heuristic algorithm starts with the Stingy algorithm and ends with the Interchange algorithm. A high-level flowchart of the proposed SI algorithm is presented in Figure 1, and an illustrative example solved by the proposed SI algorithm is presented in Figure 2. Further, the key elements of the proposed SI algorithm are summarized in the following steps.

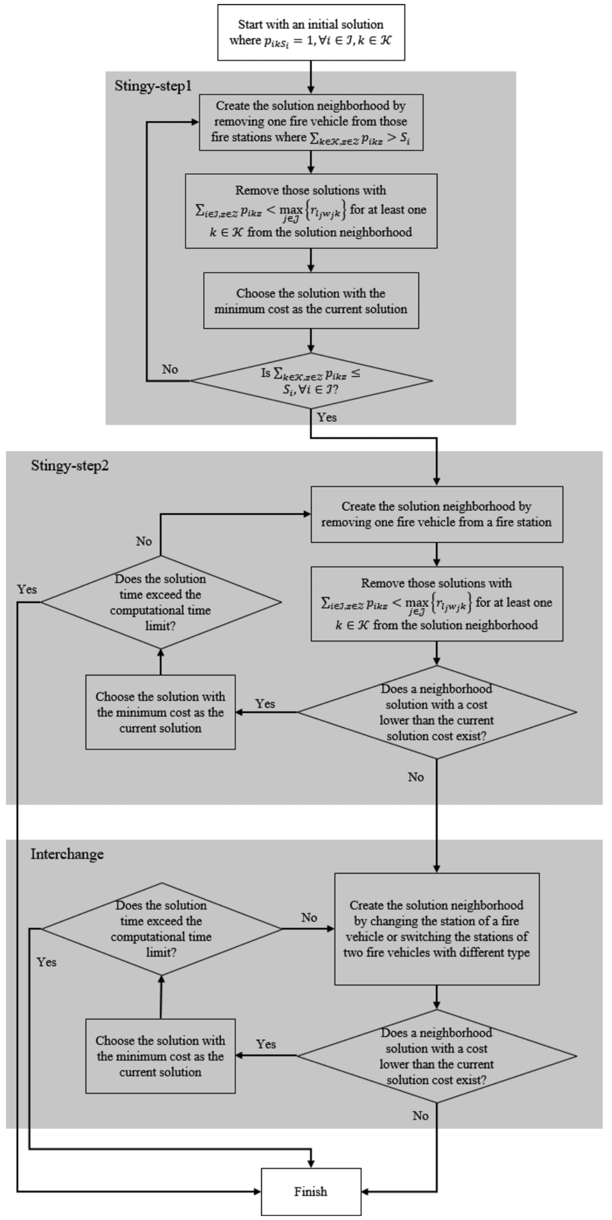
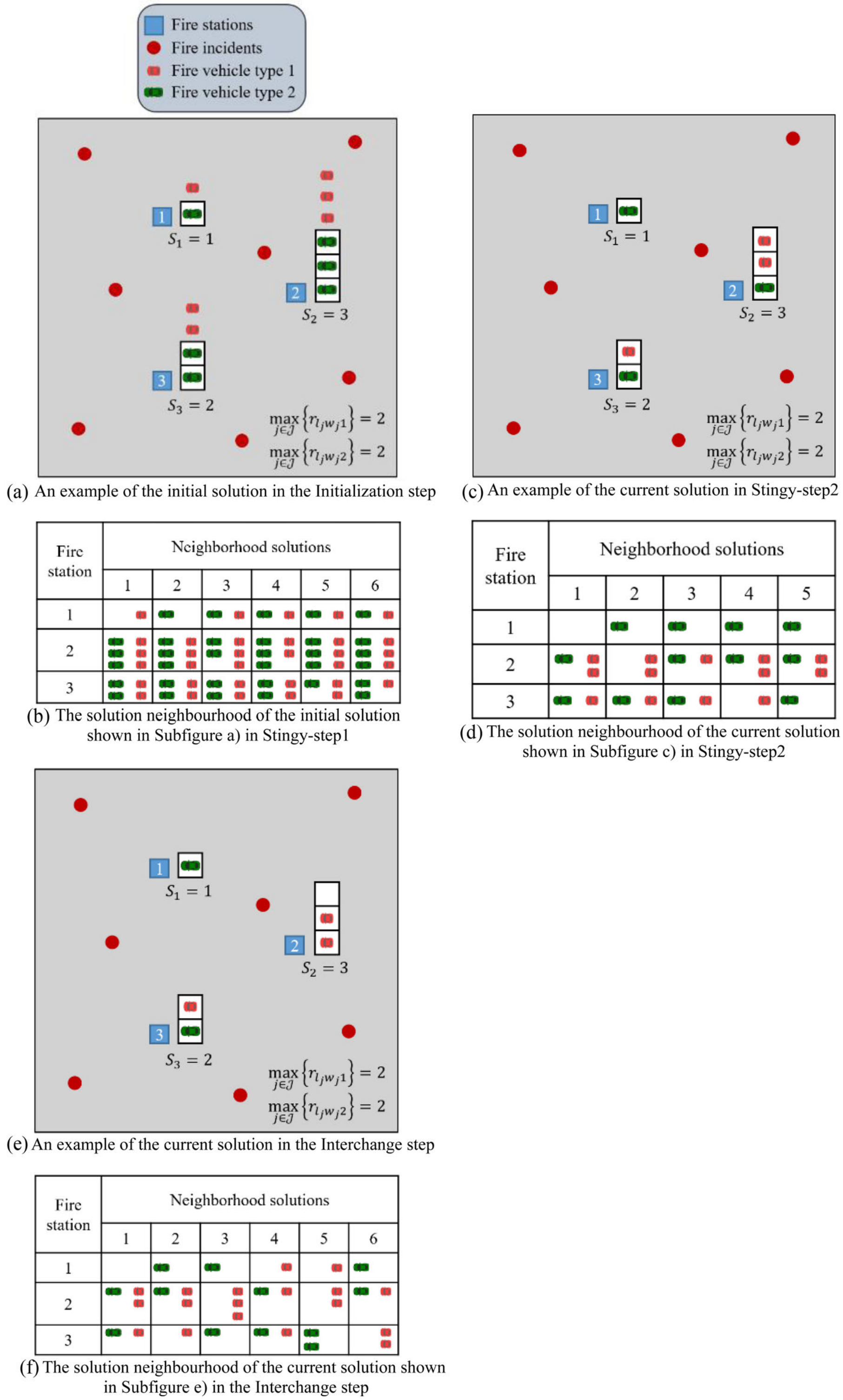


