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[Received on 22 March 2011; accepted on 19 December 2011]

As the frequency and severity of disasters around the world increase, there is an urgent need for more efficient and effective allocation of response resources to impact jurisdictions. In a disaster situation, time wasted may define the line between life and death. In this paper, we develop an integer programming model for the capability-based multi-resource multi-location allocation problem. The model is intended to take advantage of a nationwide resource inventory listing in order to allocate response personnel, facilities, supplies and equipment to impact jurisdictions.

Keywords: disaster response; emergency management; resource allocation; modeling

1. Introduction

As the world population continues to rise and urban population densities increase, concern about disasters becoming increasingly severe is very real. Munich RE reports that in 2010, a total of 950 natural disasters were the cause of 295,000 lost lives and US\$ 130 Billion in economic losses. The overall picture in 2010 was dominated by severe earthquakes with Haiti, Chile and China earthquakes being categorized as great natural catastrophes based on the definition criteria of the United Nations (Munich RE, 2011).

Disasters present challenges for resource management that are different from those in routine emergencies (Auf der Heide, 1989). Major disaster events typically cause significant stress to local jurisdiction resources. There are possibly three causes of this stress: (1) actual disaster impact damages or destroys local resources reducing available resources to respond; (2) disaster impact to the jurisdiction significantly increases the workload of the existing resources; (3) continued organizational stress from prolonged high levels of response activity through the emergency recovery period (72 to 168 h). This generates immediate or progressive shortfalls in response capability as resources degrade. Consequently, the use of resources (personnel, facilities, supplies and equipment) from multiple jurisdictions may be required. This leads to the assumption that the primary problem in disaster planning is the mobilization of enough resources (Quarantelli, 1983). Based on this assumption, disasters have even been defined as emergencies that exceed the available resources (Orr and Robinson, 1983). The inflow of resources to the impacted jurisdiction however, can complicate the already difficult problems of coordination and communication if the inflow is greater in amount than needed (Stout and Smith, 1981).

Auf der Heide (1989) points out that in many disasters the response exceeds the human and equipment resources requested and lists the reasons leading to excess resources: first, more resources than expected may have survived the disaster at the impact site; second, resources are deployed even when they are not requested and it is often difficult to refuse unsolicited assistance; third, the procedures and

responsibilities of assessing and requesting resources are neglected; and last, it is generally assumed that having an overage is better than having a shortage of resources. It is important that disaster planners and emergency coordinators understand these reasons and develop procedures for multi-agency management of resources so that requests are coordinated. Resources need to be classified so that they can be meaningfully, optimally and quickly allocated.

In the next section, we will describe the resource classification scheme used in the USA. There is still a clear need for models and systems that allow additional resources to be optimally allocated, mobilized and deployed to supplement the capabilities of impacted jurisdictions. The use of such decision support systems would help mitigate resource allocation problems in a timely manner (Thompson *et al.*, 2006). Hence, it is the objective of this paper to introduce analytical models for resource allocation in disaster response operations. To the best of our knowledge, capability-based allocation of supplemental resources in response to a disaster has not yet been modeled in the literature. Such an analytical model would require a classification scheme for resources and their capabilities.

In fact, when responding to an incident with the minimum number of resources, failing to understand the capabilities of those resources is dangerous. Furthermore, even though most commanders are fully aware of their resources in routine operations, 'problems begin to arise when the incident is of sufficient magnitude to require mutual aid, mobilizing unfamiliar agencies and equipment' (Murgallis and Phelps, 2002, p. 240).

The next section describes resource typing within the National Incident Management Systems (NIMS). Resource typing is the categorization and description of resources that are commonly exchanged in disasters via mutual aid. Salient literature on mathematical programming models for resource allocation is reviewed in section 3. Section 4 discusses the models proposed in this paper. Section 5 provides an illustrative example and section 6 concludes the paper.

