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Traffic emergency vehicle deployment and dispatch under uncertainty

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ABSTRACT

To manage traffic emergencies, cities require multiple types of traffic rescue vehicles, which need to be dispatched from various rescue stations dispersed throughout the city. A reasonable way of deploying the rescue vehicles must be determined given that the times and locations at which the traffic emergencies occur are uncertain. In this paper, we propose a two-stage stochastic programming approach to deploying multiple types of emergency vehicles in response to traffic accidents in the context of uncertainty. The first stage of the proposed model concerns decisions on the quantities of the different types of vehicles to be stocked at each rescue station. In the second stage, when the locations and accident rescue demands are realized in each scenario, the decision-making involves dispatch of the emergency vehicles to the traffic accidents. To solve the proposed model, we suggest a variable neighborhood search method. Using the road network of Jiading District, Shanghai, as an example, we perform numerical experiments to investigate the efficiency of the proposed method and the model validity. Some managerial implications are also outlined in the sensitivity analysis.

1. Introduction

Smart transportation management is becoming increasingly important as more emphasis is placed on building “smart cities.” A key smart-city issue is the design of smart transportation management systems, which includes improving the efficiency with which traffic accidents are managed in cities. We define a traffic accident as an unpredictable event that affects the smooth flow of urban traffic, and which may cause road network damage or casualties (Steenbruggen et al., 2014; Gao et al., 2023). Data issued by the Chinese National Bureau of Statistics indicate that there were 247,646 traffic accidents in China in 2019. When traffic accidents occur on urban roads, the overall capacity of the road is reduced, causing disruptions and traffic congestion. To manage traffic accidents, the city road rescue companies deploy various types of rescue vehicles in stations dispersed throughout their cities. The “type” of emergency vehicle refers to the type of service that is provided. Fig. 1 shows the main types of rescue vehicles in the stations operated by a road rescue company in Shanghai, including wreckers, multi-function recovery vehicles, cranes, etc. When an accident occurs, one or more rescue vehicles is dispatched from a nearby station to the accident site. The type and number of vehicles required depend on the specific accident. A key scientific problem for smart transportation initiatives in cities is how to deploy these various types of rescue vehicles among rescue stations dispersed throughout the city and how to dispatch suitable vehicles to accidents in an efficient and intelligent way.

From a strategic perspective, ensuring a reasonable vehicle deployment among rescue stations is fundamental for a city’s

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emergency traffic rescue work. Initially, vehicle deployment can be estimated and determined based on the type and quantity of resources required in past accidents in the city. From a tactical perspective, emergency vehicle dispatch can be planned by considering the stochastic locations of accident sites in the road network and the associated demands for rescue vehicles. Sudden traffic events give rise to the complex randomness and instability influencing urban road networks and traffic rescue management (Wang et al., 2021). Combining the strategic and tactical perspectives, we propose a systematic solution that enables coordination between pre-emptive and real-time traffic emergency rescue decisions. Variable traffic conditions have led to new characteristics in the spatial and temporal distribution of urban traffic accidents. Thus, it is essential to take the uncertain environment of the urban road network into account in our solution.

In this context, we investigate a comprehensive decision problem involving the deployment of emergency vehicles in rescue stations and their dispatch to urban traffic accidents. In vehicle routing and scheduling decisions, the uncertainty influencing the road network is the main factor that significantly increases the problem's complexity. One way to deal with this complexity is to use a stochastic optimization approach (Doulabi et al., 2020). In this paper, we present a two-stage stochastic programming approach to deal with the complex problem that we have outlined concerning traffic rescue vehicle deployment and dispatch. The first stage of the approach concerns the long-term decisions, as the decision-maker needs to determine the appropriate quantities of the various types of rescue vehicles to stock at each rescue station. As such, the decision-maker simultaneously needs to determine the scale of each rescue station. In the second stage, we consider the uncertain factors such as the location and time of the traffic accidents, the demand for various types of emergency vehicles, and the travel time between rescue stations and accident sites. The decisions are made on the dispatch of multiple types of emergency vehicles from multiple stations to respond to multiple traffic accident sites within various time windows in a set of scenarios. There are three types of decision variables in the second-stage model: (1) assignment decision for multiple types of emergency vehicles from multiple stations to traffic accident sites in each scenario; (2) sequencing decision for emergency vehicles to service traffic accidents in each scenario; (3) timing decision for emergency vehicles to start rescuing in each scenario. The objective of the decision problem is to minimize the total cost of emergency response within a limited planning budget, including minimizing the cost of overtime penalties for untimely responses. To solve the problem using the proposed model, we design and implement a variable neighborhood search (VNS) heuristic algorithm. Then, we conduct some numerical experiments using the road network of Jiading District, Shanghai, as an example to investigate the validity of the proposed model and the performance of the suggested methodology. In addition, we refine the second-stage dynamic dispatch based on the solution approach outlined above. The extension of the proposed dynamic approach in this paper could be applied in more generic and realistic contexts of the related emergency management services.

The contributions of our study are threefold. First, we explore the deployment and dispatch problem of different types of emergency vehicles, considering stochastic factors (the stochasticity of accidents in time and space, and the stochastic demands for traffic rescue), and detailed factors (travel time, the penalty costs of delay, one vehicle trip managing multiple accidents, and the different types and numbers of vehicles required by different accidents). We develop our two-stage stochastic programming model to minimize the total emergency rescue cost. The integrated decision mode for emergency vehicle deployment and dispatch proposed in this study can reduce the final cost. Second, to solve our model, we introduce a VNS algorithm that can act as a key module embedded in some decision support systems for traffic emergency management. One key feature of the proposed VNS method is that the neighborhood structures for the second-stage decision variables are embedded in the mutation neighborhood structure for the first-stage decision variables. Third, we draw some managerial insights from our numerical experiments and the sensitivity analysis. In addition, the value of the stochastic programming and the perfect information used in this study are estimated.

The remainder of this paper is organized as follows. Section 2 presents the literature review. The problem background is described in detail in Section 3, and our mathematical model is formulated in Section 4. In Section 5, we put forward our proposed VNS-based approach to solve the model. Section 6 proposes a method of scenario generation. The experimental results and analysis are provided in Section 7. Section 8 constructs a dynamic dispatching mechanism as an extension of the main analysis in this paper, and Section 9 concludes.

2. Literature review

Traffic accident rescue is a critical issue in emergency management and, as such, it has been attracting increasing attention in the operations research community. This study largely concerns three issues: long-term decision-making on resource deployment and

Wreckers Multi-function recovery vehicles Cranes

Fig. 1. main types of rescue vehicles in the stations of a road rescue company.

facility establishment; short-term decision-making on vehicle and resource scheduling for traffic accident rescue; and integrated long- and short-term decision problem on emergency management. In this section, our review of the related literature is organized according to the strands of literature concerning these three issues.

2.1. Vehicle and resource deploymen problem

The first strand of literature concerns long-term emergency management decisions. Generally, in the strategic stage of emergency rescue, pre-defined indicators are important, in particular, the location and deployment problem have received considerable attention. Location problem decides determines where to set up rescue stations to host emergency vehicles. Deployment problem decides how many emergency vehicles are attributed to each rescue station, that is, which determines the attribution of emergency vehicles to the rescue station. Pal and Bose (2009) presented a mixed integer programming model to optimize the rescue station location and assign emergency vehicle to these selected rescue stations, which considered the reliability of each accident site that can be served by a vehicle. Considering the uncertainty of demand for resources, Ozbay et al. (2013) further formulated a stochastic integer programming model with given the probability distribution of demand for resources. In addition, the literature presents emergency vehicle redeployment strategies to deal with uncertainties. Liu et al. (2016) proposed a double standard model, which combines the double service coverage standards and multi-vehicle deployments. Although some studies have separately considered multiple types of rescue vehicles, the emergency service level, and the uncertain traffic conditions, studies considering these factors simultaneously are scarce. Our study investigates long-term emergency management decisions on the deployment of multiple types of emergency vehicles and the scale of rescue stations considering uncertain traffic conditions simultaneously.

2.2. Vehicle and resource dispatch problem

The second strand of literature concerns the short-term decision on vehicle and resource scheduling. These topics have been extensively studied. The emergency vehicle dispatch and coverage problems were integrated by Ibri et al. (2012), who aimed to improve rescue reliability. Billhardt et al. (2014) proposed a mechanism to coordinate ambulance dispatch, which can dynamically reduce the emergency response time. Capar et al. (2017) argued that considering the first and last response times with the total response time contributes to more effective scheduling than considering the total response time alone. They presented a multi-objective model to combine these three metrics and used a greedy algorithm for problem solving. By providing the dispatcher with the flexibility to explore many different situations, the simulation system enables a more precise and rapid response. In a dispatch problem involving multiple firetrucks, Usanov et al. (2020) introduced the concept of driving time correlation to reduce the time to reach the emergency area. Due to the time-sensitivity of emergency rescue, in general, studies have focused on the optimization objective of minimizing rescue time in the vehicle dispatch problem.

Emergency vehicle dispatch decisions normally involve diverse scenarios. Hence, the literature considers various details that are taken into account in vehicle scheduling for traffic accident rescue. To ensure timely rescues, Chai et al. (2018) presented an emergency vehicle dispatching method that considers the vehicle queuing phenomenon caused by traffic accidents. Numerous researches have considered real-time changing traffic conditions, for instance, Henchey et al. (2015) developed a routing methodology that allows real-time information to provide interference. Park et al. (2019) suggested an online dispatch strategy, which they applied to different freeway networks, numbers of incidents, and service times. Dunnett et al. (2019) formulated a mathematical model to consider predicted traffic conditions and response unit availability, and validated this framework using a simulation. Chou et al. (2022) constructed a model comprising a cell transmission model and a nonlinear treatment impedance function to reduce delays in patient allocation resulting from traffic congestion. All of the studies in this strand of literature focus on the timeliness of rescue and how to deal with the uncertainty of the traffic environment, with vehicle paths and travel times as key factors. Our study aims to minimize the total cost of emergency response within a limited planning budget. As the research progresses, the dispatch problem should be expanded to consider the impact of other complex factors such as the accident time and locations, which should be reflected as quantifiable parameters or measurable objective functions.

2.3. Hybrid problem on emergency management

The integrated long- and short-term decision problem on emergency management is usually done at the same level, e.g., location and dispatching, deployment and dispatching, redeployment and dispatching. In emergency medical systems, Belanger et al. (2020) investigated an ambulance location and dispatching problem (ALDP) which incorporate the uncertainty of the availability of ambulances based on analytical queuing approaches. Bertsimas and Ng (2019) developed stochastic and robust formulations for the ALDP that use data on emergency calls to model uncertainty. Enayati et al. (2019) conducted a study on ALDP considering multiple levels of call priority and proposed a multicriteria optimization approach to identify good solutions for several equity and efficiency measures together. In contrast to the above studies that consider only a single vehicle type, Boujemaa et al. (2020) investigates a multi-period two types of ambulances redeployment and dispatching problem under uncertainty. The two types of ambulances are deployed to respond to both types of calls, differentiated by the severity of the case.

The combination of long- and short-term decision problems will complicate the study, and the appropriate methodology to apply to the integrated problem solving is particularly important. New research using simulation or scenario-based optimization is coming to the foreground in the literature. Zhen et al. (2014) introduced a simulation framework guided by a genetic algorithm to deploy and relocate ambulances. Coelho and Pinto (2018) employed a metamodeling-based simulation to optimize the location and allocation of ambulances. Rodriguez et al. (2021) proposed a simulation–optimization approach to solve a fire station location and vehicle dispatching problem. The scenario-based optimization methodology has also been widely applied in the integrated problems consider uncertainly. Boujemaa et al. (2020) developed a two-stage stochastic programming model to deploying two types of ambulances in response to emergency calls in the context of uncertainty. To maximize the coverage domain of demand points, Zonouzi and Kargari (2020) presented a scenario-based model to allocate rescue vehicles based on data mining. Emergency vehicles are dispatched to satisfy specific rescue demand. The deployment of emergency vehicles to each rescue station is frequently concurrently optimized with dispatching to ensure that there are sufficient resources available to meet demand. Consequently, in this study, we investigate the integrated emergency vehicle deployment and dispatch problem for multiple vehicles using a two-stage stochastic programming approach and considering several detailed factors.

2.4. Research gap

Based on the literature review above, it is evident that vehicle and resource planning for traffic emergency management is an important research field. Although the literature contains many excellent studies within the three streams reviewed above, to the best our knowledge, there are few studies that attempt to combine the long- and short-term decisions on emergency vehicle deployment and dispatching under several uncertain and detailed factors. This work is related to more classical ambulance location and dispatching problem. In contrast to most ALDP that considers only a single vehicle type (i.e., ambulances), traffic accidents rescue involves various types of emergency vehicles (i.e., wreckers, multi-function recovery vehicles, cranes, etc.) at the same station. In addition, the ambulance dispatching problem only decides which ambulance is dispatched to serve each demand point. The route of ambulance starts from their current station, goes to a demand point, and backs to station. While the dispatching of emergency vehicles involves the vehicle routing problem as each emergency vehicle is dispatched to serve multiple traffic accident sites. When it comes to location and fleet deployment problem, mixed-integer programming models are typically used. Queuing theory, which takes dispatch policies and preference lists into account, is typically used to address dispatching problem (Wang et al., 2023). However, we develop a two-stage stochastic programming model to formulate the hybrid problem.

Comparing the most similar work by Boujemaa et al. (2020), which solves the multi-period ambulance redeployment and dispatching problem considering two types of vehicles under uncertainty. The problem is modeled as a two-stage stochastic optimization problem and two heuristic solution approaches are given. Our study significantly differs from the literature in terms of problem features and methodology. First, as mentioned earlier ambulance dispatching does not involve routing problems while we consider routing optimization in the second stage of the model. Secondly, the literature only considers uncertain number of calls of two types of ambulance arriving from demand point. We further consider uncertain location and time of the traffic accidents, uncertain demand for various types of emergency vehicles, and uncertain travel time between rescue stations and accident sites, which makes the routing decision for each vehicle extremely complex. Table 1 lists and compares the uncertainty factors and modeling methods with existing literature. The algorithms proposed in the above literature cannot solve the problem efficiently in the face of these challenges. The VNS algorithm has been widely used in the study of combinatorial optimization and vehicle routing problems (Xu and Cai, 2018). In our study, the mutation and swap neighborhood structures are applicable to the deployment decision for multiple types of emergency vehicles to multiple stations in the first stage. The swap and insertion neighborhood structures are applicable to the sequencing decision for emergency vehicles to service traffic accidents in each scenario in the second stage. Since the decision variables of the two stages interact with each other, we nested the adjacency structure of the variables belonging to different stages in the VND procedure. This customized VNS algorithm differs from the independent neighborhood structure used in most studies.

