Karlsruhe Institute of Technology

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No. 51 | DECEMBER 2020

WORKING PAPER SERIES IN PRODUCTION AND ENERGY

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Abstract:

In cases where the private sector struggles to cope with the impact of a disaster, authorities try to reduce the burden on the population and set up supply chains to distribute essential goods. Therefore, they estimate demand and location of the affected people and open points of distribution to supply goods from, e.g. public buildings or sports facilities. However, the location of these points of distribution depends heavily on accurate demand estimations. Combined with a high time pressure that prevents the collection of detailed data, inefficient decisions result. However, these decisions improve significantly if private actors share their market knowledge. Since this information is strictly confidential for companies and at the same time requires a lot of coordination effort from public actors to acquire, the quantification of the benefits of the collaboration is important for both sides. Moreover, the time at which the information is received and the way the information is utilized regarding different intervention intensities is supposed to be crucial. Therefore, we develop a framework to quantify the consequences of shared information for both actors and apply it to a case study for a tap water contamination in the city of Berlin. We highlight that both actors benefit from the collaboration and that the time the information is received has a comparably low effect on the total supply. Moreover, we show that private actors can reduce the impact of market interventions on their processes significantly by actively collaborating with authorities.

Keywords: crisis management; humanitarian logistics; points of distribution; information; preparedness; facility location planning.

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1 Introduction and Motivation

While private actors manage the distribution of goods in peacetime, public authorities are responsible for guaranteeing sufficient supply to the population in times of crisis. Therefore, they need to establish new supply chains in a complex and uncertain environment (Holguín-Veras et al., 2012). However, critical decisions taken in disastrous situations are urgent, and information can therefore not be acquired in the level of detail that is required to understand the situation thoroughly (Gralla et al., 2016). The required information comprises both the supply side (production capacity, market quantities) as well as the demand side (location and demographic characteristics of people in need).

In contrast to private actors who manage to build a deeper understanding of the market every day, public actors usually only possess general market data about the firms' capacities or production quantities. For instance, German authorities conduct a survey that tracks the produced amounts of "fats, cereal, starch, feedstuffs, milk, and sugar industries" on a regular basis (Federal Office for Agriculture and Food Germany, 2019). However, it remains unclear if and how this static and production focused data can prove itself valuable in disaster relief. Furthermore, the German government installed an interface where pharmacies can report bottlenecks in critical supplies (Federal Institute for Drugs and Medical Devices Germany, n.d.). Even though this approach seems promising to reduce the response time to crises in the medical sector, a holistic approach to information acquisition seems more powerful.

To tackle this issue, the US Federal Emergency Management Agency is running a pilot study to test the value of near-real-time data in disaster relief, proactively by purchasing access to market data for 3.6 million USD for one year (Federaltimes, 2019).

A less costly approach to receive information in crises could be by collaboration. The importance of collaboration in disaster logistics has been widely acknowledged and different aspects of collaboration have been discussed (see for instance Rodríguez-Espíndola et al. (2018a); Waugh Jr. and Streib (2006)). However, market information represents a pivotal asset to companies and have therefore been highlighted as one of the key challenges for effective collaboration (Nurmala et al., 2017). Therefore, it remains questionable if private actors are willing to share their knowledge. Consequently, public actors need to both understand the value of the information and the implications of their decision under the different levels of information accuracy. However, to the best of our knowledge, no approach exists that quantifies the value of possessing more accurate information in Public-Private Emergency Collaborations (PPECs). Therefore, we propose a framework to quantify this value of information and analyze how this value is affected by the point of time and the intensity of the state's intervention.

Our paper is structured as follows. First, we provide an overview of related literature in the next Chapter. Afterward, we present the framework and discuss the different components in Chapter 3. Following, we highlight the power of the framework by applying it to a case study, in which German authorities need to open up *Points of Distribution* in the aftermath of a tap water system contamination. We conclude with a discussion of the strengths and weaknesses of our approach and highlight potential directions for further research.

2 Literature Review

This Section embeds our approach within the current body of literature. We focus on the following three aspects of disaster management: collaboration, facility location models, and information management.

