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A model for planning locations of temporary distribution facilities for emergency response

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ABSTRACT

We propose a network flow model for dynamic selection of temporary distribution facilities and allocation of resources for emergency response planning. The model analyzes the transfer of excess resources between temporary facilities operating in different time periods in order to reduce deprivation. Numerical analysis shows that the location of temporary facilities is determined by the demand and supply points. This work contributes to the emergency response planning that requires a quick response for the supply of relief materials immediately after a disaster hits a particular area.

1. Introduction

Response planning to meet the needs of people during natural disasters such as hurricanes, floods, and earthquakes is challenging because resources of more than one type have to be delivered to the demand areas in a timely manner and in right quantities. It also requires a carefully planned process of acquiring and distributing the resources. This poses further challenge as the demand in such disasters may vary over time in terms of the type of materials (or service) or in terms of quantity. Rennemo et al. [19] mentions that disasters are characterized by uncertainty and unpredictability; and therefore, demand may change rapidly in such an environment. Additionally, demand for resources in one location at a period may not exist in the next period; or, a particular location may have a very high demand in the subsequent period.

Performance of emergency services is measured in terms of the response time and the total logistics cost [23]. Therefore, if demand is not met on time, the performance of service will degrade. In order to address such a situation, a flexible and efficient emergency response system should be developed so that both social and economic losses due to the aftermath of disasters could be minimized [2]. Therefore, location and allocation of relief distribution facilities becomes critical for an effective emergency response planning.

As disaster may cover a large region, emergency supplies (also called resources) would be needed for several days and in varying quantities even at a single location. A change in demand both in terms of the location and the quantity is usually tackled through the allocation of resources at the prepositioned facilities. However, prepositioned facilities may be small in numbers and distribution of resources to the affected area may require additional funds for transportation and other overhead costs. In such a case, resources can be distributed through a number of temporary facilities that can be located near the demand centers. Research on relief distribution through temporary facilities has gained attention recently. The use of temporary relief centers will decrease response time. Holguin-Veras et al. [10,11] mention that deprivation is caused due to delayed response time. Therefore, when resources are provided as soon as possible to the needy areas, the social cost due to deprivation reduces significantly.

In this paper, we propose a model for emergency response planning. The model provides location and allocation plans for short distribution periods in a planning horizon. It considers periodically changing demand and supply. This change necessitates dynamic decisions on location of temporary relief distribution facilities and allocation of resources. Our model allows delayed satisfaction of demand when resources in a planning period are insufficient, and allows transfer of excess resources from a relief facility to another in the next time period. We believe that the consideration of the dynamic decision, transfer of excess resources and provision of delayed satisfaction of demand make the proposed model unique and more representative to the actual relief distribution.

The organization of this paper is as follows: in Section 2, we review relevant literature in emergency response planning. In

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Section 3, we present the proposed model. In Section 4, we provide numerical analysis to analyze the model. Finally, in Section 5 we provide the concluding remarks, limitations and possible future extension of this research.

2. Relevant literature

One of the comprehensive reviews of the literature on emergency logistics is given in Ref. [5]; which mentions that the research on facility location for the distribution of resources during the response period is gaining attention recently due to the need to make the distribution more efficient. However, the majority of the literature in this area has focused on the location of temporary depots for ambulance vehicles. A large number of researchers (such as [3,4,6,15,18,20]) have studied the location and allocation of relief facilities for the preparedness (pre-disaster) period.

Authors proposing ambulance vehicles location and relocation have generally considered multi-period models [8,9,21,22,25]. These models recognize that relief quantities and travel times are time dependent.

Post-disaster planning for resource allocations and temporary facility locations has gained attention recently. We have identified that three papers [1,14,24] are related to the model being proposed here. These studies consider dynamic nature of demand to propose integrated models for facility location, supply delivery and vehicle routing. Lin et al. [14] consider the total number of facilities to be located as a fixed time independent parameter, whereas [24] and [1] consider it as a time dependent decision variable.

Tzeng et al. [24] have proposed a three objectives model by considering cost, response time and distribution fairness. The cost objective includes setup and operational costs of transfer depots and distribution of relief resources. The response time objective includes the travel time between the collection points, transfer depots and demand centers. The distribution fairness objective includes maximization of satisfaction in distribution fairness by considering a weighted score for the satisfaction value for each relief supply item in different planning periods.

Lin et al. [14] extended the model developed by Ref. [13] which considered a centralized depot for distribution of relief resources. The model proposes the location of temporary facilities for relief distribution by considering the availability of required vehicles and resources. The objective function of the model minimizes the relevant operation costs of disaster relief which includes penalty cost for the delayed satisfaction of demand.

Another model that recognizes the need for temporary facilities is given by Ref. [1]. The authors expect their model to help in the centralized planning of distributing the resources. Their location-allocation model considers the flow of resources from 'source' to the demand points through a chain of facilities and minimizes unsatisfied demand based on the urgency of a particular type of supply at a given time.

