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DeGroote School of Business

McMaster University

Hamilton, Ontario, L8S 4M4

Canada

yuanyuf@mcmaster.ca

ABSTRACT

In this paper, we characterize the lifesaving objectives of emergency resource allocation and distribution in disaster response operations, and propose an integrated model that captures these objectives. We identify two types of fundamental needs in life saving operations. The need to "save as many lives as possible" is modeled as a lifesaving utility function; while the need to "save lives as quickly as possible" is modeled as a delay cost function. We also model the fairness consideration in resource allocation by balancing lifesaving utility, delay cost and equality. We also use a rolling horizon approach based on time space network to incorporate frequent information and decision updates; and integrate resource allocation and emergency distribution into one model. The integrated model is shown to be a linear or convex quadratic network flow problem. A case study on the Great Sichuan Earthquake in 2008 is used to explain the meaning of the important parameters and highlight the managerial implications.

Keywords: emergency logistics, humanitarian relief, disaster, resource allocation, distribution, mathematical programming

INTRODUCTION

After the “911” terrorist attacks in the United States, effectively responding to unpredictable and irregular emergency events has become of primal importance to society. Especially during recent years, large scale natural or man-made disasters have occurred frequently[1]. These disasters have caused large numbers of casualties and have often destroyed infrastructures such as electricity supply, transportation, and communication systems. The critical issues in such extreme events are how to respond immediately and how to schedule responses that can minimize the consequences of these disasters[2]. In this context, emergency logistics has been receiving greater attention by more and more academic scholars and emergency management practitioners[3-5]. Emergency logistics is defined as “the support function that ensures the timely delivery of emergency resources and rescue services into the affected regions”[6] while humanitarian logistics is aimed at aiding people in surviving during and after a disaster. We do not emphasize the differences between emergency logistics and humanitarian logistics, and use the term to include both emergency and humanitarian logistics.

In the existing literature, the necessity and importance of Operations Research / Management Science (OR/MS) models in emergency logistics have been well recognized[7]. Researchers in OR/MS have successfully identified many important research problems[4,8] such as resource allocation, evacuation, demand assessment, and emergency distribution. However, most existing works rely on traditional OR models, and do not address the challenging characteristics of emergency logistics well[2,3,9,10].

In this paper, we consider rescue resource allocation and emergency distribution in the response phase of a disaster, in particular during the critical 72 hour time window directly after the event[1]. We propose an integrated model that can capture the essential lifesaving objectives of emergency response to large scale disasters. Our work differs from most existing studies in several aspects. We notice there are two types of needs in emergency response. These two needs can be summarized as “save as many lives as possible” and “reduce the pain of people waiting for supplies as quickly as possible”. We model these two needs as lifesaving utility and delay cost respectively and integrate them into the objective. Fiedrich et al.[11] and Arora et al.[12] also emphasize the importance of life saving utility, but they ignore the delay cost. There are also works that focus on minimizing the time to fulfill demands[13-15]. These works do not link time delays to possible consequences of resource shortage.

We also model fairness in emergency logistics. In de la Torre et al.[16], the vehicle routing policies are divided into two classes. Egalitarian policies maximize equality of delivery quantity or time, while utilitarian policies maximize the fulfilled amount of demand. Huang et al.[17] study an egalitarian policy that minimizes the variance among the delivery times. They assume there is no need for resource allocation, which is often not the case in emergency logistics. Our approach differs in that we introduce an equality adjustment parameter, which allows us to make a tradeoff between the necessity to satisfy areas with more urgent needs and improve equality in serving all the areas.

We propose to use a time space network and a rolling horizon approach to capture the dynamic nature of emergency logistics. Our model allows arrivals of supplies and demands at different times, and the evolution of input data. The time space network approach has also been used by Haghani and Oh[18] and Rottkemper et al.[19] to tackle different but related research problems.

We integrate resource allocation and emergency distribution into one model. A similar work can be found in Balcik et al.[20], where they also consider such integration. However, their work mainly focuses on pick-up and delivery problems while our model incorporates the time space network and a different objective function.

Our model not only has conceptual appeal, but also incorporates computational efficiency. Our integrated model can be shown to be a linear or convex quadratic network flow problem, which is well studied in the literature[21,22]. This makes our model especially suitable for real time decision support.

Our paper is organized as follows. In Section 2, we conduct a literature review and identify the gaps in existing solutions. In Section 3, we build an integrated model for emergency logistics. In Section 4, we discuss the managerial implications of important model parameters. In Section 5, we present a case study based on the Great Sichuan Earthquake of May 12, 2008. Finally, we discuss the conclusions of our paper and suggest future research directions in Section 6.

LITERATURE REVIEW

In this section, we review existing research efforts that are closely related to our work. Literature regarding a comprehensive review of disaster management was reviewed[4,7,8,23]. We categorize the literature based on four dimensions and summarize the resulting classification in Table 1. The four dimensions are disaster scenarios, decision problems, objectives, and methodologies.

We first look into disaster scenarios. It is important to realize that emergency response operations may be quite different for different types of disasters. For example, an earthquake often impacts the transportation infrastructure, while a pandemic flu does not. In Table 1, although a few studies specify the disaster type, such as earthquakes[11,24] and pandemic flu[12], most works discuss general disasters.

In the second dimension in Table 1, we group the studies into decisions based on demand assessment, resource allocation, and emergency distribution.

