Last Mile Distribution in Humanitarian Relief

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Last mile distribution is the final stage of a humanitarian relief chain; it refers to delivery of relief supplies from local distribution centers (LDCs) to beneficiaries affected by disasters. In this study, we consider a vehicle-based last mile distribution system, in which an LDC stores and distributes emergency relief supplies to a number of demand locations. The main decisions are allocating the relief supplies at the LDCs among the demand locations and determining the delivery schedules/routes for each vehicle throughout the planning horizon. We propose a mixed integer programming model that determines delivery schedules for vehicles and equitably allocates resources, based on supply, vehicle capacity, and delivery time restrictions, with the objectives of minimizing transportation costs and maximizing benefits to aid recipients. We show how the proposed model optimizes resource allocation and routing decisions and discuss the tradeoffs between these decisions on a number of test problems. Finally, we identify opportunities for the use of intelligent transportation systems in last mile distribution.

The purpose of a humanitarian relief chain is to rapidly provide the appropriate emergency supplies to people affected by natural and manmade disasters so as to minimize human suffering and death. Similar to commercial supply chains, supplies flow through the relief chain via a series of long-haul and short-haul shipments. The distribution system used in humanitarian relief operations may depend on each situation’s characteristics. The distribution of emergency supplies for a typical disaster relief operation involving international actors is shown in Figure 1. First, relief supplies from different locations throughout the world arrive at a primary hub (seaports, airports). Next, supplies are shipped to a secondary hub (large, permanent warehouses in larger cities), where they are stored, sorted, and transferred to tertiary hubs (local and temporary distribution centers). Finally, LDCs deliver relief supplies to beneficiaries.

In this study, we consider last mile logistical operations in a humanitarian relief chain. Last mile distribution is the final stage of the relief chain; it refers to delivery of relief supplies from LDCs to the people in the affected areas (demand locations).

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The most significant logistical problems in the last mile generally stem from the limitations related to transportation resources and emergency supplies, difficulties due to damaged transportation infrastructure, and lack of coordination among relief actors. It is challenging for relief agencies to develop effective and efficient distribution plans in such a complex environment while simultaneously achieving a coordinated response. Therefore, nongovernmental organizations (NGOs) may make distribution decisions using ad-hoc methods, which may lead to inefficient and ineffective response. In this study, our aim is to provide an analytical framework to assist relief decision-makers in making effective and efficient distribution decisions across the last mile.

The main operational decisions related to last mile distribution are relief supply allocation, vehicle delivery scheduling, and vehicle routing. Effective supply allocation among demand locations is vital in relief aid distribution due to the high stakes associated with unsatisfied and/or late-satisfied demand. The task is made more difficult due to strict financial limitations, making cost-efficient vehicle routing decisions important.

The problems that arise during disaster relief operations may differ depending on various factors, such as the type, impact, and location of the disaster, and local conditions in the affected regions. In this study, we develop a flexible and generalized
modeling approach that not only considers the main problems related to the last mile distribution, but can also handle a variety of different situations and additional restrictions. Although various relief chain distribution problems have been studied in the literature, several aspects of last mile distribution in disaster relief operations have not been considered. In this article, we define and model the last mile distribution problem by taking these unique features into account. For instance, we consider the distribution of relief items with different demand characterizations and account for supply criticalities and hence population vulnerabilities while allocating resources among demand points.

Because resource allocation and vehicle routing decisions are closely interrelated, they should be jointly considered. In this respect, the last mile distribution problem is a variant of the inventory routing problem (IRP). The main decisions in the IRP are the customer delivery times, the number of items to be delivered at each visit, and the delivery routes. In particular, our study is a variant of the multi-item, multiperiod IRP, in which various items have different demand characteristics but share the same scarce resources. Here, equitable supply allocation among demand points is a major concern.

We consider a last mile distribution system in which an LDC stores and distributes emergency relief supplies to a number of demand locations using a fixed set of vehicles. We propose a two-phase modeling approach to determine a delivery schedule for each vehicle and make inventory allocation decisions by considering supply, vehicle capacity, and delivery time restrictions. The objective is to minimize the sum of transportation costs and penalty costs for unsatisfied and late-satisfied demand for different types of relief supplies. We use a rolling-horizon framework to capture the multiperiodicity of the problem, as well as its inherent supply and demand uncertainties. Numerical studies are conducted to show how the proposed model can be used to optimize resource allocation and routing decisions. Finally, we explain how Intelligent Transportation Systems (ITS) support practical implementation of the proposed modeling approach.

