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Agent-based simulation optimization for dynamic disaster relief distribution

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Abstract This work presents an agent-based simulation optimization framework to model the impact of transport disruptions and word of mouth on disaster relief distribution. An agent-based simulation considers uncertainties in transport conditions and further incorporates various actions by and interactions between multiple people affected by a natural hazard event. To select optimal distribution points and vehicle types, a bi-objective optimization procedure is implemented focusing on the minimization of costs and maximization of services provided. The developed solution procedure is tested on a sample setting based on the April 2015 earthquake in central Nepal. Computational experiments study the impact of transport disruptions and word of mouth on disaster relief planning. Results indicate the importance of considering such factors in planning procedures.

Keywords Humanitarian logistics · Simulation optimization · Facility location · Word of mouth · Agent-based modeling

1 Introduction

The April 2015 earthquake in central Nepal was the largest disaster striking the country in the previous 80 years. The earthquake and its aftershocks resulted in more than

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8800 human deaths and about 22,500 injured persons (Aon Benfield Analytics 2015). Major damage to infrastructure was recorded in central Nepal including the destruction of buildings, monuments and road networks. An earthquake can cause damage to roadway systems, e.g., through ground failure such as landslides or faults. Debris from buildings or masses of soil can be deposited on roadways, blocking traffic and making a road temporarily impassable. Bridges and similar structures are particularly at risk of collapsing in case of an earthquake. According to Aon Benfield Analytics (2015), 13% of the country's road networks were damaged or destroyed.

A damaged road network has an economic impact on a region, and restoration needs to occur quickly for proper operations to continue. In case of a disaster, the provision of relief aid might also be hindered or delayed, causing negative impacts on the societies affected by road blocks and closures. Although it is difficult to predict the occurrence of an earthquake, it is crucial to prepare for such potential disasters. Organizing the response to an earthquake includes logistics, which is a major challenge to disaster relief (Van Wassenhove 2006).

In order to provide the affected population with relief goods on a regular and fair basis, the anticipation of unexpected events is crucial to maintain a functioning and robust transportation network in case of an emergency. Therefore, the United Nations World Food Programme (2002) recommends to specify requirements for repairing vital road sections and critical bridges. These road segments are not only at risk during an earthquake, but subsequently due to potential aftershocks, which influence the ability of transporting relief goods in the aftermath of an earthquake.

The provision of relief goods is commonly organized from distribution points receiving shipments from a central depot. United Nations High Commissioner for Refugees (UNHCR) recommends that there should be at least one distribution point per 20,000 affected persons within a distance of 5–10 km. The closer a point can be located to those affected, the better in terms of reachability, however, the more points opened, the higher the costs rise. According to the United Nations World Food Programme (2002), in addition to costs, monitoring multiple points becomes challenging and beneficiaries might present themselves at several different sites. Fewer distribution points require less staff, infrastructure (roads and buildings for distribution) and transport, however, this implies longer distances to receive aid and more difficult access.

The selection of the number and location of distribution points affects the number of persons that can benefit from relief aid. Organizing the distribution system in the common practice of assigning beneficiaries to their closest facility in terms of distance might lead to some members of the population not receiving aid (Burkart et al. 2017). Beneficiaries tend to be influenced by other factors than distance when deciding which site to visit, e.g., the surrounding terrain, the impact of demographic and social groups, the size of a distribution facility raising expectations about better availability of relief goods. Therefore, it is crucial to incorporate human behavior into decision-making for relief distribution.

The aim of this paper is to provide a realistic decision support tool for a robust and fair distribution system of relief goods based on an agent-based simulation-optimization framework as its algorithmic core. The decisions studied include where to locate distribution points and how to transport goods from a depot to these points.

Depending on the status of the road network, different transport modes are applied, including the ability to repair damaged network links. We capture the uncertainty of impassable network links by simulating dynamic changes in the road network caused by landslides or collapsing bridges. In disaster relief, multiple stakeholders pursue potentially conflicting objectives, which we incorporate as distribution costs and service level. For determining the service level of a particular solution, the behavior of beneficiaries and word of mouth information are taken into account.

The remainder of the paper is organized as follows. Section 2 reviews related literature. The studied problem setting is defined in Sect. 3 and the developed simulation optimization framework is presented in Sect. 4. Section 5 introduces the study settings for the computational experiments, while Sect. 6 provides results and further highlights main findings of this work. Concluding remarks are given in Sect. 7.

2 Related work

In the past 100 years, three great earthquakes with a magnitude on the Richter scale of more than 7.5 occurred along the Himalayan front, i.e., the 1934 Bihar–Nepal earthquake ($M_W = 8.1$), the 1950 Assam earthquake ($M_W = 8.6$), and the 2015 Nepal earthquake ($M_W = 7.6$) (Dixit et al. 2013; Paul et al. 2017). Dixit et al. (2013) already anticipated the devastating impact of an earthquake in the Kathmandu Valley before its occurrence in 2015. The authors indicated that the earthquake disaster risk of urban areas in Nepal is ever increasing alarmingly due to rapid urbanization, poor construction practice and lack of disaster preparedness. Concerning the transportation system, the authors highlighted that the road networks pass through landslide-prone mountain slopes and the only international air-access to Nepal, the Tribhuvan International Airport, could also be affected by disruptions. Furthermore, it was estimated that almost half of the bridges in Kathmandu Valley were impassable and that 10% of the paved roads would sustain moderate damage such as deep cracks or subsidence. Additionally, roads could be blocked by the debris of collapsed buildings.

