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Chapter 14

Vehicle Routing Applications in Disaster Relief

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14.1 ▪ Introduction

The working assumption in most *Vehicle Routing Problems* (VRPs) is that profitable customer requests have to be processed at minimal cost. However, there are VRP applications where servicing a customer has no monetary benefit, but all available resources must be mobilized to provide the best possible service. These applications appear in the context of humanitarian relief, where the key principle is to prevent or alleviate human suffering. This chapter examines a class of problems that obey this principle, namely, VRPs in disaster relief operations.

We define a disaster as an extraordinary event that can occur with or without limited forewarning and has devastating effects on the population. Disasters might have different causes: natural (e.g., earthquakes and hurricanes) or man made (e.g., terrorist attacks and industry disasters). Furthermore, one disaster may be the trigger for another, such as an earthquake leading to a tsunami and a tsunami causing an industrial accident. Regardless of the cause, disasters often bring destruction, suffering, and loss of lives at a level that cannot be managed by local emergency units. The severity of the impact on the victims depends on the event's magnitude and on two additional factors (International Federation of Red Cross and Red Crescent Societies [23]): the affected population's vulnerability, expressed as the inability to resist the hazard, and the available capacities to cope with the effects of the event. As local capacities are overwhelmed after a disaster, national and international aid agencies play an important role in providing the support that is required to alleviate the suffering. Even though local authorities are responsible for the relief operations, the aid agencies are heavily involved in the disaster management process. Their functions include deploying rescue teams and providing essential supplies such as water, food, and medicine to the affected regions.

Research in the field of disaster relief routing can make important contributions to support aid agencies in their operational activities and eventually to help save lives.

14.1.1 ▪ Logistics in Disaster Management

One of the most important tools to make the best use of existing resources and to enable fast relief, even under aggravated circumstances, is logistics. After the damage has been assessed and the requirements have been determined, supplies are shipped from all over the world to the disaster area. At this stage, effective logistics strategies are needed to enable a smooth flow of commodities from the point of origin to the victims. As a consequence, more and more logistics experts are involved in the establishment of distribution networks. In fact, each disaster has different effects, yet the basic way in which a network is established is similar in all relief operations (Stephenson [57]). Typically, international supplies enter the affected area through a large port or airport. Next, these supplies are transferred to a primary warehouse that is nearby. Commodities (supplies) then flow to final storage locations and are eventually delivered to the victims. The first stage of the transportation process is usually carried out by long-haul trucks or trains. Smaller vehicles or vans cover the last miles to remote victims. This procedure is depicted in Figure 14.1. Clearly, humanitarian logistics considers several difficult optimization problems, including warehouse location and vehicle routing. In this chapter, we focus on the last-mile VRPs that involve direct victim assistance (e.g., damage assessment, evacuations, moving of rescue teams, and the delivery of essential supplies).

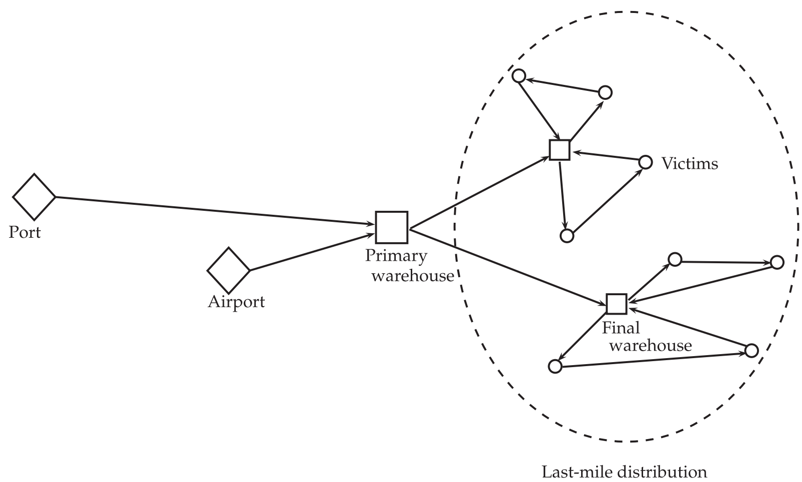

Figure 14.1. *Disaster relief supply chain* [57].

The humanitarian objective to use all possible means to alleviate human suffering clearly deviates from the classical VRP objective to minimize cost. In addition, the dangerous environment in which vehicles operate after a disaster poses new challenges in modeling and solving these problems.

The road network on which vehicles travel might be in poor condition (e.g., roads with damaged bridges might not be passable, rendering the entire planning useless). Gathering sufficient means of transportation to handle the incoming supply may be difficult due to shortages of vehicles, competition among the aid agencies for vehicles, or the refusal of local carriers to operate in areas exposed to the risk of looting. Even if the fleet capacity is sufficient despite these difficulties, fuel shortages might force some vehicles to remain idle. In addition to the extreme circumstances that have to be captured in meaningful models, decisions have to be made quickly. Typically, international rescue teams

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are able to arrive at the disaster site within 24 hours. They cannot wait a day or more for the results from an optimization algorithm. In such a case, computational efficiency is not a question of cost or user convenience, but rather a question of saving lives.

The consideration of a number of alternative objectives further complicates the modeling effort. Although it is clear that the ultimate objective is to reduce suffering, this is too vague to be used as a quantitative measure to help make good decisions. Therefore, in accordance with the literature, we define three specific objectives that directly originate from the nature of a disaster.

First, the situation in the direct aftermath of a disaster requires a quick response. People may be injured, buried under rubble, traumatized, and left without shelter and food. Every second counts at this stage, and time becomes the most important resource to prevent the further loss of lives. Hence, accelerating the response is an important aspect in disaster relief. Second, the number of affected people is very high after a disaster. As a result, there may be insufficient supplies and limited means of transportation. If transportation is the bottleneck, then vehicle routing models can be used to maximize the amount delivered.

All people have the right to assistance. The third objective is to devote impartial and fair attention to everyone. The significance of this objective increases with the scarcity of the resources. Finally, though not a humanitarian objective, we generally need to take costs into account. In fact, quick-onset disasters are often overfinanced by donations (Van Wassenhove [66]). However, in later phases of a disaster relief operation, the budget is likely to become an important concern.

In this chapter, we review the relevant literature on disaster relief routing and highlight those phases of the disaster management process in which VRP variants are involved. Given the complexity and the scope of disaster management, we examine three consecutive phases: preparedness, response, and recovery.

In addition, we describe how the humanitarian perspective is implemented in various routing models and show how the different focus and objectives affect the solution approaches and the resulting solutions. Finally, we close the chapter with suggestions for future research.

14.1.2 ▪ Complementary Literature

There have been several recent survey articles on humanitarian logistics. A survey with a special focus on disaster relief routing problems is presented in de la Torre, Dolinskaya, and Smilowitz [13]. The authors review the challenges in this field and the way in which these are captured in state-of-the-art articles. Directions for future research are given from a researcher's and a practitioner's point of view. A description of the health care, emergency, and disaster services offered by the Austrian Red Cross is given in Doerner and Hartl [16]. Here, the organization's basic optimization problem in relief operations is classified as a warehouse location-routing problem.

Several papers examine the field of humanitarian logistics in more general terms. In Kovacs and Spens [30], a deeper understanding of humanitarian logistics is promoted by examining the different actors (e.g., donors, aid agencies, and governments), phases, and processes involved in disaster relief operations and the way these relate to each other. Additionally, parallels between humanitarian and commercial logistics are drawn. A comparison of humanitarian and commercial logistics is also given in Beamon and Balcik [7] and Van Wassenhove [66]. In Van Wassenhove [66], the complexities involved in managing humanitarian supply chains and the fundamental differences between humanitarian and commercial supply chains are illustrated. The author points out that the two fields

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share many similarities that should be exploited. Humanitarian logistics can learn from new and successful concepts developed for commercial applications. The private sector can learn from the agility and adaptability of humanitarian supply chains. The lack of effective performance measures in humanitarian applications is addressed in Beamon and Balcik [7]. The authors compare humanitarian and commercial supply chains and adapt existing commercial measures to evaluate relief operations. This is done with special attention to the requirements of relief operations after quick-onset disasters. Pedraza-Martinez and Van Wassenhove [48] highlight challenges in humanitarian logistics that have received limited attention in the operations research literature. Challenges are posed by different objectives of short-term relief programs and long-term development programs, by decentralized decision making and conflicting objectives at different levels, by fundings that are earmarked for specific programs, and by difficult operating conditions in the field. The current state of humanitarian logistics and the gaps in terms of practice, research, and education are presented in Kovacs and Spens [31]. The authors find that quantitative models are still too immature to be applicable in the case of emergency situations. Early work in the field of humanitarian logistics is presented in Knott [28, 29].

