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# A decision support system for coordinated disaster relief distribution

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ABSTRACT

This paper presents a simulation and optimization based decision-support system (DSS) to facilitate disaster relief coordination between private and relief organizations. The DSS simulates disasters and plans shipments of relief goods via transfer points to demand points in the affected area. This enables decision-makers to analyze the last-mile distribution of goods by scheduling and routing trucks, off-road as well as unmanned aerial vehicles. Roads which are closed or opened during a disaster are considered allowing a dynamic adaptation to real world conditions and a comprehensive analysis over a rolling time-horizon. A mixed-integer problem formulation, an agent-based simulation, a heuristic-based scheduling and routing procedure as well as a Tabu Search metaheuristic are applied to analyze the given decision problem. Coordination between private and relief organization shows to be especially beneficial if time-losses resulting from closed roads are high and substantial unexpected demand occurs. Furthermore, results highlight the importance of selecting suitable transfer points and the potential of simulation and optimization based DSSs to improve disaster relief distribution.



## 1. Introduction

Disaster relief operations are substantially impacted by the availability of transportation infrastructure (Berariu, Fikar, Gronalt, & Hirsch, 2015). Furthermore, demand for products during disaster are highly irregular and may fluctuate drastically (Xu, Qi, & Hua, 2010), which additionally challenges operations. During the Tohoku disaster of 2011 in Japan, a sudden demand in food and water occurred, particularly in areas which were not highly damaged (Holguín-Veras et al., 2014). While average household spending on non-perishable food increased significantly, especially households with high opportunity costs of shopping were not able to stockpile food to their desired levels (Naohito, Moriguchi, & Noriko, 2014). Multiple businesses sensed this opportunity; however, faced obstacles due to power-outages, lack of experience and limited staff availability (Holguín-Veras et al., 2014). As a consequence, Holguín-Veras et al. (2014) conclude, among others, a need for supporting systems and closer cooperation between private and public organizations.

Private organizations play vital roles in disaster response. During Hurricane Katrina in 2005, Wal-Mart, e.g., supplied the affected area before the Federal Emergency Management Agency (FEMA) arrived, leading to wide-ranging praise from the public sector (Horwitz, 2009). While private organizations have substantial amount of data and the logistical know-how to deal with disruptions in supply and demand, relief organizations have the equipment and regulative decision-making power needed to ship goods efficiently through damaged areas. One potential enabler for cost-efficient coordination are unmanned aerial vehicles (UAVs), commonly called drones. For instance, one commercial release promises less than half of the costs of manned aerial cargo distribution by transporting up to 2,700 kg at approximately 150 km/h remotely (Sauvageau, 2011). While doubt exists about the widespread applicability in humanitarian logistics, mostly due to legal, ethical, safety and privacy issues, UAVs are already tested in various areas and show promising results, especially for the delivery of medical supplies (OCHA, 2014).

Fig. 1 defines coordination as studied in this paper. Goods are delivered to relief organizations at a selected receiving transfer point. After transshipment, the relief organization delivers the goods to a second transfer point, bridging the affected area either with off-road vehicles or UAVs. At this transfer point, goods are transshipped and delivered to their final location. Multiple decisions have to be taken, precisely if a coordination should be performed, where to transship as well as routing and scheduling decisions of shipments, UAVs and off-road vehicles.

Decision support systems (DSS) for humanitarian logistics used in practice mainly focus on information management and often lack optimization tools (Ortuño et al., 2013). To close this gap, vehicle routes, the selection of transfer points and scheduling of

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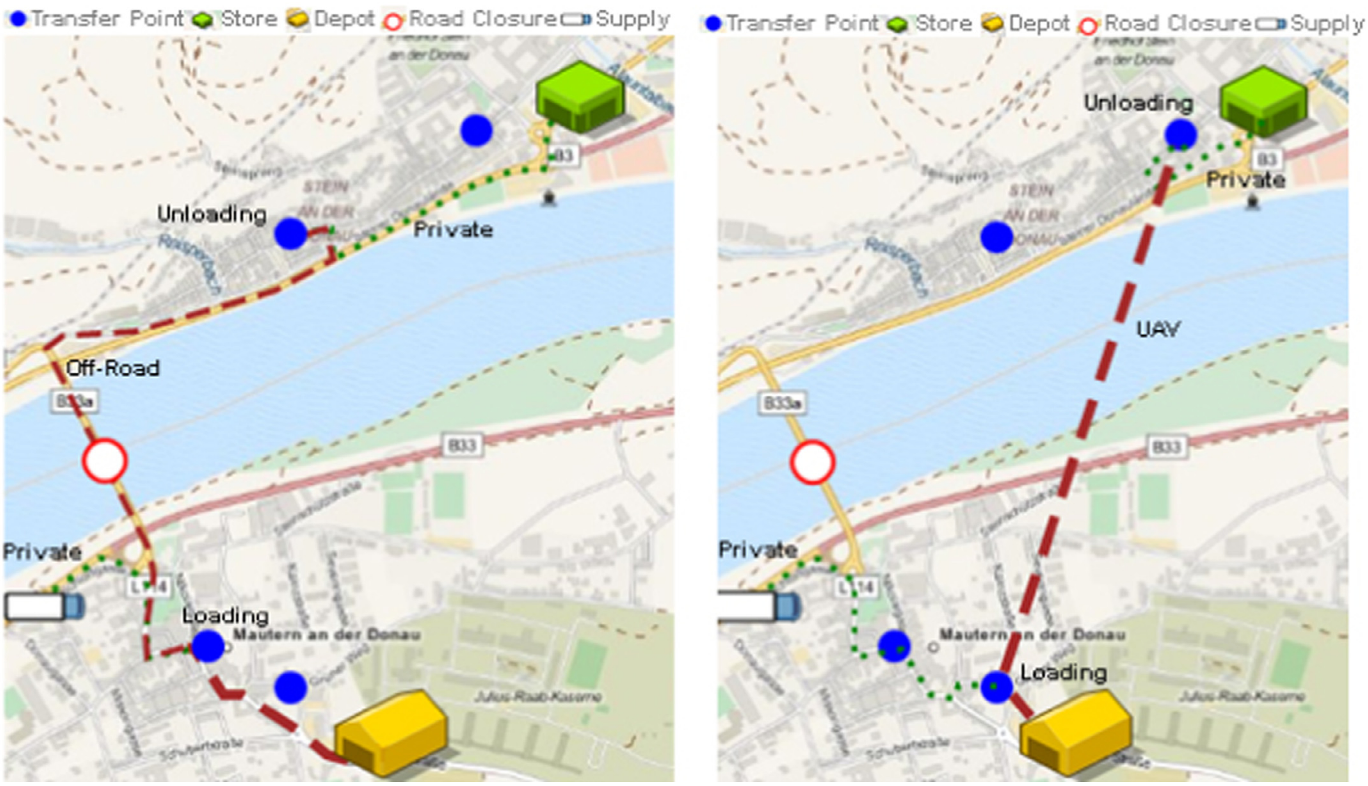



**Fig. 1.** Shipment coordination with off-road vehicles (left) and UAVs (right).

requests are optimized in our DSS. Therefore, the contribution of this paper is threefold: (i) it introduces a mixed-integer programming (MIP) model formulation to model coordinated disaster relief distribution, (ii) presents a simulation and optimization based DSS to solve and analyze the corresponding problem setting and (iii) discusses impact on disaster relief coordination. A preliminary description of the DSS and selected experiments were published in Fikar, Gronalt, Goellner, and Hirsch (2015).

The paper is structured as follows: Section 2 provides an overview of related work and Section 3 describes the problem and gives the corresponding mathematical formulation. The developed DSS is introduced in Section 4; computational experiments are presented and discussed in Section 5 and concluding remarks are made in Section 6.

## 2. Related work

DSSs are widely used in humanitarian logistics. For an overview on humanitarian logistics DSSs, refer to Ortuño et al. (2013). Van Hentenryck, Bent, and Coffrin (2010) study stochastic last-mile distribution during disasters by developing a three stage solution approach. Storage and customer allocation, repository routing as well as fleet routing are considered. Utilizing MIP, constraint programming and large neighborhood search techniques to analyze a set of different disaster scenarios, the authors report significant improvements on water allocation benchmarks. Emergency facility locations in Turkey under random network disruption are analyzed in Salman and Yücel (2015). A Tabu Search metaheuristic is proposed to place facilities in the pre-disaster stage. Whenever a direct route is damaged, i.e. a road, the cheapest alternative path is chosen. Network failures are further studied in Ahmadi, Seifi, and Tootooni (2015) by solving a two-stage stochastic program with multiple scenarios considering standard relief times. The authors report a significant reduction in costs and uncovered demand. Mitigation of network disruption is investigated by Snediker, Murray, and Matisziw (2008). A spatial DSS is introduced and results on a study of a telecommunications network are presented.