3. Problem background

There are many uncertainties influencing urban traffic accident rescue, including the time and location of accident sites, and the number of accident sites in the road network. As shown in Fig. 2, the road network that we consider is arranged as a grid. Often, this layout is preferred in medium-sized cities with flat topography, and in the center of large cities. It is the most common form of urban road network in China. Because uncertainties are unavoidable, traffic incidents may take place anywhere in the grid. The vulnerability characteristics of this grid-like road network are reflected in both spatial and temporal aspects. In spatial terms, most urban traffic

Table 1
Comparison of uncertainty factors and modeling methods.

Reference	Uncertainty factors				Modeling methods
	Accident time	Accident locations	Demand resources (i.e. emergency vehicles)	Travel time	
Ozbay et al., 2013			√		Stochastic programming
Bertsimas and Ng, 2019			√		Robust and stochastic programming
Zhen et al., 2014				√	Simulation optimization
Rodrigo et al., 2021			√		Simulation optimization
Boujemaa et al., 2020			√		Stochastic programming
This study	√	√	√	√	Stochastic programming

accidents occur on arterial roads, followed by intersections. Moreover, in terms of time, most accidents occur during rush hour, which exacerbates already congested traffic. These traffic conditions make the emergency rescue problem intractable. Fig. 2 depicts the location of a rescue station d and an accident-prone section n, which can be considered a potential demand node. Although there are multiple nodes, rescue demand may arise from only a few such nodes in a day. We suppose that there are K vehicles classified into B available types. We assume that the location of each rescue station is already known, and each is seen as a potential option in terms of the location at which the emergency vehicles can be deployed. In the decision-making process, the scale of the rescue station d (denoted by θ_{du}) and the number of vehicles it holds must be considered from an economic perspective to ensure efficiency and minimize cost. Therefore, it is essential to determine which vehicles are to be deployed at which rescue station (denoted by α_{dk}).

When an accident-prone section n becomes an accident site, there is a latest preferred rescue time (denoted by w_n) depending on the urgency of the incident. The emergency management operator must respond to the scale or significance of the accident, that is, to the extent of the negative consequences involved, and assign the required vehicles to ensure a timely rescue response. Each of these vehicles incurs travel costs as a result of traveling from their respective initial locations to the accident location. The fixed and variable costs vary between these types of vehicles and hence the type and number of emergency vehicles deployed will affect the overall cost. If vehicle k is dispatched to attend the accident n but arrives at a time (denoted by η_{nk}) that is later than the latest preferred rescue time w_n, it will incur a large penalty cost as a punishment for being late, which can be calculated as $c_p(\eta_{nk} - w_n)^+$ (where c_p is the penalty cost coefficient).

Based on the analysis above, it is evident that the integrated planning problem that we study comprises two subproblems: the rescue station vehicle deployment problem and the vehicle dispatch problem. Thus, we develop a two-stage stochastic mixed-integer programming model that considers the uncertainties influencing urban traffic accidents. In the first stage, we determine vehicle allocation and the scale of rescue stations for the initial planning components of emergency management. In the second stage, when the uncertain factors are realized (i.e., the location and time of the traffic accidents, the demand for various types of emergency vehicles, and the travel time between rescue stations and accident sites), a decision is made on the dispatch of multiple types of emergency vehicles from multiple stations to respond to multiple traffic accident sites within various time windows. These uncertain parameters can be formulated using limited scenarios in stochastic optimization (Zhen and Wang, 2015; Zhuang et al., 2023). Every scenario is composed of a series of outputs for the location of the traffic accident site, the associated demand for emergency response, and the occurrence time. Then, the variables are transformed into scenario-based decision variables.

Fig. 3 illustrates the process of assigning multiple types of vehicles from multiple rescue stations in response to multiple accidents. Each vehicle k has a type of attribute b, which indicates that it can serve all the accidents that have a demand for a type b vehicle in the grid. The same vehicle can (and is likely to be required to) attend to different accidents because the number of emergency vehicles in an area is limited. We assume that vehicle k needs to return to the station from which it was deployed after serving at the accident site n, and it can then accept its next assignment to serve at the accident site n'. This assumption is reasonable in most traffic accident rescue situations because there are generally large time intervals between accidents, which means that emergency vehicles rarely serve at consecutive accidents without returning to their stations between each accident (Pal and Bose, 2009).

4. Model formulation

This section formulates a two-stage stochastic programming model for an integrated optimization problem on deploying multiple types of emergency vehicles in response to traffic accidents in the context of uncertainty.

4.1. Notations

The notations used to formulate the model are introduced below:

Indices and sets

d Index of rescue station.

Fig. 2. Distribution of rescue stations and potential demand nodes in the road network.

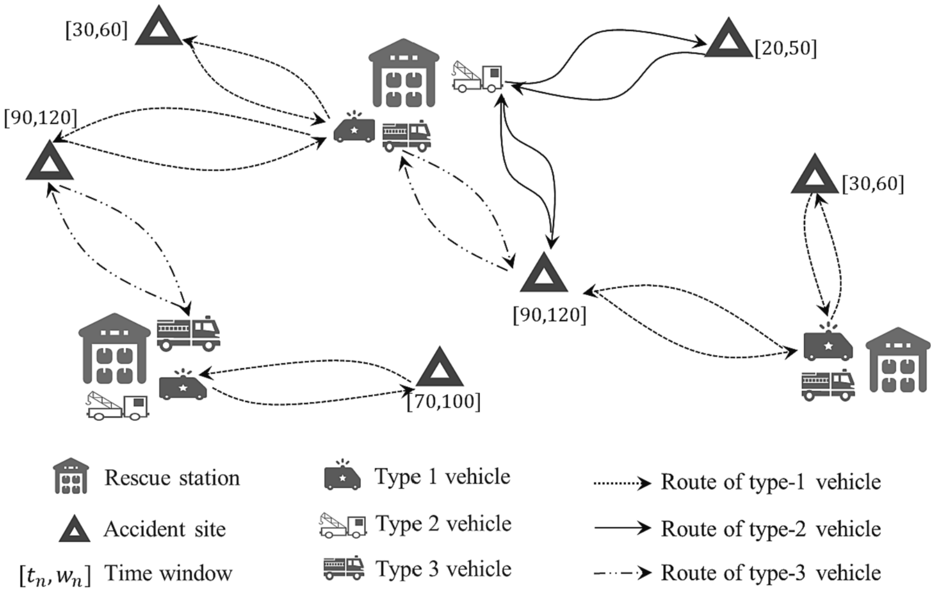

Fig. 3. An instance of emergency vehicles dispatching in the urban road network.

D Set of all rescue stations.
b Index of the type of vehicles.
B Set of all types of vehicles.
k Index of vehicle.
K Set of all vehicles.
K_b A subset of the vehicle set K, $K_b \subseteq K, \cup_{b \in B} K_b = K$.
n Index of the traffic accident site.
N Set of all traffic accident sites.
u Index of the scale of the rescue station.
U Set of all available scales of the rescue station.
ω Index of scenario.
Ω Set of all scenarios.
i, j Index of the nodes in the traffic network, including all the rescue stations and traffic accident sites.
Parameters
$e'(r)$ Rescue station, the end node for the rescue route.
e_u Maximum capacity of a rescue station with scale u.
l_{bk} Set to 1 if the vehicle k is of type b, 0 otherwise.
g_b The total demand for the vehicles of type b.
a_k The acquisition cost of vehicle k.
c_{du} The fixed cost when building a rescue station d at scale u.
f Total budget for the construction of the rescue stations.
π^ω The probability of occurrence of scenario ω.
c_k The fixed cost when vehicle k service at least one traffic accident site.
c_p The penalty cost for waiting beyond the latest time at the incident point.
p_n^ω The processing time of traffic accident site n in scenario ω.
x_{nb}^ω The demand for type b vehicles at traffic accident site n in scenario ω.
t_n^ω The time when the traffic accident site n occurs in scenario ω.
w_n^ω The latest preferred rescue time for traffic accident site n in scenario ω.
h_{ij}^ω The travel time from node i to node j in scenario ω.
c_{ij}^ω The travel cost from node i to node j in scenario ω.
M a sufficiently large positive number.

4.2. Decision variables

θ_{du} Binary variable, set to 1 if the rescue station d is constructed with the scale of u, 0 otherwise.
α_{dk} Binary variable, set to 1 if the vehicle k is attributed to the rescue station d, 0 otherwise.

φ_{nk}^{ω} Binary variable, set to 1 if the traffic accident site n is serviced by vehicle k in scenario ω, 0 otherwise.

β_{dnk}^{ω} Binary variable, set to 1 if the vehicle k is attributed to the rescue station d and services the traffic accident site n in the scenario ω, 0 otherwise.

σ_{k}^{ω} Binary variable, set to 1 if vehicle k serves at least one traffic accident site in the scenario ω, 0 otherwise.

$\varepsilon_{nn'k}^{\omega}$ Binary variable, set to 1 if vehicle k serves traffic accident site n' after traffic accident site n in the scenario ω, 0 otherwise.

ρ_{nk}^{ω} Float variable, the response time of vehicle k dispatched to service accident site n in the scenario ω.

η_{nk}^{ω} Float variable, the time when vehicle k arrives at the location of the traffic accident site n in the scenario ω.

4.3. Mathematical model

Based on the description above, the model of this research problem is formulated as follows:

$$Min\sum_{d\in D}\sum_{u\in U}c_{du}\theta_{du}+\sum_{k\in K}\sum_{d\in D}a_k\alpha_{dk}+E(Q(\alpha_{dk},\theta_{du},\omega)) \tag{1}$$

s.t.

$$\sum_{u\in U}\theta_{du}=1 \quad \forall d\in D \tag{2}$$

$$\sum_{d\in D}\sum_{u\in U}c_{du}\theta_{du}\leq f \tag{3}$$

$$\sum_{d\in D}\alpha_{dk}\leq 1 \quad \forall k\in K \tag{4}$$

$$\sum_{k\in K}\alpha_{dk}\leq\sum_{u\in U}e_u\theta_{du} \quad \forall d\in D \tag{5}$$

$$\sum_{k\in K}\sum_{d\in D}l_{b,k}\alpha_{dk}\geq g_b \quad \forall b\in B \tag{6}$$

$$\theta_{du},\alpha_{dk}\in\{0,1\} \quad \forall d\in D,\quad \forall k\in K,\quad \forall u\in U \tag{7}$$

The objective function (1) is to pursue a total cost minimization of traffic emergency rescue, which includes the construction cost of rescue stations and the acquisition cost of all vehicles. Also, this objective function contains the expected cost in a series of random scenarios of the second stage: $E(Q(\alpha_{dk},\theta_{du},\omega))=\sum_{\omega\in\Omega}\pi^{\omega}\bullet Q(\alpha_{dk},\theta_{du},\omega)$, where π^{ω} denotes the probability of scenario ω. And the second-stage cost $Q(\alpha_{dk},\theta_{du},\omega)$ that is a function of first-stage variables α_{dk} and θ_{du}. Constraints (2) determine the scale of each rescue station. Constraints (3) guarantee the fixed cost of building rescue stations must not exceed the initial budget at the first stage. Constraints (4) ensure that each vehicle can be attributed to at most one rescue station. Constraints (5) specify the maximum number of vehicles that the rescue station can be configured with for a specific scale. Constraints (6) guarantee the minimum demand of each type of emergency vehicle should be met. Constraints (7) define the first-stage variable domains.

The second-stage model is shown as follows:

$$MinE(Q(\alpha_{dk},\theta_{du},\omega))=\sum_{\omega\in\Omega}\pi^{\omega}\bullet\left(\sum_{k\in K}c_k\sigma_k^{\omega}+\sum_{d\in D}\sum_{n\in N}\sum_{k\in K}c_{dn}^{\omega}\beta_{dnk}^{\omega}+c_p\sum_{k\in K}\sum\nolimits_{n\in N}\left(\eta_{nk}^{\omega}-w_n^{\omega}\right)^{+}\right) \tag{8}$$

s.t.

$$\sum_{k\in K_b}\varphi_{nk}^{\omega}=x_{nb}^{\omega} \quad \forall n\in N,\quad \forall b\in B,\quad \forall\omega\in\Omega \tag{9}$$

$$\sum_{n\in N}\varphi_{nk}^{\omega}\leq M\sum_{d\in D}\alpha_{dk} \quad \forall k\in K,\quad \forall\omega\in\Omega \tag{10}$$

$$\sigma_k^{\omega}\leq\sum\nolimits_{n\in N}\varphi_{nk}^{\omega} \quad \forall k\in K,\quad \forall\omega\in\Omega \tag{11}$$

$$\sum\nolimits_{n\in N}\varphi_{nk}^{\omega}\leq M\sigma_k^{\omega} \quad \forall k\in K,\quad \forall\omega\in\Omega \tag{12}$$

$$\beta_{dnk}^{\omega}=\left(\varphi_{nk}^{\omega}+\alpha_{dk}-1\right)^{+} \quad \forall d\in D,\quad \forall n\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{13}$$

$$\sum_{n\in N}\varepsilon_{dnk}^{\omega}=\left(\alpha_{dk}+\sigma_k^{\omega}-1\right)^{+} \quad \forall d\in D,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{14}$$

$$\sum_{n\in N}\varepsilon^{\omega}_{ne'(r)k}=\sigma^{\omega}_{k}\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{15}$$

$$\sum_{i\in D\cup N}\varepsilon^{\omega}_{ink}=\sum_{i\in N\cup\{e'(r)\}}\varepsilon^{\omega}_{nik}=\varphi^{\omega}_{nk}\quad \forall n\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{16}$$

$$\rho^{\omega}_{nk}\geq t^{\omega}_{n}-M(1-\varphi^{\omega}_{nk})\quad \forall n\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{17}$$

$$\rho^{\omega}_{nk}+\sum_{d\in D}h^{\omega}_{dn}\beta^{\omega}_{dnk}\leq\eta^{\omega}_{nk}\quad \forall n\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{18}$$

$$\rho^{\omega}_{n'k}\geq\eta^{\omega}_{nk}+t^{\omega}_{n}+\sum_{d\in D}h^{\omega}_{nd}\beta^{\omega}_{dnk}-M(1-\varepsilon^{\omega}_{nn'k})\quad \forall n,n'\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{19}$$

$$\varphi^{\omega}_{nk},\sigma^{\omega}_{k},\varepsilon^{\omega}_{ijk},\beta^{\omega}_{dnk}\in\{0,1\}\quad \forall i,j\in D\cup N\cup\{e'(r)\},\quad \forall n\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{20}$$

$$\rho^{\omega}_{nk},\eta^{\omega}_{nk}\geq 0\quad \forall n\in N,\quad \forall k\in K,\quad \forall\omega\in\Omega \tag{21}$$

The objective function (8) of the second stage minimizes the expected value of all the scenarios' total costs, including the fixed cost of the used vehicles, the driving costs of the traveling, and the penalty costs if vehicles arrived beyond the accident sites' preferred time w^{ω}_{n}. Constraints (9) ensure that the demand for different types of emergency vehicles at each traffic accident site n needs to be met. Constraints (10) link first- and second-stage decision variables α_{dk} and φ^{ω}_{nk}, it illustrates that a vehicle k can serve the traffic accident site n only when it is attributed to a specific rescue station d. Constraints (11) and (12) link two decision variables σ^{ω}_{k} and φ^{ω}_{nk}, indicate that vehicle k enters to work state when it is allocated to serve at least one traffic accident site. Constraints (13) represent the relationship of three variables β^{ω}_{dnk}, φ^{ω}_{nk} and α_{dk}, which represents the correspondence between vehicles, rescue stations, and traffic accident sites. Constraints (14)−(16) guarantee that the paths of all emergency vehicles are continuous. Constraints (17) define that the response time of vehicle k dispatched to serve accident site n (denoted by ρ^{ω}_{nk}) is no earlier than the accident time t^{ω}_{n}. Constraints (18) and (19) indicate the relationship of the rescue time for adjacent accident sites served by the same vehicle. Constraints (20) and (21) define the second-stage variable domains.