Location-allocation models in Refs. [24] and [14] are flexible to allow satisfaction of backordered demand in later periods. Our model also includes such flexibility in demand satisfaction. The proposed location-allocation model has some similar characteristics to that of [14] mainly in terms of the cost-based objective and use of penalty cost function that increases linearly with the number of delayed periods in satisfying the demand. Table 1 summarizes characteristics of the location-allocation model presented in the three relevant papers discussed above and shows how our model differentiates from the rest. It is seen from the table that the existing models overlook the possibility of transfer of supplies between the relief facilities operating in different time periods. Our model addresses this overlooked aspect and is flexible to provide provision of inter transferability of resources between temporary relief facilities operating in different time periods. The provision of inter transferability of the resources among the facilities increase the efficiency of distribution and effectiveness in terms of meeting the unsatisfied demand as fast as possible. Therefore, the model proposed in this paper adds value to the existing literature by examining the effect of transferability of resources from one temporary facility to the next in different demand periods.

3. Emergency logistics resource distribution model

To develop the distribution model, we assume that the distribution is initiated from a central supply point (CSP), which is a collection point that continuously acquires the resources and prepares them for distribution. We consider a planning horizon discretized into short periods, which are referred to as distribution periods. Researchers mention that short distribution periods for resource supply improve the accuracy of modeling the emergency

Table 1
Characteristics of relevant location-allocation models on planning temporary relief facilities.

Reference	Objectives			Decisions variables	Constraints		
	Cost	Time	Other		Requirements and bounds	Capacity	Other constraints and decisions
Tzeng et al. [24]	Minimize logistics cost	Minimize travel time	Maximize demand satisfaction	- Location - coverage - allocation		- Truck capacity - Supply capacity	- Commodity flow - Supply assignment
Afshar and Haghani [1]			Minimize total weighted unsatisfied demand	- Location - Commodity and vehicle flow	Number of facilities	- Facility capacity - Vehicle capacity - Supply capacity	- Commodity flow - Linkage between vehicles and commodities - Vehicles flow - Transportation network decisions
Lin et al. [14]	Minimize logistics and penalty costs			- Location - Coverage - Allocations - Vehicle tours - Backordered demand - Unsatisfied demand	Number of vehicles Number of facilities	- Facility capacity - Supply capacity	- Commodity flow - Vehicles flow
Proposed model	***Minimize logistics and penalty costs***			- ***Location*** - ***Coverage*** - ***Allocations*** - ***Resource transfer*** - ***Backordered demand***		- ***Facility capacity*** - ***Supply capacity***	- ***Commodity flow*** - ***Supply assignment*** - ***Resource transfer*** - ***Demand satisfaction***

response operations [1,14,21]. Demand and supply capacity in each period are known. In the region that is affected by the disaster, individual demands in close vicinity are grouped at so-called aggregated demand points (ADPs). We also assume that total forecasted capacity at the CSP over the entire planning horizon exceeds the sum of the demands at the ADPs.

At the beginning of each distribution period, we select temporary distribution centers (TDCs) depending on the demand concentration and the capacities of the facilities. Resources from the CSP are allocated to TDCs, and from TDCs, they are distributed to ADPs. During the distribution period, demand at some ADPs may remain unsatisfied mainly if available supply at CSP for the distribution period is less than the total demand of the period. Excess demand is backordered and should be satisfied in the later periods. In a period when supply availability of a particular type of resource at CSP is larger than the total accumulated demand for the same resource, CSP may allocate extra quantity of the resource to TDCs, which would be used in subsequent periods either for distribution from the same TDC or through transfer to a nearby TDC.

For the development of the model t ($t \in \mathscr{T}$) is assumed as the distribution period and k is assumed as the type of resources ($k \in \mathscr{K}$) to be distributed. Demand and supply capacities of the CSP for the periods are forecasted at the beginning of the $\mathscr{T}$.

A complete list of model parameters and notations are given in Table 2. Further assumptions used for modeling are briefed below.

- The choice of TDCs varies from a time period to another depending on the demand at ADPs. Therefore, selected facilities can be operational only for a particular time period. Factors affecting the choice of a TDC-j depends on its capacity, V_j, the fixed cost of operation of the facility F_j, and the travel time from CSP, $\tau^0{}_j$ and travel times to the ADPs,τ_{ji}.
- For each time period t, the model provides allocations of resource k from the CSP to the selected TDC, $r^k{}_{jt}$.
- The model considers the transfer of remaining resources from a TDC in one period to next TDC in the subsequent period. Therefore, the total resource available at a TDC-j in period t, $a^k{}_{jt}$, is the sum of $r^k{}_{jt}$ and resources moved from other TDCs in period t, q^k_{mjt}, where m is the index of TDCs in period t-1. If a TDC is not able to meet the demand at an ADP in a period, either due to the insufficient resources at the period or when the duration of supply is larger than the length of the time period L_t, the demand of such ADP should be met in the following periods.
- The model considers distribution of non-consumable resources. Therefore, individual demand for the resource may not occur in every period and that there might be slight delays in the supply of resources in a particular period. Similar delayed supply possibility has been considered in literature [14] and [2]. However, for consumable resources, the individual demand is generated periodically and such delays in supply are critical.
- The total resource distributed by TDC-j in time period t, $b^k{}_{jt}$, is the sum of resources distributed to satisfy the demand of the same period t at ADPs-i, z^k_{jit} and to satisfy the backordered demand of the previous time period l at ADPs-i, w^k_{jitl}.