Özdamar and Ertem (2014) highlight two challenges of humanitarian logistics models; unacceptable computational time to solve large-scale problems and a lack of systems, which analyze disasters without being either too simple or too complex. To tackle these challenges, our paper implements an agent-based simulation and combines it with optimization procedures. Agent-based simulations are used for various stochastic problems. Within transport logistics, most of the related literature focuses on operational and single modal problems (Davidsson, Henesey, Ramstedt, Törnquist, & Wernstedt, 2005). In humanitarian logistics, agent-based simulations are, e.g., used to investigate evacuations (e.g. Wagner & Agrawal, 2014; Yin, Murray-Tuite, Ukkusuri, & Gladwin, 2014).

A wide range of work deals with the optimization of facility locations, which, from a given set of candidates, derives an optimal subset of facilities. For a survey on facility-location problems, refer to Verter (2011). To coordinate shipments in the problem studied in our paper, transfer points for coordination have to be selected, where, due to limited resources, only a subset can be in operation. In a survey on disaster relief routing, de la Torre, Dolinskaya, and Smilowitz (2012) note that few journal articles in this field exist, even though there is a high potential of optimization. Through interviews with representatives of relief organizations and the process of conducting an extensive literature review, the authors further conclude that the importance of multi-period stochastic models is that they enable practitioners to gain insights and to generate rules of thumb. The vehicle routing problem included in our DSS can be defined as an extension of the full truckload pickup and delivery problem. Gronalt, Hartl, and Reimann (2003) propose four savings based heuristics for the problem, which produce solutions of high quality within short computational times. In contrast to our optimization problem, no network disruption occurs and pickup and delivery locations are specified in advance. Location-routing problems consider vehicle routes when deciding on facility locations. A related DSS is introduced by Lopes, Barreto, Ferreira, and Santos (2008), which combines spatial information, optimization and a graphical user interface; however, the analysis under network disruptions is not enabled. For recent surveys on location-routing problems, refer to Prodhon and Prins (2014) and Drexl and Schneider (2015). Little work is found on stochastic problems and, to the best of our knowledge, no work combines network disruptions with a stochastic multi-modal location-routing problem. Combining simulation and optimization allows one to overcome uncertainties and complex interactions within optimization models (Glover, Kelly, & Laguna, 1996). One common way of implementation is that simulation models use inputs generated by optimization procedures to evaluate a solution. The simulated output acts in the following step as an input for the optimization procedure and this loop is repeated until a stopping criterion is met. In our work, an agent-based simulation generates various demand settings and facilitates routing and scheduling optimization procedures to evaluate and visualize different solutions. To select the set of transfer points, a metaheuristic is further included, which, itself, facilitates the agent-based simulation to evaluate solutions. For an extensive overview of various simulation optimization methodologies, refer to Fu (2014). A metaheuristic-driven framework to combine metaheuristics with stochastic optimization problems is further presented in Juan, Faulin, Grasman, Rabe, and Figueira (2015).

## 3. Problem description

As a disaster consequence, certain roads or bridges are not traversable without special equipment or permissions. Potential reasons are road inundations resulting from floods or road blockades as a result of earthquakes or mudslides. Furthermore, due to increased demand and emergencies, shipment requests occur during the planning horizon, associated with a supply point and a demand point. To deliver goods, either a detour on intact roads is driven or the shipment is coordinated with a relief organizations at one of the given transfer points, where, due to organizational factors, only a limited number of points can be operated. Which transfer points are selected is decided before the start of the planning horizon and cannot be altered later. In case of a coordination, goods are delivered from the supply point to a transfer point by the private organization. The relief organization ships the goods to a second receiving transfer point. From there, the final delivery to the demand point is performed by the private organization, which is assumed to have a private vehicle available for this final shipment.

Relief forces, in contrast, have a given set of vehicles, each starting at a home depot. These vehicles are classified into two different categories, off-road vehicles and UAVs. Off-road vehicles travel on a given street network, however, are not subject to road closures due to special permissions or equipment. UAVs are assumed to travel in a straight line. Each vehicle is further indicated by a traveling speed and the duration required for loading and unloading. Full truckloads are assumed, i.e. each vehicle transports at maximum one shipment at a time and split-deliveries are not allowed. Additionally, a direct delivery by relief forces to a demand point is not allowed, i.e. their vehicles only travel between transfer points. This is due to safety concerns for UAVs and the public and to guarantee supervised provision of medical supplies and other goods by ground handling operators located at the transfer points.

The objective is to minimize the average lead time, i.e. the average time it takes until shipments are delivered from when a certain request occurred. To minimize the lead times, a limited number of transfer points has to be selected and the coordination decision for each shipment has to be made. If coordination is chosen, where to transship and with which vehicle at what time has to be selected.

**Table 1**
Problem notation.

| Decision variables | Definition |
|---|---|
| $f_i$ | $i$ (transfer point); equals 1 if operated |
| $x_{ijlk}$ | $i,j$ (transfer points), l (request), k (vehicle); equals 1 if coordinated |
| $y_{lmk}$ | $l,m$ (request), k (vehicle); equals 1 if k performs m after l |
| $z_{lmk}$ | $l,m$ (request), k (vehicle); auxiliary variable for time from l to m on k |
| $u_l$ | $l$ (request); departure time of l at supply or transfer point |
| $e_l$ | $l$ (request); arrival time of l at demand point |
| Constants | Definition |
| $M$ | sufficiently large number (set to latest possible departure time) |
| $K$ | number of vehicles |
| $F$ | number of transfer point candidates |
| $R$ | number of shipment requests |
| $V$ | number of vehicle depots |
| $\mathcal{K}=\{1,\dots,K\}$ | set of vehicles |
| $\mathcal{F}=\{1,\dots,F\}$ | set of transfer points |
| $\mathcal{R}=\{1,\dots,R\}$ | set of shipment requests |
| $\mathcal{R}_0=\{0,\dots,R+1\}$ | set of shipment requests including start (0) and end depot (R+1) |
| $s_l$ | $l$ (request); start time of $l$ |
| $c_{ijk}$ | $i,j$ (location), $k$ (vehicle); duration from $i$ to $j$ on $k$ |
| $q_k$ | $k$ (vehicle); (un)loading time of $k$ for each request |
| $N$ | max. number of operated transfer points |
| $Z_k$ | $k$ (vehicle); home depot of $k$ |
| $P_l$ | $l$ (request); supply point of $l$ |
| $D_l$ | $l$ (request); demand point of $l$ |

### 3.1. Mixed-integer programming model

The problem is defined on a complete graph $G=(V,A)$ with arcs $(i,j)\in A$ and vertices $V=\{v_1,\dots,v_{F+P+D+Z}\}$ consisting of transfer points $\{v_1,\dots v_F\}$, supply points $\{v_{F+1},\dots v_{F+P}\}$, demand points $\{v_{F+P+1},\dots,v_{F+P+D}\}$ and depots $\{v_{F+P+D+1},\dots,v_{F+P+D+Z}\}$. Traversing durations on arcs with vehicle $k$ are specified by $c_{ijk}$, where $k=0$ indicates private vehicles. $R$ requests, indexed by $l$, have to be served, each starting from a supply and ending at a demand point, indexed in $P_l$ and $D_l$ respectively. The start time of a request is denoted by $s_l$, the end time by $e_l$. For coordination, $F$ transfer point candidates, indexed by $i$, are available where a maximum of $N$ can be open. Furthermore, $K$ vehicles, indexed by $k$, are given, each located at time 0 at a home depot $Z_k$. Loading duration are given by $q_k$. The binary decision variables $f_i$, $x_{ijlk}$ and $y_{lmk}$ indicate selected transfer points, coordination decisions and vehicle routes respectively. Therefore, $y_{0mk}$ and $y_{l(R+1)k}$ represent a vehicle starting from and returning to the depot. Departures times of requests are indicated by $u_l$ and the auxiliary variable $z_{lmk}$ is used to model empty vehicle movements between two requests. Table 1 summarizes the notation of the problem:

$$\text{minimize: } \frac{1}{R}\sum_{l\in\mathcal{R}}(e_l-s_l) \tag{1}$$

subject to:

$$e_l = u_l + c_{P_lD_l0}\Big(1-\sum_{i,j\in\mathcal{F}}\sum_{k\in\mathcal{K}}x_{ijlk}\Big) + \sum_{i,j\in\mathcal{F}}\sum_{k\in\mathcal{K}}(c_{jD_l0}+c_{ijk}+q_k)x_{ijlk} \qquad \forall l\in\mathcal{R} \tag{2}$$

$$u_l \ge s_l + \sum_{i,j\in\mathcal{F}}\sum_{k\in\mathcal{K}}(c_{P_li0}+q_k)x_{ijlk} \qquad \forall l\in\mathcal{R} \tag{3}$$

$$\sum_{i\in\mathcal{F}} f_i \le N \tag{4}$$

$$\sum_{j\in\mathcal{F}}\sum_{l\in\mathcal{R}}\sum_{k\in\mathcal{K}}(x_{ijlk}+x_{jilk})\le 2Rf_i \qquad \forall i\in\mathcal{F} \tag{5}$$