2. Resource classification scheme

In the immediate hours after a disaster, it quickly becomes clear that the main resource problem is to provide impact jurisdictions with units that could relieve the local emergency services agencies when they reach their operational fatigue and stress limits. This means that the mission requirement is for the deployed emergency services resources to be able to functionally duplicate the capabilities of the average emergency services station. The problem of moving resources between jurisdictions was identified relatively early in the development of resource deployment systems. In the USA, the Emergency Management Assistance Compact (EMAC), initiated as the Southern Governor's Compact in 1993 and then expanded nationwide, provided the first framework for state to state assistance independent of federal disaster response. Under EMAC, any signatory state could request any of a wide variety of resources from any other signatory state. A number of states also established statewide mutual aid systems designed to facilitate resource transfers across the state.

In 1977, following a series of major wildfires, efforts to develop a standard system for managing large wildfires in the USA resulted in the Firefighting Resources of Southern California Organized for Potential Emergencies (FIRESCOPE) system. FIRESCOPE approached the resource management problem in a structured way, developing, among other components, standard organizational structures theoretically applicable to all emergencies, terminology, communications and support systems. Along these lines, the National Interagency Incident Management System, published in 1985, established the FIRESCOPE structure as a national standard model for an Incident Command System (ICS). The ICS is the approach used by many emergency services professionals to organize and control the temporary systems they deploy to manage personnel and equipment at almost any type and size of emergency, such

as fires, mass casualty incidents, natural disasters, hazardous materials spills and so forth (Bigley and Roberts, 2001). The National Wildfire Coordinating Group (NWCG), a multi-agency wildfire consortium, has had a central influence on the development of major incidents. One of the critical contributions of the NWCG was the development of a rating system to classify resources into various capability levels. Furthermore, in the mid 1990s, the Central United States Earthquake Consortium developed an initial model for resource classifications for natural disaster response. NIMS fielded in 2005 continued the resource classification trend with efforts to develop standard resource packages for a variety of situations. Like the NWCG's classification of resources into 'Types' based on capabilities, NIMS intended to rate resources in descending order of capability.

Figure 1 describes the resource classification scheme used by NIMS. *Type* specifically defines the level of capability a resource has and may vary by power, size or capacity. Type 1 resources of any category provided the highest capability, where Type 4 represented the lowest. *Category* describes the function of the resource. Table 1 lists the categories used in the National Resource Typing Protocol (as of June 2007). *Kind* refers to broad classes that characterize similar resources, such as teams, equipment, supplies, vehicles and aircraft. For example, a construction dump truck and a dump truck with a snow plow have different capabilities, capacities and purposes. Therefore, they would be considered to be of different kinds and types. Figure 2 provides an actual resource typing example taken from the Federal Emergency Management Agency (FEMA) *Typed Resource Definitions* document.

In the USA, the information on typed resources is being inventoried by the National Integration Center through the development of a database management tool called the National Incident Management System–Incident Resource Inventory System (NIMS-IRIS). The objective of NIMS-IRIS is to

FIG. 1. The resource classification scheme used by FEMA-NIMS.