Our model minimizes the total social cost that is the sum of logistics costs and deprivation cost. Logistics costs consist of fixed setup costs and transportation costs. The cost of setting up a TDC-j

Table 2
Notations used in the mathematical model.

Symbol	Description
Acronyms	
TDC	Temporary Distribution Center
ADP	Aggregated Demand Point
CSP	Central Supply Point
Parameters	
$\mathscr{M}$	Set of potential TDCs indexed by j and by m
$\mathscr{N}$	Set of ADPs indexed by i
$\mathscr{T}$	Set of time periods indexed by t; $\mathscr{T} = \{1, 2, \ldots, n\}$
$\mathscr{K}$	Set of resource types indexed by k
S^k	Space required for storing each unit of resource type k
L_t	Length of time period t within the planned distribution period t.
N	Number of time periods
$D^k{}_{it}$	Demand of resource type k at ADP i in time period t
G^k_t	Capacity of resource type k at CSP in time period t
V_j	Capacity of TDC j
F_j	Fixed cost of operation of a TDC j
$\tau^0{}_j$	Travel time from CSP to TDC j
τ_{ji}	Travel time between TDC j to ADP i
$TC^{k0}{}_j$	Unit cost of transportation of resource type k from CSP to TDC j
$TC^{kI}{}_{mj}$	Unit cost of transportation of resource type k from TDC m to TDC j $\mathscr{M} \in \mathscr{M}$
$TC^{kE}{}_{ji}$	Unit cost of transportation of resource type k from TDC j to ADP i
P^k_{itl}	Unit cost of delay penalty of satisfying demand of ADP i of resource type k of time period l in time period t
B	Big number
Decision variable	
y_{jt}	Binary variable that equals 1 if facility j is selected as TDC in time period t and 0 otherwise
x_{ijt}	Binary variable that equals 1 if ADP i receives resources from TDC j in time period t
$r^k{}_{jt}$	Quantity of resource type k allocated from the CSP to selected TDC j in time period t
q^k_{mjt}	Quantity of resource type k transferred from TDC m of time period t-1 to TDC j of time period t
$a^k{}_{jt}$	Quantity of resource type k available at TDC j in time period t $= r^k_{jt} + \sum_{m \in \mathscr{M}} q^k_{mjt}$
$\boldsymbol{z^k_{jit}}$	Quantity of resource type k distributed from TDC j at time period t to satisfy the demand at ADP i generated at the same period
w^k_{jitl}	Total of resource k satisfied by TDC j at time period t to meet backordered demand of period l at ADP i where, $l \in \mathscr{T}$, $l < t$
$b^k{}_{jt}$	Total quantity of resource type k distributed to all ADP from TDC j in time period t $= \sum_{i \in \mathscr{N}} (z^k_{jit} + \sum_{l \in \mathscr{T},\, l<t} w^k_{jitl})$

in t is associated with the fixed cost F_j. We assume that the transportation costs are the linear functions of travel distances between the locations and the quantity shipped. The unit transportation costs depend on the mode of transportation and the type of the commodity. $TC^{k0}{}_j$, $TC^{kI}{}_{mj}$ and $TC^{kE}{}_{ji}$, are the unit transportation costs of resource type k between CSP and TDC-j, TDC-j and TDC-m, and TDC-j and ADP-i, respectively. We assume these unit costs are constant over the distribution periods.

In the model, deprivation cost at an ADP-i is the sum of individuals' sufferings at i over all the distribution periods. While there can be delay in meeting part of the demand in some distribution period l, causing deprivation at a particular ADP in the period, demand of all time periods are satisfied by the end of the last period. Deprivation cost is a function of the delayed units of resources,w^k_{jitl}, and the unit delay penalty cost, P^k_{itl}. Both the unit delay penalty cost and the deprivation cost increase with delays in time required to satisfy the demand.

The mixed integer programming (MIP) formulation for the temporary facility location and resource distribution model is given below.