$$\sum_{i,j\in\mathcal{F}}\sum_{k\in\mathcal{K}}x_{ijlk}\le 1 \qquad \forall l\in\mathcal{R} \tag{6}$$

$$\sum_{m\in\mathcal{R}_0\setminus\{R+1\}} y_{mlk}=\sum_{i,j\in\mathcal{F}}x_{ijlk} \qquad \forall l\in\mathcal{R},k\in\mathcal{K} \tag{7}$$

$$u_l+\sum_{i,j\in\mathcal{F}}c_{ijk}x_{ijlk}+2q_k+z_{lmk} \le u_m+(1-y_{lmk})M \qquad \forall l,m\in\mathcal{R},k\in\mathcal{K} \tag{8}$$

$$\sum_{m\in\mathcal{R}_0}(y_{lmk}-y_{mlk})=0 \qquad \forall k\in\mathcal{K},l\in\mathcal{R} \tag{9}$$

$$z_{lmk}\le \max_{i,j\in\mathcal{F}}c_{ijk}y_{lmk} \qquad \forall l,m\in\mathcal{R},k\in\mathcal{K} \tag{10}$$

$$z_{lmk}\ge c_{jhk}y_{lmk}-c_{jhk}(2-\sum_{i\in\mathcal{F}}x_{ijlk}-\sum_{g\in\mathcal{F}}x_{hgmk}) \qquad \forall j,h\in\mathcal{F},k\in\mathcal{K} \quad \forall l,m\in\mathcal{R} \tag{11}$$

$$c_{Z_kP_lk}+y_k\le u_l+(1-y_{0lk})M \qquad \forall l\in\mathcal{R},k\in\mathcal{K} \tag{12}$$

$$\sum_{m\in\mathcal{R}_0\setminus\{0\}} y_{0mk}=1 \qquad \forall k\in\mathcal{K} \tag{13}$$

$$\sum_{l\in\mathcal{R}_0}y_{l0k}=0 \qquad \forall k\in\mathcal{K} \tag{14}$$

$$\sum_{l\in\mathcal{R}_0\setminus\{R+1\}} y_{l(R+1)k}=1 \qquad \forall k\in\mathcal{K} \tag{15}$$

$$\sum_{m\in\mathcal{R}_0}y_{(R+1)mk}=0 \qquad \forall k\in\mathcal{K} \tag{16}$$

$$x_{ijl}\in\{0,1\} \qquad \forall i,j\in\mathcal{F},l\in\mathcal{R} \tag{17}$$

$$s_i\in\{0,1\} \qquad \forall i\in\mathcal{F} \tag{18}$$

$$y_{lmk}\in\{0,1\} \qquad \forall l,m\in\mathcal{R},k\in\mathcal{K} \tag{19}$$

Eq. (1) minimizes the average lead time over all requests. The end times of requests are calculated in (2) resulting from a direct delivery or from coordination. Therefore, the departure time of a request is bounded by (3). In case of coordination, it denotes when the request leaves the first transfer point, after loading operations are performed. Constraint (4) sets the maximum number of operated transfer points, (5) state that coordination is only possible at operated transfer points and (6) limit the number of coordinations per request to one. Connectivity of requests is achieved by (7-8), which guarantee that requests are scheduled to the correct vehicles and at feasible times, while (9) enforce that each visited request is left again. Therefore, (10–11) enforce that the time required to travel from the end transfer point of a request to the start transfer point of another request is observed. (12) set the time delays to leave the depot and (13–16) depot departures and arrivals of vehicles.

### 3.2. Preprocessing, bounding and problem reduction

While selecting transfer points close to the supply point to ship goods near to the demand point is promising, performing the shipment in the opposite direction is not. As a consequence, the direct delivery from supply to demand point sets the maximum lead time of each request. This enables one to eliminate $x_{ijlk}$ (20) if a coordination results in a greater or equal lead time

$$x_{ijlk}=0 \text{ if } c_{P_li0}+c_{ijk}+2q_k+c_{jD_l0}>=c_{P_lD_l0}\ \forall i, j\in\mathcal{F},k\in\mathcal{K},l\in\mathcal{R} \tag{20}$$

Similarly, $u_l$ can be bounded (21) to the latest possible departure time where coordination is beneficial. This value is calculated by determining the shortest possible coordination duration over all vehicles:

$$u_l\le s_l+\max(0,c_{P_lD_l0}-\min_{\substack{k\in\mathcal{K}\\ i,j\in\mathcal{F}|x_{ijmk}\neq 0}}(c_{ijk}+q_k+c_{jD_l0}))\quad \forall l\in\mathcal{R} \tag{21}$$

Additionally, routing variables can be eliminated based on start and latest completion times of requests. A request $m$ cannot be performed after a request $l$ if the latest departure time of $m$ is smaller than the earliest completion time of $l$ (22):

$$y_{lmk}=0 \text{ if } s_m+c_{P_mD_m0}-\min_{ij\in\mathcal{F}|x_{ijmk}\neq 0}(c_{ijk}+c_{jD_m0}) < s_l+\min_{ij\in\mathcal{F}|x_{ijlk}\neq 0}(c_{P_li0}+c_{ijk})+3q_k\ \forall l,m\in\mathcal{R},k\in\mathcal{K} \tag{22}$$

By preprocessing the problem, setting an upper bound for $u_l$ and reducing the number of decision variables, memory requirements and execution times are improved.

## 4. Decision-support system

Expanding on the static problem formulation, a DSS was developed to handle large-scale dynamic instances of the problem. An overview of the DSS is shown in Fig. 2.

In close cooperation with relief organizations, private partners as well as other relevant external sources (e.g., meteorology, legal consultancy), the user defines a study scenario to evaluate various coordinated disaster relief settings. Therefore, the data structure was developed considering the disaster management data model presented in Othman and Beydoun (2013) and the Multilateral Interoperability Programme Baseline 3.1 (MIP, 2016), which is a multinational program to support joint operations. Input to the DSS is data specifying demand and supply points as well as potential transfer points, each indicated by $x$- and $y$-coordinates. Arrival times of shipment requests are either based on a defined probability distribution or, alternatively, the DSS can load requests from a user-specified file. Furthermore, available vehicles with their home depots and network data are specified. The user can either start a single agent-based simulation run or an optimization experiment. Solution procedures are called to optimize routing and scheduling decisions as well as to derive the optimal set of transfer points. For evaluation in optimization experiments, the simulation is run multiple times in parallel to evaluate different promising settings of transfer points. After completion, the best found solution is saved in the scenario parameters for subsequent runs and statistics are reported. Additionally, single runs are animated in detail for the user, who, based on generated insights, can alter data and parameters for subsequent runs to investigate the impact of various decisions. Outcomes are then reported back to the various partners, who decide together which coordination setting, i.e. transfer points to operate and the fleet configuration, should be implemented.

Additionally, the following assumptions are used within the DSS:

- If a demand point cannot be reached due to road closures, all requests are instead delivered to the closest accessible demand point as demand is expected to shift there. This is required to compare multiple simulation settings. Nevertheless, the DSS always prefers solutions with more demand points operating.
- Travel speed of private trucks is based on the speed limit of each road segment corrected by a road condition factor with a maximum speed of 100 km/h. Relief vehicles travel with an average speed independent of the road type. UAVs move in a straight line, however, specifying routing graphs for relief vehicles is possible in the DSS.

