Yang, Z, Guo, L and Yang, Z

Emergency logistics for wildfire suppression based on forecasted disaster evolution

EMERGENCY LOGISTICS FOR WILDFIRE SUPPRESSION BASED ON FORECASTED DISASTER EVOLUTION

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Abstract: This paper aims to develop a two-layer emergency logistics system with a single depot and multiple demand sites for wildfire suppression and disaster relief. For the first layer, a fire propagation model is first built using both the flame-igniting attributes of wildfires and the factors affecting wildfire propagation and patterns. Second, based on the forecasted propagation behavior, the emergency levels of fire sites in terms of demand on suppression resources are evaluated and prioritized. For the second layer, considering the prioritized fire sites, the corresponding resource allocation problem and vehicle routing problem (VRP) are investigated and addressed. The former is approached using a model that can minimize the total forest loss (from multiple sites) and suppression costs incurred accordingly. This model is constructed and solved using principles of calculus. To address the latter, a multi-objective VRP model is developed to minimize both the travel time and cost of the resource delivery vehicles. A heuristic algorithm is designed to provide the associated solutions of the VRP model. As a result, this paper provides useful insights into effective wildfire suppression by rationalizing resources regarding different fire propagation rates. The supporting models can also be generalized and tailored to tackle logistics resource optimization issues in dynamic operational environments, particularly those sharing the same feature of single supply and multiple demands in logistics planning and operations (e.g., allocation of ambulances and police forces).

Keywords: Emergency logistics, disaster operation management, wildfire suppression, vehicle routing problem, multiple objective decision making

1. BACKGROUND

Globally, wildfire accidents, particularly those caused by humans, have become more common in recent years (Plucinski et al., 2012; Le Page et al., 2014; Krawchuk and Moritz, 2014). For example, from 2000 to 2013, there were 115,466 wildfires in China, the majority of which were due to human activities. Annually, there were approximately 8,248 wildfires, with over 106,127 hectares of burned area and over 117 casualties on average (China Statistical Yearbook, 2014). Wildfires can result in serious losses of forest resources and personal property. To effectively reduce and mitigate such losses, proactively developing suppression planning and emergency logistics responses within the context of Disaster Operations Management (DOM) is necessary. Measures that can drastically reduce the associated social, economic and environmental impacts caused by wildfires are especially crucial.

DOM, which was first introduced by Altay and Green III in 2006 (Altay & Green, 2006), consists of the techniques for preparing a community and reducing the severity of damages caused by all disasters by developing communications systems, stockpiling inventory, building adequate structures, etc. (Hoyos, Morales & Akhavan -Tabatabaei, 2015). If executed properly, these techniques can make a community more resilient to natural disasters, (Guha-Sapir & Santos, 2012). According to FEMA (2004), the DOM life cycle can be divided into four major stages: mitigation, preparedness, response and recovery. This four-phase life cycle provides a more focused view of emergency operations and management actions. Emergency responses involve the employment of resources and emergency procedures as guided by plans to preserve life, property, the environment, and the social, economic, and political structure of the community. The emphasis in emergency response operations is primarily placed on relief distribution, facility location and casualty transportation. Related emergency logistics planning includes the optimal pick-up and delivery schedules for vehicles within a considered time window and the optimal quantities and load types picked up and delivered on these routes. In terms of the emergency logistics planning for wildfires suppression, it includes the storage, transportation and delivery of rescue resources and the allocation and management of equipment and materials (e.g., fire-fighting forces and fire-fighting equipment). All these activities aim to reduce the damage caused by wildfires and assist with fire disaster relief operations.

Nevertheless, the decision-making process for emergency logistics planning has never been straightforward. This process differs greatly from its counterparts in normal business logistics because it involves a high level of urgency and uncertainty in terms of the number of people affected and in need of attention (Christie & Levary, 1998; Pedraza-Martinez & Wassenhove, 2012). Policy makers and technicians request scientific models to explain the damage caused by disasters and establish future scenarios of disaster risk evolution conditions (Rodrigues, Riva & Fotheringham, 2014). Therefore, employing suitable tools and techniques to model this stochasticity in the decision-making process for effective preparedness and response to disasters is essential. Regarding wildfires, the need for such tools has led to the development of several prediction models (Martínez et al., 2009; Thompson & Calkin, 2011; Ager et al., 2014) that focus on explaining spatial-temporal patterns with regard to certain variables (physiographic, infrastructural, socio-economic and weather-related) relating to the ignition of wildfires. However, in the literature, few studies incorporating wildfire propagation and logistics planning for disaster relief, revealing a research gap concerning appropriate solutions for these types of logistic problems.

In the abovementioned context, this paper aims to develop a two-layer emergency logistics system with a single depot and multiple demand sites for wildfire suppression based on the predicted trend in fire. The work described herein considers wildfires in the Daxingan Mountains in China as real investigation cases and applies the theories and methodologies of emergency logistics management, forest science and operations research. The novelty of this work arises from the improvement it makes on a well-established propagation model (i.e., the Wangzhengfei model) by rendering this model capable of accurately predicting the fire propagation behavior in the Daxingan Mountains to minimize the impact of the dynamic characteristics of fire behavior on the distribution of suppression resources. It ranks the severity of the fire sites in terms of indices representing the potential burned areas to assign the emergency priorities accordingly.. Moreover, this work presents a new method for solving the allocation problem and vehicle routing problem (VRP) for the distribution of suppression recourses by distinguishing lower and higher propagation speeds.

To achieve this aim, the paper is organized as follows. Section 2 describes the relevant studies in the literature. Section 3 presents the fire propagation models, whereas Section 4 investigates the emergency logistics planning models (i.e., VRP) based on the outcomes from Section 3. In Section 5, real-world cases based on historical data concerning wildfires in the Daxingan Mountains are analyzed to demonstrate and verify the models. Finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

Emergency logistics is distinct from general business logistics in the following four respects (Caunhye, Nie & Pokharel, 2012): a) Relief services are both urgent and highly diversified. b) Accurate real-time information regarding urgent relief demands is nearly impossible to obtain. c) The benefits of emergency logistics operations are always discounted because of non-emergency reactions. Often, emergency logistics decisions are focused more on efficiency and less on cost. d) Governments intervene the market behavior to jointly participate in emergency logistics services. Emergency logistics has also raised numerous challenging issues (Sheu, 2007): a) The definition of emergency logistics remains ambiguous. b) The timeliness of relief supply and distribution is hardly controllable in the context of emergencies. c) Resource management for emergency logistics remains challenging. d) Accurate, real-time relief demand information is required but almost inaccessible. Therefore, the existing studies are classified into two categories: (1) humanitarian or DOM during the response stage, especially for emergency logistics planning (Caunhye et al., 2016; Gutjahr & Nolz, 2016; Wang, Du & Ma, 2014) and (2) disaster dynamic prediction and evaluation of the emergency level (Sheu, 2010).