5. Solution methodology

The proposed scenario-based two-stage stochastic programming model in this study is difficult to solve since the traffic accident occurrence and demand for emergency response in real life are constantly changing, leading to a huge number of scenarios that make the problem computationally intractable. We will first discuss SAA in this section, which is used to approximation the original problem with samples. The SAA can be solved by commercial solvers (i.e., CPLEX). However, the commercial solvers cannot obtain an exact optimal solution in large-scale test instances within an acceptable time. Therefore, a VNS method based on the characteristics of the proposed model is suggested to quicken the computation. The VNS algorithm has been widely used to address combinatorial optimization problems (Lamb, 2012) and vehicle routing problems (Sadati and Catay, 2021). It obtains the global near-optimal solution by alternately searching a sequence of different neighborhoods. Compared with other intelligent algorithms, such as Particle Swarm Optimization, one distinguishing feature of this approach is that the local search strategy enables it to avoid missing the potentially optimal solution. Moreover, to take into account the fact that the two stages of the model's decision process are interactive, the improved VNS heuristic algorithm with nested neighborhood structures can fit this characteristic. In this section, we present the framework and components of the VNS algorithm.

5.1. Sample average approximation

The SAA method is a stochastic optimization problem-solving technique based on Monte Carlo simulation. The fundamental idea behind this method is to use empirical distributions derived from sample data to approximate the true distribution (Wang et al., 2023). The sample is redefined by Ω', which is a finite set of scenarios sampled from Ω with the same probability of occurrence, i.e., $\Omega'\in\Omega$, $|\Omega'|$ is the sample size, and each scenario has the same probability $1/|\Omega'|$. The SAA is formulated as follows:

$$Min\sum_{d\in D}\sum_{u\in U}c_{du}\theta_{du}+\sum_{k\in K}\sum\nolimits_{d\in D}a_{k}\alpha_{dk}+\sum_{\omega\in\Omega'}\frac{1}{|\Omega'|}\left(\sum_{k\in K}c_{k}\sigma^{\omega}_{k}+\sum_{d\in D}\sum_{n\in N}\sum_{k\in K}c^{\omega}_{dn}\beta^{\omega}_{dnk}+c_{p}\sum_{k\in K}\sum\nolimits_{n\in N}\left(\eta^{\omega}_{nk}-w^{\omega}_{n}\right)^{+}\right) \tag{22}$$

subject to (2)−(7), (9)−(21) in which Ω is replaced by Ω'.

Determining the number of scenarios in Ω' is a necessary step in the SAA problem-solving process. The model will become computationally intractable as sample size is increased while the quality of the solutions will improve. Striking a balance between accuracy and computational tractability is necessary. Algorithm 1 outlines the steps to evaluate the SAA's solution quality under given the sample size, including the computation of confidence intervals (CIs) for the lower bound, upper bound, and optimality gap.

Algorithm 1: Estimate $(1-\tau)$-CI for lower bound, upper bound, and optimality gap

Generate a set of scenarios $\Omega^{'}$.
Solve the SAA with $\Omega^{'}$ and obtain the optimal first-stage solution θ_{du}^{*} and α_{dk}^{*}.
For $m = 1, 2, \cdots, M$ **do**
  Generate a set of new independent scenarios Ω_m, $|\Omega_m| = |\Omega^{'}|$.
  Solve the SAA with Ω^m and obtain the objective value obj_m.
  Generate a set of new independent scenarios $\Omega_m^{'}$, $|\Omega_m^{'}| \gg |\Omega_m|$.
  Evaluate the quality of the first-stage solution θ_{du}^{*} and α_{dk}^{*} on scenarios in $\Omega_m^{'}$. Input θ_{du}^{*} and α_{dk}^{*} into SAA and obtain objective value $obj^m_{\theta_{du}^{*},\alpha_{dk}^{*}}$.
Let $gap_m = obj^m_{\theta_{du}^{*},\alpha_{dk}^{*}} - obj_m$
End for
Estimate $(1-\tau)$-CI for lower bound
Let $L = \frac{1}{M}\sum_{m=1}^{M} obj_m$ and $\Omega_L = \frac{1}{M-1}\sum_{m=1}^{M}(obj_m - L)^2$.
The $(1-\tau)$-CI for lower bound is $\left[L - \frac{t_{M-1,\frac{\tau}{2}}\sqrt{\Omega_L}}{\sqrt{M}}, L + \frac{t_{M-1,\frac{\tau}{2}}\sqrt{\Omega_L}}{\sqrt{M}}\right]$. //$t_{M-1,\frac{\tau}{2}}$ denotes the t-value obtained from t-distribution with degrees of freedom $M-1$ and confidence level $1-\tau$.
Estimate $(1-\tau)$-CI for upper bound
Let $U = \frac{1}{M}\sum_{m=1}^{M} obj^m_{\theta_{du}^{*},\alpha_{dk}^{*}}$ and $\Omega_U = \frac{1}{M-1}\sum_{m=1}^{M}(obj^m_{\theta_{du}^{*},\alpha_{dk}^{*}} - U)^2$.
The $(1-\tau)$-CI for upper bound is $\left[U - \frac{t_{M-1,\frac{\tau}{2}}\sqrt{\Omega_U}}{\sqrt{M}}, U + \frac{t_{M-1,\frac{\tau}{2}}\sqrt{\Omega_U}}{\sqrt{M}}\right]$.
Estimate $(1-\tau)$-CI for optimality gap
Let $G = \frac{1}{M}\sum_{m=1}^{M} gap_m$ and $\Omega_G = \frac{1}{M-1}\sum_{m=1}^{M}(gap_m - G)^2$.
The $(1-\tau)$-CI for optimality gap is $\left[0, G + \frac{t_{M-1,\tau}\sqrt{\Omega_G}}{\sqrt{M}}\right]$.

5.2. Algorithm framework

The VNS procedure is as follows. First, a feasible initial solution is generated. Second, to obtain and store an improved solution, the VNS requires an efficient local search procedure, variable neighborhood descent (VND), which is based on the neighborhood structures. The neighborhood structures are designed to produce a neighborhood solution space by functioning on the key two decision variables α_{dk} and $\varepsilon_{nn'k}^{\omega}$. Third, a shaking procedure is executed to change this improved solution within feasible limits and then use it as the basis for the following iteration. In this way, the algorithm can escape from local optimal solutions that occur throughout the solution space. The algorithm procedure stops when either of the following two conditions is satisfied: (1) the iteration count reaches the maximum iteration; or (2) the count of solutions without improvements reaches the maximum number. For a better understanding of the framework, the algorithm's pseudo-code description is given in Algorithm 2.

Algorithm 2: Variable Neighborhood Search

```
Generate the initial_solution, Global_solution; GloSol ← initial_solution
count ← 0, iteration ← 0;
While (iteration < Iter_max) // Iter_max denotes the maximum number of iterations
   CurSol ← GloSol; // CurSol denotes the current solution and GloSol denotes the best solution.
   shaking (CurSol);
   VND procedure (CurSol); // VND procedure is described in Section 5.5.
   If (CurSol.fitness < GloSol.fitness)
      GloSol ← CurSol;
      count ← 0;
   Else
      count ← count + 1;
   If (count = count_max) // count_max denotes the maximum number of iterations during which the best solution has not been improved.
      break;
   End if
   iteration ← iteration + 1;
End while
```

5.3. Initial solution

To generate the initial solution, we construct a greedy decision rule based on the personal experience of the decision-maker. The emergency vehicles are evenly allocated to each candidate rescue station in advance. Every traffic accident site is assigned to the nearest available emergency vehicle to reduce the travel time. For multiple accident sites served by one vehicle, the rescue order is

α_{dk_1}	α_{01}	α_{11}	α_{21}	α_{31}
Value	0	1	0	0

Mutate

α_{dk_1}	α_{01}	α_{11}	α_{21}	α_{31}
Value	0	0	0	1

Fig. 4. Example of mutation neighborhood structure.

developed according to the chronology of accidents. This initial solution based on this decision rule can act as a comparative benchmark to reflect the performance of VNS in subsequent numerical experiments.

5.4. Neighborhood structures

In each iteration, the algorithm approximates the global optimal solution by jumping into several neighborhood structures under a regular pattern. To explore the solution space, we define three kinds of neighborhood movements, namely mutation, swap, and insertion. These movements act on two decision variables and generate five neighborhood structures. The mutation strategy involves performing a variation operation on α_{dk}, such that each vehicle can traverse between all possible allocated rescue stations. The swap operator contains three variants that swap the allocations of two vehicles, swap two accident sites served by two vehicles, or swap the whole rescue assignments of two vehicles of the same type. The insertion mechanism is performed by selecting an accident site served by one vehicle and then inserting it into the assignment of another vehicle of the same type. The illustrations of the above neighborhood structures are shown in Figs. 4–7.

5.5. Variable neighborhood descent

In this section, we describe an improved subframe of our methodology that allows for a comprehensive search of multiple neighborhood structures. In the traditional search process, if an improved current solution is obtained, the operator returns to the first neighborhood structure and immediately conducts a new search. When the complete neighborhood solution space has been searched and no superior solution is found, the search operator proceeds to the next neighborhood structure. As previously mentioned, a key feature of the model formulated in this paper is that the first-stage variable can influence the second-stage decision variables, and

α_{d_1k}	α_{10}	α_{11}	α_{12}	α_{13}
Value	0	1	0	1

Swap

α_{d_2k}	α_{20}	α_{21}	α_{22}	α_{23}
Value	1	0	1	0

α_{d_1k}	α_{10}	α_{11}	α_{12}	α_{13}
Value	0	0	1	1

α_{d_2k}	α_{20}	α_{21}	α_{22}	α_{23}
Value	1	1	0	0

Fig. 5. Example of swap neighborhood structure of α_{dk}.

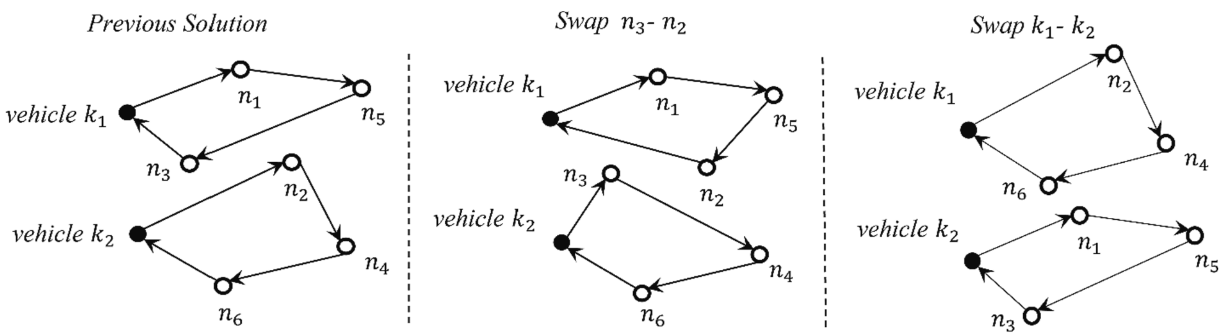

Fig. 6. Two examples of swap neighborhood structures of $\varepsilon^{\omega}_{nn'k}$.

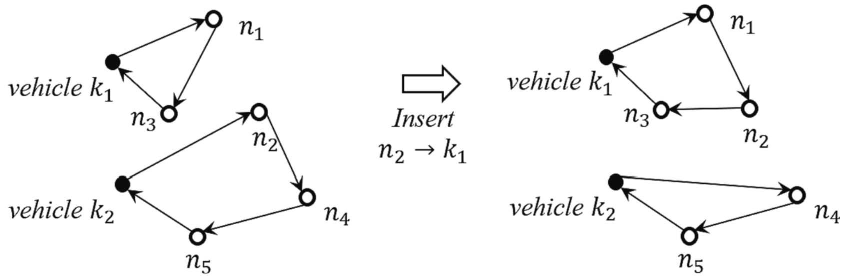

Fig. 7. Example of insertion neighborhood structure of $\varepsilon^{\omega}_{nn'k}$.