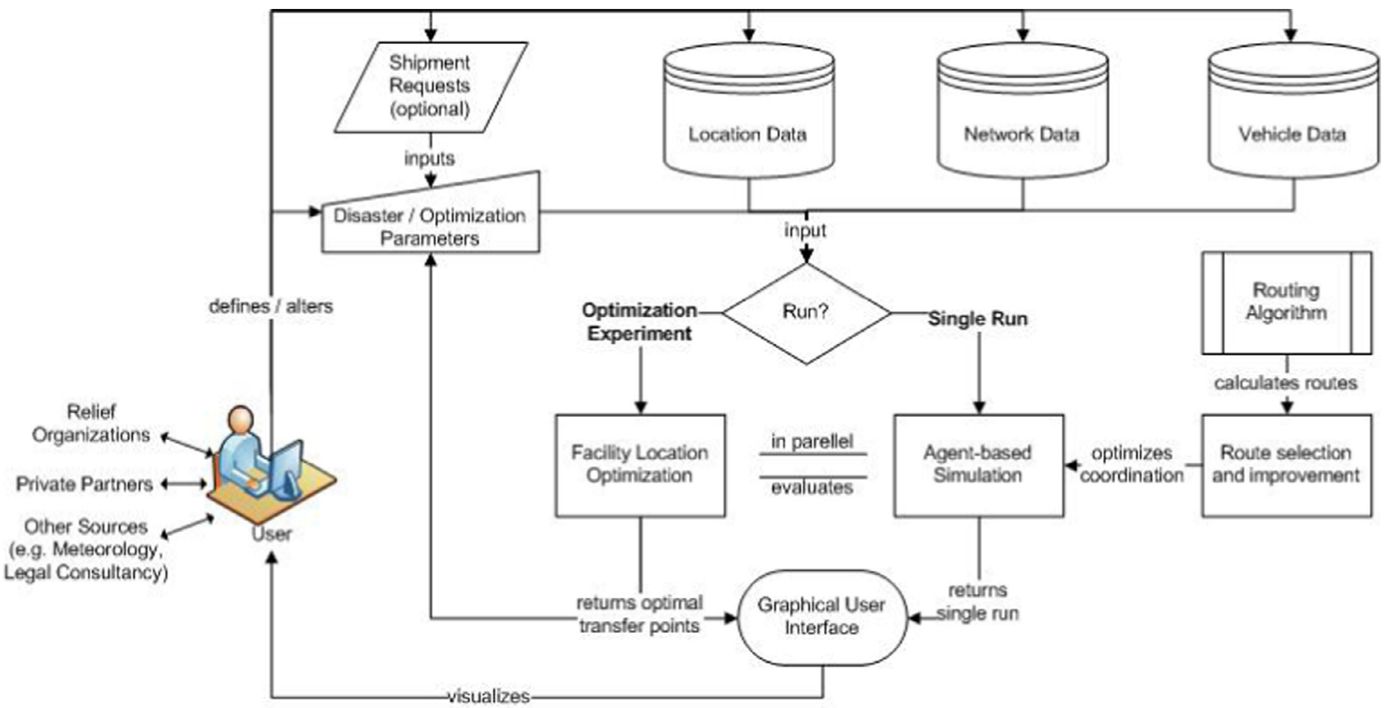



**Fig. 2.** A DSS for coordinated disaster relief distribution.

- In case of an event leading to an unavailability of a vehicle, the vehicle finishes its current trip and is set unavailable at the next location. For instance, in the case of a change in weather affecting air transportation, the UAV moves to its next location and is set unavailable there until weather improves.
- Relief vehicles return to the depot if no further requests are scheduled. As relief vehicles might be required for additional relief tasks, having them at the depot improves flexibility to react to sudden relief needs.

Key parts of the DSS are discussed in detail in the following subsections.

### 4.1. Agent-based Simulation

Four agent classes, which interact with each other via the generation of various events, are modeled in geographic space within the simulation, namely locations, requests, vehicles and closed roads. Locations further differ in depots, supply, demand and transfer points. Based on a specified probability function, supply points generate requests at random times from random supply points. Such requests specify a shipment from a supply to a demand point, potentially, if coordinated, via two transfer points. Whenever a request is generated, it is routed. If coordinated, the transfer points are specified, the request is scheduled to a vehicle of the relief forces and the private partner starts moving to the first transfer point. Otherwise, the request moves to the demand point on the shortest detour without transshipment. The vehicle agents differ between air and off-road vehicles and handle loading, unloading and routing operations. Therefore, each agent is specified with a loading and unloading duration as well as an average speed. Fig. 3 shows the modeled vehicle behavior.

At the start of the planning horizon, the agent is idle at the depot and starts moving as soon as the first request is scheduled. If the vehicle arrives before the shipment at a transfer point, it waits for the arrival of a shipment, which is indicated by an event generated by the request agent at arrival. Additionally, if resulting in a lower objective value, during the waiting period as well as while a vehicle is moving, requests can further call events to enforce a rerouting of the vehicle to different transfer points or to pick up different shipments. If both the shipment and vehicle are present, the shipment gets loaded to the vehicle, which is modeled by a time delay. In the next step, the vehicle moves to the delivery transfer point and, after unloading, the agent continues with the next scheduled shipment. If no further shipments are scheduled to the vehicle, the agent returns to the depot and is set idle at arrival. Additionally, due to various events such as a change in air weather, vehicles can further be set inactive, causing no shipment requests to be transported by the vehicle until it is activated again. During the simulation run, all vehicle and request movements are simulated on the given street network to enable rerouting from the current agent position. Furthermore, events to alter the routing graph at predefined start and end times are executed by the closed road agents. At such an event, road segments are either opened or closed for private traffic and requests are rerouted if affected.

Additional events may occur, due to either predefined probability distributions or user interactions, namely the sudden unavailability of a street segment, vehicles, stores or transfer points. In such cases, all requests are sequentially re-evaluated if transshipments should be performed or canceled considering the new setting.

### 4.2. Route selection and improvement

Shortest paths on the street network are solved by a bidirectional implementation of the A$*$ algorithm (Hart, Nilsson, & Raphael, 1968). If a road segment is currently closed, the costs of the associated arcs are set to $\infty$. As a consequence, the routing algorithm looks for the best alternative path. Fig. 4 gives a simplified example. At the start of the planning horizon a direct delivery on the shortest path is not possible as a road segment is closed. A detour on intact roads is routed as it leads to a lower lead time than coordinating the request. Later in the planning horizon, all connections are restricted. As a consequence, the shipment is coordinated. Goods are delivered to $F_1$, where relief forces take the

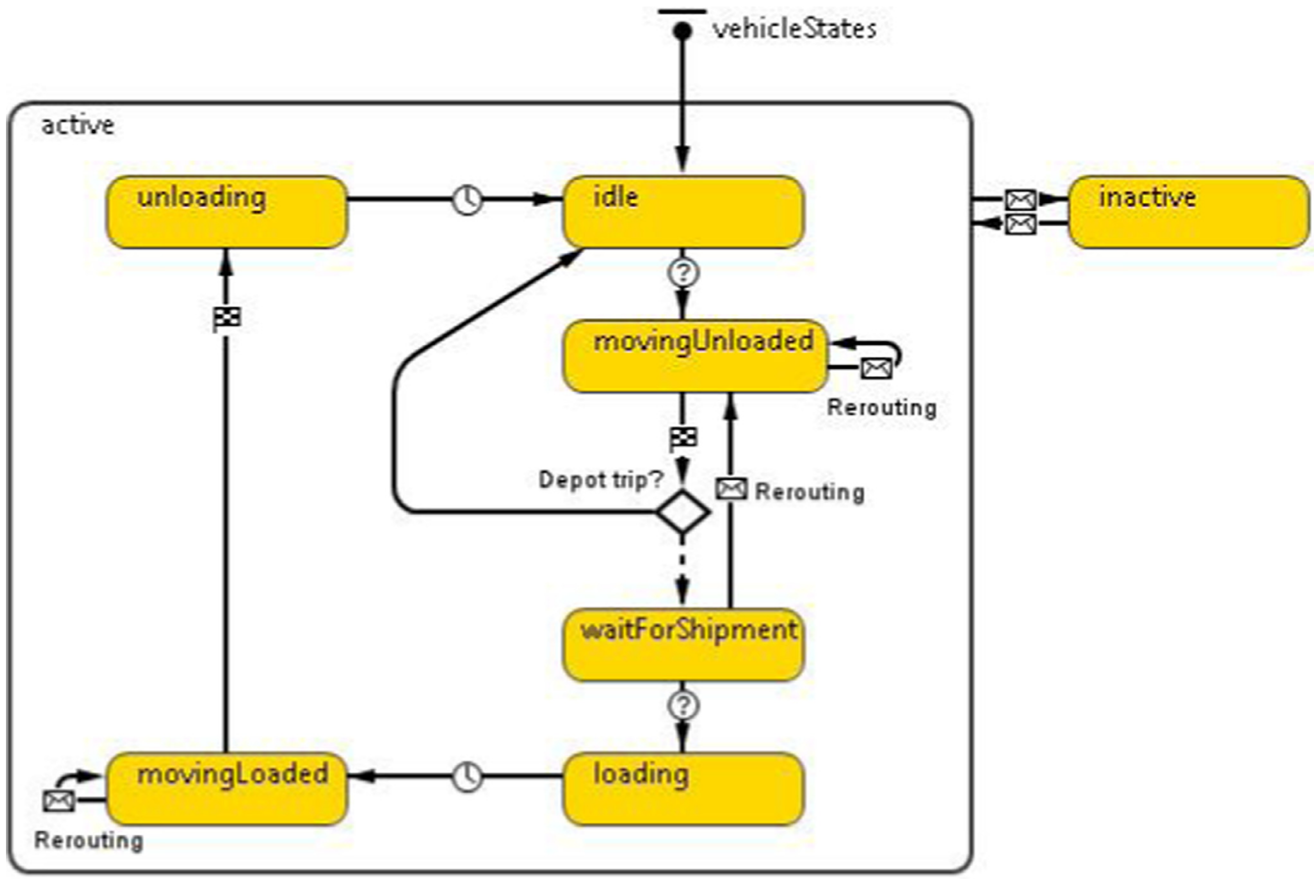
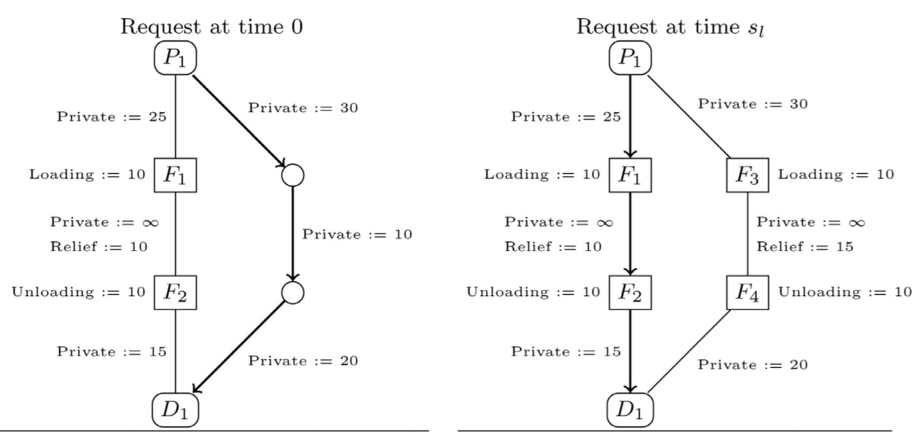