Paul et al. (2017) assess how well government and nongovernmental organizations as well as others performed during emergency relief operations after the 2015 Nepal earthquake. The authors state that the Nepalese government was partially responsible for hindering the distribution of emergency relief supplies, especially in the critical three days following the earthquake. Authorities obstructed the international disaster response efforts by insisting on following a long list of rules and regulations, including custom inspections and import taxes. As a result, supplies for the survivors were held up at the airport and other border crossings. Additionally, a severe shortage of supply trucks and drivers as well as a series of high-magnitude aftershocks delayed assistance to far-reaching areas. Paul et al. (2017) state that at the time of the first mainshock, Nepal did not have any earthmovers or cranes to clear roadblocks and start emergency relief operations. The United Nations had only three helicopters available to distribute aid, which was far too few for the size of the disaster and the demand. Additional challenges associated with the 2015 Nepal earthquake disaster relief operations were widespread discrimination based on gender, caste, and ethnicity. The authors conducted face-to-face interviews with 302 respondents from 10 study

sites in two earthquake-affected districts. They found that the houses of 295 respondents were damaged, of which 235 were completely destroyed. 27 out of the 302 respondents received no emergency aid from any source. Cash as a relief good went to 265 respondents, followed by tents (253), food (250), clothing (224), and kitchenware (186). Based on their empirical study, Paul et al. (2017) conclude that the disaster relief efforts undertaken by both public and private agencies after the 2015 Nepal earthquake seemed to run relatively smoothly and effectively, which stands in sharp contrast to the international and national press reports on relief efforts. They state that the emergency materials provided to the earthquake survivors were appropriate and adequate for their needs and the aid distribution was relatively fair and timely.

Information is essential for individuals in the preparedness phase and during a disaster. Zhu et al. (2011) describe the relationship between information credibility and perception of seismic risk in a group of people living in disaster areas. The authors state that information credibility is an important aspect of an individual's information evaluation. They also refer to the negativity bias, which is the tendency to pay more attention to negative information. Ryan (2013) investigates how people get information during a flood disaster and what they want to know. The study is based on two flood events in Queensland, Australia, in 2010 and 2011. Among others, the author highlights that word of mouth needs to be considered by relief agencies, and mobile phone networks and social media are critical outlets to such investigation. The author states that people in cities tend to inform themselves about disaster conditions and relief aid occurring in their own community through interpersonal contact via a variety of media such as mobile and fixed phones and face-to-face interactions. People in rural areas tend to use personal agency contacts where possible and are more likely to use family, friends, and knowledgeable acquaintances as well as radio stations as a source of information. The author concludes that word of mouth remains a key source of information for people in any flood disaster. Sommerfeldt (2015) examines how Haitians used information sources following the 2010 earthquake. The author states that the questions of where to turn for food, shelter, and health care in the ruined city of Port-au-Prince became of utmost importance for the citizens. The population needed information to survive and recover. The author indicates two distinct types information sources: 'traditional' including radio, TV, church and word of mouth, and 'elite' including newspapers, the internet, short-message-service, billboards, and the national police. The results of the study suggest that greater reliance on a traditional source type led to decreased information sufficiency.

Delavallade et al. (2016) considers the challenges of using social media for crisis management. The authors state that social media can provide additional insight on real-time events provided that the information relayed is accurately retrieved, evaluated and fused. Furthermore, the authors list organizations that address this issue such as the 'HOT—humanitarian OpenStreetMap team', the 'SBTF—Standby Task Force', and 'Humanity Roa'. Such organizations have federated themselves under the Digital Humanitarian Network. These networks become active in case of a major crisis in order to set up 'Virtual Operations Support Teams', teams of volunteers spread all over the world, which take care of data collection, validation, and mapping. The authors also state that given the amount of data to process, tools to at least partly automate or ease the validation stage are greatly needed. The study presents various mechanisms and

functions necessary for information fusion and understanding in social media as well as methods to identify reliable information. Andrews et al. (2016) present a method to create corroborated crisis reports from social media data. The authors state that during a crisis, citizens use smart phones to report, comment and explore information surrounding the crisis.

The importance of the availability of transportation infrastructure is highlighted in Berariu et al. (2015), which deals with the impact of cascade effects on disaster relief operations. Facility location under random network damage is investigated in Salman and Yücel (2015). Based on a sample case from Istanbul, the authors develop a Tabu Search metaheuristic and a scenario generation algorithm assisting decision makers to pre-select supply points for relief goods. Fikar et al. (2016a) introduce a simulation optimization-based decision support system for disaster relief distribution during flood disasters. The authors consider the sudden closure of links in the transportation network allowing a dynamic adaptation to real world conditions and comprehensive analysis over a rolling time horizon. The presented decision support system combines agent-based simulation with metaheuristic and heuristic methods. Fikar et al. (2016b) consider the impact of sudden rail closures on transportation networks and the local industries affected within a simulation-based decision support system. The model is tested using data originating from a major transalpine rail corridor, the Brenner Pass, which connects Austria and Italy. The study evaluates critical rail links and the impact of various disaster scenarios. Niessner et al. (2017) develop a simulation optimization procedure to manage mass casualty incidents. A discrete-event simulation is combined with heuristic and metaheuristic optimization procedures to allocate emergency staff. A gas explosion is assumed to derive policy implications such as which victims to prioritize and how to position advanced medical posts.

Consequently, to improve disaster relief operations, simulation optimization enables one to consider uncertainty and complex interactions within problem settings, extending areas in which optimization can be applied (Glover et al. 1996). Fu (2014) provides an extensive overview of various simulation optimization methodologies. Recent applications are further stated in Amaran et al. (2014). In our work, uncertainties are modeled within an agent-based simulation. For an overview of recent advances in agent-based simulations, refer to Macal (2016). This method allows one to focus on the individual actions of residents depending on the selected distribution strategy. Therefore, multiple runs of the agent-based simulation are used within the framework to estimate the performance of solutions derived by a bi-objective optimization procedure. Combining such methods with optimization procedures enables modeling the problem in a flexible manner, however, it increases computational times. A discussion on such main characteristics of agent-based simulation optimization with a focus on how to improve computational efficiency is given in Deckert and Klein (2014).