2.1 Humanitarian or disaster operations management

Regarding studies on humanitarian or disaster operations, Caunhye, Nie & Pokharel (2012) conducted a review of optimization models and classified the findings according to the type of operations undertaken (facility location, relief distribution and casualty transportation) and the model types, decisions, objectives and constraints. The urgent relief distribution problems are generally formulated as multi-commodity multi-modal flow problems with time windows (Rathi, Church & Solanki, 1992; Haghani & Oh, 1996; Lei et al., 2015; Jin et al., 2015). Fiedrich et al. (2000) developed a dynamic combinatorial optimization model to determine the optimal resource rescuing schedule in order to minimize the total deaths during a search-and-rescue period. Barbarosoğlu et al. (2002) proposed a bi-level hierarchical decomposition approach for helicopter planning during a disaster relief service operation. In this approach, the top level was used to solve the tactical decision problems involving managing the helicopter fleet, crew assignment and the number of tours undertaken by each helicopter. Özdamar et al. (2004) noted that an emergency logistics plan can be obtained by solving a dynamic time-dependent transportation problem with the objective of minimizing the unsatisfied demands of all commodities through the planning horizon. Oloruntoba, Hossain, & Wagner (2016) reviewed and analyzed three social science and management theories (i.e., internationalization, behavioral and organizational theories) as worthy of consideration by scholars and practitioners in humanitarian operations research. Finally, Rodríguez-Espíndola, Albores, & Brewster, (2017) introduced a disaster preparedness system based on a combination of multi-objective optimization and geographical information systems to aid multi-organizational decision making.

To address the uncertain and dynamic nature of disasters, Chang, Tseng & Chen (2007) developed a scenario-based, two-stage stochastic programming model for the planning of flood emergency logistics with uncertainty regarding demand locations and quantities. The first stage consisted of grouping the disaster areas and classifying their emergency levels while minimizing the expected shipping distances. The second stage consisted of a location-allocation model, which was used to select local rescue based to open, the quantities of rescue equipment to send to storehouses and the routes that emergency transportation should follow to minimize costs. Balcik & Beamon (2008) combined the problems of resource allocation and relief distribution by proposing a multi-period Mixed Integer Planning (MIP) model to determine the schedules of a fixed set of vehicles and an equitable allocation of resources by minimizing transportation and unsatisfied or late-satisfied demand costs and maximizing the benefits to aid recipients for local distribution sites using a rolling horizon to address uncertainties in supply and demand. Subsequently, Rawls & Turnquist (2012) developed a multi-period version of the same approach using a two-stage, dynamic and scenario-based stochastic programming model for the pre-positioning and allocation of facilities and the distribution of commodities after a disaster event with the objective of minimizing total costs. Chu & Wang (2012) presented a new approach to address event probability uncertainties and analyze the probability distribution for constructing probable fire scenarios, and Jacobson, Argon & Ziya (2012) studied the probability distributions of aspects such as the survival time and service time of patients to develop a model for assigning different priority levels to disaster victims. Wohlgemuth, Oloruntoba, & Clausen (2012) developed a multi-stage mixed integer model under variable demand and transport conditions in the context of disaster relief response planning and logistics. Huang & Song (2016) discussed an emergency logistics distribution routing problem based on uncertainty theory in which some parameters lack historical data and are given by experts' estimations. Alem, Clark, & Moreno (2016) developed a new two-stage stochastic network flow model to decide how to rapidly supply humanitarian aid to disaster victims considering the uncertainty about the exact nature and magnitude of the disaster.

Furthermore, Liberatore et al. (2013) established five major parameters based on which the uncertainties involved in humanitarian logistics are approached: 1) demand, including the size of the affected population and/or the quantities of required relief goods; 2) demand locations and 3) affected areas, indicating those directly related to the demographics of each location and the impact of the disaster; 4) supply, including considerations of the quality and availability of products in a post-disaster scenario; and finally, 5) the transportation network, including all possible damage to the infrastructure and the congestion effect. Iudin, Sergeyev & Hayakawa (2015) applied this new approach to develop a cellular automaton forest-fire model related to the percolation methodology. Their model combined the dynamic and static percolation problems and exhibited critical fluctuations under certain conditions. Rezaei-Malek et al. (2016) developed a multi-objective, two-stage stochastic, non-linear, and mixed integer mathematical model for relief pre-positioning in disaster management based on a new utility level of the delivered relief commodities.

In DOM, many models are NP-hard (Sheu, 2007; Caunhye, Nie, & Pokharel, 2012); therefore, the algorithms for solving them are intensively studied (e.g., Hoyos, Morales, & Akhavan-Tabatabaei 2015; Özdamar & Ertem 2015; Yuan & Wang 2009). For example, Wei & Kumar (2007) proposed an ant-colony optimization method to solve the multi-commodity and vehicle dispatch problems that arise in disaster relief scenarios. Subsequently, Zhang, Li & Liu (2012) proposed a local search heuristic with MIP for solving the multiple-disaster, multiple-response emergency allocation and disaster relief problems, which were associated with the stochastic occurrence of a secondary disaster.

2.2 Disaster dynamic prediction

During rescue operations, fire disasters may continue to develop. Therefore, forecasting the evolution of the disasters (e.g., the fire or flood propagation) and incorporating it into the rescue decisions is necessary (Altay & Labonte 2014; Altay & Pal 2014; Oloruntoba 2010).