**Fig. 3.** Vehicle start-chart.




| Route | Lead Time |
|---|---|
| Private $P_1 \rightarrow D_1$ | 60 min |
| Coordinated $P_1 \rightarrow F_1 \rightarrow F_2 \rightarrow D_1$ | 70 min |

| Route | Lead Time |
|---|---|
| Private $P_1 \rightarrow D_1$ | $\infty$ |
| Coordinated $P_1 \rightarrow T_1 \rightarrow T_2 \rightarrow D_1$ | 70 min |
| Coordinated $P_1 \rightarrow T_3 \rightarrow T_4 \rightarrow D_1$ | 85 min |

**Fig. 4.** Simplified example with loading delays of 10 minutes.

shipment and deliver it to $F_2$. From there, the final delivery to $D_1$ is performed.

Each request is initialized with the lead time of a direct delivery without coordination. Selecting the combination of transfer points which results in the shortest total travel duration is not guaranteed to be the best option due to limited availability of public vehicles and resulting wait times. As a consequence, transfer combinations are evaluated separately for each vehicle. Therefore, inserting the request on each position of the vehicles' schedules is tested and the best combination is saved. To limit the amount of potential evaluations, combinations where the shortest path without waiting is worse than the current best found evaluation value are skipped.

In case of a coordination, the request is inserted at the best found position. Due to the additional request, adjusting the transfer points of other requests on the same vehicle may be beneficial to decrease travel times between requests. Consequently, all requests on the vehicle are sequentially evaluated if changing the final transfer point decreases the lead time. Furthermore, an intra-route swap and an inter-route relocate operator are run. The former tests if swapping the positions of two requests on a single vehicle leads to an improvement, while the latter evaluates moving a request to another vehicle. Additionally, canceling coordination of earlier scheduled requests might be beneficial if capacities are needed for more critical recent requests. If beneficial, the canceled requests instead are delivered directly on the shortest detour. All moves are evaluated and, in case of an improvement, the best one is executed and the optimization procedure is rerun with all altered vehicles. Algorithm 1 summarizes this procedure.

**Algorithm 1:** Routing improvement procedure.

```
improve = true;
currentObjective = evaluateLeadTimes();
vehiclesToCheck.add(requestVehicle);
while improve == true do
    improve = false;
    for Vehicle veh : vehiclesToCheck do
        changeTransferPoint(veh);
        performIntraRouteSwap(veh);
    performInterRouteRelocate(vehiclesToCheck);
    performDropOperator(vehiclesToCheck);
    newObjective = evaluateLeadTimes();
    if newObjective != currentObjective then
        improve = true;
        currentObjective = newObjective;
```

### 4.3. Optimization of facility locations

Operating the optimal set of transfer points is not trivial as location and routing decisions have to be combined in an uncertain setting. To construct an initial solution, the problem is run with all transfer points being active and how often a transfer point is chosen for coordination is recorded. Based on these records, the most popular transfer points are selected as an initial solution. This solution is improved by a Tabu Search metaheuristic (Glover, 1989; 1990). Tabu Search shows good results for various combinatorial optimization problems and have been implemented for multiple facility location problems (e.g. Rolland, Schilling, & Current, 1997; Ghosh, 2003; Salman & Yücel, 2015). In our implementation, the neighborhood consists of all moves which swap an open transfer point with a closed one. To evaluate a solution, the agent-based simulation is run multiple times and average results are returned. While running more replications reduces the impact of stochastic effects, each run increases the computational time. The best swap is set tabu for $\tau$ iterations, i.e. swapping these two elements is not allowed to prevent the algorithm from cycling. Nevertheless, if performing this move leads to an improvement of the best found solution so far, the move is enabled. To diversify, a frequency based memory penalizes frequently added transfer points by evaluating a solution $S$ with $g(S) = f(S)(1 + \zeta k_i)$, where $f(S)$ denotes the objective function, $\zeta$ a penalty factor and $k_i$ how often a transfer point has been previously added. The algorithm stops after a specified time limit or after a maximum number of iterations and returns the best found set of transfer points.

### 4.4. User interface

Fig. 5 shows the implemented DSS. The user specifies vehicles and scenarios and defines a planning horizon as well as the number of shipments. When the simulation is started, the DSS switches to the animation screen where routes of vehicles and their movements are plotted. During a single run, user interactions can modify the problem setting, e.g. by closing certain transfer points or deactivating vehicles. Statistics are given at the end of the run indicating the distribution of lead times as well as vehicle and transfer point utilization. Additionally, the user can choose to optimize the subset of transfer points or to analyze the optimal number of transfer points to operate, the impact of enabling coordination as well as of the route optimization procedure. These procedures are based on the user-selected optimization parameters.

## 5. Results and discussion

The DSS was implemented with AnyLogic 7.1 (AnyLogic, 2015) and all test runs were run on an Intel Core i7-4930K, 64GB RAM, with MS-Windows 7 and six threads operating in parallel. The optimization procedures were coded in Java and Xpress 7.8 (FICO, 2015) was used to solve the MIP. Network data is taken from OpenStreetMap (OpenStreetMap, 2015) and routes are calculated by custom routing graphs based on GraphHopper 0.3 release (GraphHopper, 2015). Visualization is done with the implemented features of AnyLogic 7.1, using Mapquest tiles (Mapquest, 2015) to present geographic information. Additionally, ArcMap 10.2 was used (ESRI, 2015) to identify affected road segments of the investigated disaster scenarios by intersecting flood shapefiles with street networks.

### 5.1. Test settings

To test the DSS, two regions located at the River Danube in Austria were investigated, Krems an der Donau and Tulln an der Donau, which both have been struck by major river floods in the past. One day of operations is investigated with shipment requests occurring between 8 am and 4 pm. Transfer points are located at large parking lots, sport fields as well as military and industrial areas. Demand points are stores as well as pharmacies and supply points have been placed at major road exits entering the region. For the computational experiments, arrival times are uniformly distributed and each demand point requests a specified number of shipments from uniformly randomly selected supply points. One UAV is placed at each hospital and military area in the region and one off-road vehicle at each firefighter station. Off-road vehicles travel with an average speed of 45 km/h and need 3 minutes for loading and unloading operations, UAVs with 135 km/h requiring 6 minutes for these tasks. Fig. 6 plots the problem settings on a regular day without road closures.

For Krems, the 30-year and 100-year flooding scenarios acquired from the The Office of the Provincial Government of Lower Austria (Amt der NÖ Landesregierung, 2015) are modelled, denoted as *K-HQ30* and *K-HQ100* respectively. Therefore, roads and bridges are closed if they intersect with the projected flooded area. Additionally, the 7th of June, 2013 is modelled with street closures as announced by APA-OTS (2013). As an extreme scenario, the situation where all bridges entering the city are closed, for both Krems and Tulln is analyzed, denoted as *K-noBridge* and *T-noBridge*. Table 2 summarizes the instance characteristics and states the average lead time over all requests if no coordination is performed. This acts as an upper bound for the optimization problem and is calculated by averaging the time required to reach the demand points from each supply point via open roads. Additionally, *K-Regular* and *T-Regular* show the average lead times if no roads are closed. This acts as a lower bound for the instances, assuming that no relief vehicles are utilized in such a setting. All instance data is available at http://www.wiso.boku.ac.at/en/production-and-logistics/research/instances/.