Minimize

$$\sum_{j\in\mathscr{M}}\sum_{t\in\mathscr{T}}F_jy_{jt}+\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{M}}\sum_{t\in\mathscr{T}}TC^{k0}_jr^k_{jt}+\sum_{k\in\mathscr{K}}\sum_{m\in\mathscr{M}}\sum_{j\in\mathscr{M}}\sum_{t\in\mathscr{T}}TC^{kI}_{mj}q^k_{mjt}$$
$$+\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{M}}\sum_{i\in\mathscr{N}}\sum_{t\in\mathscr{T}}TC^{kE}_{ji}\left[z^k_{jit}+\sum_{l\in\mathscr{T},l<t}w^k_{jitl}\right]$$
$$+\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{M}}\sum_{i\in\mathscr{N}}\sum_{t\in\mathscr{T}}\sum_{l\in\mathscr{T},l<t}P^k_{itl}w^k_{jitl} \quad (1)$$

subject to

$$\sum_{i\in\mathscr{N}}x_{ijt}-\mathrm{B}y_{jt}\le 0 \quad \forall\, j\in\mathscr{M},\ and\ t\in\mathscr{T} \quad (2)$$

$$\sum_{j\in\mathscr{M}}r^k_{jt}\le G^k_t \quad \forall k\in\mathscr{K}, andt\in\mathscr{T} \quad (3)$$

$$\sum_{k\in\mathscr{K}}S^ka^k_{jt}\le V_jy_{jt} \quad \forall\, j\in\mathscr{M},\ and\ t\in\mathscr{T} \quad (4)$$

$$b^k_{jt}+\sum_{m\in\mathscr{M}}q^k_{jm(t+1)}=a^k_{jt} \quad \forall j\in\mathscr{M},\ k\in\mathscr{K},\ and\ t\in\mathscr{T} \quad (5)$$

$$z^k_{jit}\le \mathrm{B}x_{ijt} \quad \forall k\in\mathscr{K},\ j\in\mathscr{M},\ i\in\mathscr{N},\ and\ t\in\mathscr{T} \quad (6)$$

$$w^k_{jitl}\le \mathrm{B}x_{ijt} \quad \forall k\in\mathscr{K},\ j\in\mathscr{M},\ i\in\mathscr{N},\ t\in\mathscr{T},\ and\ l\in\mathscr{T},\ l<t \quad (7)$$

$$\tau_{ji}x_{ijt}\le L_t \quad \forall i\in\mathscr{N},\ j\in\mathscr{M},\ and\ t\in\mathscr{T} \quad (8)$$

$$\sum_{j\in\mathscr{M}}\left(z^k_{jil}+\sum_{t\in\mathscr{T},\,t>l}w^k_{jitl}\right)=D^k_{il} \quad \forall k\in\mathscr{K},\ i\in\mathscr{N},\ and\ l\in\mathscr{T} \quad (9)$$

$$q^k_{mjt}=0 \quad \forall k\in\mathscr{K},\ j,\ m\in\mathscr{M},\ and\ t=1,\ N+1 \quad (10)$$
$$y_{jt}\in(0,1) \quad \forall j\in\mathscr{M},\ and\ t\in\mathscr{T} \quad (11)$$

$$x_{ijt}\in(0,1) \quad \forall i\in\mathscr{N},\ j\in\mathscr{M},\ and\ t\in\mathscr{T} \quad (12)$$

$$r^k_{jt}, q^k_{mjt}, z^k_{jit}\ge 0 \quad \forall i\in\mathscr{N},\ j,\ m\in\mathscr{M},\ k\in\mathscr{K},\ and\ t\in\mathscr{T} \quad (13)$$

$$w^k_{jitl}\ge 0 \quad \forall i\in\mathscr{N},\ j\in\mathscr{M},\ k\in\mathscr{K},\ t\in\mathscr{T},\ and\ l\in\mathscr{T},\ l<t \quad (14)$$

The objective function (1) minimizes the logistics and deprivation costs of relief distribution. It consists of the fixed costs, the transportation costs of resource allocation, distribution and transfer between the TDCs, and the delay penalty costs.

Constraints (2) ensure that the ADP-i in time period t be assigned to TDC-j of the period. Constraints (3) ensure that the allocation of resources from the CSP to the TDCs does not exceed the amount available at the CSP on the time period. Constraints (4) are the capacity constraints of the TDC. Constraints (5) are the flow conservation constraints at TDCs, which ensure all excess amounts to be transferred to TDCs operating in the following period. Constraints (6) and (7) ensure resource distribution only between the assigned pair of TDC and ADP. The model caters to satisfying of backordered demand at period t. Backordered demand at an ADP-i is the demand not satisfied in time period l ($l < t$). This provision of satisfying backordered demand is given in Constraints (7). Constraints (8) ensure that the travel time required to serve ADP-i by TDC-j at t does not exceed the length of the period. Constraints (9) confirm the satisfaction of all demand at the ADPs by the end of the planning horizon, $\mathscr{T}$.

4. Numerical analysis

The purposes of numerical analysis are (i) to analyze impact of model feature (ii) to test computational efficiency of the model under different problem sizes, and (iii) to perform sensitivity analysis of the solution.

