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Abstract:

Social cost functions in humanitarian operations are defined as the sum of logistics and deprivation costs. They are widely regarded as appropriate objective functions, even though the way they were introduced requires cautiously formulated deprivation cost functions for the analyzed goods and do not allow decision makers to include their individual preferences. We develop this approach further and introduce a normalized weighted sum approach to increase decision makers' understanding of the trade-offs between cost and suffering and, therefore, increase transparency significantly. Furthermore, we apply the approach to a case study of a hypothetical water system failure in the city of Berlin. We show that the normalized weighted sum approach significantly improves transparency and leads to a deeper understanding of the trade-offs during the crisis. Consequently, it proved itself as a powerful tool for decision makers preparing for or navigating through a crisis.

Keywords: humanitarian logistics; social cost; deprivation cost; facility location planning

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Social cost functions in humanitarian operations are defined as the sum of logistics and deprivation costs. They are widely regarded as appropriate objective functions, even though the way they were introduced requires cautiously formulated deprivation cost functions for the analyzed goods and do not allow decision makers to include their individual preferences. We develop this approach further and introduce a normalized weighted sum approach to increase decision makers' understanding of the trade-offs between cost and suffering and, therefore, increase transparency significantly. Furthermore, we apply the approach to a case study of a hypothetical water system failure in the city of Berlin. We show that the normalized weighted sum approach significantly improves transparency and leads to a deeper understanding of the trade-offs during the crisis. Consequently, it proved itself as a powerful tool for decision makers preparing for or navigating through a crisis.

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1 Introduction and Motivation

The COVID-19 pandemic in the year 2020 distinctly highlights the vulnerability of supply chains to disasters. Despite the unprecedented support by local governments and international organizations, the WHO announced a global shortage of critical goods such as face masks or ventilators (WHO, 2020). As a response, multiple companies all over the world stepped forward and supported the population. For instance, the

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German company Trigema started to produce a large number of face masks (Irishtimes, 2020), and General Motors adapted some of their plants to produce ventilators (WSJ, 2020).

In case the private sector cannot guarantee sufficient supply in a crisis, actors like governments or NGOs become active and try to reduce the burden to the population (Kovács and Spens, 2007). However, setting up humanitarian supply chains is very challenging since they vary significantly from commercial supply chains and often need to be designed from scratch under enormous time pressure (Holguín-Veras et al., 2012). Therefore, researchers developed a large variety of optimization models to analyze and improve decisions in disaster situations.

A very critical component of these models is the objective function (Holguín-Veras et al., 2012). Various different objectives from commercial optimization models were applied, e.g. minimization of cost (Falasca and Zobel, 2011), minimization of travel time (Jánošíková et al., 2019), maximization of the covering (Balcik and Beamon, 2008), or multi-objective approaches (Ahmadi et al., 2015, Fikar et al., 2018, Nolz et al., 2011, Rath et al., 2016, Schneeberger et al., 2016). In spite of the valuable contributions of these models, the chosen objectives do not reflect the unique nature of humanitarian interventions (Holguín-Veras et al., 2013). Therefore, Holguín-Veras et al. (2012, 2013) introduce *social costs* as an more adequate objective.

They define social costs as the sum of logistics costs (LC) and a monetary representation of the suffering of the population, so-called *deprivation costs* (DC) (Holguín-Veras et al., 2012). Therefore, the concept of DC offers a considerable potential to holistically analyze the system and, in turn, to derive sustainable decisions (Kunsch et al., 2007). Deprivation Cost Functions (DCFs) highlight the development of deprivation over time. They are "monotonic, non-linear, and convex with respect to the deprivation time" (Holguín-Veras et al., 2013).

Shao et al. (2020) present an overview of the state-of-the-art in DC research. They highlight that DCFs often differ significantly from one another because the values depend on the respective goods, the country under consideration, and the specific crisis situation. Thus, different estimation approaches and data from different countries can lead to significant differences in DCFs. As an example, Shao et al. (2020), present DCFs for water or food-kits. They highlight that, in the course of a crisis, DCFs can differ by factors of 3 and higher. Combined with the "complex" process of data collection (Shao et al., 2020), the simple transfer of DCFs determined for a good and country seems to be not appropriate. Therefore, in theory, every study that uses social cost needs to first determine an appropriate DCF for the selected good and location, e.g. with the help of willingness-to-pay surveys.

Even though it is not difficult to conduct willingness-to-pay surveys (Shao et al., 2020), it requires a lot of time and effort, and, therefore, takes attention and resources away from the operations management aspects of the study. Furthermore, the practical application can be questioned since it can be doubted that decision makers are willing or able to take the time to conduct a survey in the aftermath of a disaster. Consequently, in spite of the powerful implications of the social cost approach, we argue that a more practicable approach to include social cost is favorable in situations where it is not possible to derive an appropriate DCF.

We suggest a normalized and weighted sum approach. After presenting an overview of the theoretical foundation in the next Section, we describe the main ideas and advantages of this approach with the help of an illustrative example in Section 3. Following, we apply the approach on a case study for a hypothetical tap water contamination in the city of Berlin. Afterwards, we present and discuss the results and the approach in Section 5.

2 Theoretical Foundation

Shao et al. (2020) identified 31 studies that consider DC. The majority of these studies does not regard social costs in the originally defined way, but, for instance, considers proxies for DCFs, such as the number of missing goods (Serrato-Garcia et al., 2016, Biswal et al., 2018), or a priority function (Rivera-Royero et al., 2016).

A group of studies considers DCFs without LC. For example, Yushimito et al. (2012) use a Voronoi-based approach to identify disaster relief locations, or Keshvari Fard et al. (2019) determine the size and allocation of vehicles that leads to minimized deprivation. However, Gutjahr and Fischer (2018) point out equity problems if optimization models under a fixed budget focus on minimizing DC. To increase equity, the authors suggest an extension similar to the Gini-coefficient.

On the other hand, some studies use social cost in the originally defined way, approaching a variety of aspects of humanitarian logistics. For instance, Khayal et al. (2015) develop a location-allocation model for facilities and resources, Pérez-Rodríguez and Holguín-Veras (2016) introduce an inventory-allocation-routing model to deliver critical supplies to the population, Chakravarty (2018) analyze options to invest in levee infrastructure, Loree and Aros-Vera (2018) select locations and inventory allocated to Points of Distribution, Paul and Zhang (2019) develop a two-stage stochastic program to place capacities within a supply chain for hurricane preparedness, and Cantillo et al. (2019) identify critical links in a relief network. Moreover, Cotes and Cantillo (2019) locate inventory in anticipation of a crisis, and Paul and Wang (2019) propose a robust model for facility location in the context of earthquake preparedness.

Furthermore we want to mention two ”hybrid approaches” briefly, in which DC and LC are combined in different ways. Wang et al. (2019) develop an approach to optimize the ratio of reduced deprivation and logistics cost to understand the efficiency of interventions better. Even though this approach provides a valuable basis for efficiency discussions, it only provides the chance to compare different options regarding their efficiency rather than identifying a globally optimal relief decision. Moreno et al. (2018) suggest a location-transportation problem and solve the model for the two objectives with a lexicographic approach. While it might be reasonable to argue that DC are more important than LC, and that the approach also allows to include preferences in a limited way (e.g. by introducing an attainment degree), the optimization is always focused on one objective and only regards the second objective subsequently. Even though both approaches allow decision makers to derive valuable conclusions, they have significant limitations.