TABLE 1 *Resource categories used in the National Resource Typing Protocol*

<ul style="list-style-type: none"> ● Transportation ● Communications ● Public works and engineering ● Firefighting ● Information and planning ● Law enforcement and security ● Mass care ● Resource management 	<ul style="list-style-type: none"> ● Health and medical ● Search and rescue ● Hazardous materials response ● Food and water ● Energy ● Public information ● Animals and agricultural issues ● Volunteers and donations
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RESOURCE:		Airborne Transportation Team (Fixed-Wing)				
CATEGORY:		Transportation (ESF#1)			KIND:	Aircraft
MINIMUM CAPABILITIES:						
COMPONENT	METRIC	TYPE I	TYPE II	TYPE III	TYPE IV	OTHER
Personnel	Crew Members See Note 1	Instrument-rated (IFR) pilot/co-pilot	Non-instrument rated pilot/co-pilot (1 pilot required only)	Instrument-rated (IFR) pilot/co-pilot (pilot and co-pilot required)	Non-instrument rated pilot/ co-pilot (1 pilot required only)	
Personnel	Number of Passengers	Maximum 2 additional	Maximum 3	Maximum 1	Maximum 2	
Aircraft	Fixed-Wing See Note 2 See Note 3	Airborne transport capable of operations up to 10,000' MSL Flight possible through and in overcast conditions (instrument meteorological conditions)	Airborne transport capable of operations up to 10,000' MSL Visual meteorological conditions only	Airborne transport capable of operations up to 10,000' MSL Flight possible through and in overcast conditions (instrument meteorological conditions)	Visual meteorological conditions only	
Aircraft	Cargo	Carries up to 350 lbs.	Carries up to 500 lbs.	Carries up to 200 lbs.	Carries up to 350 lbs.	
COMMENTS:		<p>Team provides limited airborne transportation and emergency airlift to support Federal, State and local agency needs using light fixed-wing platforms owned by CAP. Varying levels of specialized management support and command/control capabilities are included in team structures.</p> <p>Source: Washington State Civil Air Patrol</p> <p>Note 1: Crew members capable of at least 8 hours of flying per day and 14-hour duty day. Number of certified pilots, equipment operators, and technicians needed depends on size and capability of aircraft.</p> <p>Note 2: Fixed-wing single-engine or twin-engine aircraft capable of 120 knots (130 mph) at cruise (i.e., Cessna C182, C182RG, C206, TU206). Capable of point-to-point transport into short airfields; Capable of eye-in-the-sky coordination of tactical teams on the ground and photo/imaging; GPS guided.</p> <p>Note 3: Requires access to fuel supply and fueling points, and routine maintenance facilities and supplies for extended deployments.</p>				

FIG. 2. Sample typed resource (Source: FEMA 508-2 Typed Resource Definitions—Incident Management Resources).

establish interoperability of resources. ‘The software will allow emergency responders to enter typed resources and select specific resources for mutual aid purposes based upon mission requirements, capability of resources and response time’ (from <http://www.fema.gov/emergency/nims/ResourceMngmnt.shtm>). NIMS-IRIS is planned to have the functionality to assist in placing and mobilizing resource requests, GPS tracking of resources and resource recovery. The analytical models we provide in this paper are intended to be used for allocating/assigning resources to requests within the NIMS-IRIS system.

3. Resource allocation problems

The use of operational research and management sciences techniques in disaster operations management has been limited (Altay and Green, 2006). Amongst the papers related to this realm attention was mostly given to evacuation planning (Yi and Ozdamar, 2007), transport vehicle scheduling (Barbarosoglu *et al.* 2002), location decisions (Jia *et al.* 2007) and distribution problems (Balcik *et al.* 2008). A plethora of solution methods were used including stochastic programming (Barbarosoglu and Arda, 2004), simulation (De Silva and Eglese, 2000), integer programming (Gormez *et al.* 2010), meta-heuristics (Yi and Kumar, 2007) and constructive heuristics (Ozdamar and Yi, 2008).

The resource allocation problem seeks to optimally allocate a given number of resources to a given set of activities so that the total cost of allocation is minimized (White, 1993). Depending on the scenario on hand and the modeling approach taken, the problem can become linear or nonlinear, stochastic or deterministic and be formulated as a facility location problem, maximum network flow problem or job

scheduling problem among others (Di Domenica *et al.*, 2009). There is a sizeable literature on resource allocation problems with special mathematical structures and efficient solution algorithms as well as heuristics designed to take advantage of these structures (White, 1993). For a complete and detailed review of these models and algorithms, the reader is referred to the books by Ibaraki and Katoh (1988) and Mjelde (1983), along with the comprehensive chapter by Katoh and Ibaraki (1998).