FIGURE 1 Flowchart of the proposed Stingy-Interchange (SI) algorithm

1. Initialization: Start with an infeasible solution where at each station i, there are S_i numbers of each k-type vehicle located (see Figure 2a). Find the corresponding optimal assignment.
2. Stingy-step1: At each iteration, create the neighborhood of the current solution by removing one vehicle from the stations that have more vehicles than their capacity (see Figure 2b). Each solution in the neighborhood must contain the minimum number of each k-type fire vehicle required to address all fire incidents (e.g., two green and two red fire vehicles in the example shown



(a) An example of the initial solution in the Initialization step

(b) The solution neighbourhood of the initial solution shown in Subfigure a) in Stingy-step1

(c) An example of the current solution in Stingy-step2

(d) The solution neighbourhood of the current solution shown in Subfigure c) in Stingy-step2

(e) An example of the current solution in the Interchange step

(f) The solution neighbourhood of the current solution shown in Subfigure e) in the Interchange step

FIGURE 2 Illustration of the proposed SI algorithm

in Figure 2). Choose the neighborhood solution with the lowest cost as the current solution. Repeat this iteratively until no station has more vehicle than its capacity (see Figure 2c).

3. Stingy-step2: At each iteration, create the neighborhood of the current solution by removing one vehicle from a station (see Figure 2d). Each solution in the neighborhood must contain the minimum number of each k-type fire vehicle required to address all fire incidents (e.g., two green and two red fire vehicles in the example shown in Figure 2). If the neighborhood solution with the lowest cost has a cost lower than the current

solution, choose it as the current solution and repeat this. Otherwise, go to the next step (see Figure 2e).

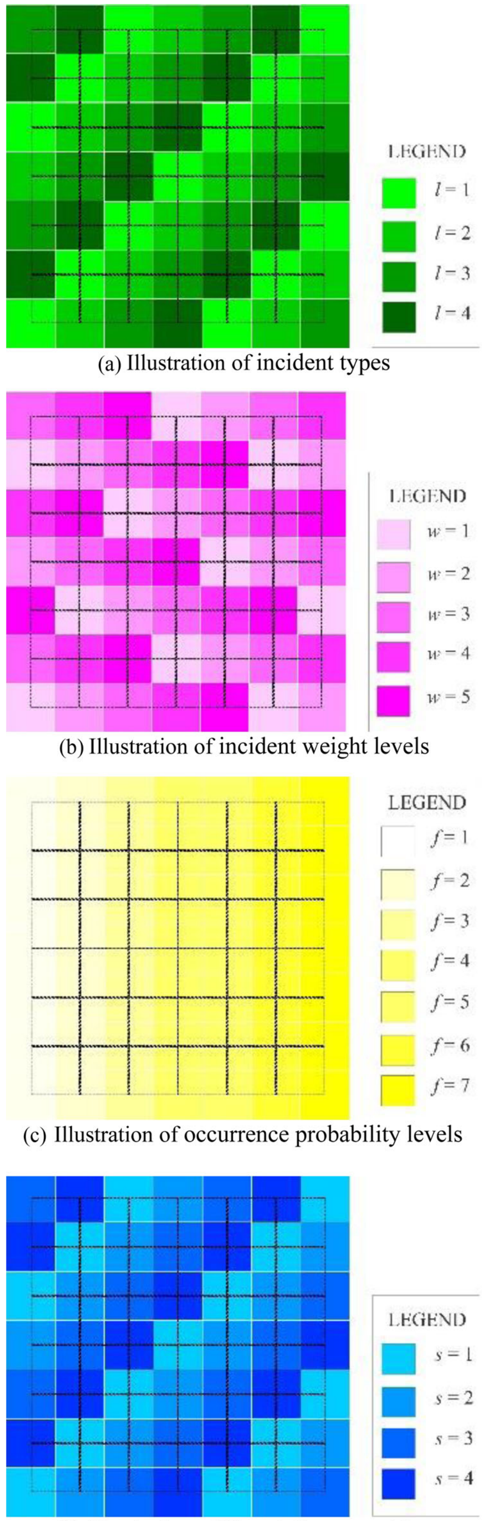
4. Interchange: At each iteration, create the neighborhood of the current solution by changing the station of one vehicle or switching the locations of two fire vehicles with different types (see Figure 2f). If the neighborhood solution with the lowest cost has a cost lower than the current solution, choose it as the current solution and proceed iteratively. Otherwise, the algorithm completes and returns the best solution.

Further, at each step of the SI algorithm, fire vehicles are optimally assigned to fire incidents by iterating over a set of possible allocations. Note that since the proposed Stingy algorithm finds a feasible solution by iteratively removing one fire vehicle from a fire station, the maximum number of the iterations in the Stingy algorithm is limited to the sum of fire station capacities multiplied by the total number of fire vehicle types, for example, $K \times \sum_{i \in I} S_i$. Therefore, the proposed Stingy algorithm is expected to obtain a feasible solution efficiently. The proposed Interchange algorithm, however, can be computationally expensive depending on the number of allocated fire vehicles to fire stations at the end of the Stingy algorithm. But the purpose of the proposed Interchange algorithm is to improve the solution quality rather than obtaining a feasible solution. Therefore, the proposed SI algorithm can guarantee finding a feasible solution efficiently while it can improve the solution quality until a stopping criterium (e.g., reaching the computational time limit, no better solution can be found) is met. With this, we can solve the JLAO problem to a near-optimal solution efficiently.