A detailed survey on general operations research and management science approaches in disaster management is presented in Altay and Green [1]. They classify the literature in terms of research methodology, disaster type, and the disaster life cycle. The review in Simpson and Hancock [56] is not limited to large-scale disaster management. The review includes urban services (e.g., police, ambulance, and fire fighters) and general emergency response.

The practitioner's point of view is illustrated by publications of different aid organizations. The Sphere Project was initiated by a group of humanitarian organizations with the aim of improving the quality of disaster management. The project's handbook is a recognized summary of common principles and universal minimum standards for humanitarian response (The Sphere Project [58]). Insights into disaster relief operations of the United Nations are given by a logistics training module provided by the United Nations Development Programme (Stephenson [57]). The importance of logistics in humanitarian operations is pointed out in Thomas and Kopczak [59]. After describing the difficulties encountered in the field of humanitarian logistics, the authors present different strategies for overcoming them.

14.2 ▪ Phases in Disaster Management

Disaster management is a complex and comprehensive process that extends over a long period of time with changing emphases and constraints. The process can be divided into four phases: mitigation, preparedness, response, and recovery.

No community can rule out the possibility of a disaster. Therefore, the management of a disaster starts long before a disaster occurs with the mitigation and the preparedness phases. The mitigation phase is concerned with activities that lessen the potential impact of a disaster. Typical activities include the reinforcement of buildings to withstand disasters or the prevention of populating dangerous areas. This phase will not be discussed further here. In the preparedness phase, arrangements are made that allow a quick and appropriate response after a disaster. Logistics-related activities include the prepositioning of important supplies and the rehearsal of distribution plans.

The response phase focuses on operations that satisfy the urgent needs of a population immediately after a disaster, including assessment of the destruction, evacuation and rescue of the disaster victims, and the supply of essential commodities. These activities are carried out under severe time constraints. The recovery phase includes long-term activities that support the population's self-sustainability and return to normalcy, including

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the removal of debris and providing health care and food. Typically, the four phases are carried out in a cyclic manner (i.e., affected communities start with the mitigation phase right after they have recovered from a disaster). Next, we describe the logistics-related problems that emerge in each phase.

14.2.1 ▪ Preparedness Phase

In the preparedness phase, strategic decisions are made before a disaster occurs. When a disaster strikes, there is a tremendous demand for essential supplies in a short period of time. It is crucial to have emergency supplies such as tents, first-aid kits, and food at hand in order to be prepared for the worst-case scenario. The better the preparation, the faster the response time after a disaster, and the more lives that can be saved. However, this phase is mostly characterized by the lack of information about the location and the scope of a disaster which makes preplanning difficult.

Several papers deal with the prepositioning of supplies close to disaster-prone areas to enable a fast response. In Dessouky et al. [14] and Jia, Ordóñez, and Dessouky [25], facility location models are presented that deal with the characteristics of disasters. The objective is to locate warehouses that provide the best possible coverage to meet the demand of an impacted area. In contrast to standard location problems, the proposed models consider the quantity and the quality of the coverage. The quantity of coverage refers to the number of facilities that must cover a location. Redundant facilities can serve as backup sites if the demand is larger than expected. The quality of coverage depends on the distance between a demand location and the facilities that cover it. In addition, Balcik and Beamon [2] and Jia, Ordóñez, and Dessouky [24] consider stochastic demand by optimizing the expected objective value over a set of discrete scenarios. Balcik and Beamon [2] maximize the total expected demand covered by the established warehouses. Jia, Ordóñez, and Dessouky [24] formulate several objective functions that represent the quality of covering the uncertain demand.

Facility location and routing decisions are made in Ukkusuri and Yushimito [63] and Van Hentenryck, Bent, and Coffrin [64]. In Ukkusuri and Yushimito [63], each node and edge in the transportation network have a chance to be destroyed by a disaster. The objective is to place facilities at positions in the network such that the probability that the stored supplies survive and can reach the demand locations is maximized. The objective in Van Hentenryck, Bent, and Coffrin [64] is to allocate sufficient supplies before a disaster to enable fast distribution after the disaster strikes. The problem is solved in multiple, consecutive stages. The first stage is a stochastic location problem with uncertainty in the demands, travel times, and surviving supplies. The routing aspect is approximated. The stages that follow the disaster deal with the routing problem when the real-world outcomes are revealed.

Two-stage stochastic programming models with recourse capture uncertainty in the supply, demand, and condition of the road network. Decisions that are implemented before a disaster strikes are made in the first stage. These decisions include prepositioning the facilities and determining the volume of supplies to be stored at each facility. The second-stage decisions provide a response to the random outcome of a disaster. At this stage, the post-event transportation is planned based on the decisions from the first stage. The objective is to place resources (e.g., warehouses, shelters, and supplies) that allow an appropriate response under various disaster scenarios. Problems and solution approaches that adopt two-stage stochastic modeling are presented in Mete and Zabinsky [35], Rawls and Turnquist [50, 51], Salmerón and Apte [53], and Zhu et al. [72]. The model presented by Döyen, Aras, and Barbarosoğlu [17] extends the second stage by considering location and routing decisions simultaneously. Regional facilities must be located before

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a disaster strikes (first stage). Local facilities are established after a disaster strikes to serve the demand locations (second stage). In Barbarosoğlu and Arda [5], both stages are transportation problems. In the first stage, decisions are made about the allocation of goods just before a disaster strikes. A recourse is made in the second stage, based on the information about the actual scope of the damage.

In order to reduce the complexity of the models, a simplified formulation of the transportation problems is considered in several papers. Barbarosoğlu and Arda [5], Döyen, Aras, and Barbarosoğlu [17], and Rawls and Turnquist [50, 51] model the transportation problem as a network flow problem with fractional commodity flows. Mete and Zabinsky [35] and Zhu et al. [72] consider only direct flows of supplies between warehouses and demand locations. In Mete and Zabinsky [35], the flows are converted into vehicle routes in a post-processing phase. Salmerón and Apte [53] have only one location per vehicle route.

Shen, Dessouky, and Ordóñez [54] give an example of a VRP in the preparedness phase. Vehicle routes are planned well in advance of a potential terrorist attack based on stochastic information about the demands and the travel times. The pre-planned routes are used to provide training opportunities for the responsible authorities. When the actual attack occurs, the pre-planned and rehearsed routes are modified and used to distribute supplies quickly.

14.2.2 ▪ Response Phase

The response phase starts immediately after a disaster and can continue for several weeks. In this phase, all available resources are mobilized to minimize the immediate threat to the population's well-being. Tomasini and Van Wassenhove [60] point out that a successful humanitarian operation is one that satisfies the urgent needs of the population in the shortest amount of time. The cost associated with the operations plays a minor role. Instead, time is the most critical factor. VRPs that explicitly aim to reduce the response time are discussed in Section 14.3.

Facility location problems that emerge in the response phase are presented in Horner and Downs [20] and Murali, Ordóñez, and Dessouky [36]. Given a set of eligible facilities, Murali, Ordóñez, and Dessouky [36] consider the problem of selecting a subset of facilities to be opened. The objective is to open facilities that maximize the coverage of the affected population. The demand is uncertain, and the number of people that can be served decreases with increasing distance between facility and demand location. (Tricoire, Graf, and Gutjahr [61] assume a similar demand characteristic in a covering tour problem.) Horner and Downs [20] try to establish intermediate depots between the demand locations and the prepositioned facilities. As soon as the disaster location is known, the population's accessibility to supplies can be improved by establishing depots that are nearby.

Van Hentenryck, Coffrin, and Bent [65] investigate recovering from power outages after a hurricane. The problem involves the selection of damaged components in the power network and the routing of repair crews to the selected sites. The objective is to restore the power infrastructure as quickly as possible. Rath and Gutjahr [49] consider the problem of placing intermediate depots between supply sources and demand locations combined with routing the vehicles. Intermediate depots are delivered in full truck loads. The supply is then reloaded to smaller vehicles and distributed to the demand locations. The strategic part of the problem is concerned with location decisions, and the operational part deals with routing decisions. Multiple objective functions are defined that maximize satisfied demand and minimize cost.