Although allocation problems are a common topic in mathematical programming textbooks, there are very few applications of them in our context. Some are developed for specific events and scenarios, such as oil spills (Psaraftis and Ziogas, 1985; Belardo *et al.*, 1984) or wild fires (Fiorucci *et al.* 2004; Minciardi *et al.* 2009). Fiorucci *et al.* (2004) formulate a real time allocation problem of continuous resources to a single demand point. The objective function of their model minimizes a cost function, which is composed of the estimated damage as a function of response, cost of inadequate assignment of resources and the cost of transfers between nodes. Minciardi *et al.* (2009) extend the idea in Fiorucci *et al.* (2004) to integrate the pre-event and during event response operations.

Others consider more general scenarios. Fiedrich *et al.* (2000) develop a dynamic optimization model that assigns and schedules search-and-rescue teams to damaged areas to minimize fatalities and is subject to time constraints. Using annual emergency frequency and resource consumption data, Yongjun *et al.* (2010) first use a grey prediction model to allocate resources and then formulate a dynamic multi-objective resource scheduling problem to dispatch allocated resources to a single sink. The resources are assumed to be consumed based on a given rate and are replaced as necessary. Wang *et al.* (2007) also consider resource consumption but extend their model to include multiple response sites (sinks). Chao *et al.* (2009) bring in transportation capacity to the set of constraints.

Another set of papers are concerned with equitable allocation of scarce resources (Katoh *et al.* 1985; Fujishige *et al.* 1988). As mentioned in the first section of this paper, it is generally assumed that the demand for response resources after a disaster would exceed the available resources (Orr and Robinson, 1983). Thus, distribution of scarce resources among competing impact jurisdictions requires just allocation methods. Suppose that response performance is measured as the deviation of the response level assigned to an activity from a specified target. The optimal solution is then called equitable 'if no performance function value can be improved without either violating a constraint or degrading an already equal or worse-off performance function value that is associated with a different activity' (Luss, 1999, p. 361).

Interestingly, the effectiveness or performance of a response effort has been pretty much correlated in literature to the quantity deficit between demand and supply of resources. For example, Fiorucci *et al.* (2004) use an objective function that minimizes cost of inadequate assignment of resources (as in quantity). Alternatively, Ozdamar *et al.* (2004) minimize the allocated resource deficits accumulated over time while coordinating the distribution. Rolland *et al.* (2010) also have a mismatch cost component in their objective function. Similarly, Kondaveti and Ganz (2009) determine the number of resources allocated to each impact location by minimizing the overall fraction of unsatisfied demands. Although there are applications of capability-based assignment problems in different contexts (e.g. Lai *et al.*, 2002), our search of the literature did not produce any papers that consider the quality, i.e. capability, of the emergency response resources. In the following section, we formulate the capability-based resource allocation problem.

4. Capability-based resource allocation problem

Winston (1995) describes the generalized resource allocation problem as follows: Suppose there are n units of a resource and m activities where this resource could be utilized. The function $g_t(.)$ calculates

the amount of resources needed to implement activity t at a given activity level. Similarly, the function $r_t(\cdot)$ finds the benefit obtained from implementing activity t at a given activity level. Then, if activity t is implemented at a level x_t , then $g_t(x_t)$ units of the resource are used for activity t , and a benefit $r_t(x_t)$ is obtained. The objective is to maximize total benefit subject to limited resource availability. The generalized resource allocation problem can then be modeled as:

$$\max \sum_{t=1}^m r_t(x_t) \quad (1)$$

$$\text{s.t. } \sum_{t=1}^m g_t(x_t) \leq n \quad (2)$$

$$x_t \geq 0 \text{ and Integer} \quad (3)$$

In this paper, we consider a scenario where multiple jurisdictions, hit by a disaster, request assistance from surrounding jurisdictions. We formulate a multi-resource, multi-location allocation problem. It is assumed that ground assessment has been completed and all services needed at the disaster locations are either known or could be closely estimated by the damage assessment teams. It is also assumed that all available resources in the surrounding jurisdictions have been typed (i.e. classified) and information on their capability, capacity and quantity is readily available (through the NIMS-IRIS resource database, e.g.). The objective then is to match these resources with the requests minimizing the total deployment time. Variable and parameter definitions and the model are as follows;

Parameters:

I set of locations with available resources.