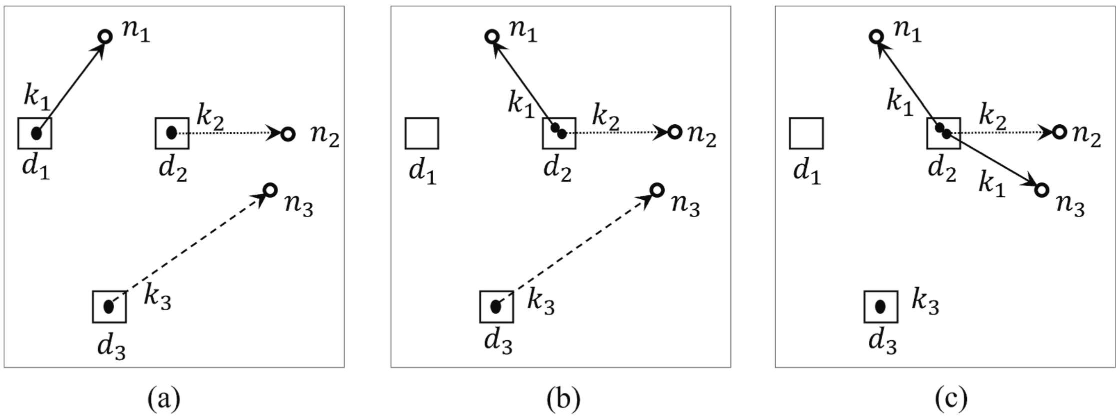

Fig. 8. Example of how the improved neighborhood solution is obtain.

further determine the value of the objective function. In the neighborhood structure of α_{dk}, a certain neighborhood solution may be abandoned because it does not reduce the object value to do so. However, if this unimproved solution is used as the current solution for the next neighborhood of $\varepsilon^{\omega}_{nn'k}$, it is possible to obtain an improved solution instead. Fig. 8 presents an example to clarify how to obtain the improved neighborhood solution. We assume that the occurrence of accident times follows the relationship $t_1 \ll t_2 < t_3$,

Which means that the accidents occur in sequence: n_1, n_2 and n_3, and there is a narrow time interval between t_2 and t_3. In Fig. 8(a), the location of the accident site n_1 is equidistant from the two rescue stations d_1 and d_2, the emergency vehicle k_1 is allocated in d_1, and n_1 is assigned to k_1. Now, we change the variable α_{dk} and reallocate k_1 to d_2, as shown in Fig. 8(b). As this variation does not reduce the total cost of rescue, the current solution will not be retained following the traditional VND process. However, We can find from Fig. 8 (b) that the available vehicle k_1 is closer to n_3 than is k_3 (k_1 has enough time to finish its rescue mission at n_1 and return to d_2, before proceeding to n_3 and arriving there before $k_3$can arrive). If we keep the current solution (reallocate k_1 to d_2) and reassign n_3 to k_1, we can obtain an improved solution that can reduce the travel time.

The crucial point of the above analysis is that to avoid missing the potential improved solution during the local search, three neighborhood structures for $\varepsilon^{\omega}_{nn'k}$ are embedded in the mutation neighborhood structure for α_{dk}. As shown in Fig. 9, the improved VND

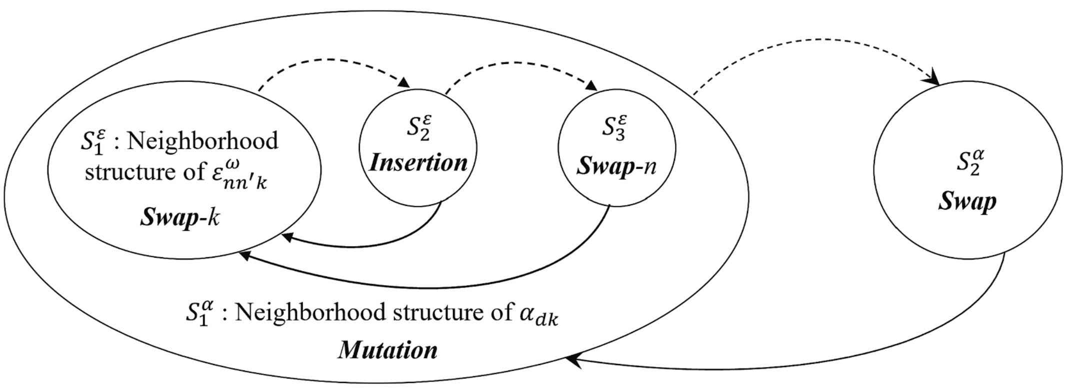

Fig. 9. The improved variable neighborhood descent procedure.

procedure begins with the mutation neighborhood structure of α_{dk}. Once the variable α_{dk} changes, whether the objective value is optimized or not, it should implement the neighborhood structure of $\varepsilon^{\omega}_{nn'k}$ and complete neighborhood search of $\varepsilon^{\omega}_{nn'k}$, including swap-k, insertion and swap-n neighborhood structures. Then the swap neighborhood structure of α_{dk} is implemented. Once a better solution can be found in the current neighborhood structure, the procedure goes back to the first neighborhood and continues searching. The pseudo-code description of improved VND procedure is given in Algorithm 3.

Algorithm 3: Variable Neighborhood Descent

Generate the initial solution, Global_solution *GloSol* ← initial solution;
S^{α}_{l} ← set of VNS neighborhood structures for α_{dk}, $l = 1, 2, \cdots, l_{max}$;
S^{ε}_{m} ← set of VNS neighborhood structures for $\varepsilon^{\omega}_{nn'k}$, $m = 1, 2, \cdots, m_{max}$;
current_solution *CurSol* ← initial solution;
$l \leftarrow 1$;
While (true)
  Switch (l)
    case 1:
      S^{α}_{1} for α_{dk} (*CurSol*);
      If (*CurSol*.fitness < *GloSol*.fitness)
        GloSol ← *CurSol*;
      $m \leftarrow 1$;
      While (true)
        Switch (m)
          case 1:
            S^{ε}_{1} for $\varepsilon^{\omega}_{nn'k}$ (*CurSol*)
            If (*CurSol*.fitness < *GloSol*.fitness)
              GloSol ← *CurSol*;
              $m \leftarrow 0$;
            break;
          case 2:
            S^{ε}_{2} for $\varepsilon^{\omega}_{nn'k}$ (*CurSol*)
            If (*CurSol*.fitness < *GloSol*.fitness)
              GloSol ← *CurSol*;
              $m \leftarrow 0$;
            break;
          case 3:
            S^{ε}_{3} for $\varepsilon^{\omega}_{nn'k}$ (*CurSol*)
            If (*CurSol*.fitness < *GloSol*.fitness)
              GloSol ← *CurSol*;
              $m \leftarrow 0$;
            break;
        default;
            return;
        $m \leftarrow m+1$;
        End while
        If (*CurSol*.fitness < *GloSol*.fitness)
          GloSol ← *CurSol*;
          $l \leftarrow 0$;
        break;
          case 2:
          S^{α}_{2} for α_{dk} (*CurSol*)
          If (*CurSol*.fitness < *GloSol*.fitness)
            GloSol ← *CurSol*;
            $l \leftarrow 0$;
          break;
      default;
        return;
    $l \leftarrow l+1$
  End while

6. Scenario generation

The generation of scenarios is a crucial issue for scenario-based stochastic programming methodology. This study proposes a model to minimize Kantorovich distance for scenario generation, which reformulated the scenario generating problem as a p-median issue (Reese, 2006). Every scenario is seen as a demand point, and the selected scenario is seen as a facility.

More specifically, given an initial set Π of scenarios originating from historical data, which has finitely many individual scenarios, indexed by $\omega = 1, \cdots, |\Pi|$. Let $\mathbb{p} = \mathscr{P}_1, \cdots, \mathscr{P}_{|\Pi|}$ be a probability vector over Π. The realization of each scenario corresponds to an actual traffic accident situation in a single day, that is, to values of p^{ω}_{n}, t^{ω}_{n}, w^{ω}_{n}, x^{ω}_{nb} and d^{ω}_{ij} in our setting. d^{ω}_{ij} denotes the travel time from node i to node j in scenario ω, which directly affects the travel time (i.e., h^{ω}_{ij}) and the travel cost (i.e., c^{ω}_{ij}). Similarly, we assume that each scenario has the same probability $1/|\Pi|$. The proposed scenario generation procedure in our study is to select a subset $\Pi' \subseteq \Pi$ such that

$|\Pi'| \leq |\Pi|$. Each of the $|\Pi|$ initial scenarios is mapped into one of the $|\Pi'|$ selected scenarios. Let $\mathbb{p}' = \mathscr{P}_1', \cdots, \mathscr{P}_{|\Pi'|}'$ be a probability vector over Π'.

The symmetric distance between two scenarios ω and ω' is calculated as follows:

$$\Delta(\omega', \omega) = \sum_{n\in N}\left(\left|p_n^{\omega'} - p_n^{\omega}\right| + \left|t_n^{\omega'} - t_n^{\omega}\right| + \left|w_n^{\omega'} - w_n^{\omega}\right|\right) + \sum\nolimits_{n\in N}\sum_{b\in B}\left|x_{nb}^{\omega'} - x_{nb}^{\omega}\right| + \sum_{i\in D\cup N}\sum_{j\in D\cup N\cup\{e'(r)\}}\left|d_{ij}^{\omega'} - d_{ij}^{\omega}\right| \quad \forall\omega', \omega \in \Pi \tag{23}$$

The Kantorovich distance between the probability vector $\mathbb{p}$ and $\mathbb{p}'$ is defined as the weighted distance over all scenarios in Π to their closest one within the selected set Π' and calculated as follows:

$$D(\mathbb{p}', \mathbb{p}) = \sum_{\omega'\in\Pi}\mathscr{P}_{\omega'} min_{\forall\omega\in\Pi'}\Delta(\omega', \omega) \tag{24}$$

Then we can calculate the weighted distance between two scenarios ω and ω', denoted by $d(\omega', \omega) = \mathscr{P}_{\omega'}\Delta(\omega', \omega)$. The scenario generation model can be formulated as follows:

parameter.

$d(\omega', \omega)$ weighted distance between scenario ω and ω' in the initial set Π.

Decision variables.

$\phi(\omega', \omega)$ Binary variable, set to 1 if scenario ω' is mapped to ω, 0 otherwise;

$\zeta(\omega)$ Binary variable, set to 1 if scenario ω is included in the subset Π', 0 otherwise.

$$Min\sum_{\omega'\in\Pi}\sum_{\omega\in\Pi}d(\omega', \omega)\phi(\omega', \omega) \tag{25}$$

s.t.

$$\sum_{\omega\in\Pi}\zeta(\omega) \leq |\Pi'| \tag{26}$$

$$\sum_{\omega\in\Pi'}\phi(\omega', \omega) = 1 \quad \forall\omega' \in \Pi \tag{27}$$

$$\phi(\omega', \omega) \leq \zeta(\omega) \quad \forall\omega', \omega \in \Pi \tag{28}$$

$$\phi(\omega', \omega) \in \{0, 1\} \quad \forall\omega', \omega \in \Pi \tag{29}$$

$$\zeta(\omega) \in \{0, 1\} \quad \forall\omega \in \Pi \tag{30}$$

Objective (25) is to minimize the Kantorovich distance. Constraints (26) ensure that at most $|\widetilde{\Omega}|$ scenarios can be selected in Π. Constraints (27) ensure that each scenario ω' is mapped to exactly one scenario in Π'. Constraints (28) guarantee that scenario ω must be selected if there exists a scenario ω' that is mapped to scenario ω. Constraints (29) and (30) define the variable domains.

7. Numerical experiments

To evaluate the effectiveness of the suggested approach, we conduct numerical experiments on a computer running an Intel Xeon E5-2643 v4 3.4 GHz 64-bit CPU with 256 GB of RAM and a six-core processor, and a Windows 10 operating system. The algorithm is coded in C# programming language with Visual Studio 2019.

7.1. Generation of test instances

We use the road network of Jiading District, Shanghai, as a case study. A 2018 report released by the Shanghai Municipal People's Government shows that more than half of the traffic accident-prone sections in Shanghai are located in Jiading District. In particular, the historical data indicate that most accident-prone locations in Jiading District are near the intersections of arterial and other roads. In Fig. 10, we depict the locations of 16 accident-prone sections. There are three rescue stations in the district, the locations of which are known, enabling us to calculate the distance from the rescue stations to the accident-prone sites. We set the average speed of emergency vehicles in the urban road network at 40 km per hour. According to the 24-hour distribution of road accidents in Shanghai published by the Shanghai Insurance Regulatory Bureau, the period from 7:00 to 19:00 is the time when traffic accidents are prone to happen. Hence we treat per 12 h as a separate scenario. We assume that *N* traffic accidents will occur on the road network in a day, and all accidents are distributed randomly over 12 h. In the experiment, to demonstrate the validity of the model, we randomly select *N* accident sites from the 16 accident-prone sections.

To determine the range of values of N, we need to estimate the daily quantity of traffic accidents in Jiading District. As shown in Fig. 11, we use the China Statistical Yearbooks to collate data on the number of traffic accidents in Shanghai from 2010 to 2019. The data indicate that the average number of traffic accidents per day in Shanghai during this period is in the interval $(2,8)$. Because our focus is Jiading District rather than all of Shanghai, we adjust the range for N in line with the proportion of accident-prone locations in Jiading District. Therefore, in the numerical experiments, we use values of N in the interval $[4,6]$. We generate a set of scenarios, each of which reflects a specific traffic accident situation and contains deterministic information about the location and time of the traffic accident, the demand for various types of emergency vehicles, and the travel time between rescue stations and accident sites. Table 2 shows the parameters setting for experiments.

7.2. Determination of sample size

Taking four accident sites as an example, the sample size for the following numerical experiments will be decided in this section. We start by explaining the generation of a sample. Then, we introduce the processes and results of solution quality evaluation. The sample size can thus be determined.

7.2.1. Sample generation

A sample consists of a predetermined number of scenarios. A scenario is an actual traffic accident situation for 12 h in a single day, which contains deterministic information about the location and time of the traffic accident, the demand for various types of emergency vehicles, and the travel time between rescue stations and accident sites. The sample size refers to the specific number of scenarios. We randomly generated a set of 300 scenario data based on the parameter setting in Table 2. All traffic accident data corresponding to a number between 1 and 300 randomly generated is extracted as a single scenario. This procedure is repeated for the remaining data set until the sample size is reached for the number of scenarios.

7.2.2. Solution quality evaluation

The performance of different sample sizes, which are set to 1, 5, 10, 15, 20, 25, and 30, is evaluated by Algorithm 1. We first use line 1 and 2 of Algorithm 1 to obtain the optimal first-stage solution Then, we iterate line 4 to 8 for 10 times with $|\Omega_m^{'}|$ set to 300. The solution quality is calculated as shown in Table 4. We can find from Table 4 that the error rate is below 1 % (valued at 0.77 %) with a high probability when the sample size is 25. To strike the balance between solution quality and computational tractability, the sample size is set to 25 in the following calculation.

Notes: (1) PE, CI: the point estimate and 95 % confidence interval;

(2) CI-L: the ratio between 95 % confidence interval for optimality gap and point estimate of lower bound;

(3) CI-U: the ratio between 95 % confidence interval for optimality gap and point estimate of upper bound;

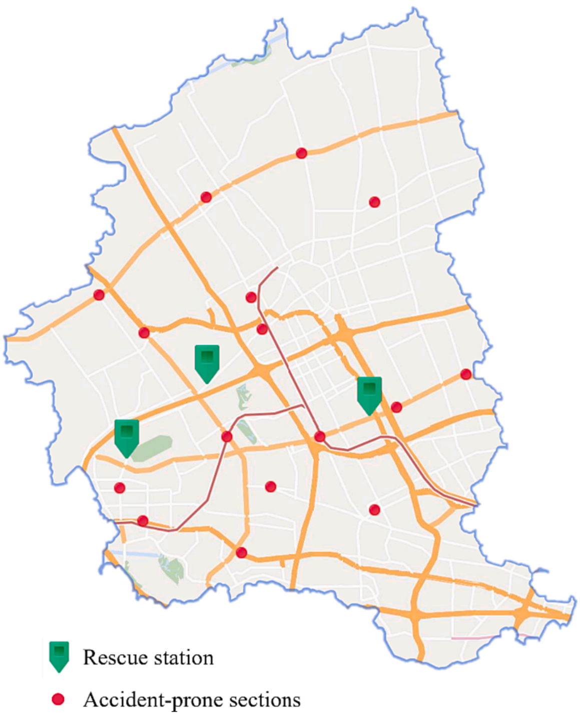

Fig. 10. The road network of Jiading District, Shanghai.