3 | NUMERICAL TEST

Numerical experiments built on hypothetical grid networks of various sizes are performed on different scales and dispatch policies to verify the effectiveness of our suggested algorithm by comparing it with a commercial solver, Gurobi. All algorithms are coded in the Visual Studio platform with the C++ language at a 64-bit Intel i7-5600U computer with 2.60 Hz and 2.59 Hz CPU and 16 GB RAM. The maximal solution time limit for each instance is set to 3600 s.

An $n \times n$ grid network is generated to construct a hypothetical case region with n^2 nodes and $2n \times (2n-1)$ links, where n varies among $\{7, 8, 9, 10, 11, 12\}$. The n^2 nodes are indexed as $1, 2, \ldots, n^2$, ascending from left to right and then from bottom to top. Every node is considered both as a demand point for a potential fire incident and as a candidate point for a fire station. The length of every edge between two adjacent nodes is set to 1. Parameters L, Z,



(a) Illustration of incident types

(b) Illustration of incident weight levels

(c) Illustration of occurrence probability levels

(d) Illustration of fire station capacities

FIGURE 3 A 7×7 grid network illustration

W, and T are set to be 4, 5, 5, and $2n$, respectively. Parameters l_j, f_j, w_j, and S_i are generated randomly as integers within predetermined ranges ($l_j \in [1,4]$, $f_j \in [1,7]$, $w_j \in [1,5]$, $S_i \in [1,4]$). Figure 3 illustrates a 7×7 grid network with our parameter designs.

TABLE 2 Matrix of $r_{l_j,w_j,k}$ under two scenarios

		Scenario I				Scenario II		
l	***w***	k_1	k_2	…	k_5	k_1	k_2	k_3
1	**1**	1	1	…	1	1	1	1
2	**1**	2	2	…	2	2	1	1
3	**1**	3	3	…	3	4	2	2
4	**1**	4	4	…	4	6	4	3
1	**2**	1	1	…	1	2	1	1
2	**2**	2	2	…	2	2	2	1
3	**2**	3	3	…	3	4	3	2
4	**2**	4	4	…	4	6	4	4
1	**3**	1	1	…	1	2	2	1
2	**3**	2	2	…	2	2	2	2
3	**3**	3	3	…	3	4	3	3
4	**3**	4	4	…	4	6	5	4
1	**4**	1	1	…	1	2	2	2
2	**4**	2	2	…	2	3	2	2
3	**4**	3	3	…	3	4	4	3
4	**4**	4	4	…	4	6	5	5
1	**5**	1	1	…	1	3	2	2
2	**5**	2	2	…	2	3	3	2
3	**5**	3	3	…	3	4	4	4
4	**5**	4	4	…	4	6	6	5

When there is no vehicle located at a station, (i.e., $Z = 0$), the parameter $c_{i,k,z}$ would be 0. Otherwise, we assume $c_{i,k,z}$ as an increasing but not linear function of the number of type-k fire vehicle located at station i as follow:

$$c_{i,k,z} = z * c_{i,k,1} + 2(z-1) * \varepsilon, \qquad \forall i \in \mathcal{I}, k \in \mathcal{K}, z \in \mathcal{Z},$$

where parameter $c_{i,k,1}$ (the cost of locating one type-k vehicle at station i) is generated randomly with the uniform distribution of [225, 275], and ε is a random value with the range [10,19].

We also generate a random function for $\pi_{j,t}$. In each network scale, when t is smaller than 20% of $T_{\max}$ (e.g., the max value in $\{t_{i,j}\}$), $\pi_{j,t}$ is set to be 0; when t is larger than 80% of $T_{\max}$, $\pi_{j,t}$ is set to be 1; otherwise, $\pi_{j,t}$ is equal to

$$1 - \{1/(1 + \exp[A(t - (0.2 \cdot T_{\max} + 0.8 \cdot T_{\max})/2)]\},$$

where A is a constant number set to be 0.25. Since different vehicle numbers in r may impact the performance of the algorithm, we have designed two scenarios with different numbers of fire vehicle types and different required numbers of fire vehicles by fire incidents as shown in Table 2. In the first scenario, each number is identical to level l. We consider different K values from 3 through 5. In the second scenario, more heterogeneous vehicle numbers when $K = 3$ are used to reflect heterogeneous needs of different incident types in the real world.

The quantitative results of the model and algorithm are shown in Table 3. In Scenario I (K equals to 3, 4, and 5), for small-scale networks (e.g., the 7×7 networks), Gurobi can find a better solution than the SI algorithm. However, in a larger scale network in Scenario I, as well as all scales in Scenario II, the SI algorithm can find near-optimal solutions with shorter computational times and smaller optimality gaps. We also observe that the gap advantage of the SI algorithm becomes more and more significant as the problem size increases in each scenario. For example, the gap benefit of SI algorithm over Gurobi in Scenario I ($K = 3$) improves from 0.66% to 32.38% with the network scale increases from 8×8 to 12×12. Further, it seems that the optimality gaps of both solution methods decrease as K increases from 3 to 5. The reason behind this might be the increase in number of eliminated solutions with tighter constraints at lager K. In practical data list in Scenario II, SI algorithm shown to be more effective than that in Scenario I ($K = 3$) in each scale. The SI algorithm can reach a near-optimum solution with a significantly smaller optimality gap. For example, the SI algorithm leaves a gap of 5.51%, while Gurobi keeps a gap of 5.94% in 7×7 network. In an 8 $\times$ 8 network, the Gurobi gap is 12.85%, but the SI gap is only 11.36% (improved by (12.85%–11.36%)/12.85% = 11.6%). However, in 8 $\times$ 8 network of Scenario I, the SI gap improves only 4.6% [(14.39%–13.73)/14.39%].