To facilitate comparison, sudden road closures and unavailabilities of stores, vehicles and transfer points are deactivated during the experiments; however, the arrival of shipment requests

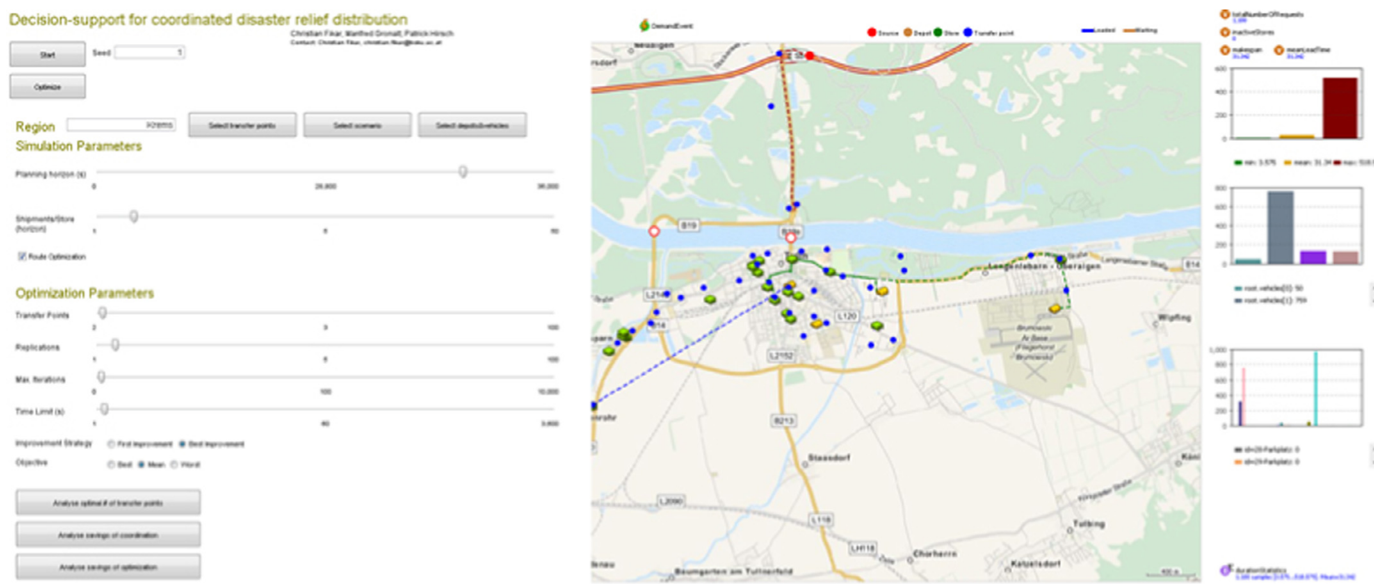



**Fig. 5.** Decision support for disaster relief distribution: user menu (left), animation (right).

**Table 2**
Instance characteristics of the test regions.

| Instance | Transfer Points | Demand Points | Supply Points | Depots | UAVs | Off-road | Avg. lead time w/o coordination |
|---|---|---|---|---|---|---|---|
| K-Regular | – | 29 | 2 | 5 | – | – | 10.2896 min |
| K-HQ30 | 80 | 29 | 2 | 5 | 3 | 2 | 17.3438 min |
| K-HQ100 | 80 | 29 | 2 | 5 | 3 | 2 | 17.4697 min |
| K-070613 | 80 | 29 | 2 | 5 | 3 | 2 | 17.3056 min |
| K-noBridge | 80 | 29 | 2 | 5 | 3 | 2 | 28.0049 min |
| T-Regular | – | 22 | 1 | 4 | – | – | 5.9331 min |
| T-noBridge | 36 | 22 | 1 | 4 | 2 | 2 | 48.7298 min |

is subject to randomness. Road closures are considered to be in effect for the entire simulation horizon.

### 5.2. Parameter setting

Within the Tabu search, six replications are run to construct an initial solution. After each iteration, $\tau$ is uniformly randomly selected in $[0, \lceil\sqrt{F}\rceil]$ and $\zeta$ in [0, 0.1]. To decrease the time required to solve the problem, solutions are evaluated in parallel and the evaluation of a solution is aborted if after a minimum of six replications, the mean, with a confidence level of 95%, is worse than the mean of the best found solution so far in this iteration.

### 5.3. Computational experiments

In the first step, the DSS is benchmarked on small static problem instances with the MIP formulation to validate the applicability of the solution procedure for large dynamic problem settings. Therefore, the MIP was run for each test instance with five sets of random arrival times of requests drawn from a uniform distribution and three transfer points to operate. Requests result from each combination of supply and demand points, i.e. 58 requests occur in Krems and 22 in Tulln. The maximum run time is ten hours and the gap to the lower bound is stated if not completed. Two different settings of the DSS are analyzed. In *DSSST*, all requests with their start times are known at time 0. In contrast, *DSSDY* receives the requests when they start, substantially limiting the information available to schedule and route vehicles. The DSS is run for one minute per run. Table 3 compares the performance of the different solution procedures. As the DSS simulates each movement of vehicles in real-time, precision varies slightly compared to the MIP.

The MIP finds an optimal solution in 19 out of the 25 instances within approximately 20 minutes. In *K-noBridge*, the MIP struggles due to the limited options to preprocess as detours are costly. This results in a high number of decision variables and weak lower bounds. Comparing the DSS to the optimal solutions, gaps vary from 0.01 to 0.49 % for the static version, which is able to find better solutions in all instances compared to the dynamic version. As all requests are known at the start, vehicles can be prepositioned to react to sudden requests leading to better coordination. This reaction time as well as lacking information about future requests leads to weaker results of the dynamic version. Nevertheless, gaps are within 0.02–3.59% from the optimal solutions, indicating its quality for dynamic settings. For the following experiments, the DSS is run in a dynamic setting.

### 5.4. Impact of coordination

The left side of Fig. 7 plots the impact of coordination for *K-070613* with 100 replications and three transfer points in operation. Therefore, the number of shipment requests per store is varied. Compared to a situation without disruption, where all roads are open and no coordination is performed, the flood has a major impact on the average lead time of requests. Nevertheless, compared to a situation without coordination, the lead time is substantially lower, especially if only a small number of shipment requests per store occur. If demand increases, the benefits of coordination diminish as vehicles are highly utilized and cannot serve all requests

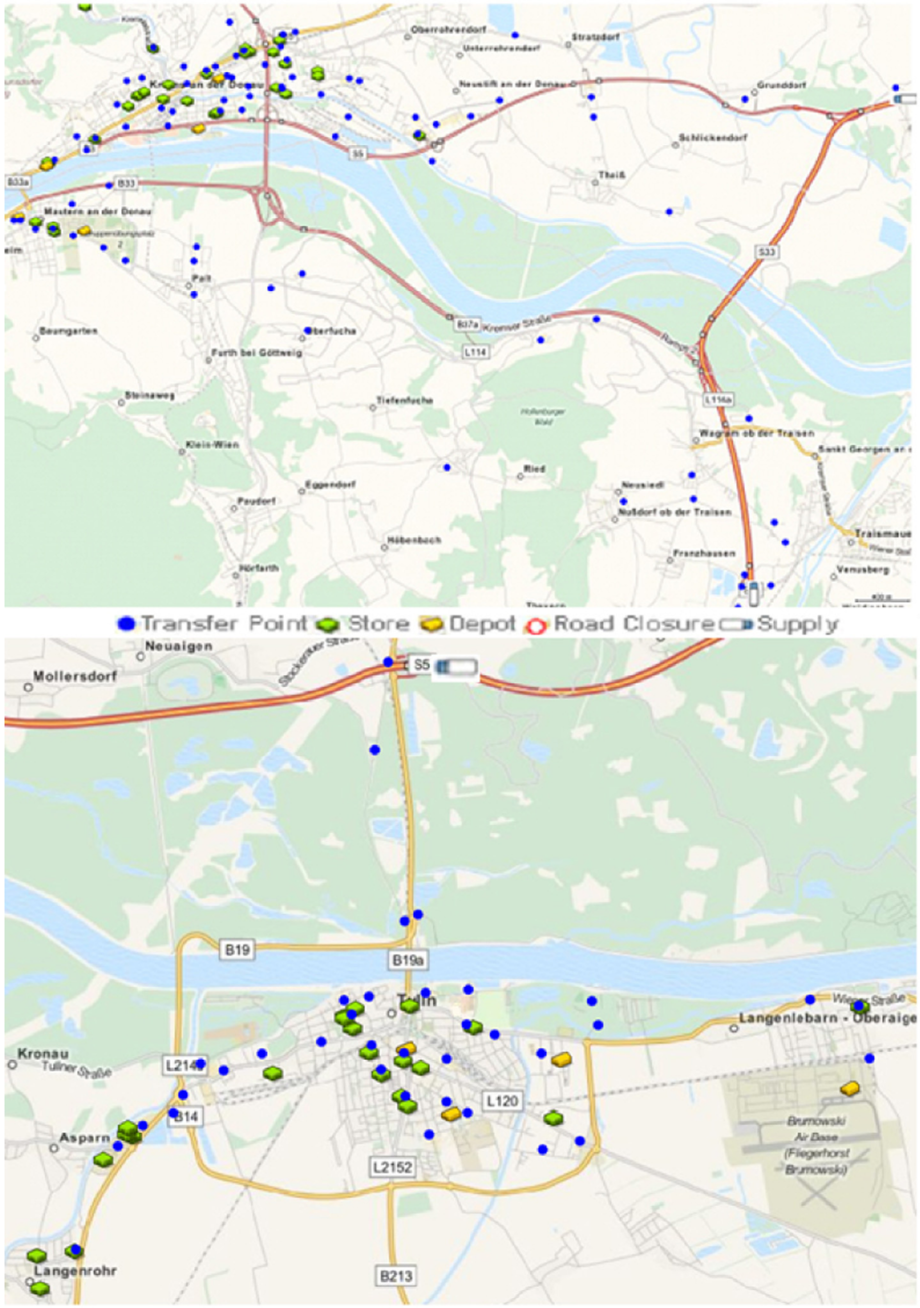



**Fig. 6.** Test regions: Krems (top), and Tulln (bottom).

without major wait times. In such a setting, adding additional relief vehicles is required.