(1) The first challenge in immediate disaster response is to gather demand information from affected geographical areas. Potential problems include information gathering and communication, demand requirement forecasting, priority ranking, as well as area grouping. In Sheu[5,25] the author investigates time-varying relief demand forecasting, area grouping and information uncertainty evaluation. Another work on the area grouping problem was conducted by Gong and Batta[24].

(2) The next issue is to allocate (limited) resources to affected areas based on their differing priorities. Fiedrich et al.[11] first pointed out the significance of optimal resource allocation to affected areas during the initial search-and-rescue period after large scale earthquakes. Sherali et al.[26] discuss general resource allocation after a natural disaster occurs. Some other works

consider specific resources. For example, Gong and Batta[24] consider ambulance allocation and Arora et al.[12] study antivirus resource allocation in a pandemic flu. Resource allocation in immediate disaster response often involves multiple resources with different requirements (e.g. periodical need vs. one-time need). Nevertheless, current research seldom models multiple relief items.

(3) The most popular research decision problem in Table 1 is emergency distribution. Most works have focused on road damage, or vehicle availability, etc. Besides such conditions, it is difficult to distinguish these models from traditional distribution problems.

In the third dimension, we consider the objectives of the research studies. Objectives can reflect the attitudes and principles of decision makers. In the context of emergency logistics, the primary goal is to save lives and reduce property loss under pressure of limited resource and time. However, most works focus on improving distribution performance through travel cost and time. A few researchers have focused on the value of life saving, and the assessment of demand fulfilment.

In terms of methodologies used in these studies, most researchers follow deterministic optimization methods. Some works model the inherent uncertainties via scenario analysis or stochastic programming[27]. In emergency logistics, it is often critical to arrive at a good solution quickly. Thus many studies use artificial intelligence methods[13,25,28]. In addition, some researchers use simulation methods.

In summary, a majority of these efforts rely on traditional OR models and do not capture the critical characteristics of emergency logistics, especially in the context of large scale disasters.

Table 1: A Classification of Emergency Logistics Literature

Disaster scenario
Non-specified [14,20,26-32]
Earthquake [11,13,15,24,25]
Pandemic flu [12]
Decision problem
Demand assessment [13,24,25]
Resource allocation [11,12, 24,26,]
Emergency distribution [13-15,20,27-32]
Objective
Lifesaving [11,12]
Demand fulfilment [13-15,20,30]
Distribution performance (time, cost, path, etc.) [13,15,20,24,27-29,31,32]
Methodology
Deterministic mathematical programming [11,12,14,15,24,29-32]
Scenario analysis / stochastic programming [27]
AI methods (fussy logic, entropy, immune affinity, etc.) [13,28]

For example, the objectives of current studies mainly focus on improving distribution performance. Moreover, many researches only consider emergency distribution, assuming resource allocation is not an issue. This is unrealistic in disaster response operations, where resource allocation and distribution issues are intertwined. In the following, we propose a model that addresses gaps in the current literature.

MODEL DEVELOPMENT

Problem Description

A disaster often causes severe damage and threatens people's lives. Humanitarian aid is urgently needed in order to save lives and relieve the suffering of people in affected areas. Our research problem is how to distribute and deliver humanitarian aids from supply locations to demand locations efficiently through a transportation network in order to maximize lifesaving and minimize human suffering.

We assume that the demands and supplies are geographically distributed and dynamically changing. Decisions have to be made dynamically based on available real-time information. We use a rolling horizon approach to cope with information updates[33]. At each decision epoch, we consider a discrete finite planning horizon, $t = 0,1,\cdots,T$, where $t = 0$ represents the present decision epoch. We consider a single rescue item. There are n locations connected through a transportation network. Let $d_j \geq 0$ be the demand at location j; let $s_{jt} \geq 0$ be the available resource or supply (for allocation) at location j at time t, also called supply. Both d_j and s_{jt} are known model inputs; and there are multiple demands and supplies. We call a location with positive d_j a demand location; a location with positive s_{jt} for **sofome** t a supply location. It is referred to as a transfer location otherwise. We denote the collection of demand locations as G. A location can be both a demand location and a supply location.

There are two types of decision variables. Let y_{jt} represent the resource *allocated* to location j and *received* at time t; we call y_{jt} the resource allocation decision variables. Let $x_{jt,j't'}$ represent the flow originating at location j at time t and arriving at location j' at time t^0; we call the $x_{jt,j}0_t0$ the distribution decision variables or routing decision variables.

We assume that all the decision variables are continuous.

The Objective Function

We consider three different elements related to lifesaving in the objective function: Lifesaving utility, delay cost, and fairness. We will address these elements separately and then integrate them into one objective function.

Linking demand and supply to lifesaving. To characterize a demand, it is insufficient to use the number of items needed. Demand is attached to people, and people differ in terms of health condition, self-help capability, etc. In humanitarian relief, the same item may have different life saving effects on different people. We define the lifesaving utility as the effectiveness of life saving of a relief item.