Overall, as the network size increases, finding an efficient solution becomes more challenging. Gurobi is shown to be able to obtain near-optimum solutions with negligible optimality gaps for up to 7×7 grid networks with multi-type demands. In comparison, the solutions found by the SI algorithm are in fact quite closer to the true optimal solutions or best known feasible solutions within a reasonable (even shorter) amount of computation time. Especially in larger scales, the SI algorithm produces better solutions within a relatively short computational time, compared with Gurobi. Also note that the effectiveness of the SI algorithm improves when K (the number of vehicle types) increases, or when the numbers in r table are erratic, which is more common in practice.

To investigate how the algorithm performance varies with the imposed computational time limit, we test the SI algorithm and Gurobi in Scenario I ($K = 3$) with various time limits (e.g., 1800, 3600, 5400, 7200, 9000, and 10,800 s). The heat map results of this sensitivity analysis are shown in Figure 4. The results indicate that the SI algorithm can obtain a closer gap than Gurobi, especially in large-scale network scenarios. For instance, the proposed SI algorithm can obtain a near optimum solution with around a 52.0% optimality gap, while the optimality gap of the solution found by Gurobi cannot become less than 85%.

TABLE 3 Algorithm performance under two test scenarios

Vehicle type number	Network scale	Gurobi objective value	Gurobi gap (%)	Gurobi time (s)	Stingy-Interchange (SI) objective value	SI gap (%)	SI time (s)
Scenario I ($K = 3$)	7 × 7	3745	6.04	>3600	3799	7.36	345
	8 × 8	4319	14.39	>3600	4286	13.73	968
	9 × 9	4902	36.60	>3600	4144	25.01	1317
	10 × 10	13,704	78.31	>3600	4691	36.62	2506
	11 × 11	24,650	87.72	>3600	6063	50.09	>3600
	12 × 12	19,956	85.14	>3600	6276	52.76	>3600
Scenario I ($K = 4$)	7 × 7	4791	0.32	3359	4896	2.45	661
	8 × 8	5659	15.31	>3600	5330	10.07	1507
	9 × 9	5613	18.91	>3600	5122	11.14	2485
	10 × 10	16,403	75.56	>3600	6617	39.41	>3600
	11 × 11	8990	56.60	>3600	7240	46.12	>3600
	12 × 12	26,641	85.40	>3600	7281	46.59	>3600
Scenario I ($K = 5$)	7 × 7	5642	0.00	730	5770	2.22	1289
	8 × 8	5776	0.53	>3600	5950	3.43	2326
	9 × 9	7515	24.79	>3600	6711	15.77	>3600
	10 × 10	8336	30.41	>3600	7248	19.95	>3600
	11 × 11	20,545	71.30	>3600	8363	29.48	>3600
	12 × 12	28,476	83.43	>3600	9468	50.16	>3600
Scenario II	7 × 7	4913	5.94	>3600	4890	5.51	360
	8 × 8	5506	12.85	>3600	5413	11.36	841
	9 × 9	6064	31.99	>3600	5242	21.32	1408
	10 × 10	10,482	61.51	>3600	5712	29.37	2682
	11 × 11	26,597	84.36	>3600	7040	40.90	>3600
	12 × 12	22,433	81.78	>3600	7507	45.56	>3600

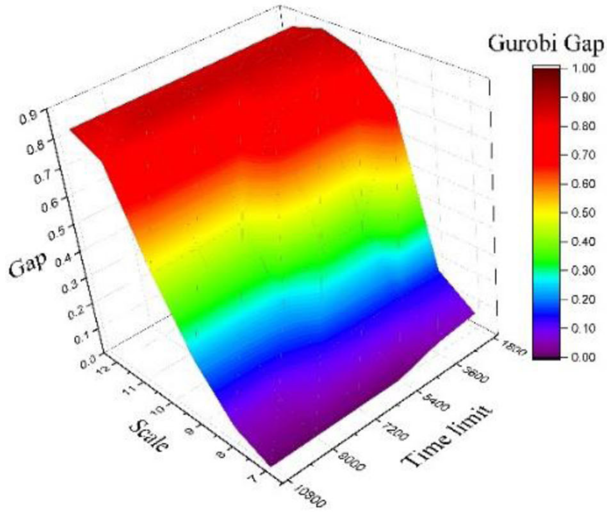
The results also show that both SI algorithm and Gurobi are not able to significantly decrease the optimality gap as the imposed computational time limit increases. This shows that the investigated problem is extremely complicated and requires much higher computational resources to be solved to the exact optimum solution. Therefore, an efficient heuristic algorithm that can achieve a near-optimum solution with a relatively low optimality gap is essential when dealing with such a problem. This shows that our suggested algorithm can effectively solve the joint location and assignment problem for large-scale networks and also has significant effects on more practical scenarios.