J set of resource types (e.g. Excavator, Type II).

K set of multiple units for each resource (this is necessary only for tracking purposes).

L set of locations with requests (i.e. impact jurisdictions) c_{ijk} capability of unit k of resource type j at supply site i (based on the NIMS resource typing scheme, we consider four levels of capability, numerically represented with values 1,2,3 and 4; 4 being the most capable).

t_{ijkl} deployment time (defined as time to get ready + travel time) of unit k for resource type j at origin i assigned to destination l .

d_{jl} capability need for resource j at impact location l .

q_{jl} quantity of resource type j needed at demand location l .

a_{ij} units of resource type j available at supply location i .

m_{ijk} number of jurisdictions by which the k th unit of resource j at location i can be shared.

Decision variable:

X_{ijkl} equals 1 if the k th unit of resource type j at supply node i is assigned to demand node l ; zero otherwise.

Utilizing the index k allows the Incident Commander to track individual resources (the resource assigned may be a type II excavator but the index k would identify the exact unit assigned; e.g. Caterpillar 3126B Diesel is sent to Cook County emergency management). Our problem could be modeled without index k if this level of information granularity is not necessary. In that case, the resulting decision variable X_{ijl} would be an integer variable (rather than binary) indicating the number of units of resource j at location i assigned to destination l .

Next, we formulate the capability-based resource allocation model for disaster response. We present two variants of the problem: Case 1 assumes that adequate resources of desired capability are readily

available (this is a straightforward matching problem). In case 2, there are not enough resources to satisfy all requests and some resources could be shared by several demand locations. In this case, an equitable allocation scheme is needed.

4.1 Case 1: Supply exceeds demand

Contrary to common assumption, Auf der Heide (1989) suggests that in many disasters there is no shortage of resources. For our modeling problem, this is a critical point since if resources are plentiful and readily available there is no need for equitable allocation of resources. They will be simply matched with requests from impact jurisdictions. If ample resources are available, then the goal should be to get them quickly to where they are needed. We can develop two alternative objective functions: (i) minimize total deployment time or (ii) minimize maximum response time. The resulting model for Case 1 is presented below:

Objective function:

$$(i) \text{ Minimize } \sum_I \sum_J \sum_K \sum_L X_{ijkl} t_{ijkl} \quad (4)$$

$$(ii) \text{ Minimize } \text{Max}[X_{ijkl} t_{ijkl}] \quad (5)$$

Subject to:

$$\sum_l \sum_K X_{ijkl} = q_{jl} \quad \forall_j \in J, l \in L \quad (6)$$

$$\sum_K \sum_L X_{ijkl} \leq a_{ij} \quad \forall_i \in I, j \in J \quad (7)$$

$$\sum_i \sum_K X_{ijkl} c_{ijk} \geq d_{jl} q_{jl} \quad \forall_j \in J, l \in L \quad (8)$$

$$X_{ijkl} \in \{0, 1\} \quad \forall_i \in I, j \in J, k \in K, l \in L \quad (9)$$

Here, constraint set (6) together with (9) make sure that each request is satisfied by a single resource. The reason for this is to prevent the following possible scenario: consider a request from impact jurisdiction $l = 1$ is for one unit of type I resource $j = 2$ (i.e. $q_{21} = 1$ and $d_{21} = 4$). The single sourcing requirement eliminates the possibility that for this request two separate units of resource 1 with capability score 2 are assigned, collectively satisfying the capability demand (i.e. two units with $c_{ijk} = 2$ is assigned). Since emergency response resources are typed based on capacity and capability, a lower capability resource cannot perform at the same level as a higher version. For example, consider the Airborne Transport Team in Fig. 2. A type I team can fly through and in overcast conditions using its instruments, while a type II team can only fly in visual meteorological conditions since they lack the instrumentation. Therefore, in a response situation with bad weather and low visibility, the type II resource in Fig. 2 cannot perform the task a type I unit can.