In addition to the challenges regarding the sensitivity of DCFs towards local economic conditions, we want to further address another factor that, in our view, inhibits the use of social cost approaches in humanitarian logistics: summing up the two cost components simply assumes that both factors are of equal importance to each actor.

We argue that this does not reflect the real conditions properly since the way social cost functions work already includes an implicit weighting: LC are the dominating component in peace time, when the population is not deprived of goods. In disaster relief, DC significantly increase, leading to a substantially reduced influence of LC (Holguín-Veras et al., 2013). Consequently, LC have only very limited effects on social costs-based decisions in relief logistics. We see this assumption rather critical since different actors might not be able or willing to (more or less) disregard the LC implications of their decisions.

An obvious example is an international corporation that delivers different beverages into a region, which is suddenly affected by a disaster. In spite of a potential altruistic or Corporate Social Responsibility-motivated initiative to set up a humanitarian supply chain and support the population with donations, it is difficult to imagine that the company would not base their decision on costs. Another example is an international NGO that is motivated to support the affected population but also bound to their budget. Even though it would be possible to determine a maximal budget and implement this as a constraint in the optimization model, this simply does not reflect the preference that money directly spent as LC can affect an organization more than shadow prices of suffering.

On the other hand, the argument "costs are less important in disaster relief" comes into play, which is based on the (normative) judgement that money should not matter if lives are in danger. Even though such considerations can be observed in some cases (for instance in the COVID-19 response, when Banks like the US Federal Reserve started huge money creation campaigns to support people and businesses (Forbes, 2020)), the assumption neglects alternative measures that could be done with the saved money. These measures could, for instance, be to purchase goods and other resources, or, in case of public actors, pay for social measures like short-term labor for the employees (as for instance happened in Germany due to the COVID-19 crisis of 2020 (DW, 2020)). Since system boundaries necessarily lead to neglecting effects outside the system, ignoring the costs seems to be only appropriate in a very limited number of cases.

Following, a social cost approach should allow to include decision makers' preferences.

The normalized weighted sum approach is an approach that solves the problems of difficult transfer of DCFs and lack of included preferences. It is especially powerful in a bi-objective case since it allows to determine normalization values comparably easy. In the following section, we first present an example that highlights the challenges of the original social cost approach and discuss the methodological advantages of our new approach.

3 Methodology and Illustrative Example

Before discussing our approach in detail, we want to briefly address the concept of deprivation level functions (DLFs), which were introduced by Wang et al. (2017) and are regarded as an alternative to DCFs (Shao et al., 2020). DLFs "provide[s] information about the degree — not the economic value — of human suffering" and can, therefore, be "defined as the degree of human suffering caused by lack of access to a good or service" (Wang et al., 2017). While DCFs are defined in terms of costs, DLFs range on a scale from 0 to 10. Even though this approach also offers a variety of advantages (see for instance Shao et al. (2020)), we will focus on DCFs in the present study since a well defined DCF, in spite of the difficulties from an ethical perspective, provides additional room for discussion of results for decision makers. However, we want to note that our approach can also be applied with DLFs.

We make use of the following example to highlight our concerns with the way social costs are defined and to show the advantages of our new approach (see Figure 1).

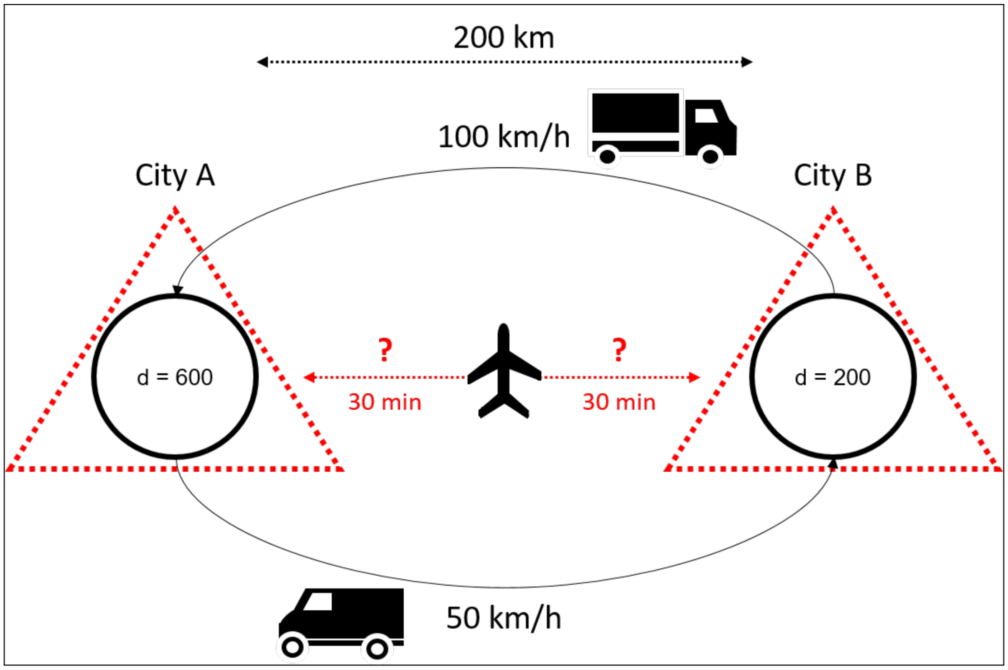

Figure 1: Overview of the example situation.

We assume that after a disaster disrupted the tap water supply of cities A and B, a humanitarian organization (HO) becomes active and plans to deliver water to the cities. Therefore, they need to decide at which airport they should land with their airplane full of bottled water for 800 people. They can either land in city A, which is inhabited by 600 people, or in city B, in which 200 people live. The roads that connect the two cities allow traffic in one direction and limit the weight and speed of trucks that are allowed to drive on them. The street from A to B is a backroad and only light trucks are allowed to drive on it, while the street in the other direction is well maintained, allowing heavier trucks to drive on it. Hence, goods transported from A to B are transported in two lightly loaded trucks at total costs of 2.80€ per km, while a fully loaded truck can transport all goods in the other direction (at total costs of 1.40€ per km). The heavy loaded truck can drive at 100 km per hour, while the small trucks are only allowed to operate at a speed of 50 km per hour due to the road conditions. The cities are located 200km away from each other, and it takes the airplane 30 minutes to both cities.

From a social cost minimizing point of view, the preferred option offers the minimum sum of LC and DC. The LC are 200 km $*$ 2.8€ = 560€ if the goods are delivered by plane to A first and then delivered by truck to B and 200km $*$ 1.4€ = 280€ if the plane lands in B and the goods are delivered by truck to A afterwards.

DC depend on the number of affected people and the time until the goods reach their city. For example, 600 people would be without water for 0.5 hours and 200 people for 4.5 hours if the plane landed in A. Assuming that it is possible to transfer DCFs from one area to another, we use the DCF of Moreno et al. (2018), in which the DC result in 1,114€ if the plane lands in A and 1,377€ if it lands in B. Consequently, the HO would prefer to land in B since the resulting social costs of 1,657€ are below the 1,674€ of the other option.

However, using a different DCF can obviously lead to different results. As mentioned in Section 1, the range of DCFs determined for one good and economy compared to the same good and another economical situation can vary at factors of above 3 during a crisis. Let us, therefore, consider an alternative DCF that is three times higher than the DCF of Moreno et al. (2018).