4 | HARBIN CASE STUDY

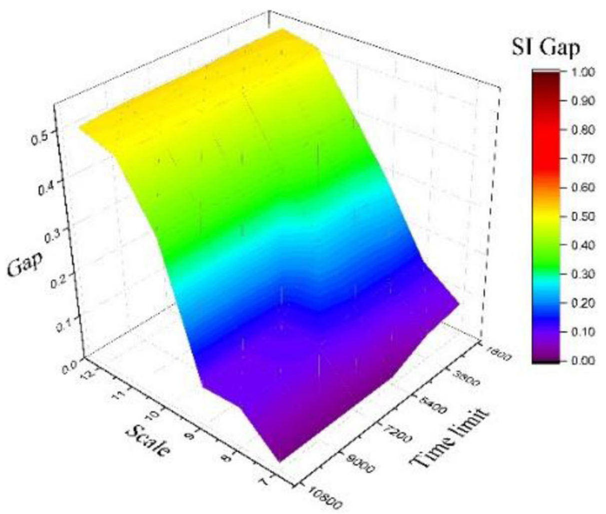
In this section, our mathematical model is applied to a full-scale location and assignment problem for cooperative services of Harbin City (China) and investigates the proposed algorithm's performance focusing on more practical scenarios. As the largest city in northern China, Harbin has a gross domestic product of more than 61.53 billion dollars per year. Since Harbin City is located in a relatively cold zone, vehicle travel time is usually considered due to the conditions of snow and ice (Liao, 2019). For incidents that require cooperative rescue, the response time of vehicles will significantly increase if the planned layout of the responding vehicle is not reasonable, which may cause great losses in fire or accidents lasted for a longer time. With this, the proposed model is tested on a real-world case with fire incident data from 2018, obtained from the Fire Department of Harbin. The purpose of this case study is not only to illustrate the proposed methodology in a realistic context but also to cast insights into the impacts of significant parameters in the JLAO problem.

4.1 | Assumptions and data preparation

Figure 5 shows the fire system layout of urban Harbin city, which has 50 fire station locations, 420 demand points, and thus 21,000 links. Fire station locations are marked as



(a) Gurobi gap



(b) SI gap

FIGURE 4 The gap sensitivity results of Gurobi and the SI algorithm

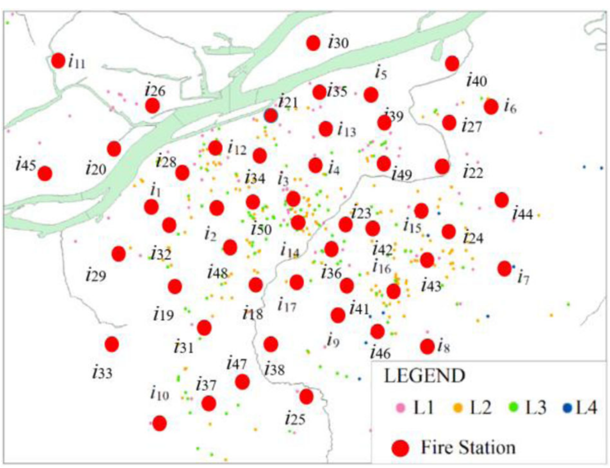


FIGURE 5 Fire protection areas in the Harbin City

TABLE 4 Matrix of $r_{l_j k}$ in Harbin Case

l	w range	k_1	k_2	k_3
1	[0, 30.77)	1	1	1
2	[30.77, 153.85)	2	1	1
3	[153.85, 307.69)	4	2	2
4	[307.69, +]	6	4	3
1	[0, 61.54)	2	1	1
2	[61.54, 307.69)	2	2	1
3	[307.69, 615.38)	4	3	2
4	[615.38, +]	6	4	4
1	[0, 92.31)	2	2	1
2	[92.31, 461.54)	2	2	2
3	[461.54, 923.08)	4	3	3
4	[923.08, +]	6	5	4
1	[0, 123.08)	2	2	2
2	[123.08, 615.38)	3	2	2
3	[615.38, 1230.77)	4	4	3
4	[1230.77, +]	6	5	5
1	[0, 153.85)	3	2	2
2	[153.85, 769.23)	3	3	2
3	[769.23, 1538.46)	4	4	4
4	[1538.46, +]	6	6	5

red pentagrams. Demand points including 103 Level-1 (L1) points, 183 Level-2 (L2) points, 122 Level-3 (L3) points, and 12 Level-4 (L4) points are marked by pink, yellow, green, and blue colors, respectively.

We assume that fire damage cost $\pi_{j,t}$ follows a sigmoid function of the response time (Karasakal & Karasakal, 2004) as follows:

$$\pi_{j,t} = \begin{cases} 0 & \text{if} \quad t \le T_0, \\ 1 - \dfrac{1}{1+e^{A\left(t-\frac{T_0+T_e}{2}\right)}} & \text{if } T_0 < t < T_e, \\ 1 & \text{otherwise,} \end{cases} \quad \forall j, t \in [0, T]$$

where A is set to be 0.25 based on the experience of Harbin fire officials. T_e is set to be 60 min, which is approximately the longest durable time for demand points on fire, based on REI (The REI marking identifies the fire-resistance rating of a structure. R = Load-bearing. E = Integrity. I = Thermal Insulation.) 60 fire resistance standard “EN13501-2.” T_0 is set to be 5 min, which is the official response time in China (Ministry of Emergency Management of the People’s Republic of China, 2018).

There are three types of fire vehicles (fire tanks, fire trucks, powerful jet engines) and the installation costs for one vehicle of each type are nearly \$40,000, \$63,077, and \$89,231, respectively. If multiple vehicles are located at a station, the concentration of the same-type vehicles can

TABLE 5 Algorithm performance of Gurobi and SI in the Harbin case study

Algorithm	Performance measures	Computational time limit							
		1800	3600	5400	7200	9000	10,800	12,600	14,400
Gurobi	Objective value	14,418.92	6401.69	1567.54	373.38	346.46	346.46	311.38	311.38
	Gap	1.000	0.978	0.872	0.462	0.413	0.413	0.347	0.347
	Computational time	1800	3600	5400	7200	9001	10,801	12,601	14,401
	Fire damage cost	14,243.85	6211.38	1277.08	73.08	74.15	74.15	109.23	109.23
	Travel cost	79.23	31.23	22.77	22.62	22.46	22.46	26.15	26.15
	Installation cost	95.85	159.08	267.69	277.69	249.85	249.85	176.15	176.15
	Vehicle number	30	59	96	100	92	92	65	65
	Response tme	23.91	15.68	6.05	5.80	5.85	5.85	6.53	6.53
SI	Objective value	327.38	327.38	306.15	302.46	298.31	294.46	290.46	289.54
	Gap	–	0.569	0.346	0.336	0.318	0.309	0.299	0.297
	Computational time	3673	3901	5526	7308	9000	10,800	12,791	14,598
	Fire damage cost	124.31	124.31	101.85	101.08	101.69	107.54	104.31	104.15
	Travel cost	28.62	28.62	28.62	28.31	28.00	28.31	28.15	28.00
	Installation cost	174.46	174.46	175.69	173.08	168.62	158.62	157.85	157.38
	Vehicle number	66	66	66	65	64	61	60	60
	Response time	5.81	5.81	5.65	5.52	5.68	5.91	5.86	5.85