**LITERATURE REVIEW**

Knott (1987) considers the last mile delivery of food items from a distribution center to a number of camps assuming a single mode of transportation making direct deliveries to camps. A linear programming model is developed to determine the number of trips to each camp to satisfy demand while minimizing the transportation cost or maximizing the amount of food delivered. The article discusses why the proposed model cannot handle contingencies for insufficient supply and concludes that the problem is too complex for classical operations research models and solution techniques. Knott (1988) combines operations research heuristics with artificial intelligence techniques to develop a decision support tool for allocation and distribution.

Haghani and Oh (1996) determine detailed routing and scheduling plans for multiple transportation modes carrying various commodities from multiple supply points in a disaster relief operation. The authors assume that the commodity quantities are known. They formulate a multi-commodity, multimodal network
flow problem with time windows as a large-scale MIP model on a
time-space network with the objective of minimizing the sum of
the vehicular flow costs, commodity flow costs, supply/demand
carry-over costs, and transfer costs over all time periods. Two
heuristic solution algorithms are developed; the first utilizes a
Lagrangian relaxation approach, and the second employs an it-
errative fix-and-run process. Oh and Haghani (1997) further ex-
plortheir heuristic algorithms for the same problem and provide
more detailed analysis.

Barbarosoglu and colleagues (2002) focus on tactical and
operational scheduling of helicopter activities in a disaster
relief operation. They decompose the problem hierarchically
into two subproblems where tactical decisions are made at
the top level, and the operational routing and loading deci-
sions are made in the second level. MIP models are formu-
lated for tactical and operational problems, which are solved
by an iterative coordination heuristic. Barbarosoglu and Arda
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This study extends the deterministic model of Haghani and
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tics problem for distributing multiple commodities from a num-
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flow model to determine pick-up and delivery schedules for ve-
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ables them to regenerate plans based on changing demand for
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Angelis and colleagues (2007) consider a multidepot, multi-
vehicle routing and scheduling problem for air delivery of emer-
gency supply deliveries for World Food Programme (WFP) in
Angola based on WFP’s operations in that country in the year
2001. Planes deliver full cargo to single clients from the ware-
houses in port cities. The authors set a service level for food
distribution and develop a linear integer programming model
that maximizes the total satisfied demand. They provide numer-
cal results for real problem instances.

Our study differs from these studies in a number of aspects,
including the consideration of relief items with different de-
mand characterizations and criticality of supplies in resource
allocation. Furthermore, we provide a formulation that han-
dles the complexities (distribution of scarce supplies to de-
mand points while accounting for vulnerabilities) unique to
last mile distribution that are mentioned by Knott (1987), but
not considered analytically in subsequent studies in emergency
logistics.

THE LAST MILE DISTRIBUTION PROBLEM

This section describes the last mile distribution problem in
detail, including the modeling approach and mathematical for-
mulation.

System Description and Problem Definition

The last mile distribution problem determines the best re-
source allocation among potential aid recipients in disaster-
affected areas that minimizes the cost of logistics operations,
while maximizing the benefits to aid recipients. More specifi-
cally, the last mile distribution problem determines (1) delivery
schedules, (2) vehicle routes, and (3) the amount of emergency
supplies delivered to demand locations during disaster relief op-
erations. Among the main differences between the last mile dis-
btribution problem and commercial distribution problems are the
unavailability/scarcity of resources (time, supplies, personnel,
vehicles, transportation, and communication infrastructure) and
the high stakes associated with delivering supplies (suffering
and/or loss of life) associated with relief operations.

In this study, we consider the distribution of relief supplies at
an LDC to a number of demand points in its service region. Once
a disaster occurs, NGOs send logisticians to the disaster areas to
assess the type and amount of relief supplies needed. Based on
this information, NGOs begin to ship relief supplies to the LDCs.
In the last mile, relief supplies are delivered from LDCs to final
destination points. LDCs are usually established postdisaster in
locations that have access to the affected regions. An LDC may
be a tent, a prefabricated unit, or an existing facility (e.g., school,
church, warehouse). There is commonly minimal interaction
among different LDCs and their service areas; that is, different
LDCs and their service areas can be considered as independent
clusters in the relief network as shown in Figure 1. We assume
that the location of the LDC is predetermined and its capacity is
sufficient to serve its service region. However, we should note
that the selection of LDC locations is itself an important problem
that will affect the performance of the distribution operations.
An LDC must be selected considering various factors, such as
security and safety, transportation infrastructure, and available
transportation modes.

Demand Characterization

Demand occurs for multiple types of relief items at each
demand location. The required set of items may vary greatly by
situation depending on factors such as the type and the impact of
the disaster, demographics, and social and economic conditions
of the area. However, it is possible to categorize emergency relief
items into two main groups-Type 1 and Type 2-based on their
demand characteristics.