4.1. Problem instance

We perform numerical tests on a distribution network consisting of 15 cities in South Carolina, USA. Fig. 1 shows the locations of CSP, ADPs and the candidate TDCs in the problem instance. The distribution network consist of a CSP (node 1), 10 ADPs (nodes 2 to 11) and 4 candidate TDCs (nodes 12 to 15).

The planning horizon is two days, which was divided into four periods of equal length. We consider the distribution of two resource types: resource 1 and resource 2. Unit space requirement of resource types 1 and 2 are 145 ft^3 and 84 ft^3, respectively. Table 3 shows the capacities of CSP and demand at the ADPs for the four periods. Table 4 shows the fixed costs and capacities of the potential TDCs. Unit space requirements and locations of CSP, potential TDCs, and ADPs in Fig. 1 are all simulated data, generated for illustration purpose only.

Transportation costs depend on the distance between the nodes, mode of transportation and type of commodity. According to [16]; air transportation is the most practical mode of transportation during disasters when the affected locations are difficult to access or when the road network is damaged. Erdemir et al. [7] considered joint air and ground transportation for emergency services. Since we have a short distribution period of 12 h, we consider shipments from CSP to TDCs through air mode. For transportation between TDCs and that between TDCs to ADPs, we assume land mode of the distribution. We assume a linearly increasing unit penalty cost for delayed satisfaction of demand. Table 5 shows the unit penalty costs used in the numerical analysis. We refer to the set of network

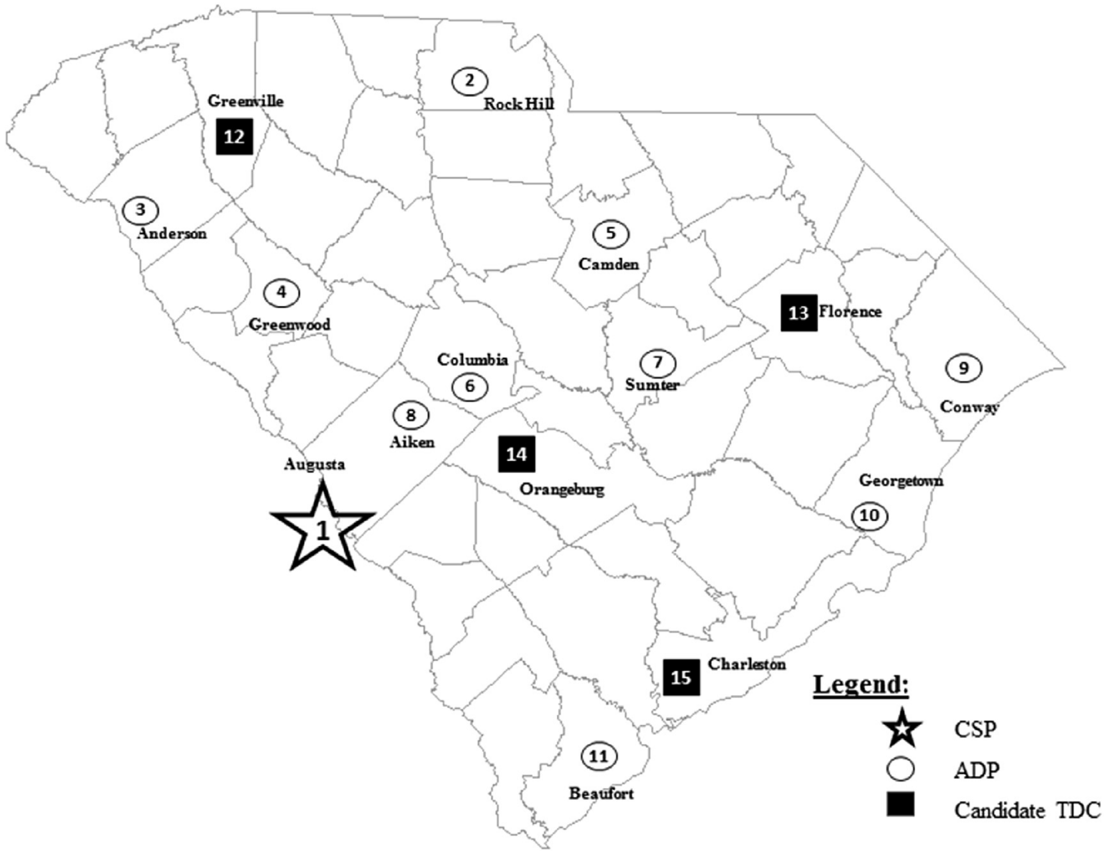

Fig. 1. ADPs, candidate TDCs and CSP locations in the basic instance.

Table 3
Supply capacities and demand in different time periods for basic problem instance.