Even though the relative values of the DC stay the same, the net difference between the DC of option A and B triples, leading to social costs that favor landing in city A. Consequently, it can be followed that the social cost approach is only robust if DCFs are defined accurately and implicitly balanced with their corresponding LC, and that the way social costs implemented in the current body of literature needs some adjustments. Consequently, we suggest to adapt the way we use DCFs and LC in social costs objective functions and normalize them.

Multiple ways to normalize exist, which all have their benefits and drawbacks (see for instance Kim and de Weck (2005) for an overview). An example in the context of disaster logistics is the approach from Zhu et al. (2019), who normalize logistical, deprivation, and relative DC with the help of its maximum and minimum and use an ant colony optimization algorithm to obtain a solution. Even though this leads to normalization in the interval of 0 and 1, the approach is regarded as "inefficient and not practical" (Mausser, 2006). If, for instance, option s_1 leads to the minimal DC at LC of l_1, every option that leads to LC $l_2 \leq l_1$ would be dominated by s_1.

Hence, a more practical way is to normalize with the so-called *Nadir* and *Ideal* Points (see Figure 2), since they lead to Pareto-efficient solutions (Mausser, 2006). The "Ideal Point" can be defined as "the vector composed of the best objective values over the search space," while the Nadir point represents "the vector composed of the worst objective values over the Pareto set" (Bechikh et al., 2015).

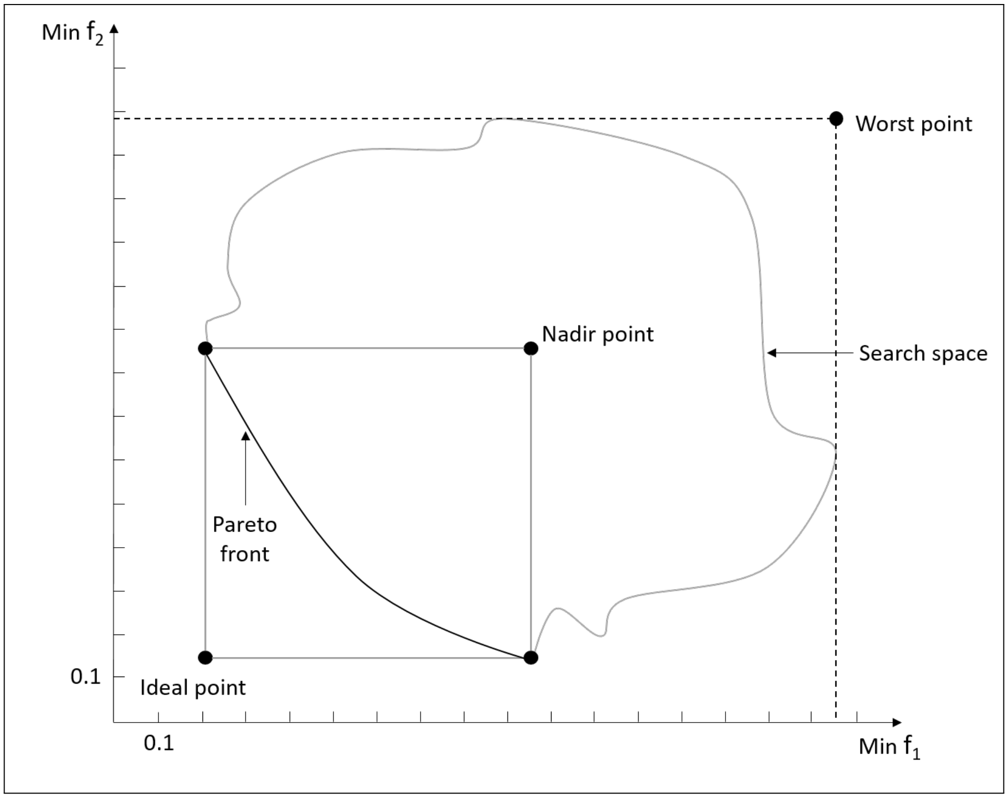

Figure 2: Visualization of Nadir and Ideal Point (adapted from Bechikh et al. (2015)).

The normalization of an objective value z_i follows Kim and de Weck (2005):

$$\bar{z}_i = \frac{z_i - {z_i}^{Ideal}}{{z_i}^{Nadir} - {z_i}^{Ideal}} \tag{1}$$

Moreover, the weighting factor α represents the relative value of the DC part of the social costs to allow decision makers to prioritize the two components in a preferred way. It follows that we choose the feasible solution x that leads to the minimal normalized weighted social costs:

$$\min \ \alpha * \frac{LC(x) - LC^{\ Ideal}}{LC^{\ Nadir} - LC^{\ Ideal}} + (1-\alpha) * \frac{DC(x) - DC^{\ Ideal}}{DC^{\ Nadir} - DC^{\ Ideal}} \tag{2}$$

In the context of our illustrative example with the DCF from Moreno et al. (2018), the Ideal point is (280€; 1,114€) and the Nadir point (560€; 1,377€). Consequently, the normalized social costs result as 1 in case the plane lands in A or B for $\alpha = 0.5$. If the decision maker has a preference towards regarding DC or LC as more important ($\alpha < 0.5$ or $\alpha > 0.5$), a solution that fits to the preferences of the decision maker results.

As we will show in the following section, more complex scenarios lead to more granular variations of solutions. Hence, the sensitivity of a decision towards social costs is reflected in more detail, leading to a significant increase in transparency for decision makers. Our approach can, therefore, provide critical support for decision makers in disaster relief.

4 Case Study

4.1 Scenario Description

We assume that authorities in Berlin want to prepare for a hypothetical failure of Berlin's tap water system, for instance due to a large-scale water contamination. The tap water cannot be used anymore. Therefore, the population needs to be quickly supplied with bottled water to fulfill their basic needs.

Consequently, public authorities need to become active and install a humanitarian supply chain to provide bottled water to the population, in our case for a time period of 48 hours. We acknowledge the time it takes to set up the supply chain by assuming that deliveries arrive in Berlin 24 hours after the start of the crisis.

The structure of the humanitarian supply chain is in line with Cotes and Cantillo (2019): The bottles enter the system at consolidation centers (CCs), from where they are transported via distribution centers (DiCs) to the demand points (DPs). Figure 3 highlights the structure of the logistical network.

In the context of our case study, we assume that the set I contains three CCs located on the outskirts of Berlin, from where the required bottles are transported via various transport routes to the city area. The set J of potential DiCs consists of 12 warehouse locations distributed across Berlin, which are currently used from private companies. We assume that the 24 hours between the start of the crisis and the arrival of deliveries is sufficient to modify the warehouses for incoming goods. Moreover, the water is delivered to 631 schools distributed all over Berlin, at which the population can pick up the water. Figure 4 highlights the positions of the DiCs and CCs on the map of Berlin.

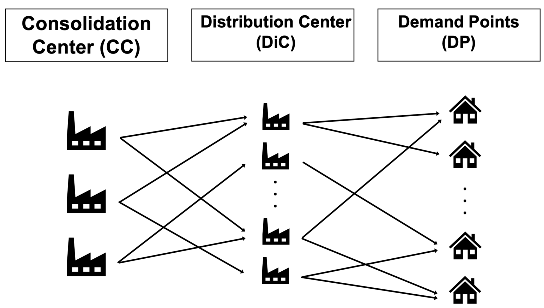

Figure 3: Structure of logistic network.

