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REAL-TIME OPTIMIZATION FOR DISASTER RESPONSE: A MATHEMATICAL PROGRAMMING APPROACH

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Abstract

Disasters are sudden and calamitous events that can cause severe and pervasive negative impacts on society and huge human losses. Governments and humanitarian organizations have been putting tremendous efforts to avoid and reduce the negative consequences due to disasters. In recent years, information technology and big data have played an important role in disaster management. While there has been much work on disaster information extraction and dissemination, real-time optimization for decision support for disaster response is rarely addressed in big data research. With big data as an enabler, optimization of disaster response decisions from a systems perspective would facilitate the coordination among governments and humanitarian organizations to transport emergency supplies to affected communities in a more effective and efficient way when a disaster strikes. In this paper, we propose a mathematical programming approach, with real-time disaster-related information, to optimize the post-disaster decisions for emergency supplies delivery. Since timeliness is key in a disaster relief setting, we propose a rounding-down heuristic to obtain near-optimal solutions for the provision of rapid and effective response. We also conduct two computational studies. The first one is a case study of Iran that aims to examine the characteristics of the solutions provided by our solution methodology. The second one is to evaluate the computational performance, in terms of effectiveness and efficiency, of the proposed rounding-down heuristic. Computational results show that our proposed approach can obtain near-optimal solutions in a short period of time for large and practical problem sizes.

This is an extended work of Kuo et al., 2015, which has been published in the *Proceedings of IEEE International Congress on Big Data (Big Data Congress) 2015*.

Keywords: disaster response; real-time disaster data; humanitarian logistics; emergency supplies; mathematical modeling; optimization; mixed-integer linear programming.

1. INTRODUCTION

Over the past decade, many cities and countries around the globe have suffered from various disasters, e.g., the hurricane Katrina in the United States in 2005, the 2010 Pakistan floods, the 2011 Tohoku earthquake and tsunami and its subsequent Fukushima Daiichi nuclear disaster, and the recent Nepal earthquake. These disasters brought hundreds of thousands of casualties, severe property and infrastructure damage, and immense economic losses. Since disasters are often difficult to predict, governments and humanitarian organizations have been devoting enormous efforts to reduce the negative consequences of disasters. The immediate impact after disasters include a huge increase in demand for medical professionals and supplies for severely-injured victims, and inadequate supply of shelters and bare necessities, such as food, clean water, clothing, and bedding. Delay in provision of essential and appropriate humanitarian assistance to the survivors can be life-altering (causing undue injuries) and even life-ending (causing unnecessary deaths). Even for victims without any life-threatening conditions, a quick delivery of basic necessities and medical supplies can relieve their mental-emotional stress due to the shock from the disaster. In the information age and the era of big data, huge amounts of data are available and can be effectively and efficiently processed to extract useful information and facilitate decision-making. In this work, we propose a mathematical programming approach to support post-disaster decision-making. More specifically, we study the problem of delivering emergency supplies from storage facilities to communities of affected areas with the use of optimization and real-time disaster-related information. Our paper is organized as follows: Section 2 reviews previous related work on the use of information technology, big data, and optimization techniques in disaster management; Section 3 describes the flow of the decision-making process for disaster response; Section 4 presents our proposed optimization model; Section 5 describes our solution approach to obtaining fast near-optimal solutions; Section 6 present a case study of Iran and the computational results of experiments for evaluating the performance of our solution approach; and Section 7 concludes our work.

2. RELATED WORK

Recent applications of big data and information and communication technologies (ICT) in disaster management include:

- Remote sensing for monitoring natural and human- disasters. ([Di Martino et al., 2007](#))
- Governments using smartphones and mobile apps to disseminate disaster warning information to the people who are close to the possible affected areas and guide them to shelters or safe locations. ([Rahman et al., 2012](#)).
- GPS systems providing governments and humanitarian organizations with the up-to-the-minute traffic information, e.g., road conditions, so that they can promptly deliver emergency supplies to victims. ([Utani et al., 2011](#))
- Crowdsourcing for collecting direct feedback from injured victims in disasters, e.g. about their physical conditions, and suggesting possible locations for treatment. ([Besaleva and Weaver, 2013](#))
- Social media for sharing information about people's locations during disasters so that rescue teams can easily locate victims. Such applications are also vital to disaster recovery efforts, e.g. for monitoring victims under heavy stress. ([Merchant et al., 2011](#))
- Cloud platforms for receiving, maintaining and sharing disaster-related information, such as locations, quantities, and description of emergency resources, so as to facilitate disaster response. ([Kelly et al., 2011](#))
- Data-mining for deriving information about the status of disaster relieve and how the community is recovering. ([Zheng et al., 2013](#))
- Twitter data for detecting earthquakes. ([Sakaki et al., 2010](#))

For more applications, we refer the reader to [Hristidis et al. \(2010\)](#) and [Schmitt et al. \(2007\)](#).

While there has been much work on the use of information technology and big data for disaster management, optimization with real-time information for disaster response is rarely studied in the big-data context. Optimization has been demonstrated to be a powerful tool for disaster decision making, with a



Figure 1. The flow of delivering emergency supplies to communities of affected areas.

wide range of applications including design of coverage networks (O' Hanley et al., 2011), set-up of evacuation centres and their pre-positioned inventory levels of emergency supplies (Irohara et al., 2013), and vehicle routing in humanitarian logistics (Huang et al., 2012). For detailed surveys on the applications of optimization for disaster relief planning, we refer the reader to Balcik et al. (2010), Kovács et al. (2007).

3. DECISION SUPPORT TOOL FOR DISASTER RESPONSE

Disaster management can be divided into four major sequential stages: *preparedness*; *mitigation*; *response*; and *recovery* (Hristidis et al., 2010). Our work focuses on disaster response, i.e., the post-disaster decisions of governments and humanitarian organizations to provide casualties with immediate support and needs. More specifically, we study the problem of delivering emergency supplies to communities of affected areas to effectively and efficiently aid victims after a disaster strikes. Figure 1 depicts the events for delivering emergency supplies to communities of affected areas. To effectively assist casualties in the affected areas, the urgent emergency supplies should reach the victims within the first 72 hours, the so called the *golden time*; the whole process depicted in Figure 1 should be done in the shortest time duration possible (Jayasuriya and McCawley, 2010). Therefore, a decision support tool for such relief delivery-planning is exceedingly helpful for disaster response because many different types of decisions have to be made simultaneously. Humans are generally unable to determine so many solutions in such short periods of time and human-made decisions in general do not guarantee optimality.

Although most governments and humanitarian organizations have already had very detailed plans for actions after disasters strike, a real-time decision support tool for disaster response is still essential because it may occur that even prepositioned stocks of emergency supplies may

be damaged during the disaster and its intensity may be unanticipated. For this reason, re-optimization is usually required when the disaster scenario is realized and real-time information is needed to improve decisions.

4. MATHEMATICAL MODEL

4.1 NOTATION

Our mathematical model consists of the following sets and parameters:

- I = the set of available emergency supplies storage facilities (SFs);
- J = the set of affected communities (ACs);
- K = the set of types of emergency supplies;
- L = the set of loading constraints that govern the types of emergency supplies that can be loaded to certain types of vehicles;
- G = the set of vehicle types;
- K_l = the set of emergency supplies that are governed by loading constraint l ;
- G_l = the set of vehicles that are governed by loading constraint l ;
- v_{ig} = the number of vehicles of the g -th vehicle type available at SF i ;
- c_g = weight capacity of the of the g -th vehicle type;
- t_{ij} = travel time from SF i to AC j ;
- m_{ik} = the amount of the k -th type of emergency supplies available at SF i ;
- a_k = weight of a unit of the k -th type emergency supplies; and
- d_{jk} = the demand of AC j for the k -th type of emergency supplies.