The right side of Fig. 7 analyzes the impact of the number of operated transfer points with five shipment requests per store. Therefore, the maximum time per run is set to 30 minutes and solutions are evaluated based on 100 replication runs. Adding an additional transfer point leads to high gains if only few are open. Interestingly, out of the 80 candidates, only 13 transfer points help to decrease the average lead time. Consequently, one of the main strengths of the DSS is to efficiently eliminate inefficient candidate locations to allow decision-makers to focus on the most relevant ones.

As shown in Fig. 8, the potential of coordination is substantially higher in Tulln. Starting with six shipment requests per store, the average lead time increases substantially as major wait times occur and the available fleet cannot efficiently serve all requests. At approximately 15 shipments per store, multiple shipments are transported via a time-intensive detour and the average lead time converges to the situation without coordination. Considering the optimal number of transfer points in Tulln, after 14 transfer points only little improvements are achieved. Minor increases in the objective value are due to the stochastic components of the algorithm.

### 5.5. Impact of the fleet configuration

In Table 4, the number of UAVs and off-road vehicles is altered to investigate the impact of the fleet configuration. Therefore, 100 replications are run with five shipment requests per store and all transfer points are open. Vehicles were added or removed from a randomly selected depot. Off-road vehicles are more beneficial in

**Table 3**
Computational benchmarks.

| Instance | MIP (1) | Gap LB | sec | DSSST (2) | Gap (2–1) | DSSDY (3) | Gap (3–1) |
|---|---|---|---|---|---|---|---|
| K1-HQ30 | 15.2473 | – | 1220 | 15.2518 | 0.03% | 15.6459 | 2.61% |
| K2-HQ30 | 15.1860 | – | 777 | 15.1901 | 0.03% | 15.6459 | 3.03% |
| K3-HQ30 | 15.1456 | – | 812 | 15.1901 | 0.29% | 15.6940 | 3.62% |
| K4-HQ30 | 15.1869 | – | 934 | 15.2291 | 0.28% | 15.6459 | 3.02% |
| K5-HQ30 | 15.1913 | – | 1025 | 15.1956 | 0.03% | 15.6511 | 3.03% |
| K1-HQ100 | 15.3732 | – | 3765 | 15.3777 | 0.03% | 15.7718 | 2.59% |
| K2-HQ100 | 15.3119 | – | 699 | 15.3160 | 0.03% | 15.7718 | 3.00% |
| K3-HQ100 | 15.2714 | – | 583 | 15.3160 | 0.29% | 15.8198 | 3.59% |
| K4-HQ100 | 15.3127 | – | 837 | 15.3550 | 0.28% | 15.7718 | 3.00% |
| K5-HQ100 | 15.3172 | – | 701 | 15.3215 | 0.03% | 15.7769 | 3.00% |
| K1-070613 | 14.8725 | – | 234 | 14.8758 | 0.02% | 14.8758 | 0.02% |
| K2-070613 | 14.8700 | – | 200 | 14.8722 | 0.01% | 14.8758 | 0.04% |
| K3-070613 | 14.8584 | – | 198 | 14.8605 | 0.01% | 14.8758 | 0.12% |
| K4-070613 | 14.8584 | – | 222 | 14.8605 | 0.01% | 14.8758 | 0.12% |
| K5-070613 | 14.8700 | – | 229 | 14.8722 | 0.01% | 14.8758 | 0.04% |
| K1-noBridge | 20.7453 | 39.26% | 36000 | 15.5190 | −25.19% | 16.2479 | −21.68% |
| K2-noBridge | 16.8768 | 13.60% | 36000 | 15.4958 | −8.18% | 16.1717 | −4.18% |
| K3-noBridge | 16.4493 | 10.61% | 36000 | 15.3651 | −6.59% | 16.1670 | −1.72% |
| K4-noBridge | 17.6074 | 18.23% | 36000 | 15.4397 | −12.31% | 16.2249 | −7.85% |
| K5-noBridge | 26.1944 | 76.00% | 36000 | 15.5971 | −40.46% | 16.1782 | −38.24% |
| T1-noBridge | 13.1081 | – | 236 | 13.1155 | 0.06% | 13.5534 | 3.40% |
| T2-noBridge | 13.2215 | – | 551 | 13.2858 | 0.49% | 13.4672 | 1.86% |
| T3-noBridge | 13.1392 | – | 209 | 13.1446 | 0.04% | 13.4082 | 2.05% |
| T4-noBridge | 13.3428 | – | 257 | 13.3469 | 0.03% | 13.6806 | 2.53% |
| T5-noBridge | 13.3781 | – | 329 | 13.4144 | 0.27% | 13.5328 | 1.16% |