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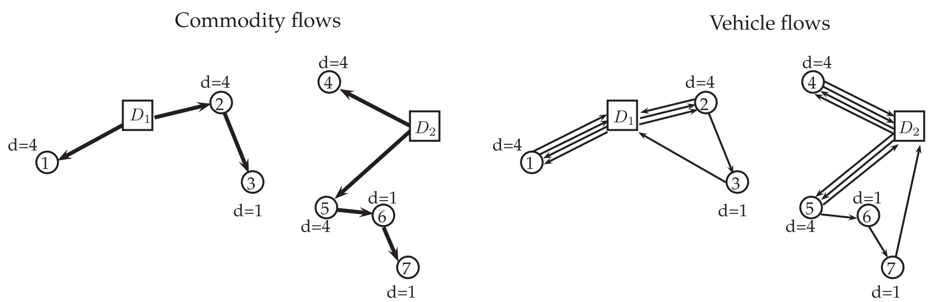
One stream of research focuses on the first stage of the supply chain. This stage is characterized by the large number of supplies that enter the affected area through the ports of entry and have to be distributed as quickly as possible. The number of locations is usually small because only larger cities and warehouses are considered. Nevertheless, the demand for essentials can be quite large and can exceed the total capacity of the vehicle fleet. To meet the demands, a single location can be visited by several vehicles or by the same vehicle several times.

This problem is modeled as a network flow problem in the literature. Here, supplies and vehicles may be dispersed over the entire network and there are no special rules on the delivery strategy; e.g., demand can be satisfied completely or partially, by one or more vehicles, from one or more depots. Accordingly, the definition of a route is rather broad. In general, any sequence of nodes is called a feasible route as long as the associated vehicle has an uninterrupted flow through the network and its capacity is not exceeded. The flow may contain cycles if vehicles need to return to a depot for replenishment. The focus is on matching commodity flows from the sources to the destinations to the corresponding vehicle flows that carry the commodities. We point out that similar single commodity flow models have been developed for the VRP (see Laporte and Nobert [32] and Magnanti [34] for a discussion of these models).

In Figure 14.2, we show an example with two depots (squares D_1 and D_2) with enough supply to serve seven locations (circles 1–7). There are four identical vehicles that have a capacity of three units each. Two vehicles are located at each depot. The left side of



Vehicle trip	From	To	Amount carried	Amount delivered
1	D_1	1	3	3
	1	D_1	0	0
2	D_1	1	3	1
	1	D_1	2	0
	D_1	2	2	2
	2	D_1	0	0
3	D_1	2	3	2
	2	3	1	1
	3	D_1	0	0
4	D_2	4	3	3
	4	D_2	0	0
5	D_2	4	1	1
	4	D_2	0	0
6	D_2	5	3	3
	5	D_2	0	0
7	D_2	5	3	1
	5	6	2	1
	6	7	1	1
	7	D_2	0	0

Figure 14.2. *Network flow model: A square denotes a depot and a circle denotes a demand location. Demand* (d) *is given next to a location.*

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the figure shows the commodity flows that are required to meet the entire demand. The right side shows the vehicle flows that are needed for a feasible solution. Since the total demand at the locations (19 units) exceeds the total vehicle capacity (12 units), vehicles have to reload at the two depots. Furthermore, locations 1, 2, 4, and 5 are visited twice to deliver their entire demand. In this example, the vehicle flows have to end at one of the depots. The solution of the network flow problem does not provide a unique routing plan. A possible routing plan is given in the accompanying table. The second and the third columns show the traversed arcs of the vehicle trips. Amount carried refers to the amount loaded on the vehicle when traversing the respective arc, and amount delivered is the amount unloaded at a visited location.

To model this problem using binary vehicle flow variables, which is common in VRP formulations, a fourfold indexing is used. Two indices capture the respective arc, one index for the vehicle and one for the trip in which the arc is traversed. Variable x_{ijkr} takes the value 1 if vehicle k traverses arc (i,j) in its rth trip, and 0 otherwise. By using a network flow model, we do not have to explicitly track each vehicle on each trip. This is possible because separate commodity flow variables guarantee that the demand will be met. Therefore, it does not matter which vehicle is involved in transporting supplies to locations. It is only important that the available vehicle capacity on an arc is sufficient to carry the assigned supplies. The binary flow variables can be replaced by integers that aggregate the total number of vehicles that flow through an arc ($x_{ij} \in \mathbb{N}$). This approach makes the model more compact and easier to solve with MIP solvers because the number of integer variables is independent of the number of vehicles. However, it is not possible to directly determine the vehicle routes from the solution or to include constraints that limit route travel time.

Transportation problems that are modeled as network flow problems are presented in Özdamar [42] and Özdamar and Demir [43]. In Vitoriano, Ortuño, and Tirado [68] and Vitoriano et al. [67], a vehicle may visit a node only once; i.e., cycles to replenish the vehicles are not allowed. The authors consider alternative objectives such as the minimization of looting risk by consolidating vehicles via a convoy or the minimization of the maximum difference in the ratio of satisfied demand to requested demand of the locations.

Several papers account for the time perspective by dividing the planning period into discrete time intervals (Clark and Culkin [11], Haghani and Oh [18], Oh and Haghani [41], Özdamar and Yi [45], Özdamar, Ekinci, and Küçükyazici [44], Yi and Kumar [70], and Yi and Özdamar [71]). Using these time intervals, urgency and time-dependent supply and demand can be modeled by adding an index to the decision variables that gives the respective time interval in which the flow between two nodes takes place. In this way, the model is more precise over shorter intervals, but the computational burden increases.

In Tzeng, Cheng, and Huang [62], only continuous commodity flows are considered and the flows have to go through candidate transshipment depots. There is a fixed cost to locate a depot. Fairness is considered by maximizing the minimum satisfaction rate among all customers.

14.2.3 ▪ Recovery Phase

The main goal in the recovery phase is to restore the self-sufficiency of the affected population (Thomas and Kopczak [59]). The recovery starts when the immediate threat is brought under control and the seriously injured people are being treated. However, it is almost always difficult to determine a specific point in time for the transition from the response phase to the recovery phase. We can associate an optimization problem with the recovery phase if it accounts for the cost at which relief operations are executed and

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promotes the self-help initiatives of the population (e.g., by asking people in unvisited locations to walk to their nearest tour stop where supply is provided). Considering the cost is important to enable long-term assistance. One goal should be to get the affected population to support the disaster relief effort (The Sphere Project [58]). In Section 14.3, we present VRPs for the recovery phase.

Another characteristic of the recovery phase is the large demand for bulk commodity transportation. The removal of debris, the transportation of construction material, and the long-term supply of essentials such as water, food, and medicine are major planning problems. These operations are extremely expensive, so cost is a major concern (Stephenson [57]). The network flow approach described above can be applied to deal with these problems on a strategic level.

14.3 ▪ Performance Metrics in Disaster Operations

The most common performance metric for evaluating commercial vehicle routing solutions is the total travel cost associated with the routes. If the cost of a route is not directly available, it can be approximated by the travel time or the travel distance. Therefore, the cost measure is convenient to differentiate between bad, good, and very good solutions and, moreover, to guide the decision-making process.

However, routing plans in disaster operations cannot be evaluated on the basis of monetary considerations. Financial aspects play a role, but the crucial question is how well the service alleviates human suffering. Accordingly, money issues fade into the background and are treated as constraints, rather than an objective (Kaplan [27]). On the other hand, the qualitative, and often abstract, goals stated by aid agencies cannot be used readily to evaluate the success of an operation. Instead, these goals have to be transformed into quantitative metrics that can be used as objective functions in mathematical models. In Beamon and Balcik [7], different performance measures are proposed to quantify the efficiency and effectiveness of humanitarian operations. The most suitable measures for disaster relief routing problems are response time (the time that elapses until urgent needs are met), service equity (the differences in the assistance provided to the people at various locations), demand satisfaction (the volume of goods distributed to the population), and transportation cost. The importance of each measure depends on the phase of disaster management with which the specific problem is associated. For example, response time is the main concern in the response phase, while cost is more important in the recovery phase.