reduce the installation costs. The capacity for each candidate fire station is set to be 4. The distances between fire stations and incidents are measured along the shortest path in the actual road network and then transferred to the travel time $t \in \{0, 1, 2, \ldots, 76\}$ (in minutes). The matrix of $r_{l_j,w_j,k}$ in the Harbin case is shown in Table 4.

4.2 | Computational results and analysis

After the computational time limit of 14,400 s is reached, the SI algorithm provides an acceptable solution with a gap of 29.7% and an objective value of 289.54, which is 5% smaller than the one Gurobi provides (a near-optimum solution with a gap of 34.7% and an objective value of 311.38). The outputs of the SI algorithm and Gurobi and their computational times are shown in Table 5.

In the initial stages (e.g., 1800 to 7200 s), Gurobi searches for an optimal solution by increasing vehicle numbers from 30 to 100, which shortens the response time from 23.91 to 15.68 min. However, the optimality gap of the solution obtained by Gurobi cannot go below 50% when the computational time limit is less than 7200 s. In later stages, the vehicle number decision decreases to 92 and ends with 65 with a 14,400 s time limitation. The SI algorithm, however, can efficiently estimate the number of required fire vehicles even when the imposed computational time limit is short (the number of fire vehicles decreases from 66 to 60 as the computational time limit increases from 1800 to 14,400 s). Consequently, the SI algorithm can obtain a near-optimum solution with much less operational costs, compared with the one reported by Gurobi.

TABLE 6 Impact of the demand growth rate on the optimal system cost and the fire vehicle number

Demand growth rate	1	2	3	4
Objective value	327.38	439.69	518.33	570.40
Fire damage cost	124.31	203.80	248.06	278.05
Travel cost	28.62	25.36	22.77	22.42
Installation cost	174.46	210.52	247.50	269.93
Vehicle number	66	80	98	105
Response time	5.81	5.39	5.09	4.97

4.3 | Sensitivity to parameters

In this subsection, we investigate how different parameter settings can affect the optimal design of the joint location and assignment problem. The investigated parameters are the demand growth rate, the travel cost rate, T_0, and A. In each sensitivity analysis, only one parameter varies at a time, while other parameters are kept at their default values.

Table 6 shows the results of the sensitivity analysis performed on the demand growth rate. As the demand growth rate increases within the range [1, 4] (implying a weight growth of demand), more fire vehicles are located to decrease the fire damage cost. Table 6 also shows that the

TABLE 7 Impact of the travel cost rate on the optimal system cost

Travel cost rate	0	0.5	1	1.5	2
Objective value	303.41	314.55	327.38	344.64	355.12
Fire damage cost	127.00	124.14	124.31	128.26	123.90
Travel cost	0.00	14.20	28.62	39.79	52.93
Installation cost	176.40	176.22	174.46	176.60	178.29
Vehicle number	68	67	66	67	68
Response time	5.95	5.81	5.81	5.81	5.63

TABLE 8 Impact of parameter T_0 on the optimal system cost and fire vehicle response design

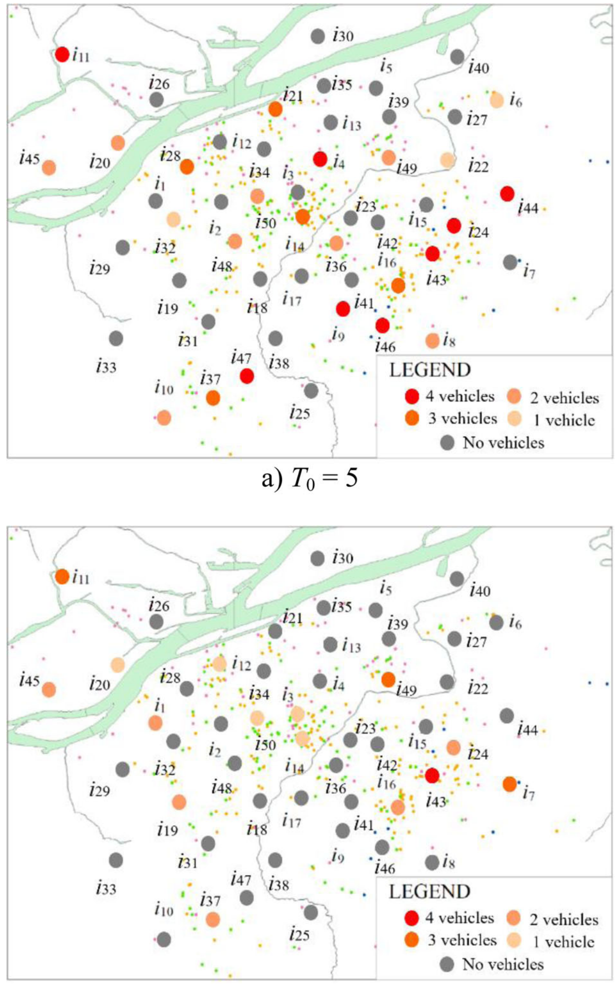
T_0	5	10	15	20
Objective value	327.38	238.67	164.25	138.09
Fire damage cost	124.31	64.17	31.05	21.70
Travel cost	28.62	32.72	34.04	37.79
Installation cost	174.46	141.78	99.17	78.60
Vehicle number	66	55	39	30
Response time	5.81	7.92	8.67	9.77

travel cost decreases while the installation cost increases as the demand growth rate increases. This indicates that a higher demand would require more fire stations to ensure a more urgent response. Finally, the response time shows a decreasing trend, which is the result of the higher number of considered fire stations.