3 Problem description

The following problem setting is assumed within this work. An area is hit by a natural hazard event, e.g., an earthquake or flood, resulting in sudden damages to the transport network and the need for relief goods. These damages to the network can occur at

random times during the planning horizon as a result of aftershocks or landslides. Residents who require relief goods respond to such events by sharing experiences on the availability of relief goods at distribution points either via phone or social media. Facing such circumstances, the relief organization has to take the following decisions on how to plan its operations: (i) where to set up distribution points in the area to hand out relief goods; and (ii) how to supply these points in an optimal manner. Both decisions have to be taken before the start of operations and cannot be adjusted later. A planning horizon of one week is considered and the focus is set on road transportation. Transport disruptions can occur during the planning horizon at any time without prior warning for the relief organization.

Relief goods are available at a depot located on the periphery of the study area. Given a list of potential candidate locations, the relief organization can operate any combination of distribution points. Selecting a distribution point results in fixed costs, which occur for setting up operations, and variable costs to deliver goods to this location. Consequently, while operating a high number of distribution points enables one to improve service coverage, it results in an increase in fixed costs. Distribution points are supplied daily and full truckload shipments are assumed. The delivery quantity is set based on the number of beneficiaries assigned to the respective distribution point by the relief organization, where each beneficiary is assigned to the nearest operated point. Three different vehicle types are considered to perform shipments between the depot and distribution points. A shipment can be transported in a convoy of regular trucks. These trucks result in the lowest costs to the organization, however, they are not able to pass any disrupted street segments. Consequently, in case of a disruption, such vehicles have to travel detours to reach their destinations. If no feasible path to the distribution point exists, the shipment cannot be delivered by this vehicle type. However, the relief organization can use special equipment or equip the convoy with repair capabilities to overcome some types of disruptions. With special equipment, i.e. off-road or lighter vehicles, the convoy is able to pass disrupted street segments, however, at lower speed and higher costs. If repair equipment is available, the convoy repairs the disruption, e.g., by removing debris or building temporary bridges, enabling other vehicles to pass this segment in the future. Having such repair equipment available results in the highest costs due to additional staff and vehicle requirements. Furthermore, each repair operation results in a time delay to conduct these measures.

During the planning horizon, multiple people or households require aid, denoted as residents from here on. Residents are located at various population centers throughout the study area and act based on individual decision-rules. To indicate the importance of fair relief goods distribution, a weight in the range of 1–2 is added to each resident, to indicate the importance of serving more vulnerable residents with a higher priority. Each day, the resident travels to a distribution point of the relief organization to collect goods. In case no goods are available, i.e., the resident arrives before the delivery vehicle, the resident enters a queue. There the resident waits for the goods to arrive, however, if the delivery vehicle is delayed by more than an individual threshold time limit, the resident stops waiting and starts moving to another distribution point. Each time a resident receives goods or decides to quit, the resident shares this information, either via social media or person-to-person. It is assumed that a percentage of all residents receive and trust this information. Positive messages, i.e., the resident

reports that he/she received goods at a distribution point, increase the likelihood of visiting this point in the future, while negative messages, i.e., no goods were received, decrease the likelihood of return. Consequently, the performance of the disaster relief distribution system impacts the movements and choices of residents, which further impact each other throughout the simulation period by sharing information on relief good availability.

The aim of this work is to provide decision-makers with a set of Pareto-optimal solutions concerning the costs of operations and achieved service level to enable the investigation of various disaster relief settings. Costs result from operating distribution points and the various vehicle types, while service is defined by the weighted number of residents receiving relief goods during the planning horizon, i.e., adjusted by the residents' weights. Consequently, the solution procedure has to consider both objectives as well as various uncertainties present in operations such as sudden transport disruptions and information sharing.

4 Methods

To solve the introduced problem setting, an agent-based simulation optimization framework was developed. Agent-based simulation enables one to view the system from an agent's perspective and to model agent behavior as well as interaction between agents and the environment in dynamic settings (Macal 2016). This dynamic perspective of the problem setting allows one to study the performance of the distribution system over time and the reaction to various changes such as rerouting decisions and word of mouth. Therefore, discrete event steps are considered focusing on a simulation horizon of multiple days and real-time reactions.

The developed framework consists of three main components, a bi-objective optimization procedure, an agent-based simulation and a multi-modal disrupted routing network. Based on a defined disaster setting, a bi-objective optimization procedure derives promising solutions, which are evaluated by multiple runs of an agent-based simulation. Various uncertainties present in disaster relief distribution are considered within this simulation such as the behavior of residents and the impact of network disruptions on operations. To model the latter, multiple routing graphs are incorporated to enable dynamic rerouting based on current disruptions in the network. An overview of this interaction is given in Fig. 1.

The following subsections introduce each component in detail.

4.1 Bi-objective optimization procedure

A bi-objective optimization procedure was implemented based on the ideas presented in Tricoire (2012). It selects distribution points and the corresponding vehicle types to supply these locations using the two competing objectives of minimizing costs and maximizing service.