Regarding disaster evolution forecasting, García et al. (1995) introduced a logit model to predict the number of fire days in the Whitecourt Forest of Alberta. Mandallaz & Ye (1997) presented a general statistical methodology for predicting forest-fire occurrence using Poisson models. Wu et al. (2015) identified three fire environment zones among the boreal forest landscapes of northeastern China using analytical methods to examine the spatial clustering characteristics of the environmental variables of climate, vegetation, topography, and human activity. This work demonstrated how a developed fire environment zone map could be used to guide forest-fire management and fire regime prediction. As these forecasts were made at a macro level, the associated results might be used to formulate preparedness plans. Sheu, Chen & Lan (2005) developed a model for forecasting relief demand and for clustering demand sites according to their individual uncertainty and urgency using a fuzzy clustering technique to allocate the daily consumption of relief commodities in disaster scenarios. The objective of this work was to minimize the costs of traveling from relief centers based on real-time analysis. The authors presented a real-time, micro-level forecast; hence, the results might be used as a basis for scheduling the operations of rescue vehicles and the delivery of emergency goods in real time. To properly support humanitarian decision makers, Charles et al. (2016) proposed a tooled methodology based on the definition of aggregate scenarios to reliably forecast demand using past disaster data and future trends.

Tzeng, Cheng & Huang (2007) developed a fuzzy multi-objective linear programming model for the design of relief delivery systems with the objectives of minimizing the total costs and total travel time and maximizing the minimal satisfaction during the planning period using a method of predicting the commodity demand at each established site and an uncertainty analysis of the achievement of each objective. This model combined emergency logistics planning and disaster spread prediction, and its dynamic planning decisions were based on the forecasted demands. Hu & Sheng (2015) conducted a similar study based on the principle of disaster spread in resource networks. They proposed a property model of resource nodes that incorporated the values of the resources, the disastrous energy of each node, the disaster spread path, and the disaster spread characteristics. To study the disaster spread dynamics, a state diagram was used to construct a microscopic behavior model for the resource nodes by treating the resource nodes as agents. Then, decision models were gradually constructed to determine the optimal time for disaster rescue and emergency resource preparation. Buscarino et al. (2015) disclosed a model that formalized an innovative methodology for simulating forest-fire propagation. This model was based on a multilayer network structure, which facilitated the establishment of flexible definitions of the spatial properties of the medium and the dynamical laws governing fire propagation. The dynamical core of each node in the network was represented by a hyperbolic reaction-diffusion equation that incorporated the intrinsic characteristics of the ignition behavior of trees.

Among the studies on disaster spread prediction (in the second category), statistical models are widely used in the risk assessment stage (Powell et al., 2016). For risk analysis of the impact of natural disasters on large-scale, critical infrastructure systems, electric power distribution systems, transportation systems, etc., Guikema (2009) proposed a statistical learning methodology that incorporated a diverse set of methods designed for performing inference analysis on large, complex data sets,. Matellini et al. (2013) developed a Bayesian network model to investigate the evolution of fires within dwellings and to assess the probabilities of the associated consequences. Holicky & Schleich (2000) studied fire protection systems and used a Bayesian network to model a building fire from its onset to the structural collapse of the building. This network included elements for the detection and automatic suppression of fires and a node representing fire brigade intervention. A fire scenario is characterized in terms of multiple interrelated variables, such as the ignition site, the nature of the fire, the fuel configuration, the number and locations of the occupants, the characteristics of the structure, and the ventilation, among others (Matellini et al., 2012). Several other studies have analyzed the emergency levels in affected areas by evaluating the degrees of severity associated with the affected areas (Sheu, 2007; Ji & Zhu, 2012).

Despite the efforts in previous works, the above review of the current literature reveals that there are few studies on incorporating dynamic disaster evaluation models into risk-based emergence logistics. To address this research gap, the kernel of this paper includes integrating models for predicting the fire propagation rates at fire sites, ranking the emergency levels of and determining the emergency priorities of the fire sites, and finally allocating resources and routing vehicles for suppression operations. The paper presents a new method developed for fighting wildfires in a typical forest area in China in terms of emergency logistics. By conducting careful calculations based on real data from wildfires that occurred in the Daxingan Mountains on March 19th, 2003, and on June 29th, 2010, we verify the model and demonstrate its advantages by comparing the findings with real-world observations.

3. PROPAGATION MODEL FOR WILDFIRES IN THE DAXINGAN MOUNTAINS

A propagation model is used to calculate the impact of factors such as combustible materials, weather conditions and terrain on forest-fire proliferation. Using a suitable propagation model enables the spread pattern of wildfires in the mountain area of interest to be estimated, and the suppression or daily protection effort to then be effectively implemented based on the forecasted results. The most studied propagation models for this purpose are those for surface fires because they are the most common type of wildfires in mountain areas. There are two well-known classes of these models: real forest-fire models, in which adjacent trees catch fire in a step-by-step manner, and simplified versions, which involve instantaneous combustion (Iudin, Sergeyev & Hayakawa, 2015).

The systematic propagation models are the Rothermel model, the McArthur model, the Canadian propagation model and the Wangzhengfei propagation model (Sullivan, 2009). The Rothermel model simulates flame front propagation according to the principle of the conservation of energy. This model has been widely applied in mountain areas, where combustible materials are evenly distributed and the effects of large clusters of combustible materials can be ignored (Rothermel, 1983). However, because the Rothermel model is semi-experimental, certain parameters have to be obtained through experiments, and considerable input data are needed. In most areas of China, this model cannot be used because of data unavailability (Weise & Biging, 1997; Perry, 1998).

The McArthur model, a mathematical description of McArthur's gauge for measuring fire risk, was developed by Noble, Gill & Bary (1980). This model can be used to forecast fire weather situations or to predict certain parameters of fire behavior. Because it can be used only in areas where combustible materials exist in discrete units (e.g., grassplots or eucalyptus plantations), it has typically been applied in areas with a Mediterranean climate and hence is not suitable for areas with other climates (e.g., the Daxingan Mountains in China) (Chai, Zhao & Du, 1988; Yue, Feng & Jiang, 2007; Miao et al., 2012).

In the Canadian forest-fire propagation model, combustible materials are divided into five categories based on Canadian vegetation types: conifers, broad-leaved trees, mingled forest, cutting bases and open ground. It is a statistical model, and the propagation rate equation was determined by inspecting the attributes of 290 forest fires. Although the Canadian propagation model can clearly reproduce the entire evolution of a forest fire and forecast the flame behavior and fire development pattern, it does not consider the heat transfer mechanisms of the combustible materials. Because it lacks a physical basis, the model's accuracy becomes questionable when the actual conditions differ substantially from those corresponding to the experimental data used to construct the model.