Table 7 illustrates the sensitivity analysis results of the travel cost rate. It is shown in Table 7 that the increase in the travel cost rate causes few fluctuations in the number of fire stations and located fire vehicles. Further, the response time and fire damage cost decreases with the increase in the travel cost rate as a result of shorter travel.

Table 8 illustrates the sensitivity of the optimal system cost to parameter T_0 in $\pi_{j,t}$ function. Note that a lower value of T_0 indicates that fire incidents need to be served more urgently. Therefore, as the value of T_0 increases, the fire incidents become less urgent, and thus the number of installed stations and located fire vehicles decreases. The fire resource layouts with different T_0 values are shown in Figure 6.

Finally, Table 9 illustrates the sensitivity of the optimal system cost to A, another parameter of the $\pi_{j,t}$ function. As the value of A increases, the growth curve of $\pi_{j,t}$ becomes steeper in the middle range, leading to a slower initial loss of a fire accident. Therefore, the relaxation of response time reduces the number of located fire vehicles and disperse their locations. At the same time, the greater workload of each vehicle causes an upward trend in travel cost and response time. It can be seen that the fire development curve is very important for the reasonable layout



a) $T_0 = 5$

b) $T_0 = 20$

FIGURE 6 Fire resource layouts with different T_0 values

TABLE 9 Impact of parameter A on the optimal system cost and fire vehicle response design

A	0.05	0.15	0.25	0.35	0.45
Objective value	2259.75	661.36	327.38	235.86	173.73
Fire damage cost	1911.89	336.96	124.31	91.37	49.50
Travel cost	22.23	22.75	28.62	32.60	33.83
Installation cost	325.62	301.66	174.46	111.89	90.40
Vehicle number	122	116	66	44	36
Response time	4.42	4.80	5.81	7.84	9.90

of fire vehicles as well as the system cost control. In the joint location and assignment design, the fire development function should be modeled accurately by evaluating the characteristics of local flammable materials so that more benefits can be obtained with fewer resources by the fire department.

In our experiments, we also find that the solution gap of the proposed algorithm tends to decrease gradually as the demand growth rate and T_0 increase. This is likely since a greater demand growth rate and T_0 imply a higher weight of fire damage cost and a smaller scale of the problem instance, respectively. As such, the proposed algorithm tends to cut more branches in the early stages and thus computes with smaller sets of candidate fire vehicles when these parameters increase.

5 | CONCLUSION

This paper focuses on a joint location and assignment problem, motivated by fire service practices implemented for the operations of multiple professional vehicles. Assuming the fire damage cannot be controlled unless the last required fire vehicle arrives at the scene, an MIP model is proposed to address the vehicle location problem and vehicle assignment problem in an integrated framework.

Since LR has shown to have poor performance on the joint location and assignment problem, we develop an SI algorithm and compare its computational performance with a commercial solver Gurobi. Several hypothetical example problems are applied to test the algorithm's effectiveness. The results show that the proposed SI algorithm can obtain a near-optimal solution to the joint location and assignment problem within a shorter time and lower optimality gap, especially for large-scale networks and practical scenarios. In the Harbin case study, we optimized the location and allocation of fire vehicles in Harbin city based on the gathered real data from the Fire Department of Harbin. Finally, sensitivity analyses are performed on a series of important parameters to reveal how different parameter values affect the optimal design.

It should be noted that the model and methodology proposed in this paper are actually quite general; it can also be applied to other emergency location and assignment designs with joint servers, such as the coronavirus disease 2019 response system performed by medical vehicles and police vehicles.

Due to the high complexity of the JLAO problem, we simplified the assumptions of the problem that could be relaxed in future research. One of the limitations is that the impact of different types of fire on fire development is not considered. Fire damage cost rates for different potential hazards can be further explored for more accurate decisions. Another limitation is the fixed probability assumption of the incident occurrence. It can be addressed with other more complex modeling methods (e.g., stochastic and robust programing). Furthermore, it will be interesting to measure the impact of vehicle operational speed (caused by vehicle types or traffic congestion) on the performance of the proposed joint location and assignment model in the future.

REFERENCES

An, S., Cui, N., Bai, Y., Xie, W., Chen, M., & Ouyang, Y. (2015). Reliable emergency service facility location under facility disruption, en-route congestion and in-facility queuing. *Transportation Research Part E: Logistics and Transportation Review*, *82*, 199–216.

Badri, M. A., Mortagy, A. K., & Alsayed, C. A. (1998). A multi-objective model for locating fire stations. *European Journal of Operational Research*, *110*(2), 243–260.

Bao, S., Xiao, N., Lai, Z., Zhang, H., & Kim, C. (2015). Optimizing watchtower locations for forest fire monitoring using location models. *Fire Safety Journal*, *71*, 100–109.

Batta, R., & Mannur, N. R. (1990). Covering-location models for emergency situations that require multiple response units[J]. *Management Science*, *36*(1), 16–23.

Berman, O., Drezner, Z., & Krass, D. (2009). Cooperative cover location problems: the planar case. *IIE Transactions*, *42*(3), 232–246.

Berman, O., Drezner, Z., & Krass, D. (2013). Continuous covering and cooperative covering problems with a general decay function on networks. *Journal of the Operational Research Society*, *64*(11), 1644–1653.

Church, R., & ReVelle, C. (1974). The maximal covering location problem. *Papers of the Regional Science Association*, *32*(1), 101–118.