In the above sets and parameters, v_{ig} , t_{ij} , m_{ik} , and d_{jk} need to be updated after the post-disaster information is obtained because damages to communities, SFs, and roads are likely to occur. d_{jk} can be estimated from the real-time information during a disaster strikes, e.g., disaster type and intensity. In

our model, we also consider a practical factor that some emergency supplies can only be delivered by certain types of vehicles. For example, water can only be transported by water tankers while other dry items are delivered by regular lorries. Such consideration is captured by the set of loading constraints L . For each loading constraint, the types of emergency supplies that are of similar nature are considered as in the same loading category and can be delivered by only a valid set of vehicle types. We further assume that $\cup_{l \in L} K_l = K$, $\cup_{l \in L} G_l = G$, $K_{l_1} \cap K_{l_2} = \emptyset$ and $G_{l_1} \cap G_{l_2} = \emptyset \forall l_1, l_2 \in L$ with $l_1 \neq l_2$. That is, $(K_1, K_2, \dots, K_{|L|})$, $(G_1, G_2, \dots, G_{|L|})$ are respectively partitions of K and G . This assumption is sensible because in practice certain types of vehicles are designated for selected types of emergency supplies.

4.2 FORMULATION

Our optimization model is as follows:

Decision variables:

- x_{ijk} = the amount of the k -th type of emergency supplies to be shipped from SF i to AC j ;
- y_{ijg} = the number of vehicles of the g -th vehicle type from SF i to AC j ;
- s_{jk} = the unmet demand of AC j for the k -th type of emergency supplies.

Our model determines the optimal number of vehicles of each vehicle type required, y_{ijg} , and the amount of each type of emergency supplies to be delivered, x_{ijk} , from each SF to each AC. As SFs, their pre-positioned emergency supplies and vehicles may be destroyed during the disaster, there can be unmet demand of the communities for emergency supplies; the amount of the unmet demand of each AC for each type of emergency supplies is measured by s_{jk} .

Objective function:

$$\min \sum_{j \in J, k \in K} M_{jk} s_{jk} + \sum_{i \in I, j \in J, k \in K} f_{ijk} x_{ijk}$$

where

$$f_{ijk} = \begin{cases} f_{ijk}^0 t_{ij} & \text{if } 0 \leq t_{ij} < t_k^1 \\ f_{ijk}^1 t_{ij} & \text{if } t_k^1 \leq t_{ij} < t_k^2 \\ \vdots \\ f_{ijk}^{l_k-1} t_{ij} & \text{if } t_k^{l_k-1} \leq t_{ij} < t_k^{l_k} \\ f_{ijk}^{l_k} t_{ij} & \text{if } t_{ij} > t_k^{l_k} \end{cases}$$

and $0 < f_{ijk}^0 < f_{ijk}^1 < \dots < f_{ijk}^{l_k-1} < f_{ijk}^{l_k} \ll M_k \forall i \in I, j \in J, k \in K$.

For disaster response, timeliness is key – because provision of medical supplies to a disaster survivor beyond the golden time is fruitless. Therefore, different from the traditional transportation models whose cost incurred for a route is directly proportional to the travel distance or time, the weights of the objective function in our optimization model are evaluated by a piecewise linear function in such a way that a higher penalty per unit of shortage of emergency supplies is imposed on a longer travel time. Moreover, a very large penalty is incurred for the unmet demand. We also use different sets of weights for different types of emergency supplies because some supplies are more urgent than the others, e.g., medical supplies are more urgent than clothing.

Constraints:

$$\sum_{i \in I} x_{ijk} + s_{jk} \geq d_{jk} \forall j \in J, k \in K \quad (1)$$

$$\sum_{j \in J} x_{ijk} \leq m_{ik} \forall i \in I, k \in K \quad (2)$$

$$\sum_{k \in K_l} a_k x_{ijk} \leq \sum_{g \in G_l} c_g y_{ijg} \forall i \in I, j \in J, l \in L \quad (3)$$

$$\sum_{j \in J} y_{ijg} \leq v_{ig} \forall i \in I, g \in G \quad (4)$$

$$x_{ijk}, s_{jk} \geq 0 \forall i \in I, k \in K \quad (5)$$

$$y_{ijg} \in \mathbb{Z}_+ \forall i \in I, j \in J, g \in G \quad (6)$$

Constraints (1) calculate the unsatisfied demand of AC j for the k -th type of emergency supplies. Constraints (2) state the restriction that each SF cannot ship more than the available stocks it has. Constraints (3) ensure that the total volume of emergency supplies that can be shipped from a SF to an AC cannot be greater than the total capacity of all the outbound vehicles for this origin-destination pair. Different from