Time periods	Capacity of CSP (resource 1/resource 2) in unit items	Demand at ADP nodes (for resource 1/for resource 2) in unit items									
		2	3	4	5	6	7	8	9	10	11
$t = 1$	2600/1546	900/837	700/651	600/558	–	–	–	–	–	–	–
$t = 2$	1800/2546	–	–	–	300/279	800/744	700/651	400/372	–	–	–
$t = 3$	2500/2081	–	–	–	300/279	400/300	700/651	400/372	300/279	–	–
$t = 4$	1000/1302	–	–	–	–	–	–	–	300/279	400/372	700/651

and data described above as the basic problem instance in this paper.

4.2. Solution performance

We coded the MIP formulation in IBM ILOG Optimization Programming Language (OPL) and solved using optimization software, CPLEX optimizer V12.6 [12].

Fig. 2 shows optimal TDC locations and resource allocations for the basic problem instance. The locations of the optimal TDCs change over the time periods because of changing demand. This is in line with the actual situation. In disaster situations such as in hurricanes, demand pattern continuously changes not only in quantity but also in terms of the locations. So, efficient distribution can be achieved through locations of regional TDCs in the affected path and this requires the location of TDCs to change over the periods.

The solution shows that, for optimal resource distribution in the basic instance, all four TDCs (nodes 12 to 15) are required in the first three periods ($t = 1$ to $t = 3$). In $t = 1$, TDCs at nodes 12, 13 and 14 are the only distributing TDCs. In $t = 4$, TDC at node 12 is not required

Table 4
Fixed costs and capacities of candidate TDCs for basic problem instance.

Nodes	Capacity (ft^3)	Fixed cost ($)
12	250,000	15,000
13	100,000	15,000
14	100,000	15,000
15	150,000	15,000

Table 5
Penalty cost for satisfying backordered demand.

Demand of time period	Unit penalty cost for satisfying the demand for resources (for resource 1/for resource 2) in time period ($)			
	$t = 1$	$t = 2$	$t = 3$	$t = 4$
$t = 1$	–	162/1355	324/2710	486/4065
$t = 2$	–	–	162/1355	324/2710
$t = 3$	–	–	–	162/1355
$t = 4$	–	–	–	–