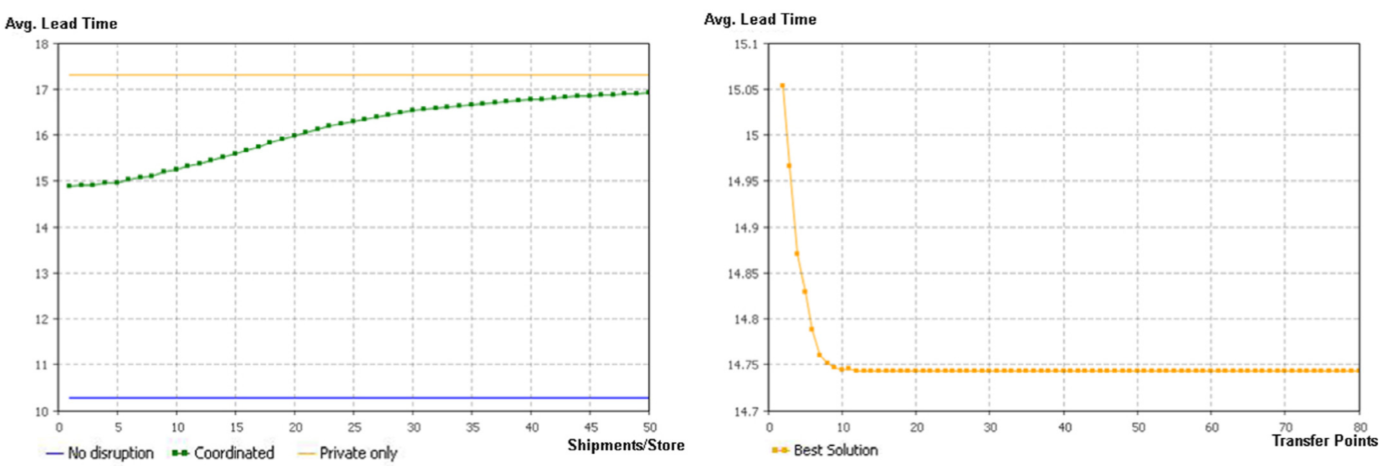



**Fig. 7.** Impact of coordination (left) and the number of operated transfer points (right) for *K-070613*.

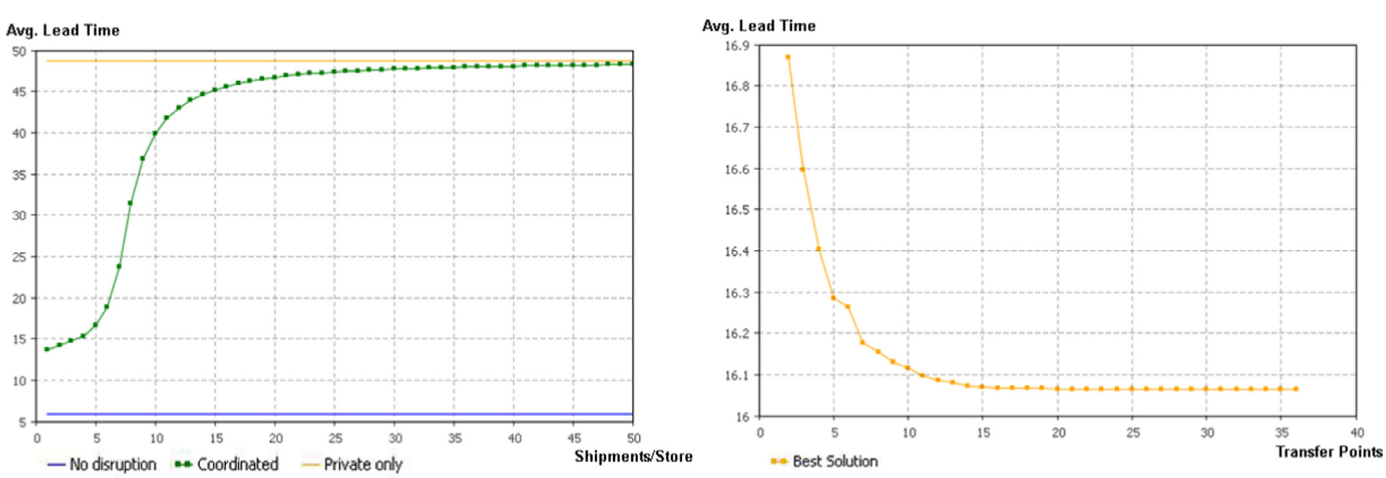



**Fig. 8.** Impact of coordination (left) and the number of operated transfer points (right) for *T-noBridges*.

**Table 4**
Marginal costs in minutes of adjusting the vehicle fleet.

| | | UAV | | | Off-road | | |
|---|---|---|---|---|---|---|---|
| Instance | Regular | Only | +1 | −1 | Only | +1 | −1 |
| K-HQ30 | 15.3686 | 2.4623 | −0.0375 | 0.0957 | −0.3054 | −0.0256 | 0.0760 |
| K-HQ100 | 15.5144 | 2.4531 | −0.0528 | 0.1290 | −0.1957 | −0.0168 | 0.0766 |
| K-070613 | 14.7429 | 2.1134 | 0.0030 | 0.0116 | −0.5777 | −0.0215 | 0.1012 |
| K-noBridge | 15.4000 | 2.4505 | −0.2105 | 0.5309 | −0.6680 | −0.0810 | 0.2841 |
| T-noBridge | 16.1252 | 7.6030 | −1.0885 | 3.5222 | −2.9855 | −1.6697 | 8.6068 |

**Table 5**
Analysis of controllable and noise factors for *K-070613*.

| | Controllable factors | | Noise: # Shipments | | | Responses | |
|---|---|---|---|---|---|---|---|
| Run | # Vehicles | # Transfer P. | 5 Shipm. | 10 Shipm. | 15 Shipm. | Mean | $SN_S$ |
| 1 | Regular | 2 Points | 15.0535 | 15.3458 | 15.6556 | 15.3516 | −2.3724 |
| 2 | Regular | 6 Points | 14.7884 | 14.9890 | 15.2712 | 15.0162 | −2.3532 |
| 3 | Regular | 10 Points | 14.7438 | 14.8734 | 15.1543 | 14.9238 | −2.3478 |
| 4 | Double | 2 Points | 14.9482 | 14.9545 | 15.0353 | 14.9793 | −2.3510 |
| 5 | Double | 6 Points | 14.6936 | 14.7032 | 14.7747 | 14.7238 | −2.3360 |
| 6 | Double | 10 Points | 14.6929 | 14.6906 | 14.7231 | 14.7022 | −2.3348 |
| 7 | Triple | 2 Points | 14.9949 | 14.9798 | 14.9999 | 14.9915 | −2.3517 |
| 8 | Triple | 6 Points | 14.7292 | 14.7172 | 14.7414 | 14.7293 | −2.3364 |
| 9 | Triple | 10 Points | 14.7292 | 14.7168 | 14.7359 | 14.7273 | −2.3362 |

$SN_S$... signal-to-noise ratio (smaller-the-better) $= -\log_{10}(\frac{1}{n}\sum y_i^2)$

**Table 6**
Analysis of controllable and noise factors for *T-noBridge*.

| | Controllable factors | | Noise: # Shipments | | | Responses | |
|---|---|---|---|---|---|---|---|
| Run | # Vehicles | # Transfer P. | 5 Shipm. | 10 Shipm. | 15 Shipm. | Mean | $SN_S$ |
| 1 | Regular | 2 Points | 16.8726 | 38.8346 | 44.9807 | 33.5626 | −3.1045 |
| 2 | Regular | 6 Points | 16.2636 | 38.8071 | 44.9395 | 33.3367 | −3.1015 |
| 3 | Regular | 10 Points | 16.1157 | 38.8071 | 44.9381 | 33.2870 | −3.1010 |
| 4 | Double | 2 Points | 14.0658 | 15.9246 | 22.8058 | 17.5988 | −2.5103 |
| 5 | Double | 6 Points | 13.5706 | 15.1495 | 22.6918 | 17.1373 | −2.4907 |
| 6 | Double | 10 Points | 13.4929 | 14.9300 | 22.5047 | 16.9758 | −2.4826 |
| 7 | Triple | 2 Points | 13.5320 | 14.2785 | 15.7954 | 14.5353 | −2.3267 |
| 8 | Triple | 6 Points | 13.0658 | 13.7554 | 14.7420 | 13.8544 | −2.2842 |
| 9 | Triple | 10 Points | 13.0423 | 13.6281 | 14.6283 | 13.7663 | −2.2786 |

$SN_S$... signal-to-noise ratio (smaller-the-better) $= -\log_{10}(\frac{1}{n}\sum y_i^2)$

both Krems and Tulln due to the short distances which have to be bridged and shorter loading and unloading durations compared to UAVs. Furthermore, as previously indicated in Fig. 8, removing vehicles results in a substantial increase in lead times in Tulln. For *K-070613*, adding an additional UAV does not improve the lead time at all.

### 5.6. Interdependencies

To analyze critical factors for coordinated disaster relief operations and interdependencies between these factors, the DSS is further investigated based on the ideas presented in Taguchi method (Phadke, 1995; Taguchi & Yokoyama, 1993). Therefore, two controlling factors, the number of operated transfer points and the size of the fleet, and one noise factor, the number of shipment requests, is considered with each factor represented by three different levels and 100 replications each. These levels were set based on the results of the computational experiments on the impact of coordination. Other outer noise factors, such as the test region as well as the specific characteristics of the disaster are not included as these are highly difficult to quantify as each disaster and region differs substantially. Nevertheless, the experiments are run on the two real-world settings presented in this paper with Table 5 showing the results for *K-070613* and Table 6 for *T-noBridge*.

As expected, the system performs best if a high number of transfer points and vehicles are operated and little demand occurs. In the *K-070613* setting, adding additional vehicles does not substantially contribute to improve disaster relief as the given number of vehicles is sufficient. Furthermore, increasing the number of vehicles even leads to slightly worse average lead times with ten shipments per store compared to five. This occurs as vehicles return to depots if idle, resulting in longer reaction times to reach the disaster area if underutilized in a dynamic setting. Nevertheless, if demand is skyrocketing and the system is overutilized, as particularly shown by the *T-noBridge* results with regular vehicle fleet size, decision-makers should primarily focus on adding additional vehicles in order to handle the increase in demand. If the fleet size is sufficient, however, operating additional transfer points can contribute to decrease the average lead time. Such trade-offs as well as resulting costs have to be closely investigated to derive policies for coordinated disaster relief operations.

### 5.7. Limitations

The computational experiments aim to explore potential benefits and cases of use for the DSS to investigate different disaster settings. For last-mile disaster relief distribution, where distances are short, results indicate that off-road vehicles are more beneficial compared to UAVs. Nevertheless, these results depend on the selected test regions and further on the specified loading delays and traveling speeds of the vehicles. Additionally, where vehicles are located at the start of the planning horizon as well as idle times are of high importance. As a consequence, it is important to note that the results are subject to the previously listed assumptions as well as the selected parameters and test regions.

Furthermore, the analysis shows a drawback of dynamic optimization procedures. As decisions are based on the current information available, decisions are taken myopically. This can lead to situations where having more transfer points results in decisions which hurt the system's performance. Relief vehicles may be sent to a distant transfer point due to minor time savings and are, as a consequence, not available on time for future requests.

## 6. Conclusion

Combining DSSs with optimization procedures allows one to investigate coordination in disaster relief decision-making. The developed DSS helps to determine potential transfer points fast and efficiently and further enables testing of the various impacts of different fleet configurations to coordinate shipments. Furthermore, the impact of road closures can be investigated to gain an overview of the consequences of different disaster relief policies. In particular, combining strengths of private and relief organizations and facilitating emerging technologies has the potential to provide fast supply of relief goods to victims.

The DSS was developed to provide decision-makers a tool to test different strategies during professional training in a risk-free environment. This enables one to perform what-if studies and to analyze worst case scenarios to foster decision-making skills and to gain a better understanding of disaster relief distribution. Future work includes the development of training cases and serious games to foster cooperative experiential learning. Therefore, the extension of the DSS to allow prototype applications during disaster trainings and interfaces to databases as well as the implementation of various decision hierarchies have to be researched. Behavioral studies on the development of demand during disasters profit the applicability. Furthermore, coordination in humanitarian logistics leads to a wide range of ethical and legal questions. While it can efficiently be modelled in DSSs, substantial future advances in technological and organizational matters are needed to allow real-world operations.

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