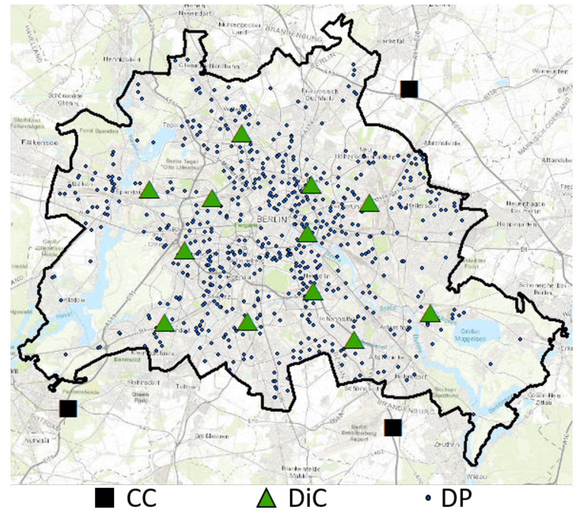

Figure 4: Locations of CCs, DiCs, and DPs.

Since CCs and DPs are considered fixed, authorities need to decide which DiCs should be opened. Opening additional DiCs costs money but leads to faster deliveries and reduced deprivation. Hence, authorities face the trade-off between logistics cost and deprivation cost described above by identifying an appropriate set of locations.

We consider two scenarios to cover the potential combinations of demand and supply: In the first scenario, the water arriving at the CCs is sufficient to match the demand of the population (Balanced Scenario).[1] In the second scenario, the demand is not sufficient to match the demand (Unbalanced Scenario).

Hence, deprivation is expected to increase significantly. In the context of our case study, we assume that only 90% of the demand can be fulfilled, even though the calculations can be easily adjusted to fewer deliveries.

4.2 Development of a Humanitarian Facility Location Model

As mentioned above, our supply chain and the connected model closely build upon the work of Cotes and Cantillo (2019) and the related literature discussed in their article. We first provide an overview of the nomenclature and the Balanced Scenario. Following, we discuss the adaptions for the Unbalanced Scenario and the necessary steps to calculate the values of parameters.

[1]Note that the developed model can also be applied to a scenario of exceeding supply. Since the results do not significantly differ from the results of the Balanced Scenario, we only focus on two scenarios.

4.2.1 Nomenclature

Sets

I: Set of Consolidation Centers (CCs)

J: Set of potential Distribution Centers (DiCs)

K: Set of Demand Points (DPs)

Parameters

α: Weighting factor for LC (relative to DC), $\alpha \in [0; 1]$

c_{ijk}: Transport costs from CC i to DP k via DiC j per unit transported

d_k: Demand in DP k

f_j: Fixed costs for setting up facility j

$\gamma(t_{ijk})$: DC as a function of transport time t

t_{ijk}: Transport time from CC i to DP k via DiC j

q_k: Population in DP k

LC^{ideal}: Value of Ideal Point of LC

LC^{nadir}: Value of Nadir Point of LC

DC^{ideal}: Value of Ideal Point of DC

DC^{nadir}: Value of Nadir Point of DC

s_i: Supply of CC i

cap_j: Capacity of DiC j

Decision variables

x_{ijk}: Proportion of demand in DP k, that is provided by CC i via DiC j

y_j: Binary variable that represents the decision to open a location

4.2.2 Mathematical Formulation for the Balanced Scenario

The model for the Balanced Scenario is a capacitated facility location problem with multi-allocation. It can be applied to find an optimal location and transportation plan that minimizes social costs in a post-disaster context.

$$
\begin{aligned}
\min \quad & \alpha \cdot \left(\frac{\sum\limits_{i \in I} \sum\limits_{j \in J} \sum\limits_{k \in K} c_{ijk} \cdot x_{ijk} \cdot d_k + \sum\limits_{j \in J} f_j \cdot y_j - LC^{\ ideal}}{LC^{\ nadir} - LC^{\ ideal}} \right) \\
& + (1-\alpha) \cdot \left(\frac{\sum\limits_{i \in I} \sum\limits_{j \in J} \sum\limits_{k \in K} \gamma(t_{ijk}) \cdot x_{ijk} \cdot q_k - DC^{\ ideal}}{DC^{\ nadir} - DC^{\ ideal}} \right) && (3) \\
\text{s.t.} \quad & \sum_{j \in J} \sum_{k \in K} x_{ijk} \cdot d_k \leq s_i && \forall i \in I && (4) \\
& \sum_{i \in I} \sum_{j \in J} x_{ijk} = 1 && \forall k \in K && (5) \\
& \sum_{i \in I} \sum_{k \in K} x_{ijk} \cdot d_k \leq cap_j \cdot y_j && \forall j \in J && (6) \\
& x_{ijk} \leq 1 && \forall i \in I,\ \forall j \in J,\ \forall k \in K && (7) \\
& x_{ijk} \geq 0 && \forall i \in I,\ \forall j \in J,\ \forall k \in K && (8) \\
& y_j \in \{0, 1\} && \forall j \in J && (9)
\end{aligned}
$$

The objective is to minimize the weighted sum of the normalized social costs (as described in Section 3). As described above, the factor α implements a weighting between the two normalized objectives.

Eq. (4) ensures that the total quantity delivered by CC i does not exceed the supply s_i and Eq. (5) guarantees complete satisfaction of the demand of each of the DPs.

Constraint (6) serves two functions: On the one hand, it ensures that deliveries only flow via a DiC j if it is actually opened ($y_j = 1$). On the other hand, it limits the flows that go through each DiC below the capacity limit (cap_j).

Eq. (7) and Eq. (8) define the decision variable $x_{ijk} \in [0, 1]$ and Eq. (9) the binary decision variable y_j. In contrast to y_j, x_{ijk} is not subject to an integer condition. Therefore, multi allocation is enabled, which allows the model to satisfy the demand of a DP by supplies of several CCs if this is advantageous for minimizing social costs.

4.2.3 Modifications for the Unbalanced Scenario

The model described above needs to be slightly adjusted for the Unbalanced Scenario, where supply and demand are not identical (see for instance Girmay and Sharma (2013) for an overview of balanced and unbalanced transportation problems).

It is common practice to transform the unbalanced problem into a balanced problem by adding a dummy supply node that artificially compensates for the lack of supply (Girmay and Sharma, 2013, Vasko and Storozhyshina, 2011). Compared to the model developed above, this implies an extension of the set I of CCs by an artificial node DK. This node accounts for the unsatisfied demand by representing a fictitious supply, whereby a feasible solution can now be calculated. Thus, the supply of the DF is equal to the amount of the missing quantity of goods.

The transport costs emanating from DK are set to 0 because there is no actual delivery. Therefore, no additional costs for these imaginary transports influence the objective function. Consequently, the people receiving a fictitious delivery from this node are not supplied in reality. To account for their undersupply in the assessment of DC, the transport time t is set to the time horizon t_{max} covered by the model, since these people do not receive any delivery until the end of the planning period.