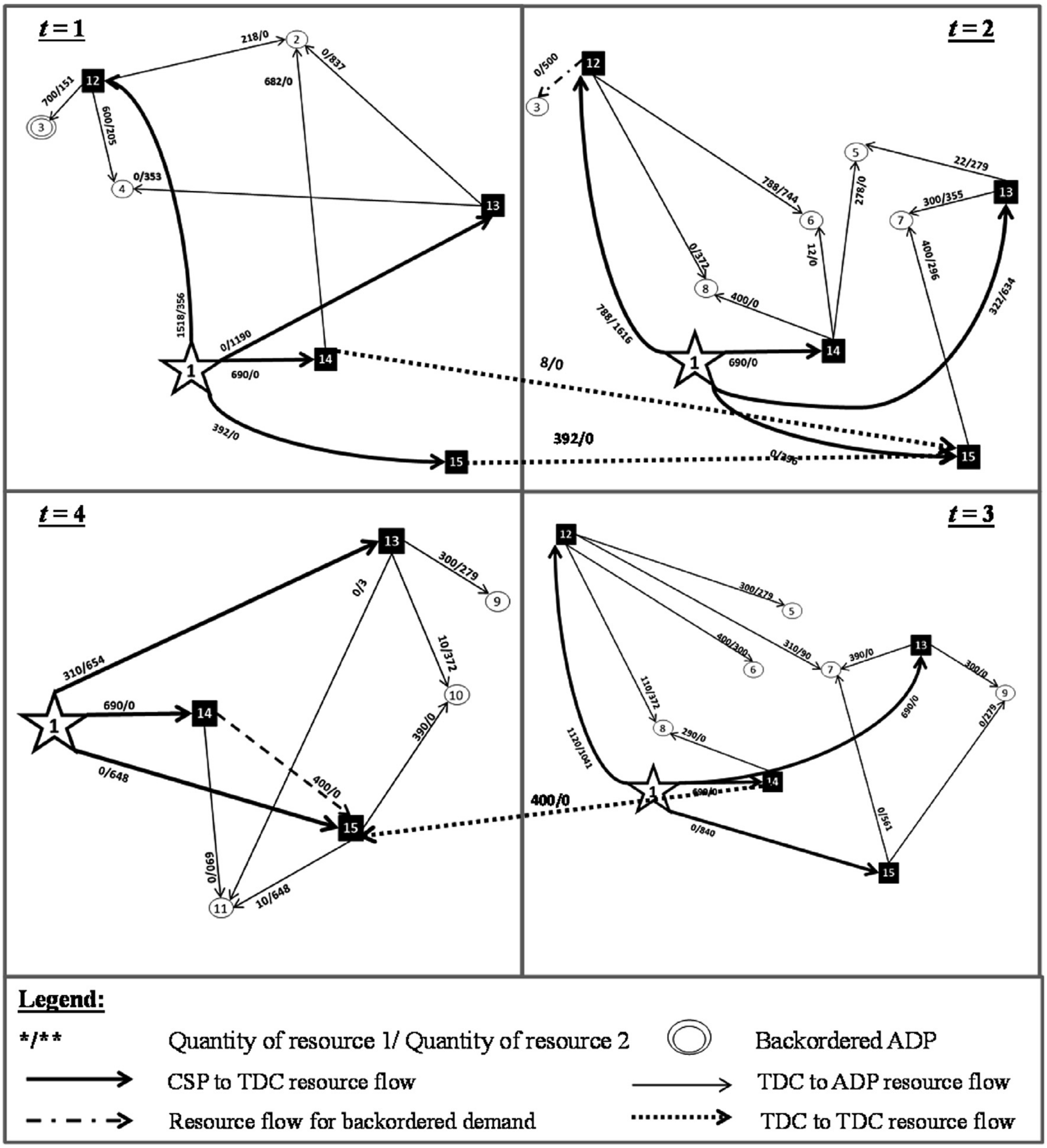

Fig. 2. Optimal allocation and temporary facility location for basic problem instance.

while TDCs at nodes 13, 14 and 15 continue to provide resource distribution.

In $t = 1$, supply capacity for resource 1 is more than its demand while for resource 2, it is less than the demand. ADP at node 3 in this period, marked as the backordered ADP in the figure, has a deficit of resource 2 by 500 units. Therefore, there is resource deprivation at node 3. In $t = 2$, 400 units of excess resource 1 from TDCs at node 14 and 15 are transferred to TDC at node 15. In $t = 2$, all backordered demand at node 3 are satisfied. The model analyses the tradeoff between the logistics cost and the deprivation cost in order to allocate resources from a particular TDC. Therefore, the deficit in a particular node is carried over to the next period when the deprivation cost is less than the logistics cost.

Supply capacity of resource 1 in $t = 2$ is less than its demand in the period and the transferred resources from previous period helps to meet the demand. For $t = 3$, the supply capacities for the resources are larger than demand in that period. Since there is no further backordered demand to be satisfied in this period, the model transfers excess resources to TDC in $t = 4$. In the numerical example, 400 units of resource 1 is transferred from node 14 (in $t = 3$) to node 15 (in $t = 4$).

The results show that both backordered delivery and transfer between TDCs are crucial for resource allocation. The former helps emergency planners to ensure satisfaction of demand of all the time periods while the later results in maximum utilization of the supply and TDC capacities.

4.2.1. *Case with and without resource transfer between the TDCs*

An important feature of our model, which differentiates it from the literature, is its flexibility to have resource transfer among TDCs operating in different time periods. In this section, we analyze impact of this feature by comparing the optimal solution of our

Table 6
Comparison of cost results based on transfer possibility between TDCs.

Model	Total cost (1000 $)	Logistics cost (1000 $)	Deprivation cost (1000 $)	Unsatisfied demand (unit items)	Resource transfer (unit items)
With transfer (as in basic problem instance)	2663	1986	677	–	800
Without transfer	4453	1953	2500	1300	–

model (basic model) to optimal solution for the case when resource transfers between TDCs are not allowed. Table 6 compares the optimal results obtained in the two cases.

We observe a higher logistics cost when transfer is allowed which is due to increased cost of transportation associated with the transfer operation. However, the transfer of the resources reduces the demand shortages and the associated deprivation cost. Table 6 also shows an unsatisfied demand at the end of planning horizon if excess resources are not transferred to the next period. This incurs a large shortage cost and deprivation cost. This result justifies the significance of considering resource transfer between the TDCs operating in different time periods.

4.3. Computational performance

To test solvability of the model under different problem sizes, we constructed five additional problem instances by extending the basic problem instance. Table 7 summarizes the number of ADPs and candidate TDCs, number of commodities, computation time and the number of iterations associated with each of problem instance including the basic instance.

We notice an increase in the computation time and the number of iterations particularly when number of nodes is large. However, even the observed computation time for the largest network is in seconds which shows models solvability with commercial solvers such as CPLEX and shows its suitability for practical implementation.

4.4. Sensitivity analysis

In the following sections, sensitivity of the results to parameters of the model is presented. Basic problem instance is used for comparison of the results.

4.4.1. Penalty of delayed service

To test sensitivity of the solution to penalty cost of delayed service, we performed numerical tests decreasing the penalty cost of resource 1 in the basic problem instance from 10% to 100%. Fig. 3 shows the backordered amounts and transferred amounts of resource 1 observed in corresponding optimal allocations. While the change in the unit penalty cost does not affect the total cost significantly, we observe an increase in backordered quantity for lower unit penalty costs as seen in the figure. This is because the lower penalty cost attaches lower urgency to the resource. Additionally, the transfer between the TDCs increases with increase in the backordered demand as seen in the figure.

Table 7
Computational performance of the model.