2.1 Collaboration in Disasters

Various actors become active in the aftermath of a disaster. For example, Kovács and Spens (2007) name Government, Military, Logistics providers, Donors, Aid agencies, and other NGOs as key actors and highlight the importance of effective collaboration. Various factors might affect the coordination of these actors significantly (Balcik et al., 2010): the number and diversity of actors, donor expectations and funding structure, competition for funding and the effects of the media, unpredictability, resource scarcity/oversupply, and cost of coordination. Consequently, a variety of articles suggest approaches to mitigate some of these obstacles (Davis et al., 2013; Dubey et al., 2019; Heaslip et al., 2012; Nagurney et al., 2019; Rodon et al., 2012; Rodríguez-Espíndola et al., 2018b; Toyasaki et al., 2017).

Most of the studies discussed above involve some sort of collaboration that includes humanitarian organizations. On the other hand, the collaboration between public and private actors is especially critical for efficient disaster management (Cozzolino, 2012). While private organizations are responsible for the distribution of goods in peacetime, public actors become responsible in times of crisis. Hence, efficient collaboration between these two actors can have a significant impact on efficient relief management.

A growing body of literature is actively discussing various aspects of these so-called Public-Private Emergency Collaborations ("PPECs"; Wiens et al. (2018)). For instance, Holguín-Veras et al. (2013) discuss different objectives of both actors and argue for extending cost-based objectives with a cost-proxy for human suffering. Since commercial actors are profit-driven, effective mechanisms are required to offer the chance to collaborate successfully (Carland et al., 2018). Furthermore, Gabler et al. (2017) mention two additional barriers for PPECs: internalization and unidirectional communication. In the context of our study, unidirectional communication is especially important since it is supposed to inhibit the willingness to share information (Gabler et al., 2017).

However, to the best of our knowledge, no study exists that quantitatively measures the effects of collaboration for both actors under combined operational and informational strategies.

2.2 Allocation and Facility Location Problems in Disasters

Researchers developed a variety of approaches to locate facilities in disasters or to allocate inventory or parts of the population to these facilities. For a recent and sophisticated review, see Sabbaghtorkan et al. (2020) who analyzed location, allocation, and location-allocation papers with a focus on the prepositioning of facilities and the allocation of inventory to these facilities in anticipation of a disaster.

Additional approaches focus on the disaster relief phase, which starts right after the impact of the disaster (Kovács and Spens, 2007). Baharmand et al. (2019) developed a bi-objective and multi-commodity location-allocation model that minimizes logistics cost and response time. Zhao et al. (2017) developed a model that minimizes opening cost and walking distance for beneficiaries dependent on the forecasted shelter demand. Görmez et al. (2011) identified shelter locations in response to an earthquake in Istanbul. None of these contributions explicitly consider strategies of information acquisition and information sharing.

Furthermore, it has to be mentioned that some covering models consider uncertainties in input values. For instance, Arana-Jiménez et al. (2020) dealt with knowledge uncertainties through fuzzy techniques, and Li et al. (2018) developed a stochastic cooperative maximum covering approach that analyzes the situation of NGOs utilizing free capacities of other NGOs' warehouses. Even though they regard different demand levels, they generalize the demand and do not regard different demand intensities for different regions simultaneously.

However, to the best of our knowledge, no study exists in which different information levels and the implications of alternative decisions are compared.

2.3 Uncertain Information in Disaster

Disasters are characterized by a high degree of uncertainty. Therefore, a variety of studies exist that deal with different aspects of uncertainty, such as for example infrastructure status (Yagci Sokat et al., 2018), travel time (Balcik and Yanıkoğlu, 2020), staff availability and customer behavior (Schätter et al., 2019), or demand and supply (Bozorgi-Amiri et al., 2013).

Our study builds upon literature regarding demand information and the exchange of information.

Even though humanitarian organizations are experts in disaster management and adapt their whole supply chain towards these uncertainties (see for instance van der Laan et al. (2016), who discuss the forecasting methods at Médecins Sans Frontières (MSF)), their supply chains are designed to be flexible towards a variety of potential disasters on a global level. Even though this increasingly leads to decentralized and more regional supply chain structures (Charles et al., 2016), the determination of concrete demand of the population after an unexpected disaster occurred still requires a significant amount of time. Therefore, humanitarian organizations use standardized guidelines like the Sphere-Handbook to define critical goods and their related demand per person in disaster settings (Sphere, 2018) and determine the required amount of goods directly after the disaster stroke (for instance via a rapid needs assessments, which is supposed to take up to seven days (International Federation of Red Cross/Red Crescent Societies, n.d.)).