Moreover, the following applies to the parameters related to DK:

Supply:	s_{DK}	$= \sum_{k \in K} n_k - \sum_{i \in I} a_i$	
Transport costs:	c_{DKjk}	$= 0$	$\forall j \in J,\ \forall k \in K$
Artificial transport time:	t_{DKjk}	$= t_{max}$	$\forall j \in J,\ \forall k \in K$
DC:	$\gamma(t_{DKjk})$	$= \gamma(t_{max})$	$\forall j \in J,\ \forall k \in K$

4.2.4 Computation of Parameters for Normalization

According to Kirlik and Sayın (2015), the nadir point in bi-criteria optimization "is attained among solutions that minimize the first objective function and vice versa" (p. 82). So $DC^{\ nadir}$ is the value of the DC that results during computation of $LC^{\ ideal}$, and vice versa.

Therefore, the presented models have to be solved twice to determine the values for the normalization. For the calculation of $LC^{\ ideal}$ we use the following function:

$$\min\ \text{LC} \quad = \quad \min \quad \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} c_{ijk} \cdot x_{ijk} \cdot d_k + \sum_{j \in J} f_j \cdot y_j \tag{10}$$

Simultaneously the following term replaces the original objective function to determine DC^{ideal}:

$$\min\ \text{DC} \quad = \quad \min \quad \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \gamma(t_{ijk}) \cdot x_{ijk} \cdot q_k \tag{11}$$

4.3 Data Collection

4.3.1 Demand and Supply

According to the city of Berlin, 3.754 million people live in Berlin (Berlin.de, 2019). In line with the Sphere-Handbook, we assume a water demand of 3 liters per person per day, which represents the absolute minimum for survival (Sphere, 2018). During the modeled time horizon of 48 hours, a total demand of 22.526 million liters results. This demand is allocated to the 631 public schools of Berlin, which serve as DPs. The allocation followed the proportion of students per school, obtained from the Berlin Senate Department for Education, Youth, and Sport (Berlin Department for Education, Youth and Sport, 2019). As mentioned above, the supply either matches the demand (Balanced Scenario) or is 10% below it (Unbalanced Scenario). The corresponding amount of water is evenly distributed to the three CCs in both scenarios.

To quantify the suffering of the population in case of water shortage, we use the DCF of Moreno et al. (2018):[2]

$$\gamma(t_{ijk})\ [€] \quad = \quad 31,752 \cdot \frac{e^{(1.5031+0.1172\cdot t_{ijk})} - e^{1.5031}}{e^{(1.5031+0.1172\cdot 72)} - e^{1.5031}} \tag{12}$$

$\gamma(t_{ijk})$ depends on the time t_{ijk} that passes until the demand of a person is satisfied. Hence, it consists of the time it takes for the goods to arrive at the CCs (t_i^0) and the transport time from CC i to DP k via DiC j.

We regard an average travel speed in regular road traffic for Berlin to compute the first stage transport time (from CCs to DiCs). According to the German "Zukunft Mobilität", the average travel speed in Berlin is about 24 km per hour (ZukMob, 2012). As a consequence of the prevailing state of emergency, we further assume a reduction of speed on the second stage (from DiCs to DPs) by 50%. Since this includes a lot of uncertainty, we discuss different options for the potential speed reduction in Section 5.3.

4.3.2 Infrastructure and Transportation

We assume fixed costs of 1€ per square meter of DiC (the average DiC has a size of 17k m^2). Moreover, we assume that 0.768 pallets of water can be stored on one m^2 storage space, taking into account the size of the pallet (1.2m*0.8m), and a cushion of 20% (e.g. for hallways or common rooms). This is in line with Gudehus (2012), who suggest a range of 0.4-1.8 pallets per m^2 for block storage.[3]

[2]Converted into EUR with the 2019 average exchange rate of 0.2268 € per Brazilian Real (ECB, 2020).

[3]Note that, even though the DiCs offer these capacities, in reality, not all necessary space would be used since the pallets will not be in the DiCs for a long time. However, it will probably also not be possible to empty the warehouse completely, leaving a part of the area blocked. Within our model, we assume that these two effects even each other out.

Regarding transportation cost, we distinguish between two different cost components - the transport from CC to DiC (first stage), and the transport from DiC to DP (second stage). All distances are based on linear distances calculated with ArcGIS Desktop 10.6, multiplyied with a tortuosity factor of $\sqrt{2}$ (Diehlmann et al., 2019). We assume that the transport on the first stage is conducted on a sizeable 40t truck with a payload of 24t and space for 33 pallets. In discussions with a German logistics service provider (LSP), we select a cost rate of 0.058€ per ton and kilometer.[4]

The cost estimation for the second transportation stage is more challenging since the LSP calculates the prices for these kinds of trips on a per-case-base (otherwise, a 5km trip would cost 7€). Therefore, we cannot use a directly verified kilometer-based rate for short-distance freight transportation.

Consequently, we developed a cost estimation for a truck with a payload of 10 tons, similar to Wietschel et al. (2019), including investment costs, insurance, taxes, maintenance, diesel, tolls, and driver wages. In contrast to the first transportation step, we need to regard the way back as well, resulting in costs of 0.568€ per ton and kilometer. Furthermore, labor costs for the time it takes to load and unload the truck is a large cost driver. A factor of in total 1.33€ per euro pallet is assumed.

These estimations have been validated with the LSP, comparing the costs with the rates they would charge for a selection of comparable trips. Even though our estimations are slightly above the rates of the LSP, we regard them as validated since some "disaster premium" can be expected.

5 Results

The models were implemented in GAMS and solved with the CPLEX-solver on an AMD-Ryzen 7 (3.8 GHz, 64 GB RAM). We consider the whole α-interval $[0; 1]$ in steps of 0.1.

5.1 Results of the Balanced Scenario

Figure 5 highlights the optimal number of DiCs dependent on different values for α. The numbers in brackets represent the set of opened DiC locations related to the respective solution. At $\alpha = 0$, when only DC are considered in the objective function, all DiCs are opened. With increasing value of α, the number of DiC locations is gradually decreasing until it reaches its minimum of 4 at $\alpha = 1$, which represents a decision only based on LC.

Taking a closer look at the solutions, some sites are more present than others. Especially the three DiCs 1,5 and 6 should be highlighted in this context since they are included in every solution independent of α.

[4]Note that this cost rate is based on the one-way distance. Therefore, we do not regard the return journey within this transportation stage.

They can be identified as robust locations and should, therefore, be opened, regardless of the decision makers preferences.

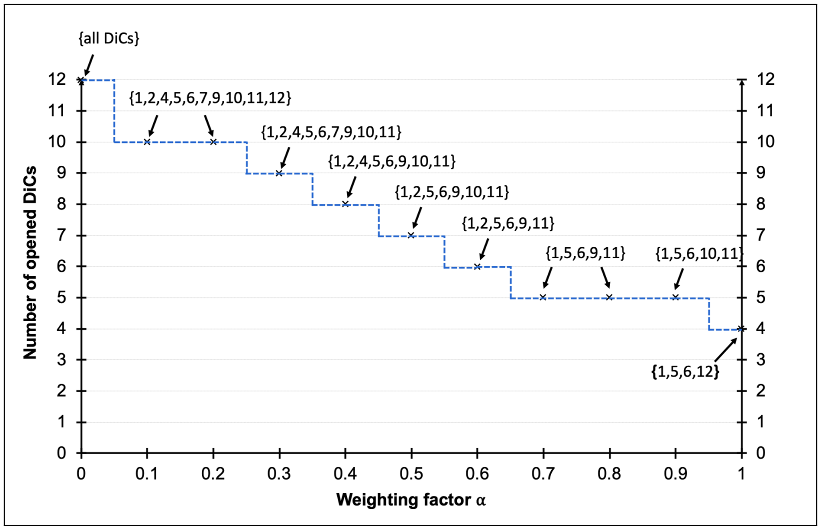

Figure 5: Opened DiCs for different values of α in the Balanced Scenario.