the approach that each vehicle has an individual variable associated with it, we consider a variable that determines the total number of vehicles of each type going from a SF to an AC, i.e., y_{ijg} . This approach can reduce the total number of variables and constraints in the model so as to reduce the computational time, which is crucial for disaster response. However, this implicitly assumes that the emergency supplies can be freely divided and allocated to any vehicles. This assumption is sensible in a humanitarian logistics setting because a unit of emergency supplies is, in general, relatively small compared to the capacity of a vehicle. Constraints (4) ensure that for each SF the total number of outbound vehicles of each type cannot be more than the available. Constraints (5) impose a non-negativity condition on x_{ijk} and s_{jk} , while Constraints (6) impose both non-negativity and integrality conditions on y_{ijg} . It is easy to verify that if all the problem parameters are non-negative, the problem is always feasible and the objective function is bounded, and therefore an optimal solution always exists. Furthermore, we notice that in practice the amounts of some emergency supplies may be integer-valued. For this case, the final solutions of those discrete quantities are rounded down. This would not change much of the solution quality as the round-off errors are insignificant compared to the large volume of shipments.

5. SOLUTION PROCEDURE: A ROUNDING-DOWN HEURISTIC

Our optimization model is a mixed-integer linear program (MILP). Note that solving general MILPs is NP-hard, and the problem size, i.e., numbers of decision variables and constraints, is huge for disaster response (as an example, there are a million of x_{ijk} -variables for a case of 1000 communities, 100 storage centres, and 10 kinds of emergency supplies). We have tried to solve the problem by using an off-the-shelf MILP solver but for some larger instances no feasible solutions could be produced within 10 minutes. This implies that solving the problem just by using an off-the-shelf solver is not acceptable in our application because rapid actions are necessary for disaster response. For this reason, we propose a rounding-down heuristic to provide a good feasible solution in a timely fashion, say within a few seconds. Our solution procedure involves two steps. In Step 1, we first solve the linear programming (LP) relaxation of the problem. That is, we solve the problem where Constraints (6) are replaced by the following non-negativity constraints.

$$y_{ijg} \geq 0 \quad \forall i \in I, j \in J, g \in G \quad (7)$$

Note that after we solve the LP relaxation of the problem, the optimal solution values of $\{y_{ijg}\}$, denoted by $\{y_{ijg}^*\}$, are in general non-integral. For this reason, we round down $\{y_{ijg}^*\}$ to recover them from fractional numbers to integers. However, rounding down $\{y_{ijg}^*\}$ may turn the solution to be infeasible due to the violations of some of the Constraints (3). In Step 2, we fix $\{y_{ijg}\}$ at their rounded-down values, i.e., $\{\lfloor y_{ijg}^* \rfloor\}$, and impose the conditions as the following constraints in the LP relaxation of the problem.

$$y_{ijg} = \lfloor y_{ijg}^* \rfloor \quad \forall i \in I, j \in J, g \in G \quad (8)$$

After we solve the problem, the optimal solution obtained is guaranteed to be feasible to the original problem. The flow of our algorithm can be summarized as follows.

Rounding-down Heuristic	
Step 1	Solve the following problem: $\min \sum_{j \in J, k \in K} M_{jk} s_{jk} + \sum_{i \in I, j \in J, k \in K} f_{ijk} x_{ijk}$ subject to Constraints (1) to (5) and (7). Let y_{ijg}^* be the optimal solution value of the decision variable y_{ijg} for the problem.
Step 2	Solve the following problem: $\min \sum_{j \in J, k \in K} M_{jk} s_{jk} + \sum_{i \in I, j \in J, k \in K} f_{ijk} x_{ijk}$ subject to Constraints (1) to (5), (7), and (8). Return the optimal solution obtained.