Constraint set (7) is a capacity constraint to ensure that the model does not assign more resources than are available. Constraint set (8) forces each assigned resource to be of equal or higher capability.

4.2 Case 2: Demand exceeds supply

When available resources are not enough to cover requests in terms of quantity and/or capability, then an equitable allocation scheme is needed. Chen *et al.* (2005) propose two allocation mechanisms that they

call ‘winner-take-all’ and ‘collaboration.’ The former assigns resources to satisfy the full demand, while the latter distributes resources to all demand points as much as it can. For example, consider a situation where the Incident Commander has to allocate 10 units of a resource to disaster sites A and B, where the demands for the resource are 6 units and 8 units, respectively. The winner-take-all scheme would allocate 6 units to location A and 4 units to location B, satisfying all demand in at least one location. Another feasible solution for this strategy is to assign 8 units to B and 2 units to A. In either scenario, one location receives all their need. The collaboration scheme on the other hand would allocate 4 units to location A and 6 units to location B.

For this scenario, we remove constraints (6) and (8) and add a second term to our objective function. In Case 2, since there are not enough resources available to satisfy all of demand, the second term in the objective function forces the model to assign resources such that the total capability deficit is minimized. In section 4.1, we argued that a resource with lower capability than what is requested cannot perform at the expected level. Our argument is still valid in this case. However, despite the shortage of resources, there still is a disaster that needs to be somehow responded. Thus, some resources could be shared by multiple jurisdictions if the impact locations are close to each other and there are not enough resources to be allocated to every impact jurisdiction.

The result is a multi-objective optimization model in which the objective function is to minimize the weighted sum of total deployment time and total capability deficit. The parameter α in the objective function sets the priority weight given to the two objectives. Using a weighted sum gives the Incident Commander, the flexibility to inject his/her judgment into the model by changing the prioritization level of the two objectives. The resulting model for Case 2 is formulated as follows:

Objective function:

$$\text{Minimize } \alpha \left(\sum_I \sum_J \sum_K \sum_L X_{ijkl} t_{ijkl} \right) + (1 - \alpha) \left(\sum_J \sum_L q_{jl} d_{jl} - \left(\sum_I \sum_K X_{ijkl} C_{ijk} \right) \right) \quad (10)$$

Subject to (7), (9) and

$$\sum_I \sum_K \sum_L X_{ijkl} = \text{Min} \left(\sum_I a_{ij}, \sum_L q_{jl} \right) \quad \forall j \in J \quad (11)$$

$$\sum_I \sum_K X_{ijkl} \leq q_{jl} \quad \forall j \in J, l \in L \quad (12)$$

$$\sum_L X_{ijkl} \leq m_{ijk} \quad \forall i \in I, j \in J, k \in K \quad (13)$$

$$0 \leq \alpha \leq 1 \quad (14)$$

Constraints (11) assure that unless demand for a particular resource is zero or the resource is not available in any of the supply nodes, that resource is allocated. Constraints (12) prevent from overloading demand to one location. Constraint set (14) controls the sharing of resources. If a resource cannot be shared then $m_{ijk} = 1$. The model above arbitrarily allocates scarce resources to demand points. It is a trivial exercise to include priority scores to the objective function so that the allocation is performed based on a ranking scheme.