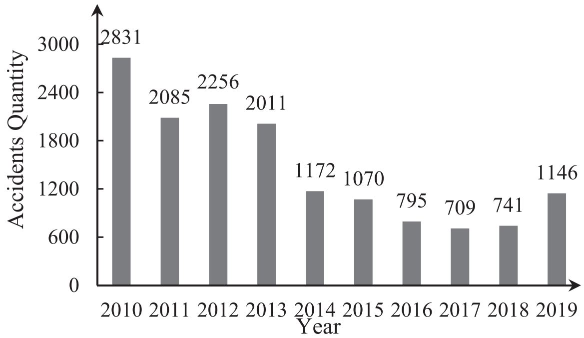

Fig. 11. Traffic accidents quantity in Shanghai from 2010 to 2019.

Table 2
Parameters setting for the experiments.

Parameter	Value	Parameter	Value	Parameter	Value
e_u	$2\times u, u \in [0, 20]$	f	500	p_n^ω	[5, 30] minutes
g_b	2	π^ω	$1/\lvert\Omega\rvert$	x_{nb}^ω	[0, 2]
a_k	25, 26, 27	c_k	1, 2, 3	t_n^ω	[0, 720] minutes
c_{du}	$[30, 50] + 2\times u, u \in [0, 20]$	c_p	3	w_n^ω	t_n^ω + [20, 40] minutes

The number of accident sites and the chosen scenarios influence the performance of our approach. Hence, for the experiments, we use nine instance groups (ISGs) of three different scales. Table 3 shows the key parameters for the nine instance groups. ISG1 to ISG3 are small-scale cases, ISG4 to ISG6 are medium-scale cases, and ISG7 to ISG9 are large-scale cases. We randomly generate five distinct examples of scenarios and settings to avoid unintended results.

Table 3
The scale of instance groups in experiments.

Group ID	No. of the vehicle types (B)	No. of total available vehicles (K)	No. of rescue stations (D)	No. of accident sites (N)	No. of scenarios (Ω)	No. of decision variables	No. of constraints
ISG1	3	6	3	4	10	2538	3016
ISG2	3	6	3	4	20	4998	6016
ISG3	3	6	3	4	50	12,378	15,016
ISG4	3	6	3	5	80	26,958	31,456
ISG5	3	6	3	5	100	33,678	39,316
ISG6	3	6	3	5	120	40,398	47,176
ISG7	3	6	3	6	150	65,778	74,716
ISG8	3	6	3	6	200	87,678	99,616
ISG9	3	6	3	6	250	109,578	124,516

(4) Time: the computation time (seconds).

7.3. Performance of the proposed method

To evaluate the performance of our proposed VNS algorithm, we compare the solutions derived by the VNS approach with the exact optimization solution for small-scale ISGs using SAA method solved by optimization software package CPLEX. To address the fact that

Table 4
Solution quality comparison of different sample sizes (95% CIs).

	Lower bound		Upper bound		Optimality gap				
NS	PE	CI	PE	CI	PE	CI	CI-L	CI-U	Time
1	309.75	(302.25, 317.25)	328.33	(326.78, 329.87)	18.58	(0, 24.64)	7.95 %	7.50 %	349.90
5	315.77	(313.65, 317.88)	326.08	(315.13, 337.03)	10.31	(0, 13.42)	4.25 %	4.12 %	371.25
10	318.71	(314.72, 322,70)	323.36	(319.19, 327.53)	4.66	(0, 7.08)	2.22 %	2.19 %	486.71
15	320.05	(313.63, 326.47)	324.22	(318.68, 329.77)	4.17	(0, 5.71)	1.78 %	1.76 %	748.06
20	322.26	(312.83, 331.69)	325.08	(316.21, 333.95)	2.82	(0, 3.57)	1.11 %	1.10 %	872.37
25	317.68	(314.90, 320.47)	319.28	(258.52, 380.04)	1.60	(0, 2.46)	0.77 %	0.77 %	1291.56
30	317.54	(314.43, 320.65)	318.81	(315.97, 321.65)	1.27	(0, 1.81)	0.57 %	0.57 %	2365.44

CPLEX cannot find the optimal solution within 2 h for medium- and large-scale ISGs, we estimate a lower bound (LB) by converting the binary variables, $\theta_{du}, \beta^{\omega}_{dnk}$, and $\varepsilon^{\omega}_{nn'k}$, to continuous variables and removing constraints (17) and (19). Moreover, in the comparison of solutions, we include the solution generated by the decision rule, which is based on the personal experience of the decision-maker, as described in Section 5.3.

7.3.1. Small-scale experiments

We first conduct the experiments on small-scale instances by comparing the results obtained by CPLEX, the VNS algorithm, a decision rule, and the LB, which demonstrate the relative accuracy of that LB to use it for the medium- and large-scale instances later. We test three groups of small-scale instances, each involving five such instances. The results, shown in Table 5, indicate that there is a narrow average gap (valued at 0.75 %) between the VNS solutions and the optimal CPLEX solutions, which demonstrates that the algorithm is valid in terms of solution quality. The VNS significantly outperforms the CPLEX solver in terms of computation time, taking an average of 5.10 s to generate the solution, whereas CPLEX takes an average of 449.98 s. In addition, as Table 5 shows, on average, the objective values obtained by the VNS algorithm are 15.69 % lower than those obtained by the decision rule. The LB value and its gap with F_{VNS} are recorded in the columns "F_{LB}" and "Gap_{Δ}", respectively. The average value of Gap_{Δ} is 1.27 %, demonstrating that this indicator will be useful in assessing experiments involving medium- and large-scale ISGs.

Notes: (1) $F_{CPLEX}, F_{DR}, F_{VNS}$: the objective value of solution solved by CPLEX, decision rule, and VNS respectively;

(2) t_{CPLEX}, t_{VNS}: the computation time (seconds) of CPLEX and VNS;

(3) $\text{Gap}_{CPLEX} = (F_{VNS} - F_{CPLEX})/F_{CPLEX}$; $\text{Gap}_{DR} = (F_{DR} - F_{VNS})/F_{DR}$; $\text{Gap}_{\Delta} = (F_{CPLEX} - F_{LB})/F_{LB}$.

7.3.2. Medium-scale experiments

The results for the medium-scale ISGs are shown in Table 6. Because the number of scenarios and accident sites increases compared with the small-scale experiments, the time required to solve the model increases substantially. In the medium-scale experiments, CPLEX cannot find the exact optimal solution within the effective time that we set (7200 s), whereas the VNS algorithm obtains the solution in a few minutes, with an average computing time of 148.67 s. As the scale of the experiments increases, the average gap between the solutions generated by the decision rule and VNS increases, reaching 19.34 %. On average, the gap between the VNS solution and the LB value is 3.53 %.

Notes: (1) F_{DR}, F_{LB}, F_{VNS}: the objective value of solution solved by decision rule, LB and VNS respectively;

(2) t_{CPLEX}, t_{VNS}: the computation time (seconds) of CPLEX and VNS;

(3) $\text{Gap}_{DR} = (F_{DR} - F_{VNS})/F_{DR}$; $\text{Gap}_{LB} = (F_{VNS} - F_{LB})/F_{LB}$.

7.3.3. Large-scale experiments

To validate the performance of our proposed solution method in solving large-scale instances, we conduct further experiments to compare the solutions presented by the VNS algorithm with those based on a decision rule and the LB. Table 7 illustrates that, on average, the VNS method can obtain a better solution than the alternative solvers within 1609.32 s. The average value of Gap_{DR} (the gap between the objective values obtained by VNS and those obtained by the decision rule) reaches a peak at 23.65 %, which means that the VNS algorithm can further improve on the traditional decision rule. The average value of Gap_{LB}, that is, the gap between the objective value obtained by the VNS method and the LB, is 4.38 % in the medium-scale experiments, as mentioned above; for the large-scale experiments, the optimality gap of the VNS algorithm is approximately 3.11 %.

Our proposed VNS method yields an average gap of 0.75 % comparing with CPLEX for small-scales. In terms of computation time, the algorithm spends much shorter time than CPLEX for all the instances. Moreover, we can observe that the VNS method is highly efficient to solve the large-scale instances, where the average computing time is 1609.32 s. The VNS method can always obtain the

Table 5
Comparison between CPLEX solver and VNS algorithm on small-scale instances.

Instance		CPLEX		Decision rule	LB	VNS		GAP		
Group	ID	F_{CPLEX}	t_{CPLEX}	F_{DR}	F_{LB}	F_{VNS}	t_{VNS}	Gap_{CPLEX}	Gap_{DR}	Gap_{Δ}
ISG1	1	342.83	10.81	404.02	338.01	345.14	0.58	0.67 %	14.57 %	1.43 %
	2	311.94	6.36	359.28	309.21	314.25	0.36	0.74 %	12.53 %	0.88 %
	3	327.19	7.13	399.68	323.25	329.05	0.64	0.57 %	17.67 %	1.22 %
	4	307.96	5.96	409.18	305.11	309.82	0.51	0.60 %	24.28 %	0.93 %
	5	342.24	6.90	402.81	336.15	344.23	0.48	0.58 %	14.54 %	1.81 %
ISG2	6	339.66	28.74	418.13	336.36	343.59	1.66	1.16 %	17.83 %	1.43 %
	7	316.13	17.50	359.31	312.63	316.96	1.62	0.26 %	11.79 %	0.88 %
	8	333.22	32.83	404.67	328.44	336.01	1.94	0.84 %	16.97 %	1.22 %
	9	322.30	27.67	376.58	320.03	324.52	2.11	0.69 %	13.82 %	0.93 %
	10	313.74	19.69	374.98	310.31	316.22	1.60	0.79 %	15.67 %	1.81 %
ISG3	11	339.13	486.29	389.96	335.82	340.71	14.75	0.47 %	12.63 %	0.99 %
	12	337.51	3269.82	411.26	331.44	341.60	12.20	1.21 %	16.94 %	1.83 %
	13	316.59	1387.91	374.50	312.47	319.65	12.75	0.97 %	14.65 %	1.32 %
	14	340.04	1017.18	411.42	333.98	343.20	14.38	0.93 %	16.58 %	1.81 %
	15	345.57	424.91	409.06	340.42	348.33	10.95	0.80 %	14.85 %	1.51 %
Average			449.98				5.10	0.75 %	15.69 %	1.27 %

Table 6
Comparison between CPLEX solver and VNS algorithm on medium-scale instances.

Instance		Decision rule	LB	VNS		GAP	
Group	ID	F_{DR}	F_{LB}	F_{VNS}	t_{VNS}	Gap_{DR}	Gap_{LB}
ISG4	1	426.26	342.68	353.42	75.09	17.09%	3.13%
	2	427.24	331.15	343.32	87.16	19.64%	3.68%
	3	439.77	341.44	353.21	74.88	19.68%	3.45%
	4	418.86	326.38	337.85	74.54	19.34%	3.51%
	5	447.15	350.88	364.62	79.65	18.46%	3.92%
ISG5	6	431.87	341.72	353.37	123.65	18.18%	3.41%
	7	425.59	330.52	343.24	147.78	19.35%	3.85%
	8	426.33	333.42	345.22	148.78	19.03%	3.54%
	9	431.57	335.54	345.78	130.91	19.88%	3.05%
	10	426.66	324.03	334.41	164.61	21.62%	3.20%
ISG6	11	423.35	331.64	343.44	227.04	18.88%	3.56%
	12	427.36	335.65	347.38	212.93	18.71%	3.49%
	13	456.30	350.02	363.11	245.51	20.42%	3.74%
	14	448.17	337.36	349.86	217.43	21.94%	3.71%
	15	434.04	343.29	356.11	220.06	17.95%	3.73%
Average					148.67	19.34%	3.53%

results that outperform the decision rule. Therefore, these results, shown in Tables 4–6, indicate the validity and efficiency of our proposed VNS solution methodology.

Notes: (1) F_{DR}, F_{LB}, F_{VNS}: the objective value of solution solved by decision rule, LB and VNS respectively;
(2) t_{CPLEX}, t_{VNS}: the computation time (seconds) of CPLEX and VNS;
(3) $\text{Gap}_{DR} = (F_{DR} - F_{VNS})/F_{DR}$; $\text{Gap}_{LB} = (F_{VNS} - F_{LB})/F_{LB}$.

7.4. Robustness evaluation of the proposed method

Optimal solutions obtained by the proposed VNS algorithm are based on generated scenarios. It is very likely that in practice the actual demand is not a member of the used samples, which will cause the solution approach to perform poorly. We conduct out-of-sample analysis, which assesses the performance of optimal solutions using out-of-sample data, to evaluate the robustness of the VNS algorithm. All scenarios are divided into two sets: in-sample-scenarios Ω^{in} and out-of-scenarios Ω^{out}, where $\Omega = \Omega^{in} \cup \Omega^{out}$. We input all scenarios in Ω^{in} into the VNS algorithm to obtain the optimal first-stage solutions θ^*_{du} and α^*_{dk}. Then N scenarios are randomly selected from Ω^{out}, and each scenario is input into the deterministic model to calculate the optimal dispatching decisions. The deterministic model calculated by the proposed original model with only one scenario of Ω^{out}, where each parameter's value is the expected value of the parameter's values in one specified scenario. More specifically, the deterministic model is calculated by the original model with only one generated scenario from Ω^{out}, where each parameter's value is the expected value of the parameter's values in the specified scenario. There are two possible outcomes: optimal solution exists and optimal solution does not exist. In the first case, we determine the emergency response level, which is the proportion of traffic accidents responded within latest preferred rescue time. Robustness is measured by robustness level (the proportion of scenarios where optimal solution can be found) and (1 −

Table 7
Performance of VNS algorithm on large-scale instances.