Let $Q_j = \sum_{t=0}^{T} y_{jt}$, i.e. the total resource received at location j in the entire planning horizon. Function $L_j(Q_j)$ represents the lifesaving utility at location j after receiving resource Q_j, defined for $0 \leq Q_j \leq d_j$; specifically, $L_j(Q_j)$ represents the increase in survival rate or welfare of the affected people at location j. This definition is consistent with Salmeron and Apte[34], in a context of pre-positioning of hurricane relief items. Clearly, $L_j(Q_j)$ is monotonely nondecreasing in Q_j. In the simplest form, $L_j(Q_j)$ is a linear function of Q_j, i.e. $L_j(Q_j) = \alpha_j Q_j$, where α_j is called the marginal utility at location j. Marginal utility represents the relevant importance of demands. For instance, if location j was more severely damaged than location j^0, α_j should be set larger than $\alpha_j 0$ to represent the relative importance in lifesaving. The total utility collected at location j is $\alpha_j \sum_{t=0}^{T} y_{jt}$. In the objective, we would *maximize* the overall lifesaving utility.

Managing urgency through delay cost. The effect of receiving the relief item and the effect of not receiving the relief item are different. In the former case, the people who get the relief item will be saved or have a higher survival probability. In contrast, the people who do not get the relief item will suffer from thirst, hunger, injury or other severe conditions that can endanger human lives. The lifesaving effect happens at the *moment* the relief item is received, while the pain is *accumulated along the time horizon* in which the relief item is missing. We define the delay cost as the *accumulated consequence along time* of not receiving the relief item. Consequence reflects urgency. If the consequence of not receiving the relief item is more serious, then the demand is more *urgent*. In summary, we distinguish the lifesaving effectiveness and the urgency by lifesaving utility and delay cost. The difference between the concepts can be illustrated by temporary shelters. If a person received a temporary shelter, the person would be protected from the cold weather and the person's survival probability would increase. If a person did not have a shelter, the person would suffer from cold. The longer the person is exposed to cold weather, the more pain the person will suffer, and the higher probability the person will not survive in cold weather.

Delay cost is measured by *the time of delay* and *the consequence of delay*. For a given demand d_j, the shortage in period t is $v_{jt} = d_j - \sum_{u=0}^{t} y_{ju}$. Let function $c_{jt}(v_{jt})$ represent the delay cost in period t caused by the shortage v_{jt}. Then the total accumulated delay cost at location j is $\sum_{t=0}^{T} c_{jt}(v_{jt})$. In the simplest form, $c_{jt}(v_{jt})$ is a linear function of shortage v_{jt} independent of t, i.e. $c_{jt}(v_{jt}) = \beta_j v_{jt}$. Then the total delay cost at location j is $\sum_{t=0}^{T} \beta_j v_{jt}$. Since we use a discrete time horizon, β_j represents the accumulated consequences of delay during one unit time caused by the shortage of one unit item, and we call it the unit delay cost.

It is also possible to assume that the shortage consequences get more serious when the delay time increases. For instance, a typical person needs two to four liters of water per day; and a lack of water causes dehydration resulting in lethargy, headaches, dizziness, confusion and eventually death[35]. In this case we may assume the consequence of unit shortage will itself increase linearly along time, i.e. $c_{jt}(v_{jt}) = (\gamma_j t+\beta_j)v_{jt}$. Then the total delay cost at location j is $\sum_{t=0}^{T} (\gamma_j t + \beta_j) v_{jt}$. Note that γ_j represents the increasing rate of β_j in one unit time, and we call this the increasing unit delay cost rate.

In the objective, we wish to *minimize* the overall delay cost. Note that we do not simply set an objective to minimize the travel time. Although travel time reduction implies delay time reduction, it does not reflect the consequence of delay. For example, the survival rate of trapped people in an earthquake decreases dramatically after a certain time window if there is no aid[11]. The decrease in the survival rate is the measurement of the consequence of delay, not the measurement of the time of delay itself.

Dealing with fairness in resource allocation. When resources are insufficient to meet the needs of all of the affected people, it becomes necessary to ration those resources.

We may allocate the supply based on the relative importance represented by α_j in the linear utility function. For example, Sheu[25] classified locations in decreasing importance. The allocation decision is to *completely* satisfy the most important location first, and then the second most important location, etc. The belief behind this approach is that it is *fair* to allocate the relief items according to relative importance. However, this definition of fairness is questionable. First, the "fairness" perceived by the decision maker could be different from the "fairness" perceived by the affected people. Sequential allocation might cause conflicts or unrest, as in the Haiti earthquake[36]. Second, the needs also have a dynamic aspect, i.e. urgency. The degree of "urgency" can change over time. For example, if we do not serve a need, the urgency could increase. It is hard to judge which is more urgent - suffering the most or suffering the longest - as can be seen in the Katrina hurricane[37].

Some researchers link "fairness" to equal allocation. Caro et al.[38] argue that under the conditions in which demand for care far exceeds capacity, the utilitarian maxim of the greatest goods for the greatest number, interpreted only as the most lives saved, needs refinement. They define fairness as considering people's needs "equally without favoritism or discrimination". In Huang et al.[17] and de la Torre et al.[16], "egalitarianism" in vehicle routing is also discussed. In these papers, "equality" or "egalitarianism" is realized by minimizing the variance in the arrival times of resources.