The Wangzhengfei propagation model was developed based on real data from wildfires in the Daxingan Mountains and is suitable for other areas with slopes of less than 60° (Yang, Tang & Li, 2011). Because the Daxingan Mountains exhibit an undulating topography with slopes of less than 15° accounting for 80% of the area, this model is selected to provide basic insights for the updated fire propagation model in this work. The Wangzhengfei propagation model is described as follows.

- **Model Assumptions**

A1: The initial fire propagation rate varies linearly with temperature and wind power;

A2: The target area exhibits an undulating topography, with no slope greater than 60°;

A3: The target area contains regions of grassy marshland, secondary forest and coniferous forest;

A4: The weather data are available in a timely manner.

- **Model Structure**

Fire propagation model: $V_F = V_0 K_S K_W K_\varphi = V_0 K_S K_\varphi e^{0.1782 V_w}$ (1)

Initial propagation speed model: $V_0 = aT + bW + c$ (2)

Here, V_F is the flame spread rate (m/s), V_W is the wind speed (m/s), V_0 is the initial flame spread rate (m/min), K_S is a coefficient representing the different types of combustible materials, *W* is the wind force (grade), K_W is the coefficient of the wind force, K_φ is the coefficient of the geographic slope, φ is the slope, *T* is the temperature (°*C*); and *a*, *b*, and *c* are parameters. Based on the research by Wang (1992), parameters *a*, *b*, and *c* in the Daxingan Mountains are usually equal to 0.053, 0.048, and 0.275, respectively.

➢ **Variables and Parameters**

(1) Initial spread speed

This quantity represents the physical and mechanical attributes of the combustible materials and their degrees of wetness/dryness; its value is typically estimated by burning samples of combustible materials and by the present temperature and wind force.

(2) Coefficients for different types of combustible materials

These quantities represent the degree of inflammability of each material and its suitability for burning. The main types of combustible materials present in the Daxingan Mountains are marshy grassland, secondary forest and coniferous forest. The corresponding coefficients are therefore $K_{s\ marshy}$=1.0, $K_{s\ secondary}$ =0.7, and $K_{s\ coniferous}$=0.4 (Wang, 1992).

(3) Coefficient of the wind force

A higher wind speed results in more rapid spreading of flames following the wind, i.e., a higher wind-induced yield value K_w. For a grassland region with zero slope, the V_F values corresponding to wind forces of grades 1-12 are listed in Table 1 (Wen & Liu, 1994).

Table 1 Wind speeds and wind forces for a grassland region with zero slope

Wind Grade	1	2	3	4	5	6
V_w *(m/s)*	2	3.6	5.4	7.4	9.8	12.3
V_F *(m/min)*	6.18	13.85	50.00	64.55	83.33	144.33
Wind Grade	7	8	9	10	11	12
V_w *(m/s)*	14.9	17.7	20.8	24.2	27.8	29.8
V_F *(m/min)*	250.00	353.55	500.00	599.02	625.00	833.00

(4) Coefficient of the geographic slope

This parameter is one of the most important factors affecting fire propagation. The impact of the slope on the propagation speed K_φ is summarized in Table 2 (Wen & Liu, 1994).

Table 2 K_φ values corresponding to different slopes

Slopes	-42°~-38°	-37°~-33°	-32°~-28°	-27°~-23°	-22°~-18°	-17°~-13°
K_φ	0.07	0.13	0.21	0.32	0.46	0.63
Slopes	-12°~-8°	-7°~-3°	-2°~2°	3°~7°	8°~12°	13°~17°
K_φ	0.83	0.90	1.00	1.20	1.60	2.1
Slopes	18°~22°	23°~27°	28°~32°	33°~37°	38°~42°	

K_φ	2.9	4.1	6.2	10.1	17.5	

4. RELIEF ALLOCATION AND VEHICLE ROUTING MODEL

Relief allocation and delivery models consider the demand at each fire site and the transportation of supplies to these sites by allocated vehicles. The vehicles begin their itineraries at depots and may serve several wildfire sites along their own routes. During this phase, the demand quantities and location uncertainties are the major factors influencing rational decisions.

Because allocation and delivery decisions determine the suppression efficiency, optimizing these decisions together based on different fire scenarios is necessary. During the suppression operations, various supplies are needed at different fire sites, and a rescue depot may store many different types of emergency resources. There are two main types of emergency resources that are needed to combat wildfires: fire-fighting forces and fire-fighting equipment. Emergency logistics involving wildfires include the storage, transportation and delivery of rescue resources and the use and management of the equipment and materials. Among the activities, the most fundamental are the transportation and scheduling of the fire-fighting forces.

4.1 Problem Statement

Rescue commanders optimize the allocation of suppression resources and the routing of vehicles based on the rate of fire propagation at each site (10 m/min is the critical rate) (Yao & Wen, 2002). In the case of rapid propagation (V_F>10 m/min), the rescue commanders may arrange several vehicles to transport suppression resources to each fire site to minimize total losses (Figure 1). When the fire propagation rate is slow (V_F<=10 m/min), the commanders may send resources to several fire sites via one vehicle (Figure 2) (Zhang, 2007; Sun, Chi & Jia, 2007). This work investigates the resource allocation and vehicle dispatch problems for both cases.