The procedure is initiated by calculating four initial solutions. To minimize costs, the best option is not to open any distribution point, i.e., not provide any relief goods at all. To maximize service, all distribution points should be open and either regular,
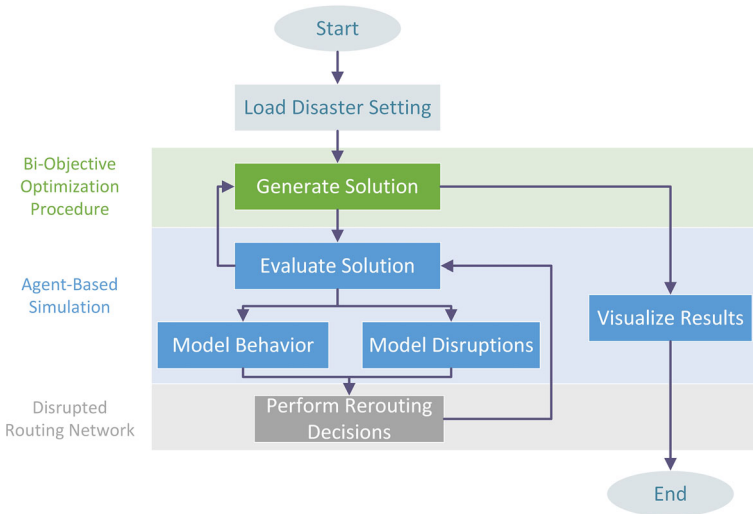
Fig. 1 A simulation optimization framework for disaster relief distribution

special or repair equipment used on all delivery routes, depending on the geographic distribution of locations and disruptions. These four solutions are evaluated and, if not dominated by another initial solution, added to the set of Pareto-optimal solutions. A single solution is evaluated by running multiple replications of the agent-based simulation and calculating the average performance. Each simulation run is initiated with a different random seed and, consequently, differs in the number and timing of network disruptions as well as demand requests by residents. Furthermore, travel choices of agents and word of mouth differ within the individual replication runs. To improve computational efficiency, a pre-check is implemented before starting the simulation runs, which calculates the maximum service and minimum costs of a solution considering that no disruptions occur. If already dominated by another solution, the evaluation is aborted. Additionally, based on the ideas presented in Deckert and Klein (2014) and Fikar et al. (2016a), after a minimum number of replications, the solution quality is compared against the current set of Pareto-optimal solutions considering a 95% confidence interval. If a solution is dominated, the evaluation is aborted, i.e., the remaining iterations are not performed. Otherwise, the procedure continues with the subsequent simulation replications. The dominance is rechecked at a set interval, e.g., based on the number of threads operating in parallel. If a run is aborted or the maximum number of replication runs is reached, statistics on the solution quality are reported.

The procedure starts from a random solution within the currently derived Pareto-front. Subsequently, a local search on each objective is performed separately, i.e., the solution is improved until no further improvements are found. Therefore, the corresponding vehicle type is indicated by an integer code $\in \{0, 1, 2, 3\}$, where 0, 1, 2 and 3 indicate a closed distribution point, regular vehicle, special equipment and repair equipment, respectively. When minimizing costs, closing a distribution point

or changing a vehicle type is evaluated, while, when maximizing service, opening and altering a vehicle type is checked. Each evaluated solution is tested if it is Pareto-optimal. If so, the set of Pareto-optimal solutions is updated by adding the new solution and removing dominated ones. To diversify, the evaluation of moves within the local search are randomly adjusted by $\pm 3\%$. After the local searches for both objectives are completed, a new random solution from the set of Pareto-optimal solutions is selected and the bi-objective procedure is repeated until a stopping criterion, e.g., maximum time or maximum number of iterations, is met. Algorithm 1 summarizes the solution procedure.

Algorithm 1 Pseudocode: Bi-objective simulation optimization framework

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1: **procedure** OPTIMIZATION
2:     generate initial set of Pareto-optimal solutions
3:     **while** termination criteria not met **do**
4:         select random solution from current set
5:         **for** both objectives **do**
6:             run local search evaluating generated solutions with the evaluation procedure
7:             update set of Pareto-optimal solutions
8:         **end for**
9:     **end while**
10:     return set of solutions
11: **end procedure**

12: **procedure** EVALUATION(Solution s, ParetoFront S)
13:     **if** pre-check does not indicate that solution is dominated **then**
14:         **while** maximum number of replication runs not yet reached **do**
15:             **for** batch of simulation replications run in parallel **do**
16:                 run simulation and update evaluation of solution
17:             **end for**
18:             **if** more simulation runs than minimum number of replications were run **then**
19:                 **if** solution is likely to be dominated **then**
20:                     abort evaluation and return solution evaluation
21:                 **end if**
22:             **end if**
23:         **end while**
24:     **end if**
25:     return solution evaluation
26: **end procedure**

4.2 Agent-based simulation

All solutions generated by the bi-directional optimization procedure are evaluated by performing multiple replication runs of an agent-based simulation. The simulation generates network disruptions at random times and models behavior and interactions between residents. Locations, vehicles, residents and network links are individually modeled as agents.

Locations define points of interest within the study area and are categorized into the depot and distribution points. The depot indicates where relief goods are available

to be picked up for shipping and further defines the start and end point of all vehicles. Distribution points indicate potential locations to distribute relief goods. Furthermore, these points are initiated with a population figure to model demand. The agent-based simulation loads the solution setting generated by the optimization procedure and accordingly sets if a distribution point is used to distribute goods or not. Additionally, vehicle agents are generated indicating with which type of vehicle a distribution point is served. These vehicles begin each day by traveling from the depot to the distribution point. Start times are set such that all vehicles are expected to arrive at the same time at the distribution points based on the current network situation and vehicle type. Each street segment within the transport network is modeled as an agent, indicating the location and likelihood of a disruption. In case of disruption, the routing graphs of the different vehicle types are adjusted and vehicles currently moving are checked if rerouting actions are required. When a vehicle arrives at a distribution point, all goods are unloaded and the vehicle subsequently returns to the depot.