In this section, we examine alternative performance metrics in more detail and show how they have been implemented in the literature. Recent papers that consider the four metrics are listed in Table 14.1. In Rath and Gutjahr [49] and Van Hentenryck, Bent, and Coffrin [64], decisions about locating a depot and routing the vehicles from each depot are made in a hierarchical fashion. In the first phase, locations for the depots are selected. In the second phase, vehicle routes are generated from each depot. Only the routing part is considered in this section.

14.3.1 ▪ Response Time

Response time is the interval from the occurrence of a need to its satisfaction. Due to the high degree of urgency in disaster relief operations, a fast response is crucial. Any delay in assistance could lead to further suffering of the affected population. Correspondingly, time is the most precious resource in the immediate aftermath of a disaster. If necessary, goods are flown in from abroad to speed up the relief operations regardless of the resulting

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Table 14.1. *Performance metrics considered in* 24 *recent papers.*

	Response time	Service equity	Demand satisfaction	Transportation cost
Balcik, Beamon, and Smilowitz [3]	√	√	√	√
Barbarosoğlu, Özdamar, and Çevik [6]	√	√		
Bish [8]	√	√		√
Campbell, Vandenbussche, and Hermann [9]	√	√		
De Angelis et al. [12]			√	
Doerner, Focke, and Gutjahr [15]			√	√
Hodgson, Laporte, and Semet [19]		√		√
Huang, Smilowitz, and Balcik [21]	√	√		√
Huang, Smilowitz, and Balcik [22]	√			
Jozefowiez, Semet, and Talbi [26]		√		√
Lin et al. [33]	√	√	√	√
Ngueveu, Prins, and Wolfler Calvo [37]	√			
Nolz et al. [38]	√	√	√	√
Nolz, Doerner, and Hartl [39]			√	√
Nolz, Semet, and Doerner [40]	√		√	√
Panchamgam et al. [47]	√	√		√
Rath and Gutjahr [49]			√	
Rekik, Renaud, and Berkoune [52]	√	√		
Shen, Dessouky, and Ordóñez [54]	√		√	
Shen, Ordóñez, and Dessouky [55]	√		√	
Tricoire, Graf, and Gutjahr [61]			√	√
Van Hentenryck, Bent, and Coffrin [64]	√	√		
Van Hentenryck, Coffrin, and Bent [65]	√			
Wohlgemuth, Oloruntoba, and Clausen [69]	√			√

costs (Van Wassenhove [66]). Vehicle routing is an important part of the supply chain and can significantly accelerate the delivery if urgency is incorporated properly in the optimization problem.

The most commonly used method for generating solutions with low response time is the minimization of the maximum arrival time. This objective function is often referred to as the min-max objective. The definition of the maximum arrival time varies in the literature. In Campbell, Vandenbussche, and Hermann [9], Nolz et al. [38], and Rekik, Renaud, and Berkoune [52], the maximum arrival time is the time when the last location is serviced. In Barbarosoğlu, Özdamar, and Çevik [6], Bish [8], and Van Hentenryck, Bent, and Coffrin [64], the maximum arrival time reflects the time when the last vehicle returns to its depot. The first definition is useful when each destination has to be visited once to satisfy the urgent needs of the population. Vehicles can then return to the depot without any further time pressure. The second approach makes more sense in certain pickup operations, e.g., evacuations, where the safe arrival of the vehicle back at the depot is important. Campbell, Vandenbussche, and Hermann [9], Huang, Smilowitz, and Balcik [22], Ngueveu, Prins, and Wolfler Calvo [37], and Van Hentenryck, Coffrin, and Bent [65] propose an alternative to the min-max objective that minimizes the average arrival time among all locations (a min-avg objective). This objective is equivalent to the minimization of the sum of arrival times (min-sum objective). The main difference between these two objectives is that the min-max objective considers only the bottleneck route with the latest arrival time and ignores all shorter routes. Accordingly, several optimal solutions may have the same objective value. In contrast, the min-avg and the min-sum objectives consider each location's arrival time and, therefore, take into account all routes.

Huang, Smilowitz, and Balcik [21] extend the min-sum objective function by considering the arrival time at each location and the amount delivered. Their objective mini-

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mizes the supply weighted arrival times and produces a solution in which large amounts of supply are distributed quickly (see Figure 14.3). In Figure 14.3, the locations (circles) are serviced from one depot (square). The demand (d) is given for each location. The figure shows how the preference to visit larger demand locations first leads to crossings of the route segments. The edges back to the depot, depicted as dashed lines, do not contribute to the objective value and might also cross other edges.

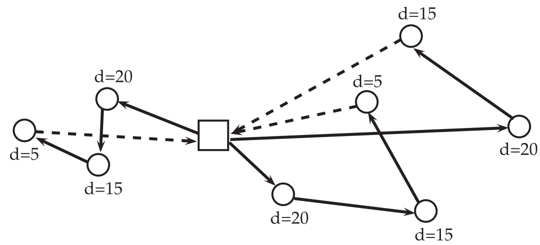

Figure 14.3. *Minimizing the supply weighted arrival times* [21].

The approaches that we have just described do not consider different degrees of urgencies at the locations. Panchamgam et al. [47] introduce the *Hierarchical Traveling Salesman Problem* (HTSP), where the sequence in which locations are visited depends on the urgency of their needs. Destinations with similar degrees of urgency are grouped together into priority classes. A location can only be visited after all locations in a higher priority class have been serviced. The authors also address a relaxed version of the HTSP. Panchamgam [46] extends the HTSP by considering multiple capacitated vehicles and presents two approaches to enforce the priority rule. The local timing priority rule restricts the visit sequence only within a single route; i.e., priorities must be obeyed on each individual route. The global timing priority rule requires that priorities be taken into account with respect to the entire solution; i.e., no location may be serviced later than any lower priority location. The two approaches are illustrated in Figure 14.4. The locations (circles) are grouped together into priority classes according to their distances from an earthquake's epicenter. The locations have to be serviced by two vehicles, located at the depot (square) and with sufficient capacity to make deliveries to three locations each. The left figure shows the solution when each route is considered separately. The local rule allows vehicles to visit low priority locations before high priority locations as long as they are not on the same route. The solution that results from applying the global priority rule is shown on the right. The global rule forces vehicles to visit all high priority locations before a lower priority location is visited. The decision on which rule to apply mainly depends on the availability of the resources. The global rule enables a fast response according to the urgency levels, but it also requires more travel time. The local rule is less binding and generates shorter routes. This can be important when the vehicle's travel time is restricted. A more flexible variant of the described priority rules is the d-relaxed priority rule (Panchamgam [46] and Panchamgam et al. [47]). If p is the highest priority class among all unvisited locations, the relaxed rule allows the vehicle to visit locations with priority $p, p+1, \ldots, p+d$ before visiting all locations in class p.

Balcik, Beamon, and Smilowitz [3] and Lin et al. [33] describe routing problems where commodities with different priorities have to be delivered over a planning horizon of several days. Urgency is considered by minimizing artificial penalty costs for unsatisfied demand. In Balcik, Beamon, and Smilowitz [3], the amount of the penalty cost at each location is weighted by the location's priority and the importance of the commodity type being demanded by the population. The more important a commodity or the

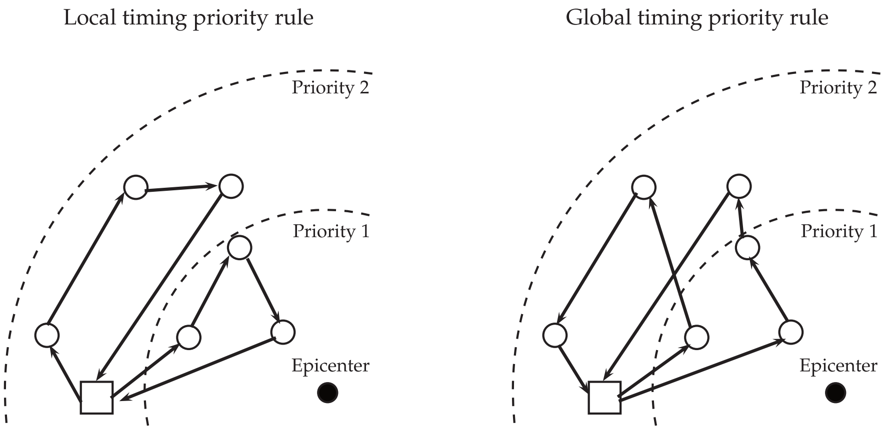

Figure 14.4. *Local vs. global timing priority rules (adapted from Panchamgam* [46]*).*

higher the priority of a location, the larger is the penalty cost. In Lin et al. [33], location priority is disregarded and only commodity priorities are considered. Goods may be delivered within a soft time window. Penalty costs are incurred when demand is not satisfied within the specified time window.