Therefore, in creating a model for emergency logistics, it is important to distinguish the relative importance of different needs, while controlling the degree of "equality" *explicitly and flexibly*. To represent this concept of fairness we introduce a demand fill rate $R_j = \frac{\sum_{t=0}^{T} y_{jt}}{d_j}$ and make an equality adjustment *negatively* related to this fill rate. The equality adjustment element in the objective function is $\omega(h - \frac{\sum_{t=0}^{T} y_{jt}}{d_j}) \sum_{t=0}^{T} y_{jt}$, where $h \geq 2$ is a constant; and $\omega \geq 0$ is called the equality adjustment factor. We restrict $h \geq 2$ to make sure the equality adjustment element will be monotonically nondecreasing in $0 \leq Q_j \leq d_j$.

The integrated objective function. Based on the previous analysis, the objective function brings together the three elements we have discussed, represented as Max $\sum_{j \in G} u_j(\mathbf{y}_j)$, where the vector $\mathbf{y}_j = \{y_{jt}\}_{t=0}^{T}$, and

$$u_j(\mathbf{y}_j) = \alpha_j \sum_{t=0}^{T} y_{jt} - \sum_{t=0}^{T} (\gamma_j t + \beta_j)(d_j - \sum_{u=0}^{t} y_{ju}) + \omega(h - \frac{\sum_{t=0}^{T} y_{jt}}{d_j}) \sum_{t=0}^{T} y_{jt} . \quad (1)$$

We can verify that the objective function is a concave function of the decision variables.

Constraint in Time Space Network

To model the dynamic nature of emergency logistics, we use a time space network to describe the distribution flows in both time and space. A node in the time space network is represented as (j,t), where j is the location index, and t is the time index. Now we intentionally distinguish "location" and "node". "Location j" refers to a node in the original geographical network; and "node (j,t)" refers to a node in the time space network.

An arc in the time space network is represented as (jt,j^0t^0), which connects node (j,t) and node (j^0,t^0). Note that there is an arc (jt,j^0t^0) *if and only if* there exists a route in the geographical network linking location j and j^0, and the travel time from j to j^0 is $t^0 - t$ $(t^0 \geq t)$. For each node (j,t) where $t < T$, there is an arc from (j,t) to $(j,t+1)$, which allows the resource to remain at one location. We use N and A to denote the collections of nodes and arcs in the time space network. The distribution plan must satisfy:

$$
\begin{aligned}
&\textstyle\sum_{j't':(j't',jt)\in\mathcal{A}} x_{j't',jt} - \sum_{j't':(jt,j't')\in\mathcal{A}} x_{jt,j't'} = y_{jt} - s_{jt} && \forall (j,t) \in \mathcal{N} \\
&0 \leq x_{jt,j't'} \leq U_{jt,j't'} && \forall (jt, j't') \in \mathcal{A} \\
&\textstyle\sum_{t=0}^{T} y_{jt} \leq d_j && \forall j \in \mathcal{G} \\
&y_{jt} \geq 0 && \forall t, j \in \mathcal{G} \\
&y_{jt} = 0 && \forall t, j \notin \mathcal{G}.
\end{aligned}
\tag{2}
$$

The first constraint is the flow balance constraint. The second constraint is the flow capacity constraint, where $U_{jt,j}0_t0$ is the transportation capacity from location j to location j^0. Note that the first and the second constraints hold for all locations including demand locations, supply locations and transfer locations. The third constraint requires that all the resources received by location j during the planning horizon cannot exceed the corresponding demand. The fourth constraint forces nonnegativity. Note the third and the fourth constraints only apply to demand locations. The fifth constraint forces the allocation to any non-demand location to be zero.

Remark 1 *Since the planning horizon is finite, it is possible that no supplies could arrive at any demand location before the end of the planning horizon. To guarantee the feasibility of (2), we can add a dummy node indexed as* $(n+1,T)$ *(where n is the number of locations), and a corresponding decision variable* $y_{n+1,T}$ $(y_{n+1,T} \geq 0)$*. For any node* (j,t) *such that* $s_{jt} > 0$*, we add an arc from* (j,t) *to* $(n+1,T)$*. We assume that the node* $(n+1,T)$ *has zero supply ,and has demand* (j,t)*:sjt>*0 *sjt, and add the constraint yn*+1*,T* ≤ *jt*:*sjt*>0 *sjt. We also add the flow balance* *constraint corresponding to* (n+1,T). *With this treatment, we can guarantee that (2) is always feasible.*

Integration of Resource Allocation and Emergency Distribution
According to previous discussions, the integrated model is represented as:

$$\begin{aligned} \text{Max} \quad & \textstyle\sum_{j\in\mathcal{G}} u_j(\mathbf{y}_j) \\ \text{s.t.} \quad & (\mathbf{x},\mathbf{y}) \in \mathcal{X}, \end{aligned} \tag{3}$$

where the vectors $\mathbf{x} = \{x_{jt,j}0_t0\}_{(jt,j}0_t0)_{\in \mathrm{A}}$ and $\mathbf{y} = \{y_{jt}\}_{(j,t)\in \mathrm{N}}$, and the constraint set X is defined by (2).

We can verify that X is the feasible region of a network flow problem, and the objective function is linear or concave. Therefore, (3) is a linear program or convex quadratic network flow problem, depending on the parameters. Convex quadratic network flow problems can be solved in polynomial time and are well studied in the literature[21,22]. Moreover, the setting of the time space network naturally implies a rolling horizon approach. At each decision epoch, we consider a planning horizon that starts from the present epoch, and lasts for T periods. We collect all the data available at present and solve the optimization problem (3). At the next decision epoch, we update the data and solve a new problem (3). And so on. This rolling horizon approach avoids the difficulty in forecasting random distributions in stochastic programming approaches, or estimating uncertainty sets in robust optimization approaches. It allows decisions to be updated when the information is updated, and thus brings flexibility to the disaster response decision making process.