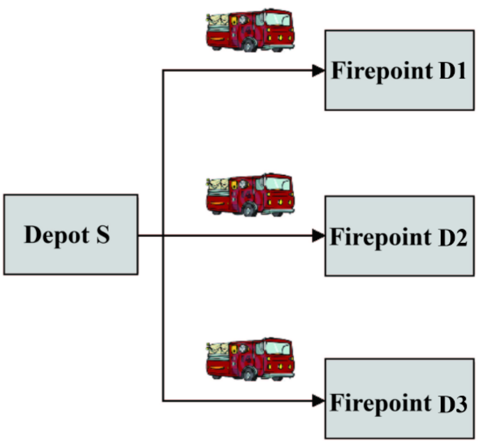

Figure 1 Rescue Operation for Fast Propagation

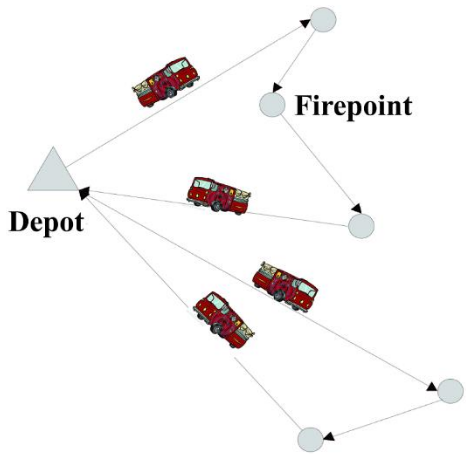

Figure 2 Rescue Operation for Slow Propagation

4.2 Optimization Model for Rapid Fire Propagation

Suppose that a system for the transportation of suppression recourses for combating a wildfire consists of a single depot *S* (with capacity *s*) and *I* fire sites (demand points with demands d_i $(i=1,2,\ldots,I)$ for each site).

For the allocation and transport of the resources, both efficiency and equity should be considered; i.e., resources should be delivered to the demand sites as soon as possible, and each demand site should receive them on a just-in-need basis. During the suppression period, the decision makers must maximize the total benefit from all fire sites. Therefore, they should rank the severities of the fire sites based on the consequences of the fire accidents and damage attributes to allocate and deliver resources accordingly. Consequently, fire propagation rate becomes the main attribute of concern, as sites where the propagation is more rapid will suffer more serious damage and thus should be given a higher priority.

4.2.1 Model Assumptions

A1: Flames spread evenly from each fire site, with a spread radius that is proportional to the burn time;

A2: The quantity of suppression resources is represented in combined units of fire-fighting resources in a way that the number of firemen and the amount of materials in each unit are fixed;

A3: The suppression efficiency of all firemen is the same;

A4: The rescue vehicles are identical in terms of their type and travel speed;

A5: The flame propagation speed can be estimated and pre-defined using the model;

A6: The supplies/resources available from the depot are sufficient to satisfy the demands at all fire sites.

4.2.2 Variables and Parameters

C_1 is the loss of burning a unit of forest (hm^2) in monetary terms, C_2 is the time cost of a combined suppression resource unit, C_3 is the cost of transporting one combined resource unit, X_i is the number of combined resource units allocated to fire point *i*, t_{i1} is the time at which suppression begins at fire site *i*, t_{i2} is the time at which the fire at fire site *i* is extinguished, V_{Fi} is the fire propagation speed at fire site *i*, $B(t_i)$ is the burned area at fire site *i* in period *t*, $C(t_i)$ is the loss due to fire at site *i* in period *t*, N is the number of firemen in a combined resource unit, V_i is the speed of suppression, V_T is the travel speed of an emergency vehicle, d_i is the distance from the depot to fire site *i*, A_i is the number of firemen allocated to site *i*, and X_i^* is the optimal number of combined resource units to allocate to fire site *i*.

4.2.3 Model Formulation

Let the time of ignition at fire site *i* be $t_{i0}=0$; then, the time at which the firemen arrive at the fire site is $t_{i1}= d_i/V_T$. From A1, we know that the change in the burned area $B(t_i)$ is continuous to the first order. In other words, the rate of increase is $dB(t_i)/dt_i$. Generally, the burning speed will decrease once the firemen begin the suppression operations. At fire site *i*, after fire-fighting begins at time t_{i1}, the propagation rate will decrease until the fire is extinguished at time t_{i2}. The burned area is represented by the triangle in Figure 3 and can be calculated as follows:

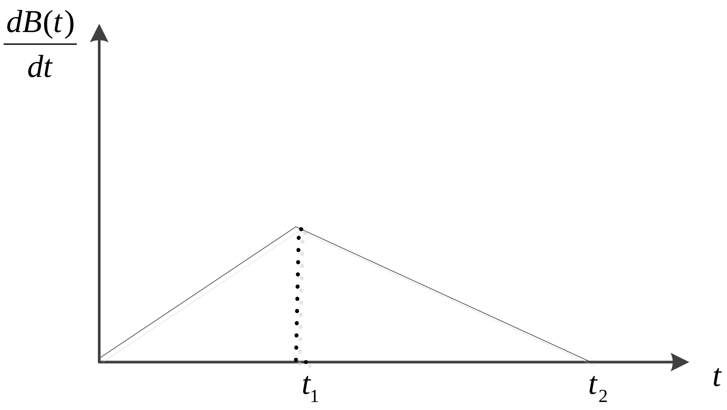

Figure 3 The area of the burned forest at a fire site

$$\frac{dB(t_i)}{dt_i}=\begin{cases}V_{Fi}t_i\,, & 0\le t_i\le t_{i1}\,,\quad i=1,2,...,I\\ V_{Fi}t_i-V_iX_i(t_i-t_{i1}), & t_{i1}\le t_i\le t_{i2}\,,\quad i=1,2,...,I\end{cases} \tag{1}$$

When $\frac{dB(t_i)}{dt_i}\Big|_{t_i=t_{i2}}=0$, $t_{i2}=t_{i1}+V_{Fi}t_{i1}/(V_iX_i-V_{Fi})$, $i=1,2,...,I$, the corresponding

area can be calculated as follows: $B(t_{i2})=V_{Fi}t_{i1}^2/2+V_{Fi}^2t_{i1}^2/2(V_iX_i-V_{Fi}), \quad i=1,2,...,I$.