Type 1 items are critical items for which the demand occurs
once at the beginning of the planning horizon. Emergency sup-
plies like tents, blankets, tarpaulins, jerry cans, and mosquito
nets are examples of Type 1 items. The demand for Type 1 items is typically very large; hence, it may be impossible to meet all Type 1 demands within a short period of time, due primarily to supply unavailability and vehicle capacity limitations. To model this situation, we charge a penalty for each unit of unsatisfied (backordered) Type 1 demand, and penalty costs accumulate over time. So, once Type 1 items arrive to the demand locations, they are immediately distributed to aid recipients. Therefore, we assume that no Type 1 inventory is held at any demand location.

Type 2 items are items that are consumed regularly and whose demand occurs periodically over the planning horizon (e.g., food, hygiene kits). If the periodic demand of a Type 2 item is not satisfied on time, it cannot be backordered; rather, the unsatisfied demand is lost and penalty costs accrue for each unit of lost demand. If an excess number of Type 2 items are shipped to a demand point, the excess amount can be held for consumption in future periods. We assume that any inventory holding costs to store these items at the demand points is ignored, because it is likely negligible in relation to the penalty costs associated with unsatisfied demand.

Because resources are limited in disaster relief environments, unsatisfied demand is common. Our objective is to develop an efficient resource allocation mechanism that minimizes suffering while achieving equity in relief aid distribution among affected areas. In practice, allocation decisions are frequently made considering the relative vulnerabilities of aid recipients. Also, Sphere standards (the minimum standards to be attained in disaster assistance determined by the Sphere Project) require that relief aid distribution be fair, equitable, and monitored closely with particular emphasis on the accessibility of the program to vulnerable groups (Sphere Project, 2004). We assume that the criticality and urgency of the relief supplies increases with population vulnerability. As demand remains unsatisfied, population vulnerability and criticality both increase (Type 1 and Type 2 shortages increase potential for suffering and loss of life). Our model serves an “equal allocation principle,” which allocates supplies proportionally among the demand locations based on demand amounts and population vulnerabilities, and balances the unsatisfied and late-satisfied demand among demand locations over time. We should note that it is very difficult, if not impossible, to quantify the real cost of unsatisfied and late-satisfied demand of each person (or groups of people) in disaster relief situations. However, assigning a relative penalty cost factor to each item type at each location enables us to model population vulnerabilities and distribute supplies accordingly.

**Planning Horizon**

A unique characteristic of the last mile distribution system is the unpredictability related to resource levels over time. For instance, shipments from the central warehouse to the LDC may continue during the planning horizon; however, it is difficult to obtain exact supply information (times and quantities). Hence, only short-term estimates of inventory levels at an LDC may be reliable. The same uncertainty exists for vehicle availability because the number and composition of vehicles in the fleet may vary over time. Demand parameters in our model are based on the assessments done by relief agencies in the affected regions after the disaster occurrence. Practically, initial assessments, which are made in the early days of the disaster, may not be completely reliable and NGOs may update the demand assessments as more information becomes available in disaster areas.

These supply- and demand-related uncertainties preclude us from readily determining the duration of the distribution activities. In other words, the length of the planning horizon is variable and unknown a priori. We assume that the planning horizon begins once the LDC is able to begin delivering relief supplies to demand locations and ends when the demand for both types of items is completed (or supply is exhausted). Therefore, the planning horizon parameter used in our model will be the worst-case estimate. The length of the planning horizon must be set to a length much longer than the expected relief horizon; the model will determine when the delivery of relief supplies will be completed (and therefore, implicitly provide the actual length of the horizon).
We use a rolling-horizon framework to capture the dynamic and stochastic aspects of the problem. This allows us to use demand assessment and resource level updates in our distribution plans. This approach has been used in a number of IRP studies (for example, Campbell and Savelsbergh, 2004; Jaillet et al., 2002) to reflect the long-term effects of short-term decisions. Accordingly, we construct a plan for long-term relief distribution based on available information, but only execute the plan for the coming planning period. The plans are updated at the beginning of a planning period if new information is obtained regarding resource or demand levels for any future planning period. The planning period is determined by decision-makers according to the characteristics of the problem. For ease of presentation, we assume the planning period is one day in the problem formulation.

Modeling Approach

Our modeling approach has two phases. The inputs and outputs of each phase are depicted in Figure 2.