In Shen, Dessouky, and Ordóñez [54] and Shen, Ordóñez, and Dessouky [55], an appropriate response time is modeled with hard constraints. This is motivated by bioterrorism attacks where the exposed population must be treated within a specified time limit. A delivery after a deadline leads to a large decline in the population's health status or the loss of lives and is, therefore, not feasible.

The risk of encountering an impassable route during the execution of a plan directly affects the response time. Nevertheless, this concern has received only limited attention in the vehicle routing literature. Given the risk values for each single path to become impassable, Nolz, Semet, and Doerner [40] examine five different measures to quantify the overall attractiveness of a solution. The measures, defined for each pair of locations, are the number of alternative paths, the minimal travel time (gives the risk of the fastest path), the minimal risk (gives the risk of the safest path), unreachability (gives the accumulated risk over all paths), and the threshold risk (gives the number of arcs along a path with a risk larger than a specified threshold). For each measure, the attractiveness of a solution is defined by the least attractive link among all pairs of visited locations. An example is presented in Figure 14.5. The figure shows a graph with one depot (square) and five locations (circles). The table next to the graph gives the attractiveness for each pair of nodes. Attractiveness can be defined according to one of the five measures described above. The higher the score, the greater the attractiveness. The table at the bottom shows two solutions. Solution 1 has an attractiveness of one because it contains the unattractive link between location 2 and 3. The least attractive link in the second solution is between location 2 and the depot, and so the attractiveness of the solution is two. Therefore, solution 2 would be preferred.

Shen, Dessouky, and Ordóñez [54] and Shen, Ordóñez, and Dessouky [55] treat the travel times as random variables and formulate the delivery problem as a stochastic programming model.

Route planning in a dynamic environment with varying travel times and unknown demand locations is investigated in Wohlgemuth, Oloruntoba, and Clausen [69]. Dynamic optimization is especially appropriate when reliable information about the scale of a disaster becomes available only during the relief operations.

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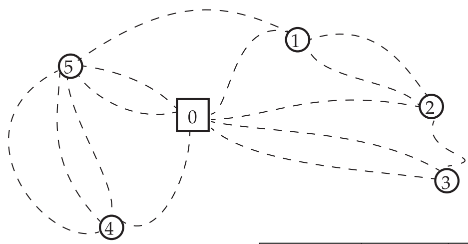

From-To	0	1	2	3	4	5
0	-	4	2	3	4	4
1	4	-	3	-	-	1
2	2	3	-	1	-	-
3	3	-	1	-	-	-
4	4	-	-	-	-	4
5	4	1	-	-	4	-

	Routes	Attractiveness
Solution 1	0-5-4-0 0-1-2-3-0	1
Solution 2	0-5-4-0 0-1-2-0 0-3-0	2

Figure 14.5. *Example of solution attractiveness in terms of risk.*

14.3.2 ▪ Demand Satisfaction

In disaster relief operations, aid agencies are faced with a large demand that must be managed with scarce resources. They need to find routes for each available vehicle such that the distributed supply is maximized, i.e., the number of lives saved is increased.

This problem resembles the *Team Orienteering Problem* (TOP) (Chao, Golden, and Wasil [10]), where as many destinations as possible must be visited within a given time limit. In the TOP, each destination has a score that is earned during a visit. The objective is to maximize the total score. In order to apply TOP concepts to disaster relief routing, the destinations are the affected regions and the score is each region's demand. An example of a TOP solution is given in Figure 14.6. Eight locations (circles) with different demands (d) have to be served from one depot (square). Due to the constraints on the number of vehicles, vehicle capacity, and travel time, only a subset of the locations can be visited. Locations with higher demand are visited with higher priority in order to maximize the distributed supply.

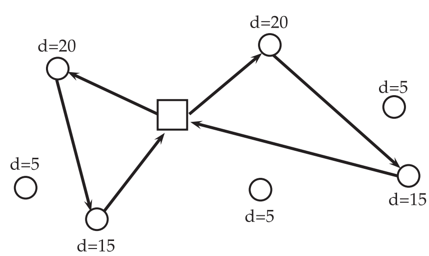

Figure 14.6. *Team orienteering problem* [54].

Rath and Gutjahr [49] extend the TOP by considering multiple depots to service the locations. In addition, a vehicle may reload at its depot as long as supply is available or the total travel time for the fleet has not been exceeded.

Several papers in the literature consider periodic delivery problems. In Balcik, Beamon, and Smilowitz [3] and Lin et al. [33], demand satisfaction is increased by minimizing a penalty cost that is incurred for unsatisfied demand. Lin et al. [33] consider demand that occurs regularly during the planning period. Balcik, Beamon, and Smilowitz [3] consider commodities with recurrent and one-time demand. In De Angelis et al. [12], supplies are delivered to locations from different depots according to the available supply. The

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demand at each location occurs once at the beginning of the planning period and is satisfied by full-vehicle loads. A tour contains only one location that has to be visited several times. The objective is to satisfy as much demand as possible within a specified planning period. Figure 14.7 shows an example of a daily schedule for one vehicle. The vehicle starts at depot D_1 and visits demand locations and depots alternately until the allowed travel time is exceeded. The vehicle is parked at depot D_3 for the night and resumes making deliveries from D_3 the next day.

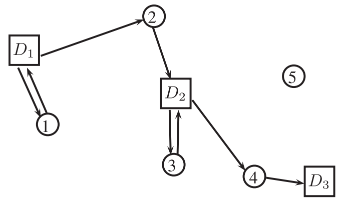

Figure 14.7. *Daily schedule for one vehicle of the problem presented in De Angelis et al.* [12].

Shen, Dessouky, and Ordóñez [54] and Shen, Ordóñez, and Dessouky [55] present a variant of the stochastic vehicle routing problem. The objective is to minimize the unsatisfied demand when demand and travel times are uncertain. Here the demand can only be satisfied if the delivery is made before a specified deadline. Because of the uncertainty in the demand and the travel times, there is a tradeoff between long-and-safe routes and short-and-risky routes. The difference between long-and-safe routes and short-and-risky routes is illustrated in Figure 14.8. The left side of the figure shows a routing plan that favors long arcs with a lower risk of long travel times (e.g., congestions) over short arcs with higher risk. Not all locations can be visited before the deadline in the routing plan, but the planned routes can be executed with a high probability. The routing plan on the right side ignores risk and has short arcs. All locations can be visited before the deadline in the routing plan. However, some locations may not be reached within the time limit if the real travel times are longer on the actual route.

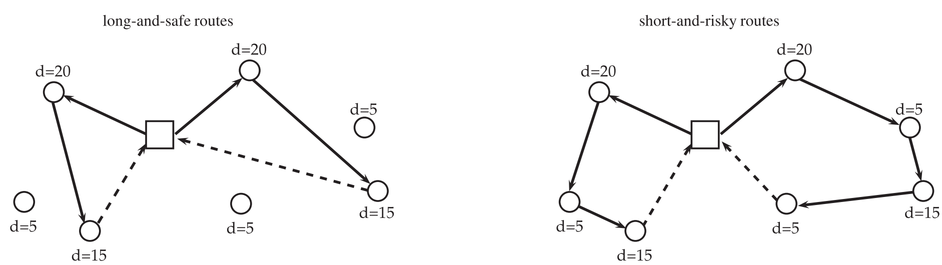

Figure 14.8. *Difference between long-and-safe routes and short-and-risky routes.*

To avoid underutilization of the vehicles due to conservative planning, all locations are scheduled on vehicle routes even if they cannot be delivered before the deadline. Locations that cannot be served in the planning phase still have the chance to be served in the execution phase. Figure 14.9 shows an example of this approach. The scheduled locations are the same as those on the left side of the example above (Figure 14.8), but here all remaining locations are appended at the end of the routes (depicted by dashed lines). These locations may also be served if the actual travel times or demands are smaller than the estimates.