Figure 6 illustrates the absolute costs of the solutions. The LC lie within the interval of $[368K€; 1,095K€]$ and decrease as α increases. Hence, they reach their minimum at $\alpha = 1$. The DC fall within the interval of $[455M€; 475M€]$ and in contrast to the LC, they increase as α increases. Consequently, the minimal DC are located at $\alpha = 0$. Furthermore, the figure highlights the need to normalize if decision makers plan to include both aspects of social costs since the DC completely outweigh the LC.

Figure 7 highlights the value of LC and DC with respect to the related value of α. Hence, the relationship between the two conflicting objectives becomes apparent, since one type of cost decreases if the other one increases and vice versa.

The results in the Balanced Scenario can be summarized the following way: DiCs 1, 5, and 6 are robust locations and should, therefore, be opened in any case. Beyond that, no general recommendation can be made since all of the presented solutions are Pareto-efficient. The decision for one of these Pareto-efficient solutions depends on the decision maker and, therefore, the preferred value of α. The preference can be influenced by factors such as the general risk perception of the decision maker, the available budget, or the underlying situation in general.

For example, if a large budget is available, a solution in the α-range between 0.1 and 0.2 could be reasonable since both types of costs remain unchanged in this area. Until $\alpha = 0.1$, the LC rapidly decrease while the DC only slightly increase. On the other hand, with a lower budget, a value between 0.7 and 0.8 could be appropriate as the LC are quite close to their minimal cost while DC are still moderate. In contrast, with α-values greater than 0.8, the DC increase at a disproportionate rate in relation to the small savings regarding the LC.

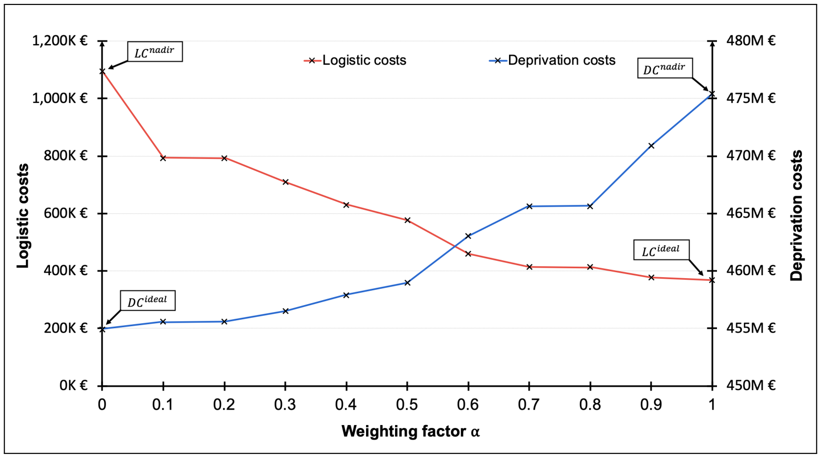

Figure 6: Logistic and deprivation costs for different values of α in the Balanced Scenario.

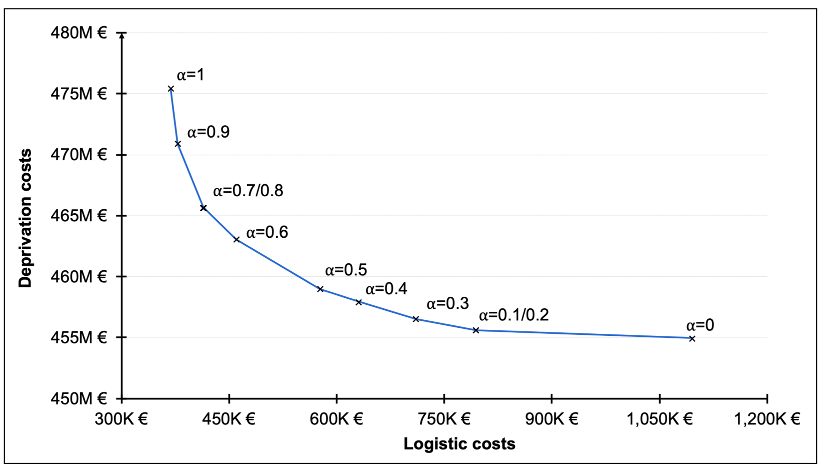

Figure 7: Pareto-front with an indication of different values for α in the Balanced Scenario.

5.2 Results of the Unbalanced Scenario

Figure 8 highlights the different optimal location decisions with respect to the value of the weighting factor α. The general course of the solutions looks similar to the course of the graph for the first scenario: all 12 DiCs are opened if $\alpha = 0$, and the number of DiCs decreases as α increases. At $\alpha = 1$, only 4 open DiCs are left.

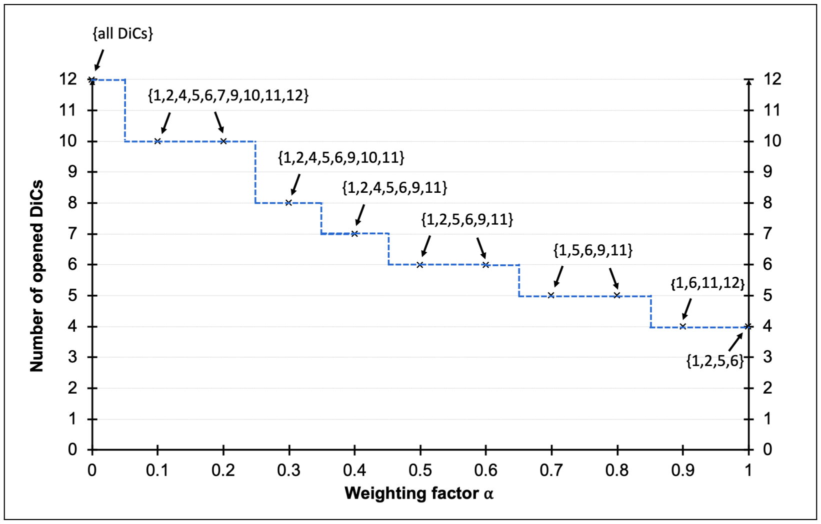

Figure 8: Opened DiCs for different values of α in the Unbalanced Scenario.

However, a comparison of the solutions reveals differences, not only regarding the number of locations but also the composition of optimal DiC-sets, especially in the higher α range. As in the balanced case, DiCs 1 and 6 are included in every solution and can, therefore, be identified as robust locations. In contrast to the first scenario, DiC 5 is no robust location in the unbalanced case. Compared to the results described above, DiC 5 is not opened in the case of $\alpha = 0.9$, but DiC is 11 opened instead. DiC 11 offers less space at less cost than DiC 5. Since fewer goods flow within the system, the size of DiC 11 combined with the other three open DiCs is sufficient now, allowing to reduce costs.