Daskin, M. S. (1983). A maximum expected covering location model: formulation, properties and heuristic solution. *Transportation Science*, *17*(1), 48–70.

Daskin, M. S. (2011). *Network and discrete location: Models, algorithms, and applications*. John Wiley & Sons.

Daskin, M. S., & Jones, P. C. (1993). A new approach to solving applied location/aiiocation problems. *Computer-Aided Civil and Infrastructure Engineering*, *8*(6), 409–421.

Fire and Rescue Department of Emergency Management Bureau (2019). *National fire situation in 2018*. http://www.119.cn/content/201901/23/c98327.html

Gendreau, M., Laporte, G., & Semet, F. (1997). Solving an ambulance location model by tabu search. *Location Science*, *5*(2), 75–88.

Hajibabai, L., & Saha, D. (2019). Patrol route planning for incident response vehicles under dispatching station scenarios. *Computer-Aided Civil and Infrastructure Engineering*, *34*(1), 58–70.

Haynes, H. J. (2017, September). Fire loss in the United States during 2016. *NFPA Journal*. https://www.nfpa.org/News-and-Research/Publications-and-media/NFPA-Journal/2017/September-October-2017/Features/2016-US-Fire-Loss-Report

Jacobs, A. (2009, February 9). Fire ravages renowned building in Beijing.. *New York Times*. https://www.nytimes.com/2009/02/10/world/asia/10beijing.html

Jiang, X., & Adeli, H.,(2003). Freeway work zone traffic delay and cost optimization model. *Journal of Transportation Engineering, ASCE*, *129*(3), 230–241.

Jiang, X., & Adeli, H. (2004). Object-oriented model for freeway work zone capacity and queue delay estimation. *Computer-Aided Civil and Infrastructure Engineering*, *19*(2), 144–156.

Karasakal, O., & Karasakal, E. K. (2004). A maximal covering location model in the presence of partial coverage. *Computers & Operations Research*, *31*(9), 1515–1526.

Larson, R. C. (1974). A hypercube queuing model for facility location and redistricting in urban emergency services. *Computers & Operations Research*, *1*(1), 67–95.

Larson, R. C. (1975). Approximating the performance of urban emergency service systems. *Operations Research*, *23*(5), 845–868.

Li, X., Ramshani, M., & Huang, Y. (2018). Cooperative maximal covering models for humanitarian relief chain management. *Computers & Industrial Engineering*, *119*, 301–308.

Liao, K. (2019). *Reducing traffic congestion and emission in chinese cities". The World Bank*. https://www.worldbank.org/en/news/feature/2018/11/16/reducing-traffic-congestion-and-emission-in-chinese-cities

Lu, L., Wang, X., Ouyang, Y., Roningen, J., Myers, N., & Calfas, G. (2018). Vulnerability of interdependent urban infrastructure networks: Equilibrium after failure propagation and cascading impacts. *Computer-Aided Civil and Infrastructure Engineering*, *33*(4), 300–315.

Ministry of Emergency Management of the People's Republic of China (2018). *Regulations of the People's Republic of China on fire and rescue ranks*. Law Press.

Nemhauser, G. L., Wolsey, L. A., & Fisher, M. L. (1978). An analysis of approximations for maximizing submodular set functions—I. *Mathematical Programming*, *14*(1), 265-294.

Ng, M., Park, J., & Waller, S. T. (2010). A hybrid bilevel model for the optimal shelter assignment in emergency evacuations. *Computer-Aided Civil and Infrastructure Engineering*, *25*(8), 547–556.

OFM. (2010). *Operational planning: An official guide to matching resource deployment and risk workbook*. http://www.mcscs.jus.gov.on.ca/english/FireMarshal/FireServiceResources/PublicFireSafetyGuidelines/04-08-10at1.html

Park, H., Shafahi, A., & Haghani, A. (2016). A stochastic emergency response location model considering secondary incidents on freeways. *IEEE Transactions on Intelligent Transportation Systems*, *17*(9), 2528–2540.

Pérez, J., Maldonado, S., & Marianov, V. (2016). A reconfiguration of fire station and fleet locations for the Santiago Fire Department. *International Journal of Production Research*, *54*(11), 3170–3186.

ReVelle, C., & Hogan, K. (1989). The maximum availability location problem. *Transportation Science*, *23*(3), 192–200.

Smith, R., Ferrebee, E., Ouyang, Y., & Roesler, J. (2014). Optimal staging area locations and material recycling strategies for sustainable highway reconstruction. *Computer-Aided Civil and Infrastructure Engineering*, *29*(8), 559–571.

Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. *Operations Research*, *19*(6), 1363–1373.

Wang, J., Liu, H., An, S., & Cui, N. (2016). A new partial coverage locating model for cooperative fire services. *Information Sciences*, *373*, 527–538.

Wang, Z., Hu, H., Guo, M., & Gong, J. (2019). Optimization of temporary debris management site selection and site service regions for enhancing postdisaster debris removal operations. *Computer-Aided Civil and Infrastructure Engineering*, *34*(3), 230–247.

Xie, W., Ouyang, Y., & Somani, K. (2016). Optimizing location and capacity for multiple types of locomotive maintenance shops. *Computer-Aided Civil and Infrastructure Engineering*, *31*(3), 163–175.

Xie, W., & Ouyang, Y. (2013). Dynamic planning of facility locations with benefits from multitype facility colocation. *Computer-Aided Civil and Infrastructure Engineering*, *28*(9), 666–678.

Yang, J., & Liang, J. (2012). Research on relationship between fire engines and fire risk. *Procedia Engineering*, *45*, 674–677.

Zockaie, A., Aashtiani, H. Z., Ghamami, M., & Nie, Y. (2016). Solving detour-based fuel stations location problems. *Computer-Aided Civil and Infrastructure Engineering*, *31*(2), 132–144.

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