In suppression, there are two kinds of costs: 1) the disposable costs of transporting suppression materials and 2) the costs of the suppression tools and the salaries of the workers. Thus, the total loss from a wildfire can be calculated as follows:

$$C(X_i)=\left(\frac{V_{Fi}t_{i1}^2}{2}+\frac{V_{Fi}^2t_{i1}^2}{2(V_iX_i-V_{Fi})}\right)C_1+\frac{C_2V_{Fi}t_{i1}X_i}{V_iX_i-V_{Fi}}+C_3X_iN_i,\quad i=1,2,...,I \tag{2}$$

The value X_i^* corresponding to the extremum of Eq. (2) is the necessary number of vehicles.

$$X_i^*=\frac{V_{Fi}}{V_i}+\frac{1}{V_i}\sqrt{(C_1V_{Fi}^2V_it_{i1}^2+2C_2V_{Fi}^2t_{i1}^2)/2C_3N},\quad i=1,2,...,I \tag{3}$$

$$A_i=N_iX_i^*=N_i\left(\frac{V_{Fi}}{V_i}+\frac{1}{V_i}\sqrt{(C_1V_{Fi}^2V_it_{i1}^2+2C_2V_{iF}^2t_{i1}^2)/2C_3N}\right),\quad i=1,2,...,I \tag{4}$$

In this suppression scheme, the earliest time that the fire can be extinguished is calculated as follows:

$$T = Max\{t_{12},\ \ t_{22},...,t_{k2}\}$$
$$= MAX\left\{t_{11} + \frac{V_{F1}t_{11}}{V_i X_1 - V_{F1}}, t_{21} + \frac{V_{F2}t_{21}}{V_i X_2 - V_{F2}}, ..., t_{I1} + \frac{V_{FI}t_{I1}}{V_i X_I - V_{FI}}\right\}, \quad i = 1,2,...,I \quad (5)$$

4.3 Optimization Model for Slow Fire Propagation

Because suppression resources must be transported within a certain time window and because the transportation cost is directly proportional to the distance that a vehicle travels, the allocation of suppression resources is a VRP concerning the routing of vehicles from the rescue depot to the fire sites under the constraints placed by the vehicles' loading capacities (Wang, Wang & Deng, 2008; Zhu, Han & Liu, 2007)

4.3.1 Model Assumptions

A1: The depot possesses sufficient vehicles, and each vehicle's loading capacity is fixed;
A2: The demands at the fire sites can be estimated based on the fire propagation rate;
A3: Each vehicle's travel speed is fixed, and the transport time is equal to the vehicle's travel time (loading/unloading times are not taken into account);
A4: A fire site with a faster propagation rate is considered to be suffering more severe fire damage and should be given a higher priority.

4.3.2 Variables and Parameters

Let S represent the depot. $D = \{i | i = 1,2,...,I\}$ is the set of fire sites; $C = \{m | m = 1,2,..., M\}$ is the set of emergency vehicles; $A = S \cup D$ is the set of all nodes, including the depot and the fire sites; C^m is the fixed cost of vehicle *m*; C_{ij}^m is the unit time cost of vehicle *m* traveling from *i* to *j*; d_{ij} is the distance between *i* and *j*; Q^m is the approved loading capacity of vehicle *m*; V_{Fi} is the fire propagation speed at fire site *i*; V_1 is the fire-fighting speed of the firemen; u_i is the demand at fire site *i* (in terms of combined resource units); $u_i = R_i / V_{i1}$; t_i^m is the time at which vehicle *m* arrives at fire site *i*; t_i^L is the latest time for the arrival of suppression materials at fire site *i*; t_{ij}^m is the time required for vehicle *m* to travel from *i* to *j*; and V_{ij}^m is the average travel speed of vehicle *m* from *i* to *j*.

$$x^m = \begin{cases} 1 & \text{vehicle } m \text{ is used} \\ 0 & \text{otherwise} \end{cases}; \quad Y_{ij}^m = \begin{cases} 1 & \text{vehicle } m \text{ from site } i \text{ to } j\ (i \neq j) \\ 0 & \text{otherwise} \end{cases} 。$$

4.3.3 Model Formulation

$$Min: F_1 = \sum_{m\in C}\sum_{i\in D} t_i^m \tag{6}$$

$$Min: F_2 = \sum_{m\in C} x^m C^m + \sum_{m\in C}\sum_{i\in A}\sum_{j\in A} C_j^m \frac{d_{ij}}{V_{ij}^m} y_{ij}^m \tag{7}$$

$$\sum_{i\in A} y_{ij}^m - \sum_{i\in A} y_{hj}^m = 0, \forall m\in C, \forall h\in I \tag{8}$$

$$\sum_{j\in D}\sum_{m\in C} y_{Sj}^m > 0 \tag{9}$$

$$\sum_{i\in A}\sum_{j\in D} y_{ij}^m u_j \le Q^m, \forall m\in C \tag{10}$$

$$\sum_{m\in C}\sum_{i\in A}\sum_{j\in D} y_{ij}^m u_j \le Q_s \tag{11}$$

$$t_i^m = t_j^m + t_{ji}^m y_{ji}^m, \forall i, j\in A, \forall m\in C \tag{12}$$

$$t_i^m \le t_i^L, \forall i\in D, \forall m\in C \tag{13}$$

$$y_{ij}^m = \{0,1\}, \forall i, j\in A, \forall m\in C \tag{14}$$

$$x^m = \{0,1\}, \quad \forall m\in C \tag{15}$$

In a suppression operation, both suppression speed and cost should be considered; thus, when the fire is propagating slowly, the optimization model may have two objectives. Eq. (6), which is the primary objective, minimizes the total travel time of the emergency vehicles. Eq. (7), which is the secondary objective, minimizes the total cost of the emergency vehicles. The constraints are as follows.

Eq. (8) means that each vehicle will depart immediately after unloading at a fire site. Eq. (9) means that the rescue depot *S* possesses sufficient vehicles to dispatch. Eq. (10) means that the demand at any fire sites should be less than the vehicle capacity. Eq. (11) means that the sum of the demands at all fire sites should be less than the inventory of depot *S*. Eq. (12) means that the travel time from depot *S* to fire site *j* is equal to the combination of the time of the vehicle's arrival at site *i* with the travel time from *i* to *j*. Eq. (13) means that the time of a vehicle's arrival at a fire site should be earlier than the latest time at which the site requires the resources.

5. Case Study

5.1 Case of Rapid Propagation

1) Fire Attributes

According to the database of the Wildfires Prevention Headquarters of the Heilongjiang province and the Scientific Data Share Center of the China Meteorological Administration, a large-scale wildfire occurred in the Nanweng River area in the Daxingan Mountains at 10:35 on March 19th 2003. There were 4 fire sites in total: Wuoduhe (WDH), Xiaogushan (XGS), Naduli (NDL) and 597-Highland (597H). The areas are mainly covered by marshy grassland, brushwood and forest. The total affected area was 133,008 hm^2, consisting of 240 hm^2 of burned forestland and 132,768 hm^2 of barren mountain grassland. The suppression operation was undertaken by 385 professional firemen and 1936 forest rangers. The fire was extinguished at 13:50 on May 23rd, 2003. Some of the detailed information that was obtained is shown in Table 3 and Table 4. Other parameters were evaluated based on the interviews with the workers in the Forestry Bureau of the Daxingan Mountains and were as follows: c_1=15 Yuan, c_2=1.3 Yuan, c_3=0.82 Yuan, v_2=100 km/h, v_1=12.5 m/min, and N=3 persons.