Instance		Decision rule	LB	VNS		GAP	
Group	ID	F_{DR}	F_{LB}	F_{VNS}	t_{VNS}	Gap_{DR}	Gap_{LB}
ISG7	1	482.78	357.88	372.62	762.00	22.82 %	4.12 %
	2	454.36	334.87	349.72	704.83	23.03 %	4.43 %
	3	461.61	343.75	359.86	694.40	22.04 %	4.69 %
	4	452.66	337.71	352.70	694.92	22.08 %	4.44 %
	5	484.90	352.63	368.65	765.86	23.97 %	4.54 %
ISG8	6	471.89	340.72	355.04	1287.81	24.76 %	4.20 %
	7	488.17	354.66	370.89	1691.45	24.02 %	4.58 %
	8	474.77	338.28	353.03	1653.77	25.64 %	4.36 %
	9	476.02	345.81	360.99	1378.29	24.16 %	4.39 %
	10	480.73	358.36	372.84	1594.14	22.44 %	4.04 %
ISG9	11	459.39	337.26	352.84	2359.98	23.19 %	4.62 %
	12	466.98	344.01	357.99	2703.98	23.34 %	4.06 %
	13	493.25	350.67	366.60	2655.69	25.68 %	4.54 %
	14	462.38	333.61	347.46	2571.87	24.85 %	4.15 %
	15	463.37	342.34	358.09	2620.88	22.72 %	4.60 %
Average					1609.32	23.65 %	4.38 %

τ)-CI of response level. The procedures are given in Algorithm 4.

Algorithm 4: Robustness evaluation

Generate a set of scenarios Ω^{in}
Solve the VNS problem with Ω^{in} and obtain the optimal first-stage solution θ^*_{du} and α^*_{dk}
For $n = 1, 2, \cdots, N$ **do**
  Generate a new independent scenario ω_n from Ω^{out}, $\omega_n \in \Omega^{out}$
  Solve deterministic model with ω_n, θ^*_{du} and α^*_{dk}
  If optimal solution can be found, calculate response level RL_n
End for
  Calculate the number of iterations N' where optimal solution can be found
  Calculate robustness level $RL = N'/N$
Let $ARL = \frac{1}{N'}\sum_{n=1}^{N'} RL_n$ and $\Omega_{ARL} = \frac{1}{N'-1}\sum_{n=1}^{N'} (RL_n - ARL)^2$.
The $(1-\tau)$-CI for response level is $\left[ARL - \frac{t_{N'-1,\frac{\tau}{2}}\sqrt{\Omega_{ARL}}}{\sqrt{N'}}, ARL + \frac{t_{N'-1,\frac{\tau}{2}}\sqrt{\Omega_{ARL}}}{\sqrt{N'}}\right]$.

The VNS and deterministic model are ran 5 times, respectively. The 10 different optimal first-stage solutions are put into Algorithm 4 to calculate robustness level and 95 % CI of response level with N set to 300. The results, shown in Table 8, indicate that compared with deterministic model, stochastic model can obtain solutions that respond to more traffic accidents within latest preferred rescue time with high probability. At least 95.68 % of the rescue demands can be satisfied in a timely manner with a high probability even though these solutions are evaluated on out-sample data. While deterministic model solutions can response at most 93.52 % of the rescue demands in a timely manner with a high probability. Robustness level for all solution types is 100 %, which means that the VNS can obtain optimal solution under every scenario in out-of-sample analysis. All these results indicate that the proposed VNS in our study is a robust solution method.

Notes: (1) VNS-1, VNS-2, VNS-3, VNS-4, VNS-5: the optimal first-stage solution obtained by running VNS 5 times separately; D-1, D-2, D-3, D-4, D-5: the optimal first-stage solution obtained by running deterministic model 5 times separately.

7.5. Comparison between independent and nested neighborhood structure

In this study, one of the main contributions is the proposed VNS method with nested neighborhood structure, which differs from the independent neighborhood structure used in most studies. The neighborhood structures for the second-stage decision variables are embedded in the mutation neighborhood structure for the first-stage decision variables. Here we conduct some comparative experiments to validate the necessity of the nested neighborhood structure. More specifically, ISG 2, ISG 5, and ISG 8 are chosen to represent the small-, medium-, and large-scale instances, respectively. We compare the solutions solved by the VNS method using nest neighborhood structure with using independent neighborhood structure. The results are shown in Table 9. We can find that the proposed VNS method with nested neighborhood structures in our study can reduce the cost by 6.60 % on average when we compare it with the independent neighborhood structure. However, the nested neighborhood structure also means that the solution time can be long.

Notes: (1)F_{Ind}, F_{Nes}: the objective value of solution solved by VNS with independent and nested neighborhood structure, respectively;

(2)t_{Ind}, t_{Nes}: the computation time (seconds) of VNS with independent and nested neighborhood structure, respectively;

(3) GAP $= (F_{Ind} - F_{Nes})/F_{Nes}$.

7.6. Benefits of stochastic programming

The occurrence of traffic accidents (i.e., the location and time of the traffic accidents, the demand for various types of emergency vehicles, and the travel time between rescue stations and accident sites) is uncertain in practical scenarios. By comparing three different methods, we conduct some experiments to investigate the value of stochastic solution and the value of perfect information (Avriel and Williams, 1970). The former evaluates the benefits of taking into account (or the cost of ignoring) uncertainties while making a decision. The latter evaluates how much traffic emergency managers are prepared to pay for recognizing random variables prior to making their decision. Here the "perfect" refers to precisely forecasting the information of traffic accidents in advance.

Method 1: Solve the proposed mathematical model in section 4.3. Let F_1 be the objective value, which is the total emergency rescue cost, including the cost of traffic emergency vehicles deployment scheme and the expected cost of traffic emergency vehicles dispatch scheme in different scenarios. $F_1 = C(fp) + \sum_{\omega\in\Omega}\{\pi^{\omega} C_{sp}(\omega, fp)\}$, here $C(fp)$ denotes the cost of traffic emergency vehicles deployment

Table 8
95% CI of response level.

VNS-1	VNS-2	VNS-3	VNS-4	VNS-5	D-1	D-2	D-3	D-4	D-5
[97.03 %, 97.87 %]	[96.78 %, 97.74 %]	[95.68 %, 96.70 %]	[95.90 %, 96.85 %]	[96.12 %, 96.94 %]	[92.76 %, 93.52 %]	[88.24 %, 89.34 %]	[89.45 %, 90.69 %]	[90.64 %, 91.20 %]	[91.82 %, 92.88 %]

Table 9
Comparison of the independent and nested neighborhood structure.

Instances		Independent neighborhood structure		Nested neighborhood structure			
Group	ID	F_{Ind}	t_{Ind}	F_{Nes}	t_{Nes}	GAP	t_{Nes}/t_{Ind}
ISG2	6	343.59	1.66	358.52	1.06	4.35 %	1.57
	7	316.96	1.62	333.75	0.89	5.30 %	1.82
	8	336.01	1.94	352.73	1.12	4.98 %	1.73
	9	324.52	2.11	340.43	1.33	4.90 %	1.59
	10	316.22	1.6	334.09	0.86	5.65 %	1.86
	6	353.37	123.65	380.13	97.53	7.57 %	1.27
	7	343.24	147.78	362.86	101.63	5.72 %	1.45
ISG5	8	345.22	148.78	367.78	99.61	6.53 %	1.49
	9	345.78	130.91	365.08	106.31	5.58 %	1.23
	10	334.41	164.61	358.96	126.64	7.34 %	1.30
ISG8	6	355.04	1287.81	383.99	1260.49	8.15 %	1.02
	7	370.89	1691.45	397.94	1584.32	7.29 %	1.07
	8	353.03	1653.77	384.74	1561.62	8.98 %	1.06
	9	360.99	1378.29	390.22	1370.22	8.10 %	1.01
	10	372.84	1594.14	404.56	1508.32	8.51 %	1.06
Average						6.60 %	1.37

scheme fp (the sum of the construction cost of rescue stations and the acquisition cost of all vehicles) in the first stage, π^{ω} denotes the probability of scenario ω, $C_{sp}(\omega, fp)$ denotes the expected cost of traffic emergency vehicles dispatch scheme in scenario ω based on fp.

Method 2: Solve a deterministic model. The deterministic model is calculated by the proposed original model with only one scenario, where each random parameter's value is the expected value of the parameter's values in specified scenarios. We solve the deterministic model and obtain a traffic emergency vehicles deployment scheme fp', whose cost is $C(fp')$. Based on fp', the expected cost of traffic emergency vehicles dispatch scheme under all scenarios is calculated by $\sum_{\omega\in\Omega}\{\pi^{\omega}C_{sp}(\omega, fp')\}$. Let F_2 be the objective value, $F_2 = C(fp') + \sum_{\omega\in\Omega}\{\pi^{\omega}C_{sp}(\omega, fp')\}$.

Method 3: Solve a series of deterministic models, each of which is related to a defined scenario with a given probability. For example, the optimal traffic emergency vehicles deployment and dispatch scheme is p^*_{ω} as to scenario ω. Let F_3 be the objective value, $F_3 = \sum_{\omega\in\Omega}\{\pi^{\omega}C(p^*_{\omega})\}$.

The following are the main differences between Method 1 and Method 2: the former solves a deployment and dispatch scheme of traffic emergency vehicles simultaneously, while the latter solves them into two steps. The solution obtained by Method 2 is also a feasible solution of Method 1. The gap between them measures the value of stochastic solution, which evaluates the benefits of taking into account uncertainties while making a decision:

$$Val_{Stoc} = F_2 - F_1 \tag{23}$$

The information of traffic accidents cannot be predicted in advance, and thus Method 3 does not exist in reality, while supplies a lower bound for Method 1. The gap between them measures the value of perfect information, which evaluates the maximum amount that traffic emergency managers are prepared to pay for knowledge value of random variables before making their decision:

$$Val_{Info} = F_1 - F_3 \tag{24}$$

We investigate two experimental groups ISG1 and ISG2 with varied location and time of traffic accidents, the demand for various types of emergency vehicles, and travel time for traffic accidents. Each group contains five randomly generated instances. The results in Table 10 shows that the value of the stochastic programming used in this study is estimated as about 2.47 % of the profit; and the value of the perfect information is estimated as about 0.92 % of the profit. F_1 is no greater than F_2, which illustrates the necessity of

Table 10
Value of the stochastic solution and value of perfect information.

Instance		Method 1		Method 2		Method 3	Val_{Stoc}		Val_{Info}	
Group	ID	F_1	C_1	F_2	C_2	F_3	Δ_1	Gap_1	Δ_2	Gap_2
	1–6	301.48	270.00	308.26	270.00	298.96	6.78	2.25 %	2.52	0.84 %
	1–7	296.54	270.00	304.14	270.00	294.69	7.60	2.56 %	1.85	0.62 %
ISG1	1–8	304.76	270.00	312.67	270.00	301.68	7.91	2.60 %	3.08	1.01 %
	1–9	307.02	270.00	316.10	270.00	304.71	9.08	2.96 %	2.31	0.75 %
	1–10	296.44	270.00	301.14	270.00	294.83	4.70	1.59 %	1.61	0.54 %
	2–6	304.14	270.00	311.29	270.00	301.47	7.15	2.35 %	2.67	0.88 %
	2–7	301.79	270.00	308.54	270.00	298.74	6.75	2.24 %	3.05	1.01 %
ISG2	2–8	307.67	270.00	316.69	270.00	304.39	9.02	2.93 %	3.28	1.07 %
	2–9	303.93	270.00	310.92	270.00	300.52	6.99	2.30 %	3.41	1.12 %
	2–10	312.19	270.00	321.39	270.00	308.06	9.20	2.95 %	4.13	1.32 %
Average		303.60		311.11		300.81		2.47 %		0.92 %

proposing a two-stage stochastic programming model to handle uncertainties. Although C_2 is equal to C_1. The best schedule can be obtained by deterministic model with the estimated parameters, may not be the best one when facing uncertainties. The gap between F_1 and F_3 highlights the benefits of accurately forecasting information of traffic accidents.

Notes: (1) F_1, F_2 and F_3: the objective value of solution solved by *Method 1*, *Method 2* and *Method 3*, respectively.

(2) C_1 and C_2: the construction cost of rescue stations and the acquisition cost of all vehicles in the first stage obtained by *Method 1* and *Method 2*, respectively.

(3) $\Delta_1 = F_2 - F_1$, $\Delta_2 = F_1 - F_3$.

(4) $Gap_1 = \Delta_1 / F_1$, $Gap_2 = \Delta_2 / F_1$.

7.7. Sensitivity analysis

The optimization of the urban accident rescue system can be influenced by changes that may occur in several parameters. To explore the impact of these changes, we conduct sensitivity analyses on the frequency of occurrence of the accidents, the average speed of the emergency vehicles, the number of emergency vehicles, the regions in which the accident-prone sections are located, and the unit penalty cost. ISG 2, ISG 5, and ISG 8 are chosen to represent the small-, medium-, and large-scale instances, respectively. In addition to comparing the changes at the objective function value according to sensitivity analyses, we also recorded changes in different indicators of the solutions obtained, particularly ones reflecting the quality of the service: average rescue time, average overtime, and maximum overtime.

(1) Sensitivity analysis on the occurrence frequency of accidents

We define the accident occurrence frequency as $\mu = N/T$, where N indicates the number of accidents and T is the length of the time horizon during which accidents may occur (measured in hours). In other words, there are N accidents distributed in the time interval $(0, T)$. The simultaneous occurrence of multiple accidents within a relatively short period can present a huge challenge for emergency response vehicles. However, the impact of increasing frequency varies for instances of different scales. Therefore, in Fig. 12, which shows the results for instances of different scales, the values on the x- and y-axes vary between charts (a), (b), and (c), which represent ISG 2, ISG 5, and ISG 8, respectively. As the three charts show, the total rescue cost is sensitive to the accident occurrence frequency, especially in charts (b) and (c), for the medium- (ISG 5) and large-scale (ISG8) incidents. The results indicate that the accident occurrence frequency has an impact on the effectiveness with which emergency rescue vehicles are dispatched, particularly as the scale of instance increases.

(2) Sensitivity analysis on the average speed of emergency vehicles

The second sensitivity analysis further investigates the influence of the average speed of emergency vehicles. The occurrence frequency of accident sites is fixed as 1.0. Considering the minimum speed during peak congestion and the maximum speed limit on urban roads, we set the average speed range in the interval $[25, 60]$. The results are summarized in Fig. 13, which records changes on objective values and different service indicators. The results in Fig. 13(a), Fig. 13(b) and Fig. 13(c) show that the vehicle speed has a remarkable impact on the objective value, and the results indicate the different vehicle speed required for different scale instances. In other words, the emergency vehicles dispatching decision making is limited by the time efficiency of the road network, and the average speed of vehicles affects the time to start rescue directly. The results in Fig. 13(d), Fig. 13(e) and Fig. 13(f) show that the average rescue time decreases as the average speed of vehicles increases. However, when the speed of vehicles increases above a threshold, the average overtime and maximum overtime seems to flatten. It means that the average speed of vehicles no longer affects whether the rescue is overdue or extend the overtime of rescue. At this point, the emergency manager should focus on balancing both rescue cost and service quality.