Phase 1 generates all possible delivery routes for each vehicle. To construct the list of routes, we first consider all combinations of the demand locations that could be visited on a route. Next, we find the route with the minimum traveling time for each vehicle by solving a Traveling Salesperson Problem (TSP) for each combination. Finally, the routes with total traveling times less than the planning period remain on the list of possible routes. This preprocessing phase enables decision-makers to consider the transportation network infrastructure and eliminate infeasible and undesired routes. The list of routes obtained in Phase 1 can be updated by adding new routes or removing existing routes as a result of the changes in network structure and/or vehicle fleet composition and compatibilities. However, if these updates are frequent and the transportation network is large, solving the TSP to optimality may not be practical. In this case, heuristics could be used to construct routes in Phase 1.

Because we allow the same vehicle to take the same route on any given day, we add the same route to the list of possible routes multiple times when we generate the possible delivery routes in Phase 1. The number of times a route is replicated is equal to the number of times that the route can be taken in a day. For instance, assuming 20 hours of operation time in a day, a 14-hour-route exists in the route list only once, but a 10-hour-route is listed twice.

After we generate the candidate set of routes in Phase 1, we solve the model presented in the section below to determine the periods to visit each demand location, the delivery amounts

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**Figure 2** Two-phase model: Inputs and outputs.
by item types, the vehicle loads, and the delivery routes. The Phase 2 model results are implemented for the coming periods until new model parameters become available, at which time the Phase 2 model is resolved. Phase 1 needs to be executed again only if there are structural changes in the network and vehicle fleet.

**Model Formulation**

The following notation is used to formulate the last mile distribution problem:

### Sets

- \( T \): set of days in the planning horizon; length of planning horizon
- \( K \): set of vehicles
- \( R \): set of routes (generated in Phase 1)
- \( N \): set of all demand locations
- \( N_r \): set of demand locations visited on route \( r \in R \)
- \( E \): set of demand types: \( E = \{1, 2\} \)

### Routing parameters

- \( c_{rk} \): cost of route \( r \) for vehicle \( k \in K \) (from Phase 1)
- \( q_k \): capacity of vehicle \( k \in K \) (volume)
- \( T_{rk} \): duration (as a fraction of a day) of route \( r \in R \) for vehicle \( k \in K \) (from Phase 1)

### Demand parameters

- \( d^1_i \): demand of type 1 at location \( i \in N \) (volume per planning horizon)
- \( d^2_i \): demand of type 2 at location \( i \in N \) on day \( t \in T \) (volume per day)
- \( p^1_{irk} \): penalty cost factor for unsatisfied type 1 demand at location \( i \in N \) by day \( t \in T \)
- \( p^2_{irk} \): penalty cost factor for unsatisfied type 2 demand at location \( i \in N \) on day \( t \in T \)
- \( a^e_t \): amount of type \( e \in E \) relief supplies arriving to the LDC at the beginning of day \( t \in T \)

### Routing decision variables

- \( X_{rk} \): 1 if route \( r \in R \) is used by vehicle \( k \in K \) on day \( t \in T \)

### Delivery decision variables

- \( Y^e_{irt} \): amount of demand of type \( e \in E \) delivered to location \( i \in N \) on day \( t \in T \) by vehicle \( k \in K \) via route \( r \in R \)
- \( W^e_t \): penalty cost associated with unsatisfied type \( e \in E \) demand on day \( t \in T \)

The formulation for the last mile distribution problem is as follows:

\[
\begin{align*}
\text{min} & \quad \sum_{r \in R} \sum_{t \in T} \sum_{k \in K} c_{rk} X_{rk} + \sum_{t \in T} \sum_{e \in E} W^e_t \\
\text{subject to} & \quad W^e_t \leq p^e_{irt} S^e_{itr} \quad \forall i \in N, t \in T, e \in E \\
& \quad S^1_{itr} = \left( d^1_i - \sum_{r \in N(r)} \sum_{t=1}^T \sum_{k \in K} e \ Y^1_{irtk} \right) / (d^1_i) \quad \forall i \in N, t \in T \\
& \quad S^2_{itr} = \left( d^2_i + I^2_{i, t+1} - \sum_{r \in N(r)} \sum_{k \in K} Y^2_{irtk} - I^2_{it} \right) / (d^2_i) \quad \forall i \in N, t \in T \\
& \quad \sum_{t \in T} \sum_{e \in E} \sum_{k \in K} Y^1_{irtk} \geq d^1_i \quad \forall i \in N \\
& \quad \sum_{t \in T} \sum_{e \in E} \sum_{k \in K} Y^2_{irtk} \leq \sum_{t=1}^T a^e_t \quad \forall t \in T, e \in E \\
& \quad \sum_{i \in N(r)} \sum_{e \in E} Y^e_{irt} \leq q_k X_{irk} \quad \forall r \in R, t \in T, k \in K \\
& \quad \sum_{r \in R} X_{irk} T_{rk} \leq 1 \quad \forall t \in T, k \in K \\
& \quad 0 \leq S^e_{itr} \leq 1 \quad \forall i \in N, t \in T, e \in E \\
& \quad I^2_{it} = 0 \quad \forall i \in N \\
& \quad I^2_{it} \geq 0 \quad \forall i \in N, t \in T \\
& \quad Y^e_{irt} \geq 0 \quad \forall i \in N, r \in R, t \in T, k \in K, e \in E \\
& \quad X_{irk} \in \{0, 1\} \quad \forall r \in R, t \in T, k \in K
\end{align*}
\]
unsatisfied (lost) Type 2 demand at a location on a day. Constraints (1e) guarantee that the entire Type 1 demand is satisfied by the end of the planning horizon. Constraints (1f) ensure that the total amount of relief items of each type delivered to all locations on a day is less than or equal to the amount of supplies available at the LDC. Constraints (1g) and (1h) are vehicle capacity constraints and vehicle time constraints, respectively. Constraints (1i) ensure that the fraction of unsatisfied demand is between zero and one. Constraints (1j) set the beginning inventory level to zero at each location for Type 2 items. Constraints (1k) and (1l) are nonnegativity constraints, and (1m) define the binary routing variable.

**ILLUSTRATIVE EXAMPLE**

In this section, we present numerical examples to show how the proposed model can be used to optimize resource allocation and routing decisions in the last mile and discuss the tradeoffs between these decisions. We use different test problems to show how different decisions interact and highlight the relationships among different components of the problem. We also illustrate how demand amounts, penalty cost factors, and network characteristics may affect routing and supply allocation decisions. The results reported below were obtained using GAMS/Cplex on a PC equipped with an Intel Pentium III processor.

**Allocation of Vehicle Capacity Among Different Item Types**

In this subsection, we illustrate how the model splits vehicle capacity to satisfy demand for multiple item types and the effects of penalty cost factors on supply allocation decisions. We consider a problem in which a single vehicle at an LDC ships relief supplies to a single demand location, as depicted in Figure 3. The Type 1 demand is 400 units, and there is a single period of demand for 10 units of Type 2 items. The capacity of the vehicle is 100 units and the vehicle can make at most one delivery to the demand location per day. We assume that sufficient supplies for both types of items are available at the LDC throughout the planning horizon.

In this problem, the only routing-related decision is whether the node should be visited each day. Therefore, routing costs only depend on the length of the planning horizon; that is, the number of times the route is taken. On the other hand, allocation costs depend on how the capacity of the single vehicle is split between the two types of items over time, and hence the shortage amount incurred for both types of items throughout the planning horizon. The optimal solution for the one-node problem is achieved by balancing shortage penalty costs for Type 1 and 2 items and vehicle routing costs. Table 1 shows results obtained by changing the Type 2 penalty cost factor, while fixing the Type 1 penalty cost factor. We can observe how the delivery amounts, shortage percentages, and total costs change as the relative values of the penalty cost factors are modified. The one-node problem includes 181 columns and 441 variables, and each instance could be solved in less than one second.

Two different solutions exist for this problem: the entire Type 2 demand is either completely satisfied or lost depending on the relative values of the penalty cost factors. Therefore, the trade-off is between incurring five-period routing costs and only Type 1 shortage and incurring four-period routing costs and shortage costs for both types of items. Note that solutions involving partial satisfaction of Type 2 demand are dominated by the full satisfaction of Type 2 demand.

As observed from Table 1, if the penalty cost factor for Type 2 is greater than or equal to 16, Type 2 demand is fully satisfied; otherwise, Type 2 items are never delivered. For this problem, we can find this penalty cost factor breakpoint empirically, since routing and allocation decisions are separable and the number of allocation alternatives is manageable. That is, given a fixed penalty cost factor level for Type 1 demand, we can calculate a penalty cost factor breakpoint, where Type 2 demand begins to be completely satisfied. However, it becomes difficult to determine the penalty cost factor breakpoints when the problem gets more complicated; for example, when LDC-supply is limited and dynamic or when Type 2 demand exists for longer periods. Nevertheless, analyzing a simplified one-node problem is valuable because such analysis reveals the tradeoffs in satisfying the demand for a specific demand location and, hence, helps us to set the relative values of penalty cost factors for different item types in the network.