Table 3 Meteorological data at the fire sites

	WDH (i=1)	XGS (i=2)	NDL (i=3)	597H (i=4)
Av. Temperature (°C)	6	7	5.5	6
Av. Wind Speed (m/s)	7.5	6.2	5.1	5.5
Av. Wind Force (G)	4	4	3	3

Table 4 Geographical data at the fire sites

	WDH (i=1)	XGS (i=2)	NDL (i=3)	597H (i=4)
Slope (°)	0	15	2	10
Types of combustible materials	grassland	grassland	grassland	grassland
Dis. to Rescue Depot (km)	24.7	30.5	31.2	28.6

2) Solution Results

According to the models presented above (i.e., Eqs. (1-2)), the propagation rates at the four fire sites (WDH, XGS, NDL and 597H) were V_{F1}=179.38 m/min, V_{F2}=318.94 m/min, V_{F3}=105.84 m/min, and V_{F4}=188.64 m/min, respectively. The calculated allocation results for the combined suppression resource units and firemen teams are listed in Table 5. Comparing Table 5 with Table 6 reveals that with the optimized allocation of the combined suppression resource units and firemen teams, the wildfires could have been extinguished in a much shorter period of time. The shortest time required for putting out the fire at a single site is found to be 19.3 hours. Compared with the actual period of 2 months, the optimized resource allocation and transportation scheme is much more efficient, albeit higher in cost. In the optimized analysis, 27,903 firemen are needed, which is 10,000 more than the number of firemen who participated in the real case, and the number of combined fire-fighting resource units is 9,301, which is 4 times greater than the actual number used. However, the higher cost may be well justified by the actual loss of forest resources suffered.

Table 5 Allocation scheme for emergency supplies

	WDH (i=1)	XGS (i=2)	NDL (i=3)	597H (i=4)
Number of combinations (unit)	1804	3951	1350	2196
Number of firemen (people)	5412	11854	4049	6588
Cost for fire-fighting (yuan)	4718.4	10332.9	3529.3	5743.2
Shortest extinguish fire time (m)	15.4	18.9	19.3	17.8

Table 6 Comparison of real and optimized results

	Time to extinguish fire	Combinations	Needed firemen	Cost for fire-fighting	Expense of forest resources
Actual	2.0 Months	3897	16,143 Persons	2,296 Yuan	1,995,120 Yuan
Optimal	19.3 Hours	9301	27,903 Persons	24,324 Yuan	1,803,611 Yuan

5.2 Case of Slow Propagation

1) Description of the Wildfire

At 10:40 on June 29th 2010, a wildfire was caused by lightning strikes in the Huzhong zone in the region administered by the Huzhong Forest Administrative Bureau. There were 7 fire sites: 1231-Highland (1231H), H311 Line (H311), X59 Line (X59), H59 Line (H59), LWM12 Line (LWM12), LWM3 Line (LWM3) and T6 Line (T6). The area involving the fires was approximately 138.5 hm^2. The suppression activities were undertaken by 500 professional firemen and 140 forest rangers. The wildfire was extinguished on July 3rd. The distances between fire sites and the meteorological and geographical data, which were obtained from the Forestry Bureau of the Daxingan Mountains, are provided in Table 7, Table 8 and Table 9.

Table 7 Distances between fire sites

	Depot	1231H	H31	X59	H59	LWM12	LWM3	T6
Depot	0	42	56	63	65	50	66	45
1231H	42	0	20	33	45	35	48	64
H31	56	20	0	46	53	44	42	58
X59	63	33	46	0	60	55	52	54
H59	65	45	53	60	0	62	64	56
LWM12	50	35	44	55	62	0	65	66
LWM3	66	48	42	52	64	65	0	63
T6	45	64	58	54	56	66	63	0

Table 8 Meteorological data at the fire sites

	Depot	1231H	H31	X59	H59	LWM12	LWM3
A. Temperature (°C)	25	23	22	26	24	23	22
A. Wind Speed (m/s)	3.6	2	2	3.6	3.6	3.6	2
A. Wind Force (Grade)	2	1	1	2	2	2	1

Table 9 Geographical data at the fire sites

	Depot	1231H	H31	X59	H59	LWM12	LWM3
Slope (°)	10	2	5	15	13	8	8
Type of Combustibles	Meadow	Meadow	Meadow	Meadow	Meadow	Meadow	Meadow
Time Limit (h)	4	6	6	3	4	5	6

The Huzhong Forest Administrative Bureau fire station used 3 vehicles to send suppression materials to the 7 fire sites. The capacity of each vehicle was 9 tons, and the travel speed was 100 km/h. The fixed cost and unit time cost of each vehicle were 150 Yuan and 100 Yuan/h, respectively. One combined resource unit consisted of two instruments, one water cannon, one water pump and three firemen. The weight of one combined resource unit was 1000 kg, and the suppression speed was 2.5 m/min.

2) Results of the Allocation Model

The fire propagation rates at the 7 fire sites were calculated using the above propagation model (i.e., Eqs. (1-2)), and the results are shown in Table 10.

Table 10 Fire propagation rates at the seven fire sites

	Base	1231H	H31	X59	H59	LWM12	LWM3
Propagation Rate (m/min)	5.16	2.20	2.55	6.98	6.56	4.83	3.40

Based on these speeds, the rescue priorities were ranked. A site with a higher priority ranking requires suppression materials more urgently. Therefore, the emergency vehicles should proceed from sites with higher scores to sites with lower ones. With the depot coded as 0, the demands calculated according to the suppression speed and the fire propagation rate at the fire sites are shown in Table 11 in terms of combined resource units.