Note that in our solution procedure, we only need to solve two LPs where no MILP techniques are required. This ensures that we can obtain a fast solution because solving an LP, which is no longer NP-hard, has the advantage that it can be solved by polynomial algorithms, e.g., by interior point methods, or by the simplex method, which has been shown to be efficient for practical problems. Moreover, although in general our solution procedure loses solution quality due to the rounding-down procedure, the increase in the objective value should not be significant as the scale of the rounding difference is very small compared to the solution value of y_{ijg} , if non-zero, in a humanitarian logistics

setting (given that there are in general tens to hundreds of vehicles to be deployed at each SF). Computational results in Sub-section 6.2 also show that the solutions provided by the rounding-down heuristic are close to optimal.

$$f_{ijk} = \begin{cases} 0.001\beta_k t_{ij} & \text{if } 0 \leq t_{ij} < 30; \\ 0.002\beta_k t_{ij} & \text{if } 30 \leq t_{ij} < 60; \\ 0.003\beta_k t_{ij} & \text{if } 60 \leq t_{ij} < 120; \\ 0.004\beta_k t_{ij} & \text{if } 120 \leq t_{ij} < 180; \\ 0.005\beta_k t_{ij} & \text{if } t_{ij} > 180, \end{cases}$$

where $\beta_{\text{water}} = 5$, $\beta_{\text{food}} = 3$ and $\beta_{\text{shelter}} = 1$, and $M_k = 5\beta_k$.

6. COMPUTATIONAL STUDIES

In this section, we conduct two computational studies. The first computational study aims to present a case study for examining the characteristics of the solutions provided by our solution methodology. The second one aims to evaluate the computational performance, in terms of the effectiveness and efficiency, of our solution procedure. In the two sets of experiments, we adopt SYMPHONY (Ralphs et al., 2010), an open-source programme developed by the Computational Infrastructure for Operations Research (COIN-OR), as our MILP/LP solver. All the computations were conducted on an 8-core machine with the Intel Xeon 3.07 GHz X5675 processor.

In all the computational instances, we consider 3 types of commodities – water, food and shelters – and 4 types of vehicles – large lorry and trailers (LLT), large articulated lorries (LAL), medium lorries (ML) and water tankers (WT). Water tankers are designated for transporting water while lorries are designated for transporting shelters and food. In other words, in our model there are two kinds of loading constraints, which we denote them by $L = \{1,2\}$. We set $K_1 = \{\text{water}\}$, $K_2 = \{\text{food, shelter}\}$, $G_1 = \{\text{WT}\}$, and $G_2 = \{\text{LLT, LAL, ML}\}$. For the parameters relevant to the weights of the emergency supplies and the capacities of the vehicles, we adopt the figures provided on p. 550 and 551 in the Handbook for Emergencies by the United Nations High Commissioner for Refugees (2007): $a_{\text{water}} = 4.5$, $a_{\text{food}} = 1$, $a_{\text{shelter}} = 24$, $c_{\text{LLT}} = 25000$, $c_{\text{LAL}} = 35000$, $c_{\text{ML}} = 6500$ and $c_{\text{WT}} = 8000$, all in kilograms. For the number of vehicles available at each SF, we use the above volumes of the emergency supplies, the capacities of the vehicles, and the amounts of emergency supplies available at the SF to calculate the numbers of each types of vehicles required to transport all the pre-positioned emergency supplies from the storage facility, with the assumption that the number of the three types of lorries being equal.

For the objective function, we set

By the above setting, the first goal is to minimize the unmet demand for the emergency supplies and the second goal is to deliver the emergency supplies to the affected areas as soon as possible, with the most important commodity being water, followed by food, and the least important being shelters.