MANAGERIAL IMPLICATIONS OF CRITICAL MODEL PARAMETERS

In the integrated model (3), we have three types of critical parameters. First, the marginal utility α_j characterizes lifesaving utility. Second, the unit delay cost β_j and the increasing unit delay cost rate γ_j characterize urgency. Third, the equality adjustment factor ω characterizes the ethical equality belief of the decision maker. In this section, we discuss the managerial implications of α_j, β_j and γ_j, and ω. We show that these parameters lead to different resource allocation rules under certain conditions. In the following, we assume that any supply can arrive at any demand location before the end of the planning horizon, and that there are no transportation capacity limitations.

Property 1 Relative importance first rule. *In the objective function of (3), if we only include lifesaving parameters, and ignore delay cost and equality parameters, i.e.* $u_j(\mathbf{y}_j) = \alpha_j \sum_{u=0}^{T} y_{ju}$, *then the optimal solution is to allocate the resources to the demand locations sequentially according to decreasing relative importance, estimated by marginal utility* α_j.

Proof: See Appendix.

Property 1 indicates that if we only consider the lifesaving feature, then it is optimal to allocate and distribute the resources according to the relative importance of the demands, estimated by marginal utility α_j. The relative importance first rule was used by Sheu[25].

Property 2 Shortest path first rule. *In the objective function of (3), if we only consider delay cost parameters, and ignore lifesaving and equality parameters, with delay cost parameters the same for different locations, i.e.* $u_j(\mathbf{y}_j) = -\sum_{t=0}^{T}(\gamma t + \beta)(d_j - \sum_{u=0}^{t} y_{ju})$, *then the optimal solution is to allocate resources to the demand locations sequentially according to increasing travel times.*

Proof: See Appendix.

Property 2 indicates that if we only consider the urgency feature, and the different locations have the same delay cost parameters, then it is optimal to satisfy the location with smallest travel time first, then the location with the second smallest travel time, and so on.

Property 3 Equality fill rate rule. *In the objective function of (3), if we only consider equality parameters, and ignore lifesaving and delay cost parameters, i.e.* $u_j(\mathbf{y}_j) = \omega[h - \frac{\sum_{u=0}^{T} y_{ju}}{d_j}] \sum_{u=0}^{T} y_{ju}$ *, and the total supply is less than the total demand, i.e.,* $_{jt\in \mathrm{N}:s_{jt}>0}\, s_{jt} <_{j\in \mathrm{G}} dj$*, then the optimal solution is to allocate the resources to the demand locations according to the same fill rates, defined as follows:* $R^* = \frac{\sum_{jt\in\mathcal{N}:s_{jt}>0} s_{jt}}{\sum_{j\in\mathcal{G}} d_j}$*. The optimal resource allocation decisions* y_{jt}^* *satisfy* $\sum_{u=0}^{T} y_{ju}^* = R^* d_j$.

Proof: See Appendix.

Property 3 indicates that if we ignore lifesaving and delay cost parameters, then it is optimal to allocate and distribute the resources "equally" in terms of the fill rate. This is similar to the "fair share" allocation policy used in an Assemble-To-Order manufacturing system[39]. Moreover, even when lifesaving and delay cost parameters exist, if the equality adjustment factor ω becomes larger, the allocation tends to be more equal among locations. This approximation result can be expressed as:

Property 4 *In (3), if the total supply is less than the total demand, and the optimal solution is unique, then when* $\omega \to \infty$*, the optimal solution will converge to the equal fill rate rule defined in Property 3.*

Proof: See Appendix.

Property 4 is very useful when the input data are inaccurate, which is often the case in emergency logistics. It implies that the lifesaving and delay cost parameters don't matter, as long as we use a large ω, the allocation tends to be approximately equal among all locations in terms of fill rates.

Our analysis of Properties 1, 2, 3 and 4 reveals managerial insights for these critical parameters. In practice, a supply may not be able to arrive at a demand location before the end of the planning horizon, or there may exist transportation capacity limitations. Then Property 1, 2, 3 and 4 may not hold. Moreover, when all the parameters are considered simultaneously, equation complexity will make analytical solutions impossible, and a numerical approach becomes necessary.

THE GREAT SICHUAN EARTHQUAKE CASE STUDY

To illustrate the use of our model in practice, we analyze a case arising from the Great Sichuan Earthquake that happened in the northwestern province Sichuan in China at 14:28 p.m., May 12, 2008[40]. The main shock was magnitude 8.0, and many major aftershocks occurred. The Great Sichuan Earthquake resulted in the deaths of at least 69,016 persons, 368,565 persons were injured, and 18,498 persons were missing. Direct economic loss exceeded 845.14 billion Chinese Yuan (more than 100 billion USD).