Table 11 Demands for emergency materials at the seven fire sites

Priority Ranking	Fire Point	Demand Combination
1	H59 Line (Point 1)	3
2	SWM12 Line (Point 2)	3
3	1231 Highland (Point 3)	2
4	SWM3 Line (Point 4)	2
5	T6 Line (Point 5)	1
6	X59 Line (Point 6)	1
7	H31 Line (Point 7)	1

3) Vehicle Routes

The VRP model could be effectively solved using an immune clonal algorithm (ICA) (Ma, Gao & Shi, 2009). The ICA, which is derived from the traditional evolutionary algorithm, introduces the mechanisms of avidity maturation, cloning and memorization. The performance of the corresponding operators is characterized by rapid convergence and a good global search capability. The property of rapid convergence to a global optimum of ICA is used to accelerate the searching for the most suitable subset among a number of vehicle routing plans (Zhang et al., 2005). The parameters of the algorithm were denoted as follows: initial population of an immune body, N=100; number of codes in each immune body, $a_i(it)$=21; terminating generation, g_{max}=100; clone ratio, q=5; the expected remaining population of an immune body, N_n=20.

Given that objective 1 (i.e., Eq. (6)) carries much more importance than objective 2 (i.e., Eq. (7)) in the decision-making process, we assigned them different weights, w_1=α=0.9 and w_2=(1-α)=0.1, to combine them into the integrated objective function F=αF_1+(1-α)F_2. After

50 generations of calculations, the output results were obtained as follows.

1) The optimal routes of the 3 vehicles were found to be 0→1→5→0 (for Vehicle 1), 0→2→6→0 (for Vehicle 2), and 0→3→4→7→0 (for Vehicle 3). The total transportation time of all vehicles is 6.05 hours, and the corresponding cost is 6,720 Yuan.

2) The vehicle arrival time, transportation costs and travel distances on each path are listed in Table 12.

Table 12 Vehicle routes and the corresponding costs and distances

	Vehicle	R-0	F-1	F-2	F-3	F-4	F-5	F-6	F-7	R-0	Sum.
Arrival Time	1		0.65	-	-	-	1.21	-	-	1.66	1.86
	2		-	0.5	-	-	-	1.05	-	1.68	1.55
	3		-	-	0.42	0.90	-	-	1.32	1.88	2.64
Trans. Cost (yuan)	1	-	-	-	-	-	-	-	-	-	2160
	2	-	-	-	-	-	-	-	-	-	2180
	3	-	-	-	-	-	-	-	-	-	2380
Trans. Dis. (km)	1		65	-	-	-	121	-	-	166	166
	2		-	50	-	-	-	105		168	168
	3		-	-	42	90	-	-	132	188	188

The results indicate that the vehicles can reach all the fire sites in less than two hours without compromising the efficiency of suppression. Meantime, on each path, a site with more severe fire conditions will be given a higher priority. The vehicles always travel from high priority sites to the low priority sites.

6. DISCUSSIONS and CONCLUSIONS

This paper proposes a new two-layer emergency logistics system for wildfire suppression involving a single depot and multiple demand sites. The real case analysis substantiates that during a wildfire suppression operation, the plans for allocating and transporting suppression resources have a strong impact on the efficiency of the operations. Compared with the existing findings in Lee et al. (2013), the resource deployment is optimized and shifted from the planning sites with the highest fire burned areas to the planning sites with the highest standard response requirements (i.e., highest priority). As a result, the optimal resource allocation and vehicle routing plans based on our optimization model are a better solution compared to the existing findings in the literature. Thus, the proposed optimization models provide powerful insights into emergency logistics planning for wildfire suppression operations. Because of the high research demand on emergency logistics for dynamic disaster relief (taking into account risk evolution), the findings from this study can also be generalized to tackle other logistics resource optimization issues in dynamic operational environments, particularly those sharing the same feature of a single supply and multiple demands in logistics planning and operations (e.g., allocation of ambulances and police forces).

The major contributions of this work are the ability of the models to analyze the emergency logistics operations by considering different fire propagation patterns and the factors affecting those patterns. Fire propagation models are constructed to calculate the fire propagation rate and the damaged area at each fire site. The outcomes can serve as suitable criteria for determining the priority of demand for suppression resources. An emergency logistics delivery plan based on dynamic fire propagation behavior is applied to address wildfire suppression in real time. According to historical data from wildfires that occurred in the Daxingan Mountains, two case studies are analyzed to verify the proposed models and validate the findings that different logistics planning schemes should be adopted for wildfire accidents with different fire propagation rates. The optimal results based on minimizing the disaster losses and logistics costs in the case of slow propagation demonstrate that transporting suppression resources to several fire sites using a single vehicle is more effective. In this case, the VRP is the most important concern. By contrast, in the case of rapid fire propagation, each fire site must be served by one or more dedicated vehicles; therefore, matching the fire sites to the corresponding vehicles is the most important consideration.

The study left some problems unsolved. First, when combining objective 1 and objective 2 into the integrated objective function, we consider α to be 0.9 in the empirical study and analyzed the case in which objective 1 carries much more importance than objective 2 in the decision process. Assigning α different values in a sensitivity analysis to test its influence on the final decision could reveal the optimal solutions in dynamic and different scenarios and thus aid in better decision making. Second, in the fire propagation model, we use the flame spread rate as the dominant indicator to predict the fire development pattern; however, several other indicators (e.g., fire intensity and flaming area et al.) could possibly have some effects on the fire propagation trend. Therefore, investigating how their individual/combined effects influence the accuracy of the fire propagation model is a worthwhile future direction. Finally, in the relief allocation and vehicle routing model, the impact of the conditions of wildfires suppression paths on the optimization results can be further investigated. Given that the conditions of the suppression paths may also affect the total cost of the emergency vehicles, a comparative study of the relief allocation problem and VRP under different suppression path conditions based on the existing research would be interesting.

Our possible future research plan includes studies of the relief allocation problem and VRP for wildfire suppression with multiple depots and a single demand site or multiple depots and multiple demand sites. This research plan may also involve comparative analysis the suitability of different optimization algorithms (e.g., the ant-colony algorithm and genetic algorithm) for solving these kinds of relief allocation and vehicle routing issues.

ACKNOWLEDGEMENTS

The authors would like to thank the EU FP7 Marie Curie IRSES project "ENRICH" (PIRSES-GA-2013-(612546)) for its financial support.

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