To model demand for relief goods for a certain number of households living at a population center, a resident agent is generated. These agents start each day at a random time during the simulation horizon to travel to a distribution point. A maximum travel duration is assumed and only locations within this range can be visited. Upon arrival at a location where goods are distributed, the resident enters a first-in-first-out queue to receive goods. The resident waits for the expected arrival time of the vehicle and, at arrival, collects goods and returns home. Due to transport disruptions, the vehicle may be delayed requiring the resident to wait longer for the relief goods. Therefore, each resident is initiated with a maximum waiting time. It indicates the time an agent is waiting past the expected arrival time of a vehicle. In case this threshold is reached and the vehicle has not yet arrived, the resident leaves the distribution point and randomly travels to a new location within close proximity to his or her home location.

These experiences of the collection of relief goods are shared among residents. If relief goods are available at a location, the resident sends a message within the simulation, e.g., a call or a post on social media networks. This message is received and trusted by a certain percentage of all residents, i.e., each resident reacts differently. Receiving residents process this message. In case of a recommendation to visit a certain location, it is placed on a whitelist, indicating locations that are preferred the next time a travel decision is taken. In case of a negative experience, the location is placed on a blacklist, indicating that a resident will avoid this location in the future. Therefore, the most recent received message is always determining the respective list, i.e., if a previously blacklisted location receives a positive message, it is removed from the blacklist and added to the whitelist. When choosing which location to visit next, the resident primarily selects a location on the whitelist. If the whitelist is empty, all non-blacklisted locations are evaluated and only in case all locations within the maximum range are on the blacklist, a blacklisted location is chosen. Which specific candidate location of the selected list is taken is based on a geometric distributed biased-randomized selection procedure (Grasas et al. 2017). Therefore, all locations of the considered list are sorted by distance and candidate locations close to the resident are preferred. Figure 2 summarizes the implemented travel choice of a resident.
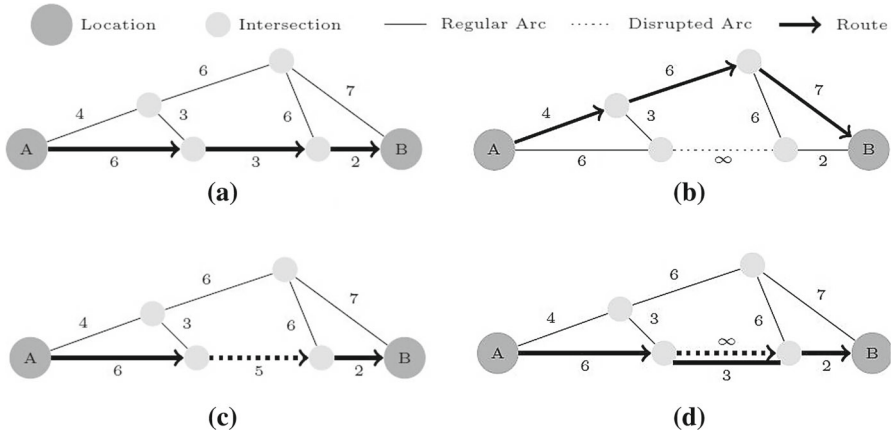
Fig. 2 Implementation of travel choice and agent interactions

4.3 Routing network

The different vehicle types considered in this work are modeled on separate routing graphs to handle the various actions in case of network disruptions. Each point within the network, which is potentially disrupted within the studied disaster area, is assigned geographic coordinates and a disruption probability. The system subsequently matches the point with the closest street segment on the real-world routing graph. At the start of each simulation run, a random number is drawn for each disruption agent. If smaller or equal to the disruption probability value, a disruption event to close the respective street segment is generated at a random time within the simulation horizon. Otherwise, no disruption occurs on this road link within this single simulation run.

In case of a disruption, the weight of the disrupted arc is adjusted. For the regular vehicle routing graph, the weight is set to infinity, i.e., the arc is no longer included in any shortest path. For vehicles traveling with special equipment, the weight is multiplied by a delay factor to penalize movement on this segment. For vehicles which are able to repair disrupted arcs in the transport network, the arc weight is not adjusted, however, the disrupted segment is marked. Furthermore, the procedure tests if any of the current vehicle routes are affected by the disruption. Therefore, the new shortest path from the current vehicle position to the end location is calculated. If no feasible solution can be found, i.e., if all street segments connecting a location are disrupted, the vehicle is marked inactive. In such cases, it is assumed that the vehicles wait at their current locations for the disruptions to be repaired. Therefore, the repair graph constantly tests if a repair vehicle passes a disrupted arc. In such a case, a repair operations is started, after which the street segment is reopened and can be passed by any vehicle at no extra cost or time delay. As such changes in the routing graph impact potential route choices of all vehicles, the rerouting procedure is again started

Fig. 3 Routing decisions considering disruptions and various vehicle classes. **a** No disruptions. **b** Regular vehicle. **c** Special equipment. **d** Repair equipment

in such settings for all vehicles. Additionally, all vehicles currently marked inactive by a disruption are tested if movements can be continued.

Figure 3 provides a simplified example for routing decisions of the various vehicle types in different situations. A routing graph consisting of six nodes and eight arcs is assumed with each vehicle currently positioned at point A and traveling to point B on the shortest feasible path. If no disruption occurs, each vehicle type takes the same route by traveling on the straight path. If a disruption occurs, rerouting is based on the individual routing graph of the vehicle type. Regular vehicles cannot traverse the disrupted arc and, consequently, take a detour. All potential detours are evaluated and the fastest one is taken. In contrast, the special equipment vehicle has the additional option of continuing to take the original route, however, at a time penalty on the disrupted arc. Consequently, the special vehicle only continues traversing the disrupted arc if it results in a shorter travel duration than the detour. The repair vehicle always continues traveling on the original shortest path. When it arrives at the disrupted arc, the vehicle stops and starts repairing the arc. After a time delay for this operation, the street segment is repaired and subsequently open again for all vehicle types. To model such interactions, each time a disruption occurs or is repaired, the procedure re-evaluates all routing decisions of each vehicle considering current locations and updated routing graphs.