In the case design, all the data was derived from newspapers, online news, and official reports[41]. Throughout the case, we rounded all fractional numbers to integers. We summarize the time sequence of rescue activities in Table 2. From this table, we can see that the local governments responded about half an hour after the earthquake, and the provincial and national governments responded within six hours. In this case, we focus on providing decision support for provincial and national governments. We set one time unit at 2 hours. To illustrate how the proposed model works in a rolling horizon manner, we consider two decision epochs. The first decision epoch happens 2 hours after the earthquake; the second decision epoch happens 4 hours after the earthquake. For each decision epoch, we consider a planning horizon of 4 time units (T = 4), i.e. 8 hours. Note that the planning horizons of two decision epochs may overlap.

Table 2: Sequence of rescue activities in the Great Sichuan Earthquake

Time	Rescue events
14:28 p.m.	The earthquake happened.
30 mins later	Local hospital, government and rescue agencies arrived at affected areas.
2 hours later	Rescue teams from local counties arrived at affected areas.
4 hours later	Paramilitary forces organized by the Sichuan Military Region arrived at affected areas.
6 hours later	Chinese national rescue team flew to Chengdu City to assist emergency rescue.
The next day	Rescue teams from neighboring provinces arrived at affected areas.
The following days	Rescue teams from other provinces and other countries arrived

We consider five locations: Chengdu City, Dujiangyan City, Wenchuan County, Beichuan County and Qingchuan County; and denote them as A,B,C,D,E. Related geography information can be found online from Google Maps. Note that Chengdu City (*A*), as the provincial capital of Sichuan, played a central role in deploying and allocating rescue resources. During the rescue, almost all resources arrived at Chengdu City (*A*) first and then moved to the affected areas. Therefore we will treat the physical distribution network as a bipartite network, which consists of one supply location (*A*) and four demand locations (*B,C,D,E*). We used Google Maps to compute the regular travel times between *A* and *B,C,D,E* (in hours) as 1, 2.4, 5.2, 2.5. Since the transportation infrastructure was severely damaged and the travel times were much longer than usual due to the earthquake, we set the travel times from *A* to *B,C,D,E* as 2, 6, 6 and 8 (hours), i.e. 1, 3, 3 and 4 time units.

After the earthquake, medical workers were an extremely important resource. Medical workers often carry multiple first aid medicines and equipment. We assumed that each medical worker could deal with 10 persons at a time. According to statistics in Wang et al.[42], the ratio between injured people and available medical workers exceeded 50:1 during the first few hours after the earthquake. So we assumed that the available medical workers at supply location *A* could only satisfy 10% of the total demand at the first decision epoch, and 20% at the second decision epoch. Demand information can be obtained from casualty statistics from the earthquake. According to Tencent.com[43], the casualties in locations *B,C,D,E* were 7,457, 58,454, 18,298, and 20,272 respectively. After an earthquake, the actual number of casualties changes over time due to rescue activities and information updates. Hence we assumed that the demands at locations *B,C,D,E* were gradually revealed. Specifically, the demands revealed at these locations were 30% at the first decision epoch, and 50% at the second decision epoch. Injuries revealed at locations *B,C,D,E* at the first decision epoch were 2237, 17536, 5491 and 6082 respectively, and the corresponding demands for medical workers were 224, 1754, 550 and 609. The total demand requirement for medical workers was 3137, and the medical workers available at location *A* were 314 (3137 multiplying 10%). Similarly, at the second decision epoch, we assumed that the number of available medical workers was 731.

We tested six different cases and show the data and results in Table 3. In all the cases, we set the constant *h* as 2 (see equation (1)). For each case, we considered the decisions at two consecutive decision epochs. The input data are $\alpha_j,\beta_j,\omega,d_j$ (for simplicity we assume $\gamma_j \equiv 0$). Note that ω is uniform for all locations. When a certain type of parameter was zero for all locations, we omitted this in the input data in Table 3. For example, in Case 1, only α_j parameters are positive, and all the β_j and ω parameters are zeroes. So the input data only show d_j and α_j. There are two types of outputs. Q^*_j represents the optimal total resource allocated to location *j*, i.e., $Q_j^* = \sum_{t=0}^{T} y_{jt}^*$, where y_{jt}^* represent the optimal resource allocation decisions. R_j^* represents the fill rate for location *j* in the optimal solution, i.e., $R_j^* = \frac{Q_j^*}{d_j}$. For each case, the demand is the revealed demand at the second decision epoch found by subtracting the satisfied demand at the first decision epoch. Note that we assume that 50% of the demand are revealed at the second decision epoch, so we can find that the revealed demands for locations *B,C,D,E* at the second decision epoch are 373, 2923, 915 and 1014 respectively. For example, in Case 1 the Q_j^*, the for location *C* is 314, so the demand for location *C* at the second decision epoch is 2923 − 314 = 2609.

At the first decision epoch, we do not have much information about the severity of damage at different locations. Note that Wenchuan County (*C*) is the earthquake epicenter. In general, damage severity decreases with distance from the earthquake epicenter. So the values of α_j (lifesaving parameter) are set according to the distances of locations from the earthquake epicenter, i.e., the closer to the epicenter, the higher the value of α_j. We set α_j for locations *B,C,D,E* as 4, 5, 3, 2 respectively. At the second decision epoch, we set the values of α_j based on more accurate casualty information from the demand locations. For example, locations *D* and *E* were found to be affected much more severely than location *B*, although they were further away from the epicenter *C*. So we set α_j for *B,C,D,E* as 2,5,4,3 respectively (importance levels decreasing as *C,D,E,* and *B*) at the second decision epoch. We would like to emphasize the difference in the distance to the earthquake epicenter (*C*) and the distance to the supply location (*A*). In our case, the former plays a role in Property 1 (at the first decision epoch), while the latter plays a role in Property 2.