6.1 A CASE STUDY: DISASTER SCENARIOS IN IRAN

We first conduct a case study to examine the characteristics of the solutions obtained by our solution methodology. Since we aim to provide practical insights into disaster response decisions, we consider the case of Iran which was presented in Bozorgi-Amiri et al. (2013). While in their case study the objective was to determine the optimal locations of SFs in Iran before disasters strike, our goal is to determine the post-disaster optimal shipments of emergency supplies to the ACs. We assume that the five locations of suppliers and the 15 affected areas in their study are respectively the emergency supplies SFs and the ACs in our study. In the case, the five locations of the SFs are also located at some of the ACs and thus the emergency supplies can be delivered to their located communities immediately, if needed. We consider the four independent scenarios presented in their paper, which differ only by the post-disaster demands of the affected areas for emergency supplies (i.e., d_{jk}). We assume the amounts of emergency supplies available at the SFs (i.e., m_{ik}) equal to the capacities of the suppliers in their study. The travel time from each SF to each AC is obtained by the Google Maps Distance Matrix API (<https://developers.google.com/maps/documentation/distance-matrix/intro?hl=en>).

The solutions obtained by our solution methodology, which are represented by the flows of commodities from the SFs to the ACs, for the four scenarios are shown in Figures 2 to 5, where the top, middle, and bottom plots respectively show the shipments of water, food, and shelters. Red triangles represent the SFs and yellow circles represent the ACs.



Figure 2 The flows of delivering emergency supplies from storage facilities to affected communities in scenario 1. (Map data: Google)



Figure 3 The flows of delivering emergency supplies from storage facilities to affected communities in scenario 2. (Map data: Google)



Figure 4 The flows of delivering emergency supplies from storage facilities to affected communities in scenario 3. (Map data: Google)



Figure 5 The flows of delivering emergency supplies from storage facilities to affected communities in scenario 4. (Map data: Google)

The size of the circle surrounding each AC is proportional to the amount of demand for the emergency supplies at the community. The thickness of each flow is proportional to the amount of commodities delivered. The flows of water, food and shelters are represented by blue, cyan and green arrows respectively.

In the figures, unsurprisingly, the flows tend to deliver the commodities from the SFs to their closest ACs; but this is not always true. For example, we observe that in Scenario 1, for water and food, there is a SF which has water and food pre-positioned and the optimal solution suggests it delivers some amounts of the two types of commodities to another AC, and at the same time this SF receives the two types of commodities from another SF. This is due to the choice of a piecewise linear objective function of the travel time. In a humanitarian logistics setting, some types of emergency supplies should reach the ACs within a certain time (say, 2 hours), a strategy that an AC delivers some of its emergency supplies from its own pre-positioned inventory to another AC and waits to receive emergency supplies from another SF may benefit the overall affected population if most, if not all, of the affected communities can receive the required supplies within an acceptable time. This also illustrates that the decisions made in a humanitarian logistics setting are not intuitive and require to be determined from a systems perspective. Our solutions also demonstrate the needs of the coordination of different parties, information sharing, and the optimization of decisions. Another observation is that although the flows of water and food are very similar, the flow of shelters is quite different from those two. This also indicates that the transportation decisions may vary from commodity to commodity.

6.2 COMPUTATIONAL PERFORMANCE

In the second computational study, we aim to evaluate the computational performance of our solution methodology. We randomly generated instances of various problem sizes to enable us to understand the effectiveness and efficiency of our solution approach. The problem size is defined by the numbers of SFs and ACs in the model. To be consistent with the previous study of Iran, we kept the ratio of the number of SFs to the number of ACs at 1/3 and randomly generated five instances for each of the following problem sizes:

- 20 SFs and 60 ACs
- 30 SFs and 90 ACs
- 100 SFs and 300 ACs
- 300 SFs and 900 ACs

In each instance, we generated the demands for the emergency supplies with a normal distribution with the same mean and standard deviation as those in the previous case study of Iran. We also randomly generated the locations of the SFs and ACs on a 1000×1000 grid with a uniform distribution to resemble a region of 1000km×1000km. The other settings follow those in the previous case study of Iran.