5 Computational experiments

The solution procedure was developed with AnyLogic 8.10 (AnyLogic 2017), embedding OpenStreetMap data (OpenStreetMap 2017) for visualization and to generate real world routing networks. To calculate shortest paths on various distributed routing graphs, a customized version of GraphHopper (2016) 0.5 is integrated in the simulation-optimization framework. Therefore, travel times between two locations depend on the individual speed on each street segment to allow accurate travel dura-

tion. To speed up the calculation of shortest paths, various memory techniques are used to store frequently used routes, e.g., between depot and distribution points. Multiple simulation replications are executed in parallel. The optimization procedure is coded in Java and can be initiated by the user through the graphical user interface of the simulation. All test runs were run on an Intel Core i7-4930K, 64GB RAM, with MS-Windows 7 and six threads operating in parallel. Results of 400 iterations are provided with average results of 50 replication runs, i.e. simulations, for each evaluated setting reported. After 12 replications, the procedure checks every six replications if an evaluation can be aborted based on a confidence level of 95%.

5.1 Real-world setting

The Federal Democratic Republic of Nepal is a country in the central Himalayan region in South Asia. Nepal consists of seven provinces and 75 districts, housing a population of about 26 million people. The country includes eight of the world's highest mountains in the Himalayan region. It lies within the active collision zone of the Indian and the Eurasian tectonic plate. Due to this location on the subduction zone of the Indian and the Tibetan crust, Nepal is prone to regular seismic hazards (Aon Benfield Analytics 2015). The central region of Nepal was struck by an earthquake of magnitude M_W 7.6 on April 25, 2015, followed by several aftershocks in the next days. Major damage to infrastructure, including buildings and monuments, was recorded in central Nepal. 13 percent of the country's road network were damaged or destroyed, which made it very challenging for relief teams to reach certain areas (Aon Benfield Analytics 2015).

Based on real-world data from the April 2015 earthquake in Nepal, a sample setting was generated. Assumptions are based on interviews with the Austrian Red Cross, who provided ground relief services during the aftermath of the earthquake. In our test setting, one depot for relief goods and vehicles is located in Nepalgunj, securely located outside the affected region. 28 major cities were determined as candidate locations for distribution centers, which are installed in existing buildings such as schools or municipal buildings. Based on population figures, 3912 agents represents the residents living in these cities. A transportation network from the depot to the candidate locations for distribution centers was generated based on the existing road connections. Risks in the transport network, e.g., due to collapsing infrastructure or landslides, were assumed based on a detailed analysis of aerial images of the affected regions. Therefore, major hazards in the transport network were identified. These points were evaluated by comparing the impact of the corresponding road segment being disrupted to a non-disrupted network. In total, 35 points showed major impacts on relief operations. Figure 4 plots the study area and considered locations for potential network disruptions. All input data are available at http://short.boku.ac.at/instances.

Table 1 states the investigated settings within the computational experiments. For comparison, the static setting ignores the possibility of sudden transport disruptions and assumes that each resident travels to the closest active distribution point. The dynamic setting incorporates such sudden transport disruptions, however, it also assumes that residents always travel to the closest distribution point. Furthermore,
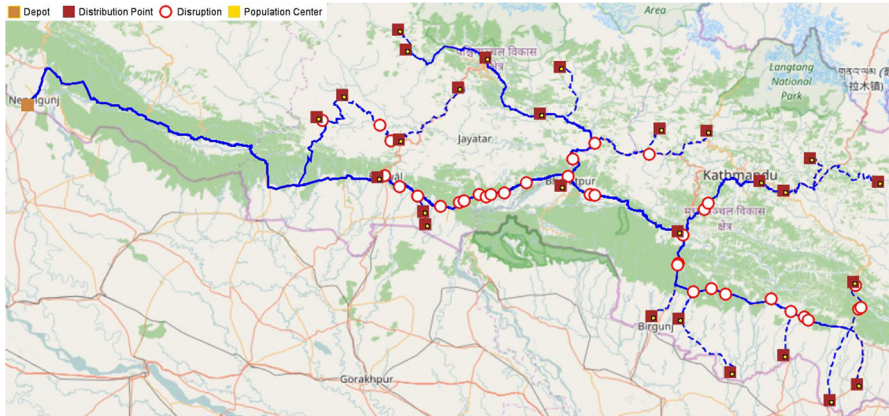
Fig. 4 Study region indicating the depot and distribution points as well as the locations of potential network disruptions during the simulation

Table 1 Settings investigated within the computational experiments

Setting	Network disruptions	Agent behavior	Word of mouth
Static setting	No disruptions	Assigned distribution point visited and unlimited waiting times	No interactions
Dynamic setting	Sudden damages	Assigned distribution point visited and unlimited waiting times	No interactions
Choice setting	Sudden damages	Distribution point visited based on travel distances and limited waiting times	No interactions
Joint setting	Sudden damages	Distribution point visited based on word of mouth and limited waiting times	Availability of relief goods shared

both settings assume that residents wait an unlimited time for the relief goods in case of a delayed arrival. In contrast, the choice setting assumes that residents are more likely to travel to closer distribution points, however, some randomness in the selection of the distribution point is considered based on a biased-randomized selection following a geometric distribution. Additionally, each resident has an upper limit on the maximum waiting time after which the resident decides to travel to another location. Agent interactions are analyzed in the joint setting, where information on the availability of relief goods is shared among residents. This information impacts travel choices by favoring locations that received positive word of mouth recommendations and penalizing ones which received negative feedback.