Table 3 illustrates how the proposed model works, and tests the impact and sensitivity of parameters α_j, β_j and ω. Case 1 only considers the lifesaving utility. Property 1 holds in Case 1. Since there is a severe shortage of the resource (availability of medical workers), all of the resource is allocated to the location with the highest marginal utility, i.e. location *C*. Case 2 considers both lifesaving utility and delay cost. At the first decision epoch, the interaction between these elements results in a partial shift to location *B* which is closer to *A* than *C* but whose marginal utility is smaller than that of *C*. At the second decision epoch, this shifting effect is more obvious. The result is that all the resource goes to location *D*, which has the largest unit delay cost. Cases 2 and 3 keep lifesaving parameters constant, and use different delay cost parameters. Note that this setting does not make a difference between the optimal solutions of Cases 2 and 3 at the first decision epoch, but it does make a difference at the second decision epoch. In Case 3, the unit delay costs of both *B* and *C* increase to 2, *B* is closer to *A* than *D*, and *C* is more important than *D*. So the resource allocation shifts to locations *B* and *C* at the second decision epoch. Case 3, 4, 5 and 6 keep the same lifesaving and delay cost parameters, and increase the equality adjustment factor from 0 to 2 to 20 to 200. It is clear that the allocations to *B,C,D,E* become more even when ω increases. In Cases 1, 2, 3, location *E* never receives any resource because it is not the most important, and is the farthest away. When ω increases, the allocation to location *E* increases. When ω equals 200, the fill rate for location *E* is almost the same as those of other locations. This is compatible with Property 4.

Table 3: Case data and results

Cases	Parameters	1st decision epoch				2nd decision epoch			
		B	C	D	E	B	C	D	E
1	d_j	224	1754	550	609	373	2609	915	1014
	α_j	4	5	3	2	2	5	4	3
	Q_j^*	0	314	0	0	0	731	0	0
	R_j^*	0	18%	0	0	0	28%	0	0
2	d_j	224	1754	550	609	149	2833	915	1014
	α_j	4	5	3	2	2	5	4	3
	β_j	1	1	2	0	1	1	2	0
	Q_j^*	224	90	0	0	0	0	731	0
	R_j^*	100%	5%	0	0	0	0	80%	0
3	d_j	224	1754	550	609	149	2833	915	1014
	α_j	4	5	3	2	2	5	4	3
	β_j	2	2	2	2	2	2	2	2
	Q_j^*	224	90	0	0	149	582	0	0
	R_j^*	100%	5%	0	0	100%	21%	0	0
4	d_j	224	1754	550	609	188.5	2793.5	915	1014
	α_j	4	5	3	2	2	5	4	3
	β_j	2	2	2	2	2	2	2	2
	ω	2	2	2	2	2	2	2	2
	Q_j^*	185	129	0	0	91	640	0	0
	R_j^*	82%	7%	0	0	48%	23%	0	0
5	d_j	224	1754	550	609	327.6	2698.9	872.2	1012.3
	α_j	4	5	3	2	2	5	4	3
	β_j	2	2	2	2	2	2	2	2
	ω	20	20	20	20	20	20	20	20
	Q_j^*	46	224	42	2	65	464	128	74
	R_j^*	20%	13%	8%	0.3%	20%	17%	15%	7%
6	d_j	224	1754	550	609	348.3	2742.6	861.2	959.0
	α_j	4	5	3	2	2	5	4	3
	β_j	2	2	2	2	2	2	2	2
	ω	200	200	200	200	200	200	200	200
	Q_j^*	25	180	54	55	54	414	128	135
	R_j^*	11%	10%	10%	9%	15%	15%	15%	14%

The case study shows that the proposed approach has the potential to support decision making in emergency logistics.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

In this paper, we propose an integrated model that focuses on lifesaving in emergency logistics. In our model, we formulate a utility function which reflects the lifesaving effectiveness of humanitarian supplies. We introduce a delay cost to reflect time urgency and measure the consequence of human suffering due to the delay of humanitarian aid. Our model also represents a method to deal with supply shortages by balancing priority and equality among affected areas. The modeling approach we use is innovative and different from traditional formulations of logistics problems that focus on cost saving and efficiency of logistics. Moreover, we allow multiple supply locations to satisfy multiple demand locations through multiple intermediate locations, in contrast to most traditional logistics models that only consider the distribution of goods from a single warehouse to multiple locations.

We also use a time space network to capture the dynamic aspects of emergency logistics. The time space network, together with a rolling horizon approach is especially suitable for real time decision support for emergency logistics. We also integrate resource allocation and emergency distribution into one model. This integration helps to make better decisions when the feasibility of resource allocation is highly dependent on transportation network conditions, which is often the case in disaster response. The integrated model also has computational appeal. It is a linear or convex quadratic network flow problem that can be solved efficiently, allowing for the design of decomposition algorithms.