The above described multi-objective optimization model can easily be reduced to a single objective model if the Incident Commander already knows the maximum tolerable (or desirable) response time, T . In such a case, the single objective would become to minimize the total response capability deficit,

TABLE 2 *Illustrative example data for supply of resources A, B and C*

	Node 1			Node 2			Node 3				
Resource	A	B	C	A	B	C	A	A	B	C	C
Quantity	2	1	1	1	1	1	2	1	0	2	1
Capability	2	1	4	3	3	3	3	4	0	1	2
dtime to S1	1	3	8	3	5	10	5	5	0	9	9
dtime to S2	2	4	10	3	5	10	2	2	0	6	6

TABLE 3 *Illustrative example data for demand of resources A, B and C*

	Sink 1			Sink 2		
Resource	A	B	C	A	B	C
Quantity	2	2	3	2	1	3
Capability	3	2	3	2	4	2

while a new constraint set is added to ensure that no deployed resource exceeds the tolerable response time T . This time constraint could be modeled as:

$$X_{ijkl}t_{ijkl} \leq T \quad \forall i \in I, j \in J, k \in K, l \in L \quad (15)$$

5. Illustrative examples

We now demonstrate the usefulness of our capability-based multi-resource multi-location resource allocation model on a small illustrative example problem. We use the simulated data presented in Tables 2 and 3. The problem consists of allocating three types of resources (A, B and C) from three supply locations (nodes) to two disaster response locations (sinks). The supply quantity of resource type A exceeds the demand quantity, while resource types B and C have a shortage. Note that supply node 3 has three units of resource type A, two of which have a capability of 3 units, while the third unit has a capability of 4 units. A similar scenario applies to resource type C in node 3. Node 3 does not have any resource type B in inventory. We assume that resources cannot be shared; i.e. $m_{ijk} = 1$ for all resources. In Table 2, the last two lines indicate the deployment time from the supply node to the sinks.

It is reasonable to assume that an Incident Commander would consider minimizing deployment time and capability deficit equally important (i.e. $\alpha = 0.5$). To see the effect of ignoring one of the objectives, we solved our example problem with $\alpha = 0, 0.5$ and 1. The first α value eliminates the minimum deployment time from the objective function, while the last one ignores the capability deficit minimization. Results are listed in Table 4. As expected, the best capability deficit is found when deployment times are ignored but the same cannot be said for the opposite. Total deployment time value did not change even when capability deficit was brought in as an equally important objective. The third row in Table 4 hints that there is an optimal α value that minimizes the sum of the two objectives.

This small example does not however provide any indication about the solvability of the models introduced. Consequently, data for a more realistic size problem are generated based on the aftermath of a severe winter storm which dumped 20 inches of snow on the Midwest region of the USA. The February 2011 storm hit the state of Illinois hard. The estimated cost of emergency work, repair or replacement

TABLE 4 *Solution to the illustrative problem*

	$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$
Total deployment time	62	50	50
Total capability deficit	5	7	8
Sum of the two	67	57	58
Optimal solution	5	28.5	50

of facilities damaged by the snowstorm, emergency protective measures, and snow assistance was \$64 Million. The U.S. Department of Homeland Security's FEMA declared 60 counties in Illinois federal disaster areas (shaded in Fig. 3 below).

We chose to use the state of Illinois' response to the blizzard as our test case because Illinois Emergency Management Agency (IEMA) has long ago established the Illinois Emergency Management Mutual Aid System and the Mutual Aid Response Network (MARN). The former is similar to the NIMS resource inventory system and enables local governments to share equipment, personnel and services with impact jurisdictions. MARN on the other hand, connects local governments with the private sector for a deployment of additional resources through Memorandum of Understandings. Thus, an inventory of available resources was available for the use of IEMA in response to the blizzard. What was missing was a capability-based resource allocation model that could efficiently and effectively allocate resources to impact jurisdictions.

As mentioned above, 60 Illinois counties were declared disaster areas after the February blizzard (i.e. 60 sink nodes). Since we do not know the exact number of local and neighboring emergency management organizations responding to this event, we looked at how many counties are located within a 300 miles radius from central Illinois (i.e. about 6 h driving distance). We found about 180 counties from Illinois and its neighboring states Wisconsin, Iowa, Missouri and Indiana (i.e. 180 source nodes). We then randomly generated deployment times (between 1 and 12 h) from a Uniform distribution.