5.2 Parameter setting

Table 2 provides the specific parameter values used within the computational experiments. Fixed costs, variable costs and maximum travel duration for residents to reach

Table 2 Parameters used within the computational experiments

Parameter	Description	Value
Fixed costs	Costs to run distribution point	€200.00
Variable costs	Costs of kilometer traveled	€1.00
Vehicle arrival time	Time at which relief goods are expected to arrive	11 a.m.
Resident departure time	Time when a resident starts moving to a distribution point	8 a.m → 2 p.m.
Maximum waiting time	Maximum duration a resident waits for a delayed vehicle	60 min → 120 min
Maximum travel time	Maximum duration a resident travels to a distribution point	120 min
Word of mouth range	Percentage of agents receiving the message of the resident	2%
Disruption speed reduction	Percentage of maximum speed a special vehicle travels on a disrupted arc	75%
Repair time	Duration for a repair vehicle to fix a disrupted arc	150 min
Regular cost factor	Cost factor used to adjust costs of regular vehicle	1.00
Special cost factor	Cost factor used to adjust costs for special equipment	1.25
Repair cost factor	Cost factor used to adjust costs for repair equipment	1.50

a distribution point are based on Burkart et al. (2017). It is assumed that all shipments are scheduled to arrive at 11 a.m. at the distribution points and residents start moving to these distribution points each day at a uniformly randomly selected time between 8 a.m. and 2 p.m. Similarly, the maximum waiting time of each resident is uniformly randomly drawn between 60 and 120 min and a word of mouth range of 2% is set, indicating which percentage of all residents receive and process the resident's message.

Variable costs are multiplied by a cost factor depending on the vehicle type to consider the different cost levels for the various vehicles and equipment. This cost factor is set to 1.00, 1.25 and 1.50 for regular, special and repair vehicles respectively. Additionally, it is assumed that the special vehicles travel at 75% of the regular speed on disrupted arcs. To repair a street segment, a time delay of 150 min is set.

The focus is set on the first response phase where little data on transport damages and residents' needs are known. In this phase, fast relief is crucial to avoid panic reactions such as stockpiling, which complicates resource deployment, e.g., if supplying residents or repairing street damages should be prioritized (Berariu et al. 2016). Therefore, a single week of operations is considered within the computational experiments in which distribution points are supplied daily and vehicle types are fixed.

6 Results and discussion

Figure 5 shows the approximated set of Pareto-optimal solutions derived by the developed solution procedure for each of the calculated problem settings. If a static system
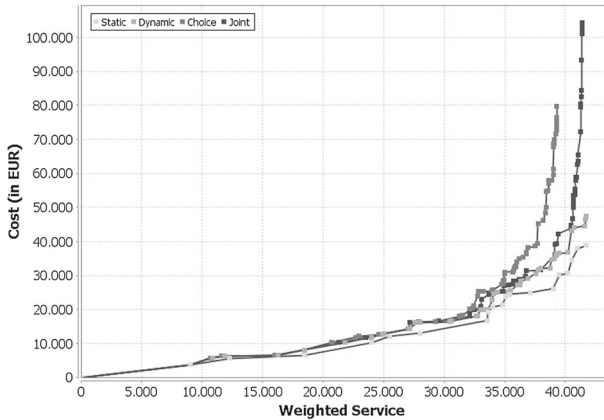
Fig. 5 Approximated set of Pareto-optimal solutions for the various problem settings

Table 3 Detailed results of the derived set of solutions

Setting	# Solution	Av. distribution points	Regular (%)	Special	Repair
Static setting	20	3.30	100	–	–
Dynamic setting	47	3.45	62.96	27.16%	9.88%
Choice setting	72	4.96	36.13	61.90%	1.96%
Joint setting	69	5.57	30.73	67.19%	2.08%

is assumed in the planning procedure, i.e., disruptions and the behavior of residents are ignored, the results indicate that the highest service coverage can be achieved at relatively low costs compared to the other settings. Real-world operations, however, are subject to such uncertainties. The impact of transport disruption is analyzed in the dynamic setting. It enables relief organizations to serve all residents at higher costs by facilitating special or repair equipment. If resident behavior is incorporated as done in the choice setting, costs further increase and service decreases as multiple residents do not receive any goods due to stock-outs. Additionally, compared to the choice setting, considering word of mouth improves performance as residents know where goods are available and consequently travel to promising distribution points. This results in shorter waiting times and fewer residents not receiving any relief goods.

Details of the test runs are provided in Table 3, indicating the number of non-dominated candidate solutions, the average number of operated distribution points and the relative amount of times a certain vehicle type was chosen within the derived solutions. When impacts of word of mouth and transport disruptions are incorporated in the planning of relief operations, the results show that it is beneficial to operate more distribution points than in static settings where such characteristics are ignored. If a single distribution point can no longer be reached due to road damages, residents can still shift to other nearby locations, particularly if information on availability of goods are shared. Nevertheless, operation costs increase as more distribution points and vehicles need to be operated.
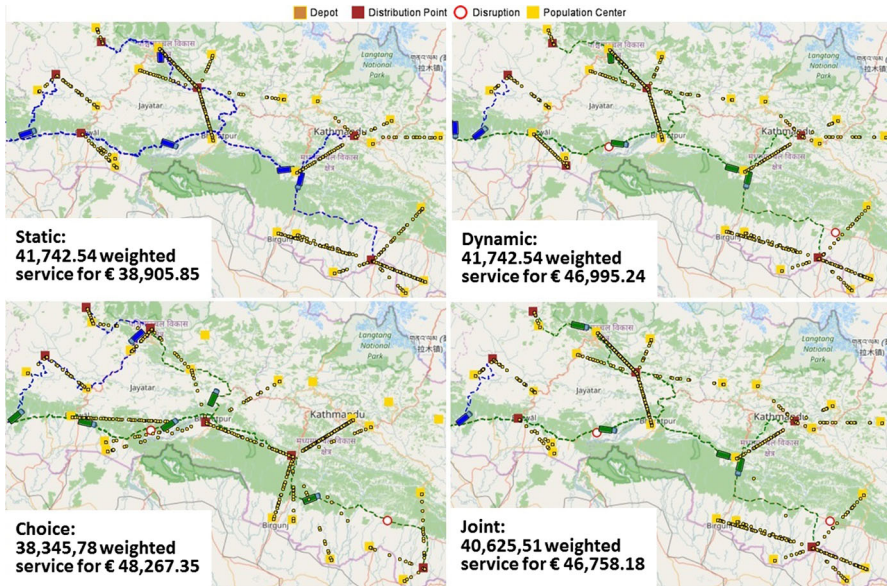
Fig. 6 Snapshots after 2000 simulated minutes for a sample solution for each problem setting indicating vehicles types (blue = regular, green = special) and resident movements (yellow dots) (color figure online)