The proposed model establishes a new avenue for further research in emergency logistics. For instance, in our model we did not incorporate transportation capacity limitations on vehicle availability and load capacity. Further research should characterize this aspect as constraints. In our model, we only considered a single type of aid. In reality, different types of humanitarian aids are needed simultaneously. In this case, it will be more difficult to express the objective function and incorporate routing decision variables. In our model, we only considered the delivery of humanitarian aid to the affected areas. The same concepts in this paper could be applied to the evacuation problem in which people, especially those severely injured, need to be quickly transported to safe areas or medical treatment centers. Finally, to integrate our models with a real time decision support system, it is essential to design fast and robust algorithms that are able to solve large scale problems.

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APPENDIX: PROOFS

Proof of Property 1: If we ignore the delay cost, then we can treat $Q_j = \sum_{u=0}^{T} y_{ju}$ as a whole in the objective function, since no matter when a fraction of Q_j arrives, the marginal utility α_j will be the same. Through a marginal analysis[44] we can verify that in the optimal solution, the demands will be satisfied in a sequentially decreasing order of the α_j's.

Proof of Property 2: There is a finite number of nodes in the time space network. Therefore, we can enumerate all the routes between the supply locations and the demand locations. Consider any two routes r_1 and r_2, connecting the same pair of supply location and demand location. Suppose we transport one unit rescue item on both routes. If the travel time of route r_1 is smaller than that of r_2, then the delay cost incurred on route r_1 will be smaller than that on route r_2. Therefore, we will always prefer to transport the rescue item on route r_1. Since the argument holds for general r_1 and r_2, the conclusion follows.

Proof of Property 3: We assume that any supply can arrive at any demand location before the end of the planning horizon, and there is no delay cost. Thus the travel time between any two locations can be set to zero. Then the time space network can be omitted and the original model will reduce to a resource allocation problem

$$\text{Max} \quad \sum_{j\in\mathcal{G}} \omega\left(h - \frac{\sum_{u=0}^{T} y_{ju}}{d_j}\right) \sum_{u=0}^{T} y_{ju}$$

s.t. $\quad \sum_{j\in\mathcal{G}} \sum_{u=0}^{T} y_{ju} \le s_0$

(4)

$\sum_{t=0}^{T} y_{jt} \le d_j \quad \forall j \in G$

$y_{jt} \ge 0 \qquad \forall t,j \in G,$

P $\qquad Q_j = \sum_{u=0}^{T} y_{ju}$

where $s_0 = {}_{jt\in N:s_{jt}>0}\, s_{jt}$. In this formulation, we can leave and replace the decision variables y_{jt} by Q_j. We can easily verify the solution in the result is optimal by induction. Indeed, (4) allocate resource among |G| locations. If we select any $j_1 \in G$, and consider the resource allocation among j_1 and all the locations in G\{j_1}. Then we can reduce the problem (4) to

$$\text{Max} \quad \left(h - \frac{q_1}{\tilde{d}_1}\right) q_1 + \left(h - \frac{q_2}{\tilde{d}_2}\right) q_2$$

s.t. $\quad q_1 + q_2 \le s_0$

$0 \le q_1 \le \tilde{d}_1$

$0 \le q_2 \le \tilde{d}_2,$

where decision variable q_1 represents the resource allocated to location j_1, and q_2 represents *all* the resource allocated to locations $\mathcal{G}\backslash\{j_1\}$, and $\tilde{d}_1 = d_{j1}$, and $\tilde{d}_2 = \sum_{j\in\mathcal{G}\backslash\{j1\}} d_j$. Since $s_0 < \tilde{d}_1 + \tilde{d}_2$, $q_1 + q_2 = s_0$ holds in the optimal solution. By substituting q_2 by $s_0 - q_1$ and taking the derivative of the objective function with respect to q_1, and setting it to 0, we can verify that the optimal solutions q_1^* and q_2^* satisfy $\frac{q_1^*}{\tilde{d}_1} = \frac{q_2^*}{\tilde{d}_2} = \frac{s_0}{\tilde{d}_1+\tilde{d}_2} = \frac{\sum_{jt\in\mathcal{N}:s_{jt}>0} s_{jt}}{\sum_{j\in\mathcal{G}} d_j}$. We can further allocate the resource q_2^* among locations $\mathcal{G}\backslash\{j_1\}$ the same way, and so on. Therefore the conclusion follows.

Proof of Property 4: Note that the optimal solution of (3) is equivalent to the optimal solution of

$$\text{Max} \quad \sum_{j\in\mathcal{G}}[\frac{\alpha_j}{\omega}\sum_{t=0}^{T} y_{jt} - \sum_{t=0}^{T}\frac{\gamma_j t+\beta_j}{\omega}(d_j - \sum_{u=0}^{t} y_{ju}) + (h - \frac{\sum_{t=0}^{T} y_{jt}}{d_j})\sum_{t=0}^{T} y_{jt}]$$

s.t. $\quad$ (x,y) ∈ X.

Clearly, when $\omega \to \infty$, $\frac{\alpha_j}{\omega} \to 0$ and $\frac{\gamma_j t+\beta_j}{\omega} \to 0$ for all j, so the objective function converges to $(h - \frac{\sum_{t=0}^{T} y_{jt}}{d_j})\sum_{t=0}^{T} y_{jt}$. Since the optimal solution exists and is unique, the conclusion follows.

McMaster University
1280 Main St. W. DSB A202
Hamilton, ON
L8S 4M4

Tel: 905-525-9140 ext. 23956
Fax: 905-521-8995
Email: ebusiness@mcmaster.ca
Web: http://merc.mcmaster.ca