FEMA defines 15 Emergency Support Functions (ESFs) as resource categories (<http://www.fema.gov/emergency/nrf/>). We assumed that each ESF has 10 listed resources. This is a reasonable assumption since some ESFs will have only 1–2 resources such as specialized teams (e.g. search and rescue), while others may list more than 10 (e.g. dump trucks). Each resource is then typed randomly between 1 and 4 for its capability. Thus, our test problem contains $15 \times 10 \times 4 = 600$ resource types. For simplicity, we assumed that each resource type has a single copy (i.e. $K = \{1\}$). Requested resource quantities and number of available resource types were also randomly generated.

The resulting problem with 60 demand locations, 180 supply nodes and 600 resource types contains 6,480,000 X_{ijkl} binary decision variables. The problem was solved with CPLEX version 12.3 using a PC running a 64-bit Windows 7 Operating System with Intel Core2 Duo 2.93 GHz processor. Case 1 with objective function (4) was solved in 154.6 s. However, the same problem instance with objective function (5) was not solvable within 3600 s. To examine the problem behavior under objective function (5) we created a smaller problem with 4 demand nodes, 10 supply nodes and 20 resource types (single copy, i.e. $K = \{1\}$). We found that although Case 1 with objective function (5) reduces the maximum deployment time, it takes about three times longer to solve and results in 50% higher total deployment time than the version with objective function (4). Even though it makes sense for an Incident Commander to focus on maximum deployment time as a single objective, excessive solution times for realistic size problems may deem applying total deployment time minimization as an objective necessary.

FIG. 3. Map of Illinois: counties declared disaster areas are shaded in grey (Source: digital-topo-maps.com).

We also generated test problems for Case 2. This time we assumed that response was generated from within the state of Illinois using state resources only. Illinois has 102 counties. With 60 of them declared as disaster areas, we assumed that the other 42 counties were the source nodes. Thus, Case 2 was tested with 60 demand nodes, 42 supply nodes and 600 resource types. For purposes of simplicity, we kept the parameter m_{ijk} equal to 1. This still results in 1,512,000 binary decision variables. Using a balanced objective function (i.e. $\alpha = 0.5$), Case 2 instances were solved under 3 s.

6. Conclusions and further research

Responding to emergencies such as forest fires, floods, snow storms, earthquakes and alike is one of the most important services a government provides to its residents. Unfortunately, there is strong evidence that the frequency and strength of disasters are increasing around the world. This fact has ignited a large amount of much needed research on disaster operations management. Sophisticated analytical models have been developed for evacuation scenarios, relief distribution problems and location of emergency vehicles. Despite its popularity in common operational research textbooks, we found that resource allocation models have not been widely applied to disaster response and the ones that have are not concerned with resource capability.

In this paper, we provide two variants of a capability-based multi-resource multi-location resource allocation model. One version of the model assumes that resources are plentiful and readily available, while the other considers the case where the demand for resources overwhelms supply. Our work has tremendous managerial implications because although systems for classifying and inventorying response resources are already in place, allocating resources to impact jurisdictions is still a very much manual process. There is a clear need for timely and effective allocation of response resources.

We first show how the models work on a small illustrative example and then test their practicality on realistic size problems inspired from the response to a recent blizzard in Illinois, USA. We did not inquire into solution algorithms and computational studies. Clearly, this should be the next step in furthering our research in this area. Additionally, our model is based on a snapshot of the disaster situation in which the needs are known and the assigned resources satisfy those needs. A further improvement to our model would be the dynamic demand scenario where resources can only be operational for a given time period and need to be scheduled throughout a given time horizon. The realism of the model could also be improved by considering additional constraints, such as a budget constraint.

Acknowledgement

The author would like to thank his former colleague Prof. Walter G. Green, III for his input on the historical development of resource categorization in the USA.

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