(3) Sensitivity analysis on the number of emergency vehicles

The third sensitivity analysis is based on the changeable emergency vehicle quantity with a fixed ratio of 1:1:1 of three-type vehicles. The results are summarized in Fig. 14, which records changes on objective values and different service indicators. The results in Fig. 14(a), Fig. 14(b) and Fig. 14(c) demonstrate there is a direct link between the scale of emergency fleets and the total rescue cost, and the tendency indicates that six emergency vehicles are most economical for the instances based on ISG 5 and ISG 8. This result shows the importance of determining the number of allocated vehicles. Maintaining a sizable fleet in service although guaranteed to

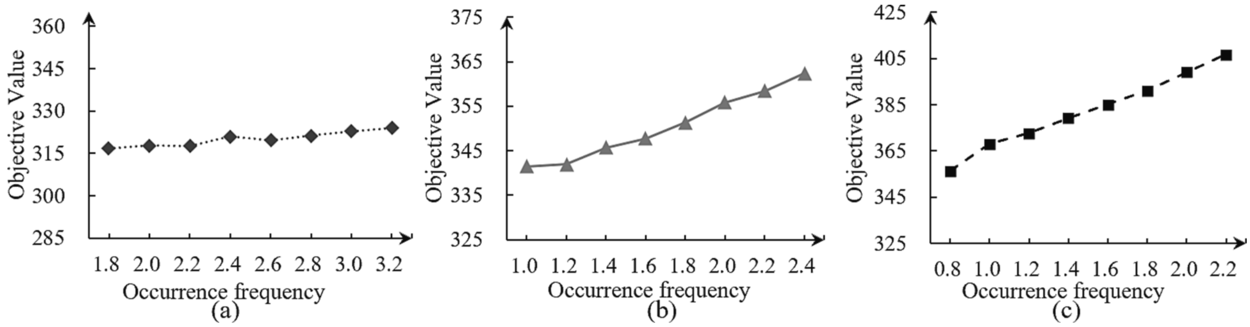

Fig. 12. Sensitivity analysis on the occurrence frequency of accidents.

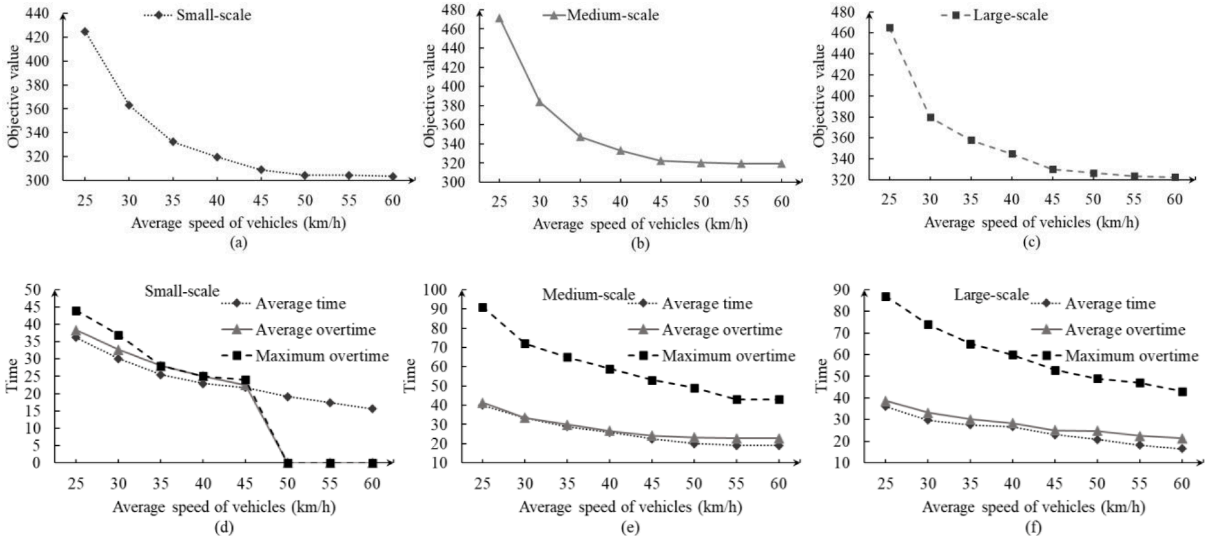

Fig. 13. Sensitivity analysis on the average speed of emergency vehicles.

meet emergency demands, will increase some unnecessary fixed costs. It is necessary to identify a trade-off between cost reduction and rescue demand satisfaction. The results in Fig. 14(d), Fig. 14(e) and Fig. 14(f) show that the average rescue time has a significant reduction during the change in the number of vehicles from three to nine. However, when the number of vehicles reaches nine, the average rescue time seems to flatten. The tendency means that nine emergency vehicles are most economical in terms of service quality. Moreover, when the number of vehicles reaches six, nine and 12 for small-, medium-, and large-scale instances, respectively, the average speed of vehicles no longer affects whether extend the overtime of rescue.

The results in Fig. 14(g), Fig. 14(h) and Fig. 14(i) to validate the marginal effects of additional resources (i.e., emergency vehicles). We can see that the average response time saved decreases with the increase in the number of emergency vehicles of each type per unit. More specifically, the response time has a most significant reduction during the change in the number of additional vehicles of each type from one to two. Then this downward trend slows down as each type of vehicle increases by one until it reaches zero.

(4) Sensitivity analysis on the regions of rescue stations

We perform the fourth sensitivity analysis on the radius of regions in which rescue stations are distributed. As shown in Fig. 15, the 16 accident-prone sections in the numerical experiment are distributed within a circle of radius $r_1 = 9.6km$, it is assumed that the three rescue stations are uniformly distributed in a circle of radius r_2 and these two regions are concentric circles. With the center of the circle as the origin, the Cartesian coordinate system is created and the coordinates of each node in the road network can be obtained. We use the Manhattan distance to estimate the distance between rescue stations and accident sites.

Chart (a), chart (b), and chart (c) in Fig. 16 show the results of three different scale instances with different r_2 values. The range of y-axis of these three charts are separate since there is a large span of objective values for different scale instances. It is obvious that the total rescue cost is significantly related to the region of rescue stations distributed. These results show that once the region of accidents is given, a specific radius of the rescue stations region is available to be determined that can minimize the objective value. This experiment demonstrates to emergency managers the importance of planning the proper location and distribution of rescue stations.

(5) Sensitivity analysis on the regions of accident-prone sections

The fifth sensitivity analysis is based on different scales of the region in which accident-prone sections are distributed. The experiments reset the locations of the 16 accident-prone sections according to the rule as followed. As shown in Fig. 17, a triangle composed of three rescue stations and its center of gravity (tagged by o) can be obtained. It is assumed that the 16 accident-prone sections are randomly distributed in a circle with radius r, taking the node o as the center. The distances from rescue stations to accident sites can be realized.

Fig. 18 shows the results with different r values, it can be seen that the larger the radius of the distribution of accident sites, the more pronounced the trend of increasing objective value, however, a significant increase only occurs up to a specific radius. The results also indicate that given a fixed center of rescue stations, it is able to find an acceptable size of region for rescue. Reasonably statistics or forecast locations of potential accidents in the road network must be crucial to ensure timely rescue.

(6) Sensitivity analysis on the unit penalty cost

The last experiment is performed to explore the impact of unit penalty costs on the total rescue cost. The results are summarized in Fig. 19, which records changes on objective values and different service indicators. The results in Fig. 19(a), Fig. 19(b) and Fig. 19(c) shows the unit penalty cost of untimely rescue has a remarkable influence on the objective value for large-scale instances. The results in Fig. 19(d) show that the three indicators has a significant reduction during the change in the unit penalty cost from one to three. However, when the unit penalty cost reaches three, the three indicators seems to flatten for small-scale instances. While Fig. 19(e) and Fig. 19(f) shows that the effect of unit penalty cost on service quality is not significant for medium-, and large-scale instances.

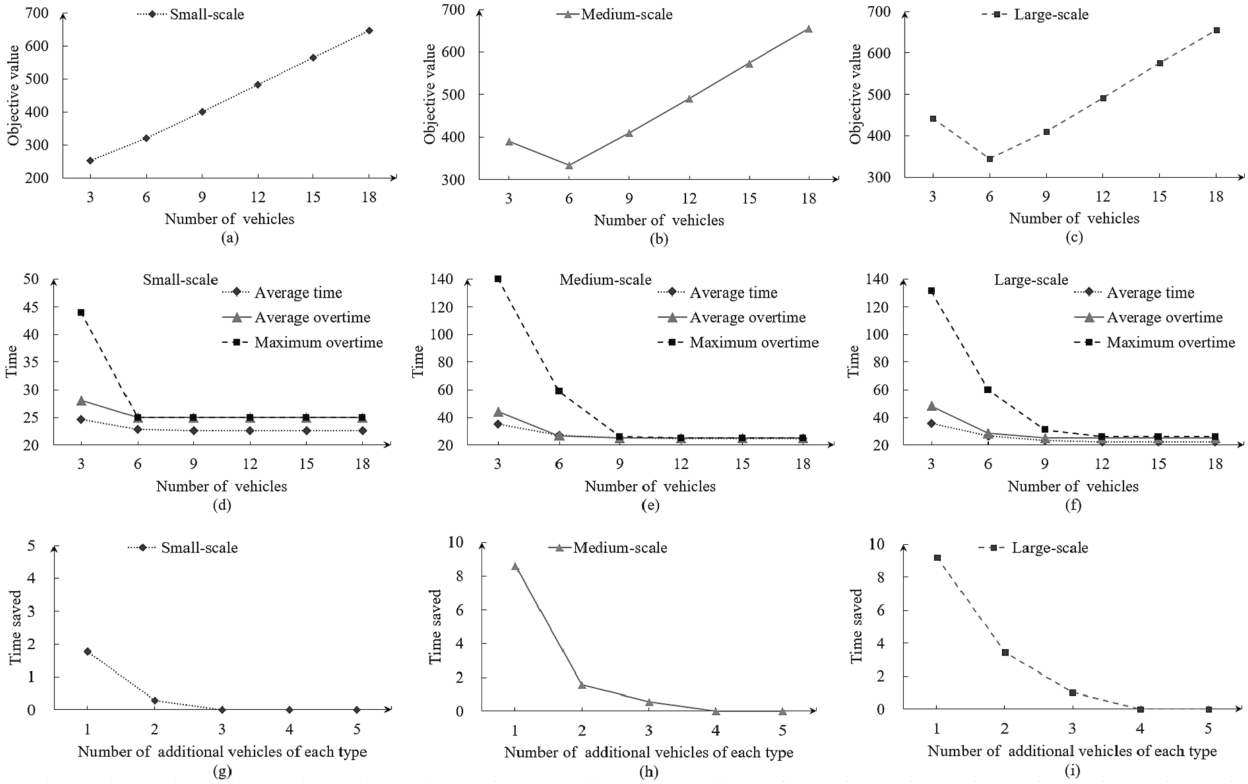

Fig. 14. Sensitivity analysis on the number of emergency vehicles.

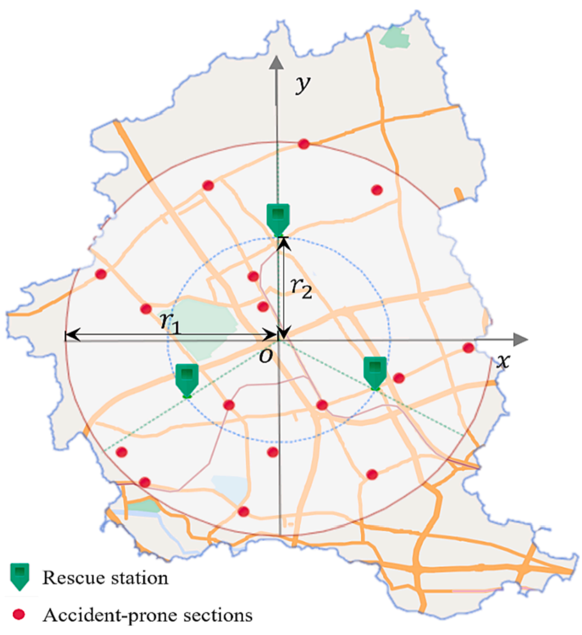

Fig. 15. An example for the region of rescue stations.

(7) Comparison of decision rule and VNS on different vehicles deployment planning

To provide more insights on the vehicles deployment planning in practice and consider adapting their decision makers performance accordingly. Here some comparative experiments are conducted to validate the necessity of different vehicles deployment planning in practice. More specifically, we allocate six emergency vehicles to three rescue stations according to different ratios. Note that the

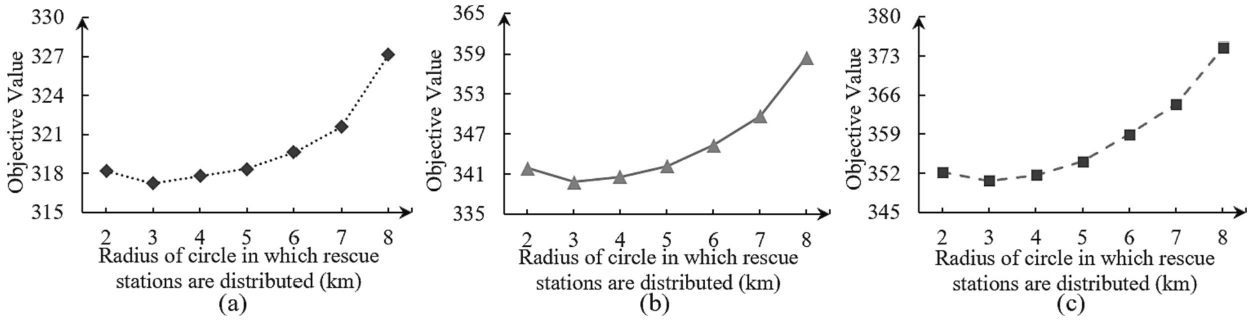

Fig. 16. Sensitivity analysis on the regions of rescue stations.