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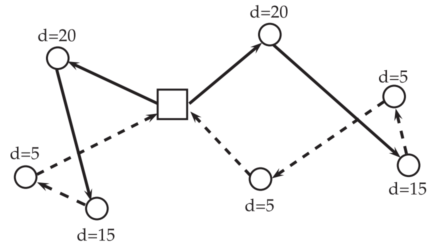

Figure 14.9. *Avoid underutilization of the vehicles due to conservative planning* [54].

Several papers focus on routing and allocation problems in which only a subset of the locations must be visited. However, the routes must be generated in such a way that people in an unvisited location have the opportunity to reach a location on a vehicle's tour without difficulty. The underlying assumption is that the people from the unvisited locations will be able to collect the supply on their own. This assumption restricts the usability of the models in the immediate aftermath of a disaster. Typically, people require direct assistance in the early phase of disaster relief. It may be difficult to inform the people about their nearest tour stop when the local environment is chaotic. However, involving the entire affected population in this way enables a larger distribution of supplies when transportation resources are scarce. This is shown in Figure 14.10. Again, only four locations are delivered directly (solid lines). The unvisited locations are assigned to their closest tour stop to collect supplies that are demanded (dashed lines).

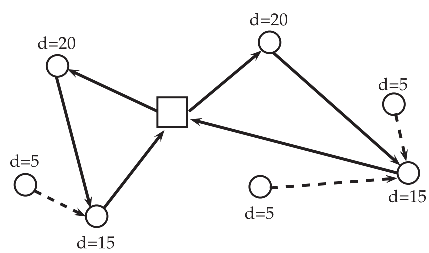

Figure 14.10. *Routing and allocation problems.*

In Nolz et al. [38], Nolz, Semet, and Doerner [40], and Nolz, Doerner, and Hartl [39], the objective is to minimize the average walking distance and maximize the proportion of the population that is covered within a certain distance. Both objectives aim for a large distribution of supplies. Tricoire, Graf, and Gutjahr [61] assume that the demand at each location is stochastic. In addition, the proportion of the population that collects supply at stops on a tour depends on the walking distance. With longer walking distances, fewer people are able to satisfy their demands.

14.3.3 ▪ Service Equity

Disaster relief operations are conducted with limited resources in terms of time, supply, and transportation. Therefore, it may not be possible to meet all urgent requests to the same extent. The concept of sequential visits on vehicle routes implies that not all tour stops are reached at the same time; some are visited before others. The short time frame in which operations have to be performed may be better utilized if vehicles visit easy access locations with larger demands first instead of trying to visit remote locations. Each person

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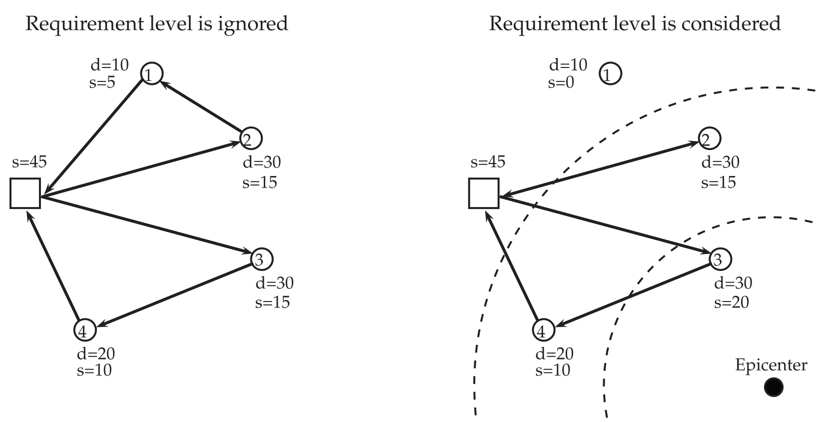
has the same right to receive assistance, so operations should be planned to avoid the unfair treatment of any group. Furthermore, unfair supply distribution may cause tensions between close-by communities and increase the risk of looting (The Sphere Project [58]). Therefore, appropriate equity metrics must be considered during operations planning in order to balance the service levels between different locations.

A review of equity in VRP applications is given in Balcik, Iravani, and Smilowitz [4]. The authors state that an operation is equitable when it has equal effects on the beneficiaries. This does not mean that all parties should be treated equally. Rather, differences in the initial needs have to be taken into account when estimating the effect of a service (e.g., severely injured people benefit more from quick assistance than uninjured people, who have lost only property). The goal is to balance the initial requirements and to ensure that all persons have similar living conditions and health after the relief operation. Equity metrics do not indicate how well the requirements have been satisfied. Instead, they consider the service level at each location and reflect the differences in the effects caused by the service. The smaller the differences, the more equitable is the service and the more balanced are the requirements after the operation. Clearly, equity is difficult to measure quantitatively.

In Figure 14.11, we show two different solutions to a distribution problem with scarce supply. The left figure shows the solution when the objective is to service all locations equally. The figure and the accompanying table show that each location obtains half the requested demand (second and third columns in the table). Even though there is no difference between the fractions of unsatisfied demand (fourth column), this solution is only considered equitable if all locations have similar initial needs. In the right solution, different need levels are considered based on the different distances from the origin of a disaster (e.g., the epicenter of an earthquake). The closer that a location is to the epicenter, the greater the level of destruction and the more important it is to satisfy the demand. To capture these differences, the unsatisfied demand rates are weighted by a penalty term (sixth



		Equal Distribution		Equitable Distribution			
Location	Demand (d)	Supply (s)	Unsatisfied Demand (1-s/d)	Supply (s)	Penalty (p)	Unsatisfied Demand (1-s/d)	Weighted Unsatisfied Demand ((1-s/d)p)
1	10	5	0.50	0	1	1.00	1
2	30	15	0.50	15	2	0.50	1
3	30	15	0.50	20	3	0.33	1
4	20	10	0.50	10	2	0.50	1

Figure 14.11. *Solutions with equal distribution and equitable distribution when supply is scarce.*

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column). The right figure shows the solution obtained by minimizing the differences in the priority weighted unsatisfied demands (last column). The corresponding satisfaction rates (seventh column) indicate that this approach assigns supplies in proportion to the need. Therefore, the solution is considered equitable.

In the literature, different approaches have been presented to consider equity in terms of delivery quantity and response time. In Lin et al. [33], supply equity is achieved by minimizing the maximum difference in the demand satisfaction rates among all locations. The satisfaction rate is defined as the ratio of the satisfied demand to the requested demand. The model formulated by Lin et al. [33] incorporates several commodities that are required with different urgencies. To account for differences in the initial requirements, the satisfaction rates are weighted by the priority with which supplies are needed.

Response time and supply equity are considered in Balcik, Beamon, and Smilowitz [3] and Huang, Smilowitz, and Balcik [21]. Balcik, Beamon, and Smilowitz [3] consider a periodic routing problem where two types of commodities with different priorities have to be delivered. For each location, a penalty cost for unsatisfied demand is incurred for each day for each commodity type. The penalties are weighted by the urgency level of each location to account for different initial needs. Equity is obtained by minimizing the sum of the maximum penalties over all days and over both commodity types. Given that the unsatisfied demand is backordered, this objective also balances the time at which deliveries are made in order to avoid accumulating large penalties. In Huang, Smilowitz, and Balcik [21], different performance metrics are examined that measure the equity of routing plans when demand satisfaction may be split among several deliveries. The authors point out that not all equity metrics are suitable to guide an optimization process. For example, the minimization of the maximum difference in the supply weighted arrival times might lead to solutions with equal, but equally bad, service levels. This type of solution is shown in Figure 14.12. Here, two vehicles traverse the same route in opposite directions and deliver one unit of supply. The total demand of each customer (two units) is satisfied after time tt, where tt is the travel time of each vehicle (we assume a symmetric distance matrix). This solution minimizes the objective function at the cost of the response time.

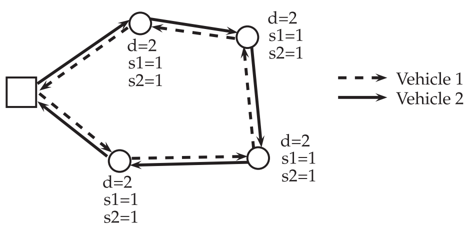

Figure 14.12. *Equal but inefficient delivery when demand satisfaction may be split. Demand* (d) *is given for each location. The supply* $s1$ *is delivered by vehicle* 1 *and supply* $s2$ *is delivered by vehicle* 2 [21].