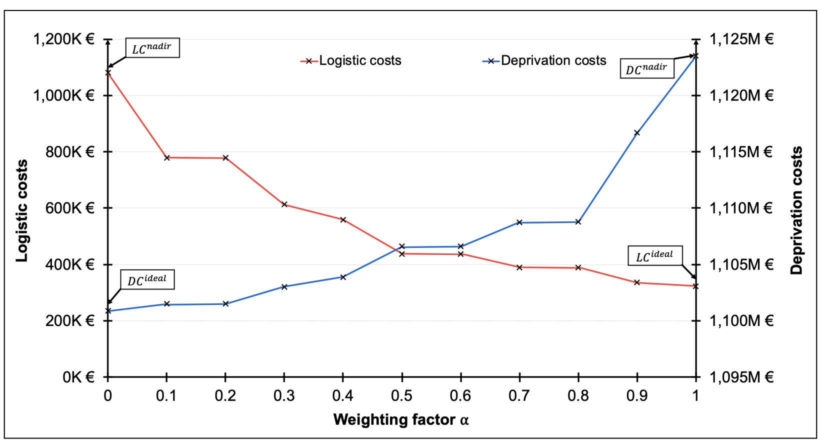

Figure 9: Logistic and deprivation costs for different values of α in the Unbalanced Scenario.

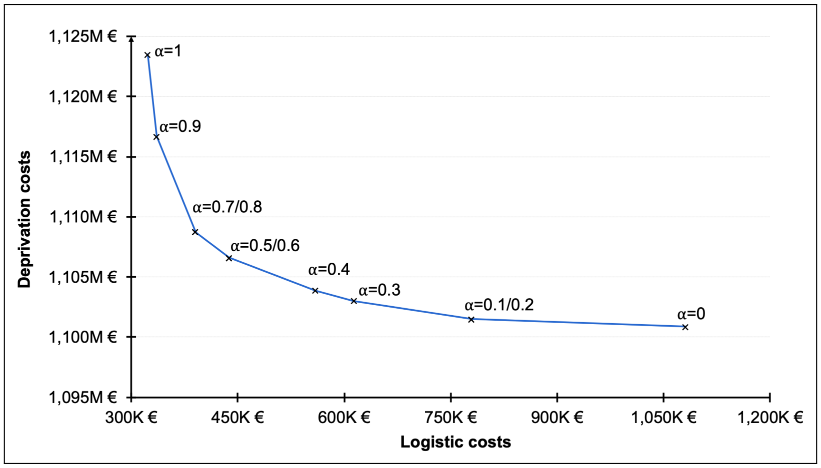

Figure 10: Logistic and deprivation costs for different values of α in the Unbalanced Scenario.

The costs are illustrated in Figure 9. They show a similar pattern as in the Balanced Scenario. However, it is noticeable that, compared to the first scenario, DC are much higher. They range from 1,100M€ to 1,124M€. This high number results from the undersupply underlying this scenario. Even though only 10% of supplies are missing, total deprivation more than doubles, highlighting the exponential structure of DCFs.

Figure 10 highlights the Pareto-front and, therefore, the trade-off between LC and DC. Even though the absolute numbers differ in magnitude, the course is very similar to Figure 7 and, thus, underlines the competitive nature of the two objectives as well.

The results in the Unbalanced Scenario can be summarized in the following way: DiCs 1 and 6 are robust locations and should be opened in any case. As stated before, the final decision depends on the preferences of the decision maker. Similar to the first scenario, α-values between 0.1 and 0.2 could be reasonable for high budgets. On the other hand, α could be set to a value between 0.7-0.8 for low budgets.

5.3 Analysis of the Sensitivity Towards Travel Speed and DiC Capacities

As mentioned above, we furthermore want to discuss the sensitivity of the results towards two key assumptions: the travel speed and the number of pallets per m^2 of DiC area.

Table 1 highlights this analysis for the Balanced Scenario. In addition to the combination discussed in detail above (12 km/h and 0.768 pallets per m^2), the table shows the LC, DC, and number of opened DiCs for different combinations of travel speed and capacity. Note that an equal number of open DiCs does not automatically lead to equal DC or LC. Since the number of pallets that fit in one DiC strongly depends on the capacity of pallets per square-meter, travel distances change within the selected combinations. Moreover, we calculate DCs based on travel time. Consequently, they increase if travel speed slows down.

	speed 2nd stage		6 kmh	speed 2nd stage		12 kmh	speed 2nd stage		18 kmh	speed 2nd stage		6 kmh	speed 2nd stage		12 kmh	speed 2nd stage		18 kmh
	pallets per m2		0.768	pallets per m2		0.768	pallets per m2		0.768	pallets per m2		2	pallets per m2		2	pallets per m2		2
alpha	LC[k€]	DC [k€]	#DiCs	LC[k€]	DC [k€]	#DiCs	LC[k€]	DC [k€]	#DiCs	LC[k€]	DC [k€]	#DiCs	LC[k€]	DC [k€]	#DiCs	LC[k€]	DC [k€]	#DiCs
0	1,093	477,585	12	1,096	454,943	12	1,102	446,967	12	1,093	477,494	12	1,096	454,871	12	1,103	446,885	12
0.1	1,093	477,585	12	794	455,600	10	800	447,134	10	947	478,508	11	794	455,543	10	744	447,202	9
0.2	792	480,343	10	794	455,601	10	744	447,334	9	792	480,271	10	794	455,544	10	665	447,736	8
0.3	792	480,343	10	711	456,543	9	587	448,440	7	708	482,488	9	616	457,868	8	463	449,230	6
0.4	708	482,557	9	631	457,923	8	587	448,440	7	440	494,049	6	459	460,865	6	423	449,745	5
0.5	575	488,730	7	577	458,988	7	535	449,181	6	440	494,050	6	409	462,809	5	373	450,784	4
0.6	418	500,346	6	460	463,073	6	416	452,499	5	440	494,053	6	408	462,821	5	373	450,784	4
0.7	418	500,349	6	414	465,654	5	416	452,499	5	368	506,882	5	371	465,164	4	373	450,793	4
0.8	418	500,365	6	414	465,675	5	416	452,508	5	331	514,776	4	332	469,839	4	373	450,793	4
0.9	369	516,690	4	379	470,913	5	379	457,202	5	303	529,663	3	303	478,569	3	303	462,905	3
1	369	517,023	4	369	475,433	4	369	462,508	4	298	544,792	2	298	487,092	2	298	469,503	2
Mean	640	492,901	7.82	604	461,850	7.36	578	451,337	6.82	560	499,730	6.73	535	464,635	6.27	499	452,396	5.55

Table 1: Results for different combinations of travel speeds and pallet per area.

An increase in travel speed leads to a reduction in both types of costs - LC and DC. However, the significance of the effect differs. The mean drop in LC is on average 0.033% for each percent increase in travel speed in case of 0.768 pallets per m^2 (and 0.036% in case of 2 pallets per m^2). Moreover, the mean DC drop by an average of 0.028% (and 0.032%).

However, an increase in the number of pallets per m^2 comes along with more complex effects. On the one hand, the mean LC decrease by 0.048% for each percent increase in pallet capacity in case of a second stage travel speed of 6 km per hour (0.044% for 12 km per hour and 0.052% for 18 km per hour). On the other hand, mean DC slightly increase in all cases - 0.001% in case of 6 km per hour and even smaller increases for different travel distances. This is unexpected since the increased capacity of DiCs allows for additional options to deliver goods through them. Consequently, it can be followed that the positive effects of the LC significantly outweigh the changes in DC. This, furthermore, underlines the importance of considering both objectives simultaneously and to take a close look at the trade-offs between both objectives.