Table 1 presents the problem sizes of the instances and the solution times required and solution qualities achieved by our solution approach. First we report that we tried to solve the mathematical model presented in Section 4 as a MILP. However, we were unable to obtain even a feasible solution within 10 minutes for some large instances. In our solution approach, the relaxation of the mathematical programme from a MILP to a LP and our proposed rounding-down heuristic have greatly reduced the time required for obtaining a solution. We observe that, in all the cases the solution times for solving Step 1 and Step 2 were within a second, and the total time for solving was less than a second in all the cases except that for two largest cases it was slightly longer than a second. In a humanitarian logistics setting, timeliness is key. The fast solution time for solving some practical instances (say 300 SFs and 900 ACs) is necessary; human decisions would not be able to be made within such a short period of time. Moreover, manual solutions do not guarantee solution quality. On the other hand, our solution procedure is able to provide near-optimal solutions. We observe that the optimality gap (which is defined as the percentage difference between the best solution found and the lower bound) for all of the instances was kept below 1%, except for Instance 5, which had an optimality gap of slightly more than 1%. More importantly, the optimality gap appears to be very stable; it did not increase as the problem size increased. This shows that our rounding heuristic does not lose much solution quality due to the rounding differences. Furthermore, since this rounding-down heuristic is very likely *not* to deploy all the available vehicles (due to the rounding differences), in practice the decision maker will notice the excess of vehicles from the solution and they can deploy those

Inst- ance	# SFs	# ACs	# Decision Variables	# Cons- traints	# Non- zero Coeff.s	Sol. Time (s) for Step 1	Sol. Time (s) for Step 2	Total Sol. Time (s)	Opt. Gap ($\times 10^{-3}$)
1	20	60	8580	2720	29160	0.001907	0.001710	0.003617	4.603
2						0.001889	0.001803	0.003692	5.931
3						0.001859	0.001682	0.003541	5.832
4						0.001909	0.001737	0.003646	2.631
5						0.001850	0.001784	0.003634	10.91
6	30	90	19170	5880	65340	0.003871	0.003826	0.007697	5.987
7						0.004303	0.004271	0.008574	7.060
8						0.004172	0.004223	0.008395	6.627
9						0.004172	0.004263	0.008435	5.536
10						0.004361	0.004366	0.008727	6.335
11	100	300	201900	61600	721800	0.050685	0.047632	0.098317	6.556
12						0.042806	0.049672	0.092478	6.216
13						0.043222	0.050102	0.093324	6.224
14						0.042790	0.050164	0.092954	6.578
15						0.042744	0.050851	0.093595	7.290
16	300	900	1892700	544800	6485400	0.429854	0.443206	0.873060	6.415
17						0.427686	0.435606	0.863292	6.904
18						0.428817	0.446112	0.874929	6.440
19						0.524294	0.717764	1.242058	6.183
20						0.868887	0.470420	1.339307	7.858

Abbreviations: Coeff.= coefficient; Sol.=solution; and Opt.= optimality

Table 1. Problem size of each instance, and the solution time required and the optimality gap achieved by our solution approach

unassigned vehicles to transport emergency supplies to satisfy uncovered demands, if any. Therefore, if post-solution assignments are made, the optimality gap should be smaller than what we have reported.

7. CONCLUSIONS

Big data and ICT have effectively facilitated disaster management with various applications. As a result, substantial losses (including human losses) can be reduced. While there has been much work on information extraction and dissemination in this area, optimization with real-time information to improve operations is rarely addressed in big data research on disaster management. In this paper, we propose a real-time decision support tool, with the use of optimization, to aid post-disaster decision making. We adopt a mathematical programming approach to model the problem, where the decisions are the shipments of

commodities from emergency supplies storage facilities to affected communities. We also consider multiple types of commodities and heterogeneous vehicles for transportation. The objective function of our model involves the cost of shortage and a piecewise linear cost of travel time to penalize the delays within different time intervals. We conduct a case study of Iran to examine the characteristics of the solutions provided by our methodology. Our case study also illustrates that information sharing and coordination among different storage facilities are important in a humanitarian logistics setting. Thus, big data can be an enabler to facilitate disaster response decisions. We also conduct a computational study to evaluate the computational performance of our solution approach. Since we experienced a long computational time for obtaining even a feasible solution in some large randomly generated instances, we propose a rounding-down heuristic to obtain near-optimal solutions within a very short period of time. Computational results show that our approach could produce rapid solutions of insignificant optimality gap.

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