The authors propose an objective function that promotes partial deliveries to locations in order to save goods for delivery to other destinations. However, in contrast to the previously described objective, this one favors a rapid delivery through the use of a convex penalty term that depends on the fraction of unsatisfied demand at each location. The lower the satisfaction rate, the higher the penalty; i.e., the penalty decreases with each unit delivered. The objective is to minimize the sum of the penalty costs that are incurred over time. Initial differences in the needs are not considered.

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In terms of equity in response time, there are many similarities with the performance measurements presented in Section 14.3.1. The minimization of the maximum arrival time bounds the difference between the earliest arrival time and the latest arrival time (Barbarosoğlu, Özdamar, and Çevik [6], Bish [8], Campbell, Vandenbussche, and Hermann [9], Nolz et al. [38], Rekik, Renaud, and Berkoune [52], Van Hentenryck, Bent, and Coffrin [64]). Therefore, this objective also bounds the differences between the effects on the locations. This approach does not consider differences in the initial requirements and leads to equitable tour schedules when all locations have similar initial requirements.

Setting urgency-dependent precedence constraints on the sequence in which locations are visited, as done in the HTSP (Panchamgam et al. [47]), favors equitable solutions. In this case, equity is enforced by hard constraints in the model rather than the objective function.

Routing and allocation problems emerge when the urgent needs have been satisfied, but the population depends on further assistance in health care or in the supply of essential goods. In these problems, equity is taken into account by bounding the longest distance a person has to walk to the nearest tour stop (Hodgson, Laporte, and Semet [19]). Instead of bounding the maximum walking distance, it is minimized in Jozefowiez, Semet, and Talbi [26]. Both approaches yield solutions with balanced walking distances because the differences are bounded either by a constraint or by the objective function.

14.3.4 ▪ Transportation Costs

Minimizing costs is not the primary objective of aid organizations, even though disaster relief can require lots of money. Immediately after a disaster, urgent needs are satisfied regardless of the expenses. However, after the situation has stabilized, aid agencies have to operate economically in order to be able to provide assistance until self-sustainability of the population is recovered.

Commercial and relief routing models are very similar in terms of cost as a performance metric. Relief routing models consider travel costs with lower priority or in conjunction with humanitarian constraints. The first priority in Bish [8] and Huang, Smilowitz, and Balcik [21] is the optimization of humanitarian oriented metrics. Routing costs are only considered to break ties if the primary objective has multiple optimal solutions. In Balcik, Beamon, and Smilowitz [3] and Lin et al. [33], humanitarian objectives and routing costs are aggregated into one objective function. The respective weights are set to favor the humanitarian metrics. Minimizing the travel distance is the only objective in Panchamgam et al. [47]. The urgency of need at locations is taken into account by precedence constraints in the sequence of visits. The objective function in Wohlgemuth, Oloruntoba, and Clausen [69] minimizes the number of vehicles used and the total travel time. The applied dynamic solution approach incorporates two features of disaster relief operations: changing road conditions (i.e., varying travel times) and the arrival of new orders during the execution of the tours.

In the routing and allocation problem presented in Hodgson, Laporte, and Semet [19], transportation costs are minimized while the walking distance from the unvisited locations to their nearest tour stop is constrained. In Doerner, Focke, and Gutjahr [15], Jozefowiez, Semet, and Talbi [26], Nolz et al. [38], Nolz, Semet, and Doerner [40], Nolz, Doerner, and Hartl [39], and Tricoire, Graf, and Gutjahr [61], a multi-objective optimization approach is applied where costs are optimized along with the walking distance or the share of the population that is covered within a specified distance.

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14.4 ▪ Commercial VRPs vs. Disaster Relief VRPs

The different requirements in commercial vehicle routing and disaster relief routing raise the question of how much the corresponding solutions are different from each other. Examining the differences in the performance metrics is important since routing models, algorithms, and software products have been developed mainly for commercial applications. In order to justify adapting these routing tools, the service provided to the disaster victims by humanitarian-oriented approaches must be significantly better after applying the tools to the problem. In this section, we illustrate the improvement in solutions that can be achieved by using humanitarian-focused models instead of models that only minimize cost. At the same time, we highlight the increase in transportation cost that results when we focus on optimizing humanitarian objectives.

14.4.1 ▪ Low Cost vs. High-Quality Relief

In Campbell, Vandenbussche, and Hermann [9], classical TSP and VRP models are used to investigate the impact of two objective functions on the service quality and on the total travel cost. The first objective is the minimization of the latest arrival time at a location (min-max). The second objective is the minimization of the sum of arrival times (min-sum). The return trip from the last node visited by a vehicle to the depot is ignored in both cases. The authors derive theoretical worst-case bounds on the relationship between the cost-based objective and the min-max and min-sum objectives. The results show that the optimal TSP tour could double the latest arrival time compared with the optimal min-max solution. The optimal min-max tour increases the TSP travel cost by at most 50%. The TSP solution might also be significantly worse in terms of optimal min-sum objective. However, in this case, the increase in the travel cost caused by minimizing the sum of arrival times cannot be bounded theoretically. So, the min-sum objective might not be applicable when the budget for relief operations is scarce.

The differences in the solutions, as a result of using the two alternative objectives, increase with the size of the vehicle fleet. If the triangle inequality holds, there is no incentive in the classical VRP to use more vehicles than required to serve all locations. However, the min-max and the min-sum objectives can be improved by visiting locations simultaneously with multiple vehicles. In addition to the worst-case bounds, Campbell, Vandenbussche, and Hermann [9] use empirical experiments to demonstrate that solutions for commercial routing problems differ significantly from those found with the two alternative (min-max and min-sum) objectives. In fact, the numerical results show modest differences in the solutions when compared to the worst-case bounds. The results confirm that by minimizing the travel cost, the increase in the latest arrival time is much larger than the increase in total cost when the maximum arrival time is minimized. The same is true in the context of the sum of arrival times.

An extension of the min-sum objective is examined in Huang, Smilowitz, and Balcik [21]. In their paper, a location's demand can be satisfied by more than one vehicle. Thus, each location may be associated with several arrival times. The objective is to minimize the sum of the arrival times weighted by the supply delivered to a location. The authors use empirical experiments to identify the impact of the weighted min-sum objective on the solution. A comparison with a cost-based objective reveals that the alternative objective causes the travel cost to increase by 17% to 18% on average. When cost minimization is the primary objective, the value of the weighted min-sum objective deteriorates by 29% on average.

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These large differences occur because the min-max and the (weighted) min-sum objective implicitly consider the cost by favoring shorter routes. The ignored trip back to the depot drives up the cost to a minor extent. The cost-based objective, on the other hand, does not consider any humanitarian-related requirement.

Bish [8] presents a bus evacuation problem where bus routes have to be planned to transport transit-dependent people to shelters in the case of an emergency. The vehicle capacity is constrained, but buses may perform several trips to manage the enormous demand. The objective is to minimize the duration of the evacuation, i.e., the maximum route length. In this problem, the evacuation duration includes the final trip back to the shelter. Therefore, this objective has an impact on the solution different from the min-max objective, which ignores the final trip. If only one vehicle is involved, the minimization of the evacuation duration and the minimization of the routing cost are equivalent and generate the same solution. When the fleet consists of multiple vehicles, the minimization of the travel cost can lead to evacuation durations that are arbitrarily larger than the optimal duration. Again, this is a worst-case bound that has not been observed in empirical experiments.

In general, the min-max objective leads to shorter maximum route lengths with a larger fleet size. Bish [8] shows that the min-max objective value does not always decrease in a convex manner with more vehicles. Adding one more vehicle to a fleet might have larger effects in some cases and smaller effects in others. A small effect can be expected when several vehicles have the same maximum route length and not all routes can be shortened by adding a single vehicle. Furthermore, increasing the fleet size above a certain threshold does not affect the optimal solution. In Figure 14.13, we illustrate these observations. Four routing plans are presented with one, two, three, and four vehicles. Vehicles start from the depot (square), visit the assigned locations (circles), and return to the depot. All unmarked arcs have a length of 1. The graph at the bottom of the figure shows the relation between the min-max objective and the number of vehicles.