6 Discussion

The results of both scenarios underline the wide range of applications and the great versatility of the developed approach. The weighting factor α allows the decision maker to integrate individual preferences into the calculation of an optimal location decision based on the available budget and the particular situation.

In the case of $\alpha = 0$, only the DC are included in the objective function. Accordingly, if α is set to 1, only the LC are considered. Every other value for the weighting factor in between these two extremes represents a weighted mixture of both cost objectives. This allows the decision maker not only to implement a prioritization for one of the cost factors according to the disaster situation but also to identify potentially suitable options for action by examining the entire interval $\alpha \in [0; 1]$.

Moreover, different phases of the disaster can lead to different preferences and, consequently, different values for α. For example, it is possible to use a lower value for α in disaster relief than in preparedness.

Additionally, by examining the entire α-interval, some DiCs can often be excluded entirely from the set of potential DiC locations because they do not occur in any of the calculated solutions. Furthermore, robust DiC locations may be found that appear in each of the solutions and should, therefore, be in the focus of authorities preparing for a disaster.

In contrast to the original definition of social costs in the objective function by Holguín-Veras et al. (2013), this leads to a significant increase in transparency and, therefore, provides valuable support for decision makers. Figures 11 and 12 highlight this by presenting the number of opened DiCs and the cost structure for the Balanced Scenario without normalization.

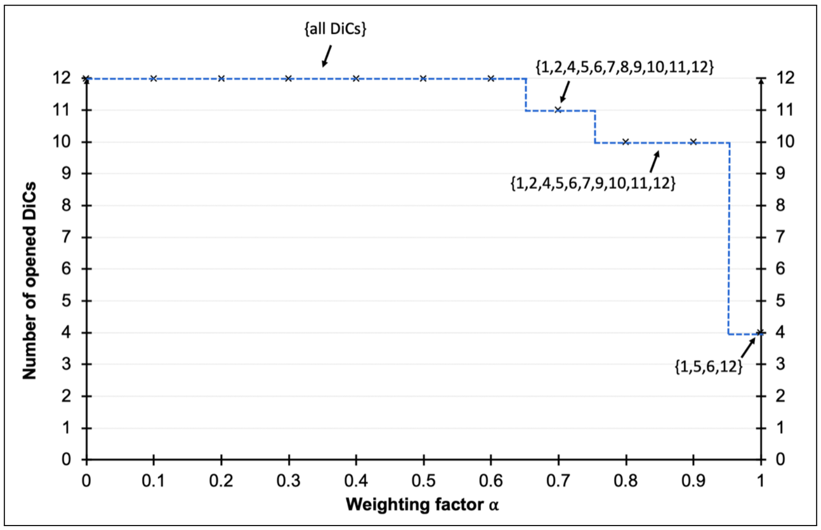

Figure 11: Opened DiCs for different values of α without normalization in the Balanced Scenario.

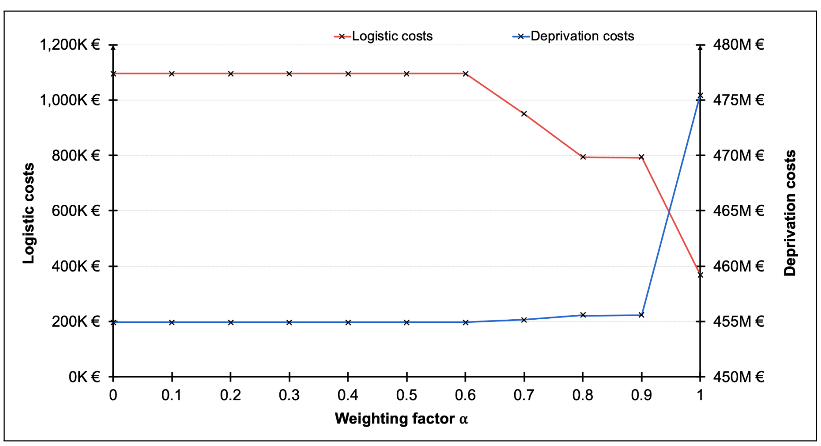

Figure 12: Logistic and deprivation costs for different values of α without normalization in the Balanced Scenario.

It follows that before we introduced our approach, decision makers would open all DiCs since they would only regard the outcome of $\alpha = 0.5$. Furthermore, the implicit prioritization of DC leads to a comparably rigid function behavior and a sudden drop for α between 0.9 and 1. This drop highlights the benefits of normalization since it allows decision makers to understand the sensitivities of the SCF more thoroughly.

In addition, as shown in our solution analyses of the two scenarios, the model can provide a good overview of the possible trade-offs between different options by analyzing the Pareto-front in respect to $\alpha \in [0, 1]$. Therefore, it supports the whole decision making process and, thus, facilitates to tailor decisions to the specific disaster context.

7 Conclusion

The use of social cost functions in humanitarian logistics depends on well-defined deprivation cost functions. However, only very few of these functions have been scientifically developed. Combined with the lack of transferability due to a strong sensitivity towards local economic conditions, the application of social cost functions is difficult. Moreover, the original definition of social cost functions in humanitarian logistics comes along with two potential weaknesses. First, it does not allow to include preferences of decision makers towards one of the two cost components. Second, it contains an implicit weighting since deprivation costs can completely outweigh logistic costs in disaster relief.

Therefore, we further developed the concept of social costs in humanitarian logistics and introduced a normalized weighted sum approach. After presenting the methodological foundations of the approach, we applied it to a case study for a hypothetical water system failure in the city of Berlin. Assuming that authorities want to prepare for such a scenario, we developed a model that identifies an appropriate distribution network. Since it is not clear if the supply is sufficient, the model needed to be flexible enough to consider both cases (Balanced and Unbalanced), which we investigated in two scenarios. Furthermore, we compared the results with the results of the original definition, highlighting the increase in transparency, in particular with respect to the sensitivity of the decision.

Future studies can complement our approach in many ways. For example, it would be possible to derive "rule-of-thumb factors" for α in a survey of decision makers from different institutions (e.g. private sector, NGOs, authorities). While the approach supports decision makers to understand their decisions better, they still need to decide for an appropriate α by themselves. Therefore, standard values could work as a starting point for discussions with decision makers.

Moreover, the application of the approach in the context of collaboration seems promising. If, for instance, public and private actors work together in a Public-Private Emergency Collaboration (PPEC, Wiens et al.

(n.d.)), different combinations of individual preferences would affect the outcome of the PPEC significantly. Hence, our approach could support them aligning their objectives and finding compromises for long term collaboration. Moreover, it is possible to derive Pareto-fronts for different collaboration scenarios and, therefore, allocate budget to a portfolio that fits the individual preferences best. Consequently, this could enable a better coordination of resources and, thus, likely improve the outcome of future interventions (Maghsoudi et al., 2018).

Despite the potential fields of further investigation, we can conclude that our approach significantly increases transparency for decision makers and allows them to include their preferences into the objective function. Thus, it leads to more substantiated decisions and, consequently, to a more efficient relief logistic.

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Conflict of interest

The authors declare that they have no conflict of interest.

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