**Allocation of Supplies Among Multiple Demand Locations**

In this subsection, we focus on allocation of Type 1 supplies among multiple demand points and illustrate effects of demand amounts, penalty cost factors, and network characteristics on allocation and routing decisions. We consider a network with two demand locations, as shown in Figure 4. Both demand locations are assumed to have only Type 1 demand, and the distances and traveling costs between two demand nodes and LDC are identical. The single vehicle has a capacity of 100 units and can make at most one delivery per day. We assume no supply capacity limitation at the LDC throughout the planning horizon.

In this problem, a node can be visited in a day either via: (1) a direct delivery route, or (2) a route that visits both nodes sequentially. Therefore, three candidate routes are generated in Phase 1: routes 1 and 2 are direct delivery routes to nodes 1 and 2, respectively, and both nodes are visited in route 3. The Phase 2
Table 1  Solutions for the one-node problem

<table>
<thead>
<tr>
<th>Penalty cost factor</th>
<th>Supply Allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>(same for all periods)</td>
<td>Total Type 1 penalty cost</td>
</tr>
<tr>
<td>Day</td>
<td>Day</td>
</tr>
<tr>
<td>Type 1</td>
<td>Type 2</td>
</tr>
<tr>
<td>100</td>
<td>4</td>
</tr>
<tr>
<td>100</td>
<td>5</td>
</tr>
<tr>
<td>100</td>
<td>12</td>
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<tr>
<td>100</td>
<td>16</td>
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<td>100</td>
<td>20</td>
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<td>24</td>
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<td>100</td>
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</tr>
<tr>
<td>100</td>
<td>32</td>
</tr>
</tbody>
</table>

The model selects routes for each day and determines supply delivery amounts on these routes. The two-node problem includes 191 columns and 1,091 variables, and each instance could be solved in less than one second. The parameter settings and results for these problems are shown in Table 2.

Table 2a shows the number of supplies delivered to each location on each day and resulting shortage percentages over time when two demand locations have identical demands and criticalities. It is observed that nodes are serviced via route 3 and the capacity of the vehicle is allocated among the demand locations equally; hence, both nodes get the same level of service over time. The cost of the optimal solution is $422. Assuming that the instance with identical demand locations represents the base case, we next examine three modifications of the two-node problem to illustrate the effects of demand volumes, penalty cost factors, and network characteristics on the results.

First, we modify the problem such that one of the locations has greater demand than the other, while maintaining the same criticality for both locations. The solutions obtained for this problem are shown in Table 2b. In this case, we observe that both nodes are visited at each period via route 3 and relief supplies are allocated among the demand points proportionally to demand. That is, shortage percentages for both locations over time are the same indicating equitable supply allocation. The cost of the optimal solution is $422.

Next, we modify the base case problem such that the population vulnerabilities differ among demand locations. That is, demand locations have identical demand volumes but have different vulnerabilities; so, the criticality of demand satisfaction at node 1 is increased from its base level. According to the results (Table 2c), allocation decisions serve the equal allocation principle reasonably; that is, supplies are preferentially allocated to the more highly vulnerable node 1. We observe that node 1 is visited via a direct delivery route during the first day, and all capacity is allocated to this critical region. Then, supply deliveries are made to both locations until the end of the planning horizon such that shortage percentages at node 1 are always lower than those at node 2. However, node 2 still receives a reasonable level of service in accordance with its penalty cost factors. The cost of the solution is $496.50; the cost increase over the base case is due primarily to increased penalty shortage costs at the critical node 1.

Equal and proportional allocation over time is achieved easily in the previous examples. However, this might not always be the case, due to network characteristics and potential transportation problems in the last mile environment. For instance, suppose that route 3 is not a good choice due to road conditions. In this case, both demand locations can be accessed only through direct delivery routes. To illustrate this, we modify the base case problem by increasing the travel cost of route 3 significantly. According to the results (Table 2d), the shortage percentages at demand locations differ over time. Because there is one vehicle making one delivery per day, it is impossible to achieve equal shortage percentages for the demand locations at the end of each day, although nodes have identical demand volumes and criticalities. It is observed that routing and allocation decisions are made such that neither demand location is neglected; routes are selected such that demand locations receive comparable levels of service. The cost of the solution is $448; the cost increase over the base case is due to increased routing and shortage costs.