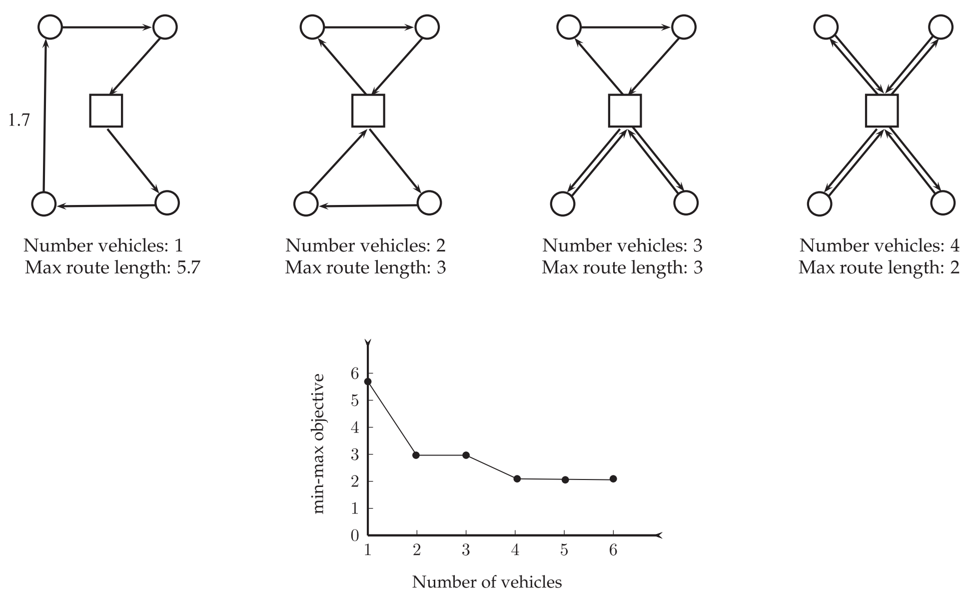

Figure 14.13. *Non-convex relation between number of vehicles and the maximum route length.*

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The results suggest that aid agencies should not be overeager to acquire vehicles. Instead, the available vehicles should be shared among different agencies and regions such that the overall service quality is improved.

In the HTSP, locations are assigned to different priority classes. The additional cost associated with serving the locations in the strict order of their priorities is examined in Panchamgam et al. [47]. The comparison between the classical TSP and the HTSP shows that, in the worst case, the ratio of the optimal HTSP length to the optimal TSP length is equal to the number of priority classes.

All four papers (Bish [8], Campbell, Vandenbussche, and Hermann [9], Huang, Smilowitz, and Balcik [21], and Panchamgam et al. [47]) indicate that the approaches developed for commercial VRPs are not readily applicable to solve humanitarian-focused problems. Much better service quality can be provided for those in need if the models and solution approaches are adapted to comply with the requirements in real-world relief operations.

14.4.2 ▪ Solving Disaster Relief Problems

The significant differences in the optimal solutions between commercial and relief routing problems require special attention in the design of solution algorithms. Changing the objective function of an algorithm that performs well on commercial routing problems may not be a viable option to solve humanitarian routing problems. This point is made in Campbell, Vandenbussche, and Hermann [9]. The authors state that modifying existing heuristics in order to achieve good results for the min-max and the min-sum objective functions is nontrivial.

An interesting characteristic of optimal min-max and min-sum solutions can be observed with regard to crossings of route segments. Given the triangle inequality, crossings are always associated with additional travel cost. Even though crossings might not be avoidable because of certain constraints, several approaches have been developed to avoid them. In the min-max and min-sum solutions, however, crossings might not influence the objective value at all or, in some cases, they might improve it. For example, consider the case where the objective function ignores the trip from the last location back to the depot. An example is shown in Figure 14.3. The last edge (depicted by a dashed horizontal line) crosses another edge without having any impact on the latest arrival time or the sum of arrival times. The same figure shows the positive effect of a crossing in terms of supply weighted arrival times. Vehicles are primarily routed to high-demand locations in order to deliver large amounts of supply. The benefit of serving large amounts quickly outweighs the loss from crossings at the end of the routes. Campbell, Vandenbussche, and Hermann [9] show that this effect is observable even if the supplied amounts are neglected. This is illustrated on the graph in Figure 14.14. The optimal route in terms of cost is the sequence 0-1-2-3-4-5-0 (called tour A) that does not contain crossings. The sequence 0-1-4-3-2-5-0 (called tour B) has a smaller sum of arrival times. This is because the longest edge with cost $3\sqrt{7}$ is traversed later and only contributes to the arrival times of location 2 and 5. The savings that result outweighs the loss from the crossing.

Computation time is a major concern in disaster relief. Stephenson [57] points out that locally organized relief actions are the most effective and appropriate. Usually, only laptops are available for solving hard optimization problems in the field. When every second counts, decision makers cannot wait long to generate reasonable solutions. Furthermore, the continuously changing environment requires frequent revisions and modifications to the generated solutions. Researchers need to develop robust, low-complexity

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Tour	Min-cost	Min-sum
A	17.13	44.20
B	17.96	43.53

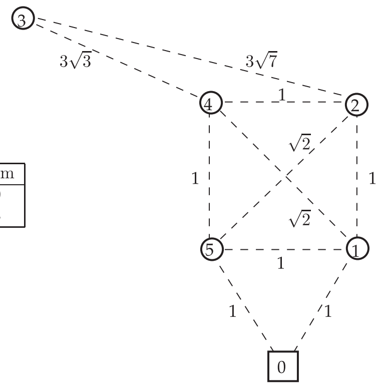

Figure 14.14. *Positive influence of edge crossing in min-sum objective* [9].

algorithms that provide good solutions quickly for a variety of input parameters. Solving problems to proven optimality or struggling to close the last few percent in the optimality gap is neither important nor possible when time is short.

14.5 ▪ Conclusions and Future Research Directions

Disaster management is a complex process that includes several difficult optimization problems. In this chapter, we illustrated how vehicle routing is integrated into the disaster management process and showed how VRPs are different from other transportation-related problems in this area. We argued that disaster management can be divided into three phases that depend on the timing of the decisions. In the preparedness phase, decisions are made under uncertainty, before a disaster occurs. In the response phase, the main objective is to provide assistance to the victims immediately after a disaster. In the recovery phase, both humanitarian-focused objectives and cost-based objectives are taken into account to enable long-term assistance. Routing problems occur in all three phases.

Each phase has specific objectives and constraints with the overriding goal to alleviate human suffering and provide equitable assistance to all victims. Cost-based performance metrics, such as transportation cost, are not suitable to evaluate the success of humanitarian operations. We examined three performance metrics that reflect how much an affected population will benefit from a planned activity. These metrics are response time, demand satisfaction, and equity.

The most sensitive phase in disaster relief is the response phase. Here, decisions are made under extreme time pressure. Fundamental differences arise in the solutions by optimizing either cost or response time. We provided two important insights. First, a much higher service quality occurs if humanitarian requirements are considered cautiously in the models. Second, solution approaches that have been developed for commercial applications cannot be used directly to solve humanitarian-focused problems.

Research in the field of disaster relief routing can make an important contribution to provide the best possible service to those in need. Work in this field may be attractive to researchers because of its unique and interesting characteristics. The humanitarian objectives and the associated environment in which routes are generated pose new challenges in modeling and solving these problems. Many aspects of disaster relief have already been addressed in the literature. Nevertheless, there is need for a deeper understanding of the effect of humanitarian objectives on different kinds of disaster relief scenarios. One as-

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pect that requires further consideration is vehicle-location compatibility. This extension is important when the transportation network is damaged and roads are impassable so that only off-road vehicles or aircraft can be used to reach some locations. Furthermore, evacuation operations modeled as pickup-and-delivery problems have received little attention in the disaster routing literature. Another aspect that requires further research is the lack of information about travel time, demand, and urgency of demand after a disaster. The lack of information could be taken into account by using stochastic models and perhaps by deterministic models that optimize artificial risk measures for route interruptions. In situations where time is short, the assessment of the destruction and the delivery of supplies might occur at the same time. In this case, the information gathered during the execution could be incorporated into dynamic solution approaches to route the vehicles to locations with larger needs.

From an algorithmic point of view, the development of solution approaches that account for the humanitarian requirements generates many possibilities for future research. Due to the complexity of disaster relief routing problems and the fact that solutions have to be generated in the shortest amount of time, the focus should be on heuristic approaches. The development of exact algorithms and examining their performance on test instances could be used to identify good solution features. Knowing the characteristics of optimal solutions enables good solutions to be implemented even without sophisticated computational support.

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