Problem instance	Number of ADPs and candidate TDCs	Number of resource types	Computation time (seconds)	Number of iterations
P1(Basic problem instance)	14	2	3	290
P2	14	4	2	448
P3	28	2	4	6,627
P4	28	4	3	1,646
P5	42	2	6	20,163
P6	42	4	14	20,548

4.4.2. Short distribution period

The basic instance consists of 4 distribution periods each with of length 12 h. To test sensitivity of the length of the distribution periods on the optimal resource allocation and distribution, we solved the problem instance shortening its length of distribution period to 8 h. For consistency, we kept the total supply capacity and total demand of the planning horizon same as in basic setting. Table 8 shows decrease in the backordered demand and significant increase of resource transfer between the TDCs when the distribution period is short. This is mainly due to the fact that short distribution periods allow frequent distribution planning and the demand can be satisfied more efficiently due to location of appropriate TDCs for the time periods. The deprivation cost decreases due to decrease in the backordered demand. In Table 8, we also observe a decrease in logistics cost when the distribution period is short. This is due to the decrease in the total distribution costs. Therefore, when the distribution periods are shorter, response planners can achieve resource distribution with reduced logistics and deprivation costs.

4.4.3. Direct supply from CSP

In the basic model, direct distribution of resources from CSP to ADPs is not considered. In this section we test the sensitivity of the solution when the direct supplies from CSP to ADPs are allowed. We observe that the direct supply increases the logistics cost but decreases (or eliminates) the deprivation cost due to decrease in the delayed satisfaction of demand (Table 9). Therefore, the total cost can decrease significantly when direct transfer between CSP and TDCs are possible.

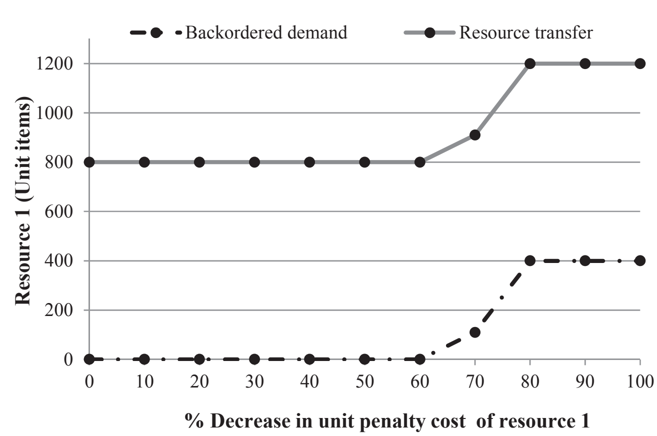

Fig. 3. Sensitivity of optimal allocation to penalty cost.

Table 8
Sensitivity of the optimal allocation to length of time periods.

Problem instance	Total cost (1000$)	Logistics cost (1000$)	Deprivation cost (1000$)	Backordered demand (unit items)	Resource transfer between TDCs (unit items)
Basic problem instance	2663	1986	677	500	800
Short distribution period	1934	1902	32	202	3717

Table 9
Sensitivity of the optimal allocation to direct supply from CSP.

Problem instance	Total cost (1000$)	Logistics cost (1000$)	Deprivation cost (1000$)	Backordered demand (unit items)	Resource transfer between TDCs (unit items)
Basic problem instance	2663	1986	677	500	800
CSP direct supply	2145	2145	0	0	442

5. Conclusions

In this paper, we propose a response planning model to dynamically locate and allocate temporary distribution centers in different time periods. The model provides information to emergency response planners to decide on a resource distribution plan that considers dynamically changing demand over different periods of distribution. The proposed model extends existing temporary facility location models for relief distribution by including the possibility of transfer of excess resources among temporary distribution centers operating in different time periods.

Numerical analysis shows the location of TDCs in a time period influences the total cost of response. The results show that relief response can be more effective if movement of excess resources from one period to next is allowed. When such a movement is not allowed, it can increase shortage cost and also the total cost of emergency response.

Solvability of the model in large and complex problem instances within a short computation time shows the models' robustness and applicability to solve practical size distribution problems. The use of penalty cost function is also important in the model. When penalty for deprivation is high, backordered demand gets minimized and therefore, deprivation of resource in a period is also minimized. Deprivation can also be minimized by using shorter distribution periods and allowing direct supplies from supply points for the same network as shown by the numerical analysis presented in this paper. However, the direct supply is only possible when there is an access to unlimited transportation capacity.

The proposed model focuses on the distribution of non-consumable resources and assumes a linear penalty cost for any delay in satisfaction of the demand. In reality, the deprivation cost increases as an exponential function of the delayed time. For consumable resources, demand occurs repetitively and the total deprivation cost depends on the temporal and terminal deprivation costs [11,17]. Incorporating such detail characteristics of the deprivation cost can be the first possible extension of the model. Another possible extension of this research would be to consider a service-based approach of optimization. This will help to achieve a higher service level thus by meeting the demand as they occur in a particular disaster affected area in a particular period.

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