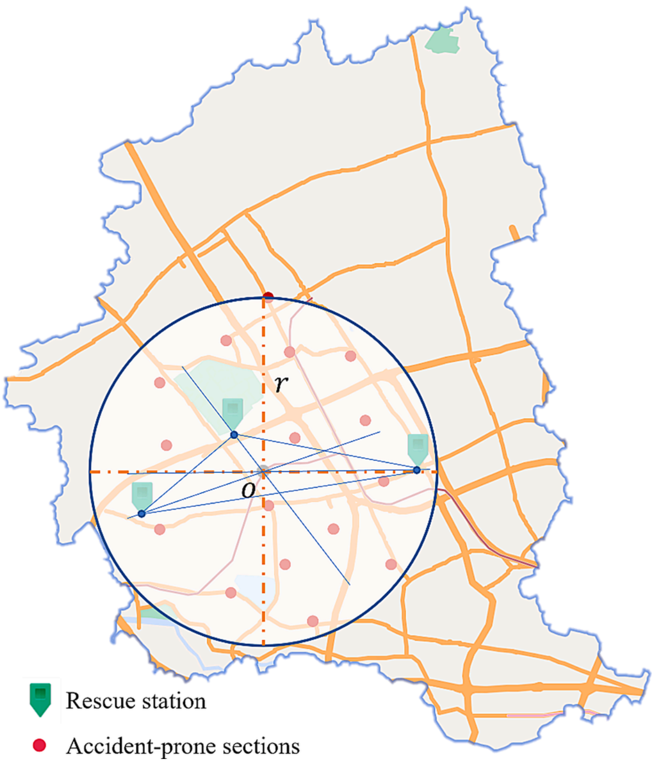

Fig. 17. An example for the region of accident-prone sections.

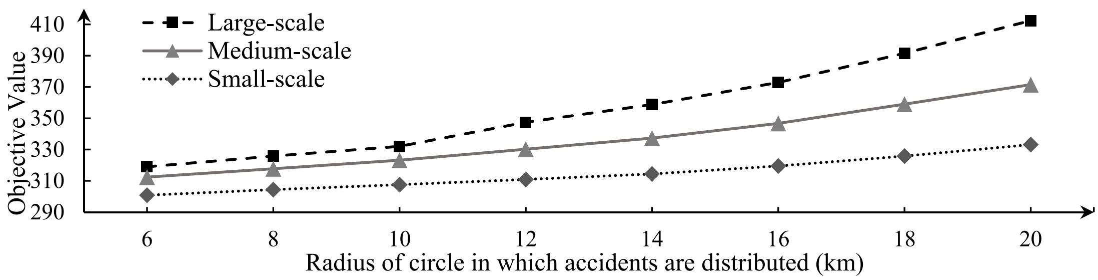

Fig. 18. Sensitivity analysis on the regions of accident-prone sections.

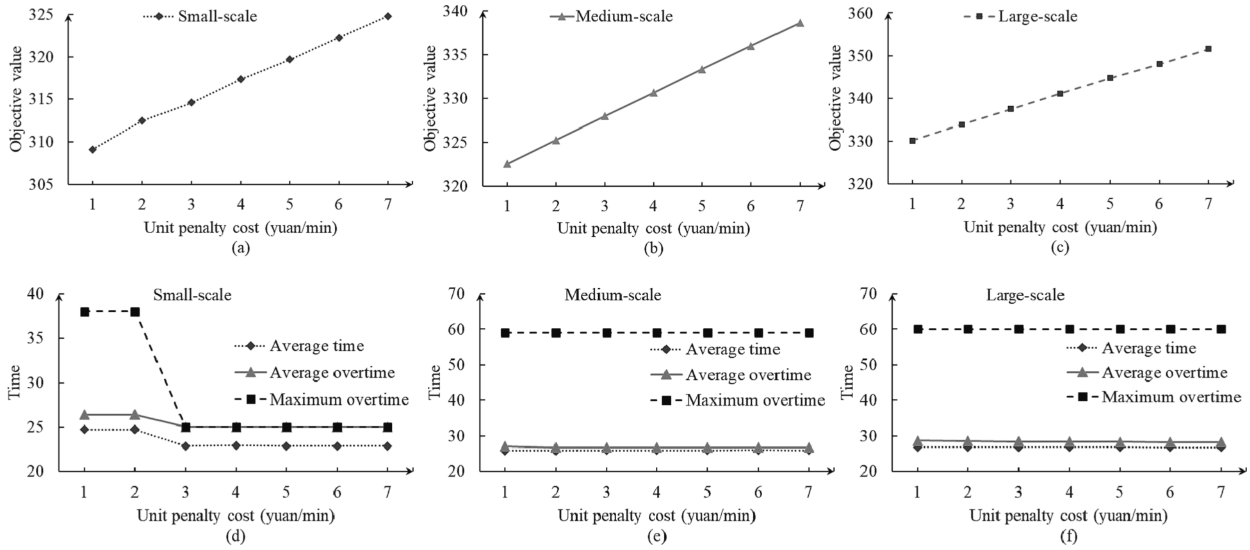

Fig. 19. Sensitivity analysis on the unit penalty cost.

deployment planning of vehicles is predicated on meeting limited budget and station capacity constraints. The results in Fig. 20 show that the more evenly the vehicles are distributed, the better the solution obtained by the decision rule. As shown in Fig. 20, the relative gap between our proposed VNS method and the decision rule is significant, which is about 17 %~45 %. Therefore, our proposed scientific algorithm is more applicable to emergency management decision makers for vehicles deployment planning than previous experience.

8. Extension

In the processes outlined above, we consider future events in the decision-making process by generating scenarios of potential outcomes. This approach involves generating multiple scenarios of future customer requests and including them in the planning process, so that the solutions to possible future requests are prepared. However, if accidents arise that require more urgent treatment during the implementation of the second-stage solution, the previous solution must be dynamically adjusted. Thus, in this section, we refine the second-stage dynamic dispatch based on the solution approach outlined above.

In Fig. 21, we present an example to demonstrate the necessity of dynamic dispatching. We assume that the rescue call regarding the dynamic accidents is made after the call to respond to the static accidents. As chart (a) shows, vehicle k_2 is available to attend the static accident site n_1 and its dispatch is the optimal solution at that moment. If this solution is unalterable and we apply the first-call, first-rescue rule, vehicle k_1 has to be assigned to the dynamic accident site n_2. However, this assignment does not always ensure that the total rescue time is minimized. To address this situation, we can reassign vehicle k_1 to n_1 and vehicle k_2 to n_2, as shown in chart (b) of Fig. 21. Next, in chart (c), we assume that another vehicle k_3 becomes idle a few minutes later. At this time, the optimal solution is to assign k_3 to n_2 and k_2 to n_1. This example illustrates that rescheduling of the emergency vehicles assigned to accidents is required whenever unexpected accidents occur.

We propose a dynamic dispatching mechanism to address this problem. The set N of traffic accident sites in the previous mathematical model is redefined as a set N_s of static accidents and a set N_d of dynamic accidents. We retain the fundamental assumption that emergency vehicles are re-dispatched to accident sites that are still waiting for rescue whenever a new accident arises. First, we need to generate the initial solution for the dynamic dispatching mechanism. By solving the mathematical model presented in Section 4.3 with the VNS algorithm, we can obtain a number of routes for all static accident sites. When dynamic accidents occur within the planning horizon, it is preferable to assign them to an unused vehicle and create a new route. If this is not feasible, dynamic accidents are

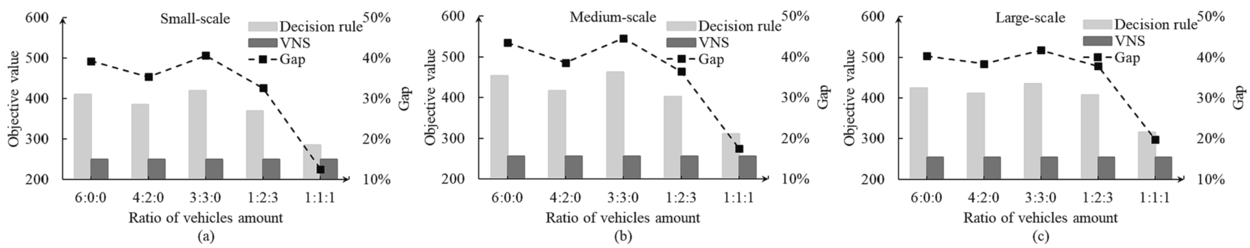

Fig. 20. Comparison of decision rule and VNS on different vehicles deployment planning.

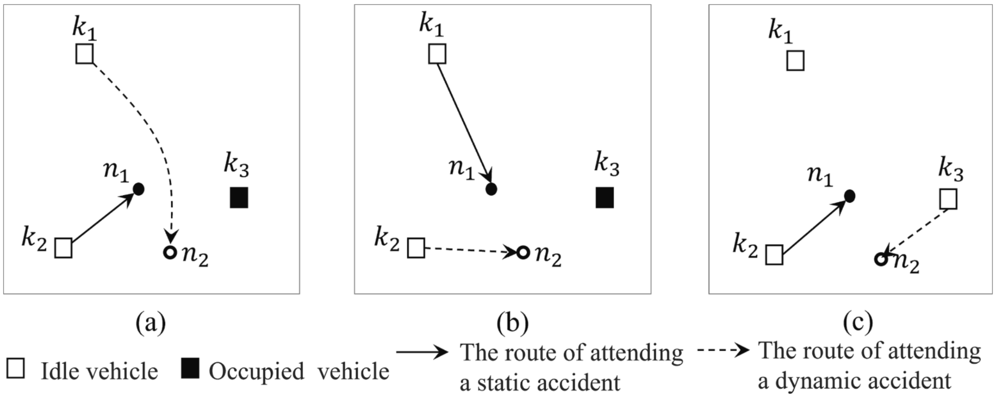

Fig. 21. An example of emergency vehicle dispatching in dynamic environments.

inserted into the current route of the nearest vehicle according to the emergency demands. Second, to optimize this initial solution, we apply the core component of our solution, the VND procedure, which is constructed in Section 5.5, with the pseudo-code description of this mechanism given in Algorithm 5.

Algorithm 5: Dynamic Dispatching Mechanism

Obtain the optimal solution *GloSol* containing static accidents by VNS;
While (a new dynamic accident *n* arises)
  If (an unused emergency vehicle is available)
    create a new route to serve dynamic accident *n*;
  Else
    Insert accident *n* to the closest route;
  Obtain the initial solution *DynSol* containing static and dynamic accidents;
  Apply VND procedure (*DynSol*);
End while

The degree of dynamism in this problem is related to the ratio of static to dynamic accidents, which affects the performance of the dynamic dispatching strategy. Lund et al. (1996) define the degree of dynamism as $\tau = N_d/(N_s + N_d)$. We conduct some numerical experiments to evaluate the performance of the proposed mechanism compared with the proposed VNS algorithm. The test instances and results are shown in Table 11. In the static mechanism, based on the proposed VNS, the dynamic accidents are served as if they are static accidents. The total number of accidents is stationary, but the degree of dynamism is variable. Table 11 shows that as the value of τ increases, the optimized performance of the dynamic dispatching mechanism becomes better than that of the static mechanism. These results illustrate that the VND procedure plays a crucial role in searching for the optimal solution.

9. Conclusion

This paper explores an integrated decision issue concerning deployment of emergency vehicles in rescue stations and dispatch of

Table 11
Performance of the proposed dynamic dispatching mechanism.

Instance				Static mechanism	Dynamicmechanism	Gap
degree of dynamism	N_s	N_d	ID	F_S	F_d	Gap_{sd}
12.5 %	7	1	1	361.55	354.47	2.00 %
			2	350.72	339.78	3.22 %
			3	354.91	342.01	3.77 %
			4	345.18	336.67	2.53 %
			5	342.44	340.82	0.48 %
25 %	6	2	6	349.90	333.25	5.00 %
			7	368.16	339.52	8.44 %
			8	350.59	333.10	5.25 %
			9	360.37	344.61	4.57 %
			10	345.65	330.05	4.73 %
50 %	4	4	11	368.01	328.84	11.91 %
			12	364.51	316.94	15.01 %
			13	376.82	341.15	10.46 %
			14	373.60	338.92	10.23 %
			15	360.34	331.52	8.69 %
Average						6.42 %

the vehicles in response to traffic accidents within the urban road network. We deal with the uncertainty that influences the road network environment using a stochastic optimization approach. We develop a two-stage stochastic programming model and design a VNS algorithm for problem solving. We perform a series of numerical experiments, using Jiading District in Shanghai, China, to evaluate the performance of the suggested approach. We summarize our contributions to the literature as follows.

(1) The decisions on emergency vehicle deployment and dispatching are interacted. Emergency vehicles are dispatched to satisfy specific rescue demand. The deployment of emergency vehicles to each rescue station is frequently concurrently optimized with dispatching to ensure that there are sufficient resources available to meet demand. Therefore, our model is designed to solve an integrated long- and short-term decision problem on deployment and dispatch of traffic emergency vehicles. This study considers more a comprehensive suite of uncertainties than those considered in the literature to obey the realistic environment of emergency vehicle dispatching. We further consider uncertain location and time of the traffic accidents, uncertain demand for various types of emergency vehicles, and uncertain travel time between rescue stations and accident sites.

(2) To develop a tool for model solving, it is essential to emphasize the relationship between the flow of the VNS algorithm and the model characteristics in the design process. Because the decision variables in the two stages of the model are mutually influencing, we nest the neighborhood structure of the two decision variables belonging to the different stages in the VND procedure. Unlike the independent neighborhood structures used in most studies, this approach is highly likely to prevent the algorithm from missing any possible optimal solution during the local search. To validate the necessity of the nested neighborhood structure, the results obtained by comparative experiments shows that the proposed VNS method with nested neighborhood structures can reduce the cost by 6.60 % on average when we compare it with the independent neighborhood structure. In addition, the extension of the proposed dynamic approach show that rescheduling of the emergency vehicles assigned to accidents is required whenever unexpected accidents occur.

(3) We conduct a series of sensitivity analyses to reveal the influences of detail factors such as the region of rescue stations or accidents. The results of our sensitivity analysis reveal some practical managerial insights. In particular, to reduce rescue costs, traffic rescue managers should consider the appropriate region of rescue stations and how accident sites are distributed. In addition, they should be aware that there is a trade-off between economics (that is, reducing costs) and timeliness (accident response times) in determining the size of their fleets and their travel speed. The marginal effects of additional resources (i.e., emergency vehicles) show a downward trend until reaching zero.

There are some limitations to this research. Scenario-based optimization needs to identify the locations of every accident-prone sections and rescue demands to establish scenarios. In future, studies should attempt to consider robust optimization in the context of dynamic roadway conditions. The point of solving the traffic rescue problem in this paper is to define a proper uncertainty set for the accident-prone sections. The new model could be applied in cases where there are not enough data to calibrate the stochastic programming model. Moreover, although we extend our model to the case where unexpected accidents are likely to arise dynamically by proposing a simple dynamic dispatching mechanism, in future, alternative approaches, such as predictive routing algorithms, could be used to improve the performance of traffic rescue teams in practical settings.

CRediT authorship contribution statement

Lu Zhen: Conceptualization, Funding acquisition, Methodology, Writing – review & editing. **Jingwen Wu:** Methodology, Software, Writing – original draft. **Fengli Chen:** Investigation, Methodology, Software, Validation, Writing – original draft. **Shuaian Wang:** Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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