The results obtained for the two-node problems reveal the tradeoffs between routing and allocation decisions in conjunction with tradeoffs associated with servicing locations with different vulnerabilities. The proposed model enables us to make

![Figure 4](image-url)
Table 2  Solutions for the two-node problems. (a) $d^i_1 = 400 \forall i$ and $p^i_1 = 100 \forall i, t$. (b) $d^i_1 = 600$, $d^i_2 = 200$, and $p^i_1 = 100 \forall i, t$. (c) $d^i_j = 400 \forall i$, $p^i_1 = 150 \forall i, t$, and $p^i_2 = 100 \forall i, t$. (d) $d^i_1 = 400$, $d^i_2 = 400$, $p^i_1 = 100 \forall i, t$, and $c(3) = \infty$

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allocation and routing decisions by considering the vulnerability of the populations at different locations simultaneously with transportation availabilities and cost efficiencies. The results indicate that the relative values of penalty cost factors are important in supply allocation decisions.

**General Problems**

In this subsection, we present results for a more general problem and discuss the effects of network characteristics on model solutions. We consider a problem in which the LDC serves four demand nodes in the disaster area using two identical vehicles, each with 200 units of capacity, as shown in Figure 5. Each vehicle can complete multiple trips per period. All nodes demand both types of items. Penalty cost factors are equal for each location and item type, and set to 400. We assume the LDC has sufficient relief aid to distribute in all periods. Network transportation times and costs are presented in Table 3a. We assume that routing parameters are the same for both vehicles.

First, we execute Phase 1 and generate a list of candidate routes. We assume that each vehicle can spend 15 hours to make

$$d^i_1 = 400; \quad d^i_2 = \begin{cases} 20 & \text{for } t = 1,2,3,4 \\ 0 & \text{otherwise} \end{cases}$$

$$d^i_1 = 800; \quad d^i_2 = \begin{cases} 40 & \text{for } t = 1,2,3,4 \\ 0 & \text{otherwise} \end{cases}$$

$$d^i_1 = 600; \quad d^i_2 = \begin{cases} 30 & \text{for } t = 1,2,3,4 \\ 0 & \text{otherwise} \end{cases}$$

$$d^i_1 = 200; \quad d^i_2 = \begin{cases} 10 & \text{for } t = 1,2,3,4 \\ 0 & \text{otherwise} \end{cases}$$
As observed from Figure 6, the service levels achieved at each demand location for Type 1 items are not the same for the modified problem as they were for the base case problem. For the base case solution, the shortage percentages at each demand location were the same over time. For the modified problem, the distribution of both types of supplies are completed by the end of the fourth day for all demand locations; and the shortage percentages at node 1, which has large demands and is remotely located, are higher than those of the other nodes throughout the planning horizon. If this solution is found undesirable, in terms of achieving equitable allocation, the penalty cost factors must be modified in favor of the remote location to improve service for this location. However, it should be remembered that any increase in service level at the remote node will occur at the expense of higher routing costs and lower service provided to the other nodes.

INTELLIGENT TRANSPORTATION SYSTEMS SUPPORT IN PRACTICAL IMPLEMENTATIONS

ITS has a wide range of applications including traffic flow management, traveler information systems, public transportation, emergency management, fleet management, and commercial vehicle operations. In emergency management, one application of ITS is to improve the routing and management of emergency vehicle fleets. For instance, Savvaids and colleagues (2002) address guidance of emergency vehicles, such as ambulances and fire trucks, in an urban area responding to extreme events. The authors describe a control and navigation system that uses real-time Global Positioning System (GPS) data to assess traffic conditions and support emergency vehicles responding to such events. ITS also play an important role in supply chain integration and customer value creation. For instance, ITS technologies enable companies to monitor shipments and manage vehicle fleets, and enable customers to track their orders.

While ITS have a lot to offer for improving disaster relief operations, the required infrastructure for effective implementation is limited or nonexistent in many disaster-prone parts of the world. Moreover, although information and communication technologies are vital for effective management of disaster relief operations, the utilization of these technologies has historically happened in an ad-hoc manner (Sargent and Michael, 2005). However, with the advances in technology and increased awareness in the relief sector regarding the criticality of information and communication technologies in disaster response, initiatives are underway to integrate such technologies and systems into disaster response planning and management, which would also support the development and implementation of ITS in disaster response. For instance, only telephone and radio-based communication methods were available for providing communication and information exchange among agencies, staff, and relief partners during the Somali crisis (1992–1993). However, technology...
Table 4  Solutions for the four-node problems. (a) Base case problem. (b) Modified problem.

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Through the use of advanced technologies, information that would support logistics and transportation decisions in emergency humanitarian operations is becoming increasingly available. For instance, the United Nations Joint Logistics Centre (UNJLC) offers GIS products and services, including maps, geographic data, and up-to-date database on transport infrastructure that can be accessed and utilized by relief organizations during relief operations (UNJLC, 2007). Also, the Federal Emergency Management Agency is using GPS technologies to track vehicles and relief supplies in real time (GPS World, 2006).