Concerning fleet mixes, in the static setting, regular vehicles are exclusively used. As transport disruptions are not considered, no need to employ special or repair equipment occurs. The consideration of such disruptions in the dynamic setting leads to an increased utilization of special equipment, while the option to repair road segments is used for highly critical links in the segment. If maximum waiting times and travel choice of residents are considered, it is critical to minimize delays. Consequently, special equipment gains importance due to the benefit of traversing roads amid disruptions. In contrast, repair equipment is rarely facilitated due to long repair times and the high need to reach residents on time, particularly within the first days where word of mouth occurs and residents select their distribution points.

Figure 6 shows snapshots of a single simulation run of selected solutions for each setting. Six distribution points are operated and vehicle types as well as resident movements are visualized. Furthermore, costs and achieved service coverage are reported. All solutions represent settings where a high service coverage is desired. The results show that the derived solutions differ substantially, particularly concerning the operated distribution points. Nevertheless, if transport disruptions are incorporated, the planning procedure favors employing special equipment on long trips to mitigate potential delays, while shorter routes are performed by less costly regular vehicles.

Consequently, the results indicate that if transport disruptions and agent behaviors are not considered in the planning of disaster relief distribution, costs of the relief processes are underestimated and service coverage overestimated. This gives various implications for relief operations. It shows the importance of providing residents with accurate estimated arrival times of relief vehicles and further indicates benefits of

developing counter-measures to reduce delivery delays. Additionally, results highlight that the behavior of residents impacts disaster relief operations and, therefore, needs to be incorporated in planning procedures. Such considerations further allow one to adjust delivery quantities to improve service coverage or actively share information with residents to influence travel choices. As a result, in case of transport disruptions, providing information on the availability of relief goods, e.g., through social media channels, can help to improve service coverage.

Nevertheless, the following limitations and assumptions of this study have to be considered when interpreting the results. A study period of one week was chosen to focus on the first response phase where high uncertainty exists in the problem setting. Consequently, the long-term impact of performed decisions, e.g., benefits of repairing street segments or setting up a distribution point, are not explicitly considered. If the study period is extended by a post-disaster phase, i.e., a time period where relief goods are distributed, but no further sudden disruptions occur, preliminary experiments indicate benefits of employing more repair equipment early. Such a longer time horizon, however, also enables the relief organizations to alter supply and vehicle decisions based on continuous developments, which is not modeled within the simulation optimization framework. Additionally, the risk of transport disruption is set to the same probability for each location of a potential network disruption and no interdependencies among multiple segments are considered. If such data is available, it can easily be integrated into the framework by adjusting the likelihoods of disruptions. Additionally, each resident is placed according to their home location and prefers traveling to distribution points within close range. Consequently, due to a lack of data, no further influencing factors on travel choices are integrated such as work places or where family members are living. Furthermore, we consider that all information spread by word of mouth contains accurate data on the availability of relief goods, i.e., no information distortion occurs within the studied problem setting.

7 Conclusions

A simulation optimization framework was developed to provide decision-makers the option to both investigate the impact of word of mouth and uncertain transport conditions on relief operations in a dynamic manner. It combines an agent-based simulation to model behavioral factors with a bi-objective optimization procedure. Various routing networks are further implemented to enable one to consider various transport disruptions present in disaster relief operations. To evaluate the performance, computational experiments based on the April 2015 earthquake in central Nepal were conducted, evaluating the impact of word of mouth on the performance of relief operations. Results show that it is of high importance to both consider transport disruptions and travel choices of residents in the planning of disaster relief distribution. Ignoring such factors potentially leads to a substantial underestimation of expected costs and an overestimation of the expected service level provided.

A main benefit of employing an agent-based simulation within this work is that the framework can be easily adjusted to varying regional characteristics in both operational area and the culture of residents. The former can be achieved by adjusting

vehicle types, e.g., by adding special routing graphs for air or water transportation, while the latter is enabled by adjusting or extending residents' behaviors and interactions. Nevertheless, computational efficiency is a major drawback as the solution evaluation is time-consuming when modeling complex interactions within the simulation. Additionally, as shown in this work, more studies focusing on word of mouth during natural hazard events is required to improve understandings of its impacts and characteristics.

Consequently, various research directions for future work are derived by this work. Evaluating methods on how to improve the computational efficiency of agent-based simulation optimization frameworks in detail, e.g., by limiting the number of replication runs or working with restricted neighborhoods, facilitate the implementation of such systems in operational settings. Studying residents' behavior and actions during various natural hazard events supports applicability and quality of results. In this context, it would be of further interest to study the impact of wrong information shared via word of mouth on operations. Considering such factors enables implementing developed simulation optimization methods in real-world decision support system to provide decision-makers an integrated view of the various interrelated factors impacting relief operations.

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