The current advances in developing and utilizing information and communication technologies in humanitarian relief offer opportunities to integrate these systems into disaster response planning and operations. In that respect, information and communication technologies would enable and improve practical implementation of the proposed last mile distribution model. Because the last mile distribution problem is an operational problem, the solutions and plans are sensitive to information updates; that is, a minor information update related to arriving supplies, transportation times, and vehicle status may greatly affect scheduling and supply allocation decisions. If integrated properly, ITS can support last mile logistical decisions and improve the effectiveness and efficiency of the response by relieving the challenges and difficulties arising from the dynamic and stochastic characteristics of the operational relief environment. In particular, ITS technologies would support last mile distribution in the following ways:

- Monitoring vehicle status. As previously explained, transportation resources constitute an important limitation in planning and operating local relief distribution. The proposed last mile distribution model assumes a fixed set of vehicles that can take multiple routes per period. Available vehicles are dispatched at the beginning of a period and the route transportation times are assumed to be deterministic. However, there
may be cases that would require updates to available transportation resources. For instance, unexpected delays may occur for some vehicles or routes due to road/weather conditions or security problems that would affect vehicle scheduling and supply allocation plans for the coming periods. In this case, vehicle positioning technologies that provide real-time vehicle location and travel time information would enable practitioners to monitor two important resources in relief aid distribution, transportation and relief supplies, and update plans accordingly. Because road-mounted sensors may not be established in many parts of the world, simple and affordable vehicle-mounted sensors, such as GPS receivers, would be reasonable to use for vehicle monitoring.

- **Transportation network infrastructure.** Because a disaster may severely damage the transportation infrastructure, obtaining accurate information about the condition of the transportation network is important during aid distribution. ITS could be used to assess the impact of the disaster on transportation infrastructure through surveillance systems and sensors and communicate infrastructure information to the vehicles to update routes, when necessary. However, these systems are not yet widely available, even in many urbanized regions of the world. Nevertheless, organizations such as the UNJLC provide real-time GIS data on logistics infrastructure, thereby making up-to-date regional transportation infrastructure information available to relief organizations. Such data would be valuable in last mile distribution if it could be transmitted to vehicles using available communication devices. In this way, drivers could be apprised of road conditions and changes to delivery schedules.

- **Relief supplies.** Uncertainties related to relief supply availabilities may lead to difficulties in developing effective supply allocation plans across the last mile. Therefore, reliable information related to supply movement in the upstream relief chain (e.g., arrival times and amounts of supplies in transfer to ports, central warehouses, and the LDC) would reduce uncertainty when developing last mile distribution plans. Today, the most prominent ITS technologies used in commercial cargo tracking include Radio Frequency Identifications (RFIDs), barcodes, smart cards, and GPS (Tsao and Rizwan, 2000). In the relief sector, tracking is not well developed; in fact, it is usually performed using spreadsheets or manual processes (Russell, 2005). Although some relief organizations have recently implemented commodity tracking software to track supplies (Russell, 2005), this software does not integrate tracking information into operational distribution plans. However, recent applications of GPS technologies in the relief sector offer opportunities for tracking cargo for long-haul and short-haul shipments. Moreover, recently emerging partnerships between relief sector and commercial logistics companies may present additional opportunities for the relief sector to utilize more advanced technologies to track relief supplies throughout the relief chain.

CONCLUSIONS AND FUTURE RESEARCH

In this study, our objective is to characterize the last mile distribution problem and develop an analytical approach that will enable relief practitioners to make efficient and effective last mile distribution decisions. We present a modeling approach and a formulation that optimizes resource allocation and routing decisions. We also present illustrative examples and highlight the relationships and interactions of various decisions and the effects of various parameters on model’s behavior. We show that the model considers the tradeoffs among interacting decisions reasonably and achieves equitable aid distribution and cost-efficient routings under different settings.

We observe that optimal routings, allocations, and penalty cost factor breakpoints could be easily obtained for small
problems. However, the interactions among different decisions become more complex as the number of nodes, routes and partial-allocation options increase, penalty costs are nonstationary, LDC-supply and vehicle capacities become very limited, vehicles have different characteristics, and vehicles can complete multiple tours per period. Solution times also increase as the problems become larger and also when the resources are more limited. Therefore, we are developing heuristic algorithms that provide good solutions to the last mile distribution problem in our current work. Faster algorithms would also enable us to test the model using larger and more complex problems and would therefore be useful for further analysis of the last mile distribution problem.

REFERENCES