To speed up the time it takes to determine demand, some researchers tried to define criteria to quickly identify areas in which potentially vulnerable parts of the population live (Kapucu, 2008; Kawashima et al., 2012; Sandholz, 2019). For instance, Sandholz (2019) surveyed the population of the German city of Cologne and identified that the likelihood of a person to possess specific emergency goods like flashlight, matches, radio, and others increases with the duration a person lives in this apartment. In spite of the power of this information, a high dependency on the availability of such data results.

In contrast to public actors or relief organizations, commercial business-to-customer (B2C) business units are interacting directly with their customers on an everyday basis. Therefore, they are used to dealing with demand fluctuations in response to unexpected incidents in the context of their Business-Continuity-Management (BCM) and have therefore a good understanding of the population's potential reaction to the disaster (Schätter et al., 2019). Consequently, other actors in disaster relief would benefit from this information significantly.

Even though information exchange in disasters is widely understood as a crucial aspect of disaster management (Celik and Corbacioglu, 2010), many impeding factors exist. Day et al. (2009) conducted interviews with relief logisticians active during Hurricane Katrina and identified eight impediments on information flows: inaccessibility, incompatible formats, inadequate flow of information, low information priority, source information, storage, medium-activity misalignment, and unwillingness. Moreover, Altay and Labonte (2014) analyzed challenges for information flows (extracted from "27 evaluations, lessons learnt reports, and mission reports") from the Active Learning Network for Accountability and Performance in Humanitarian Action. They highlighted that factors such as information quality and willingness to share information are especially important and argue that this could be improved by installing the Global Logistics Cluster as coordinator of the exchange of information. This could be combined with an approach from Sheu (2010) who developed an entropy-based fusion approach that generates information estimations based on multiple sources and their related belief strengths.

In spite of the possibilities to verify the quality of the information and to ensure that the information reaches the right decision maker faster, it remains questionable if private actors are willing to share their information with the whole cluster rather than in an exclusive and bilateral public-private setting. Moreover, sharing information is not necessarily every actor's objective. For instance, after the Haiti earthquake 2010, "some organisations simply did not feel the need to coordinate or share information, especially those with their own unrestricted funding." (Altay and Labonte, 2014).

Furthermore, the consequences of information exchange can be crucial for both actors - especially for private actors that are, in the long run, dependent on monetizing their knowledge. Before private actors agree on exchanging information, they therefore need to understand the consequences. At the same time, public actors need to understand the value of the information in case they consider purchasing or seizing critical information. However, to the best of our knowledge, no approach exists that quantifies the value of the information and puts it in perspective with the consequences of sharing the information for both actors. In the next Section, we describe the framework we developed to fill this gap.

3 Model Framework

3.1 Problem Statement

We take the perspective of public authorities, which aim to supply the population of a city or an urban district with essential goods (e.g. water) during a crisis. Therefore, they need to decide which Points of Distribution (PoDs) they should open to supply goods to the population. However, they do not possess detailed information about the distribution of the total demand within the area. This demand depends on the goods people stockpiled at home. On the other hand, private actors possess this knowledge since they interact with their customers every day, e.g. by analysing Point of Sales data, and can therefore extract information regarding the purchasing behavior and goods people store at home. An example could be a district in which many diabetic people live, resulting in an increased number of diabetic-friendly products in stores.

Before authorities start to contact private actors and ask them to share the information, they need to determine the value of the information to decide for measures to take (extreme measures such as seizure can only be considered in case obtaining the information makes an extremely significant difference).

3.2 Framework to Quantify the Value of Information

The following framework describes the problem mentioned above and an approach to quantify the value of the information (see Figure 1). Three steps are required to determine the value of information.

First, we analyze the Scenario, in which the decision-maker possesses no accurate demand information. Therefore, the demand of the population is assumed to be equally distributed ("ED"-Scenario; grey boxes in Figure 1 and aggregated to Demand Points (DPs)). In the next step, we allocate these DPs to supermarkets, so that the utilization of the capacities of the supermarket is as high as possible. Moreover, a maximum walking distance is regarded. If the crisis is severe, the state - or in extreme cases NGOs - becomes active

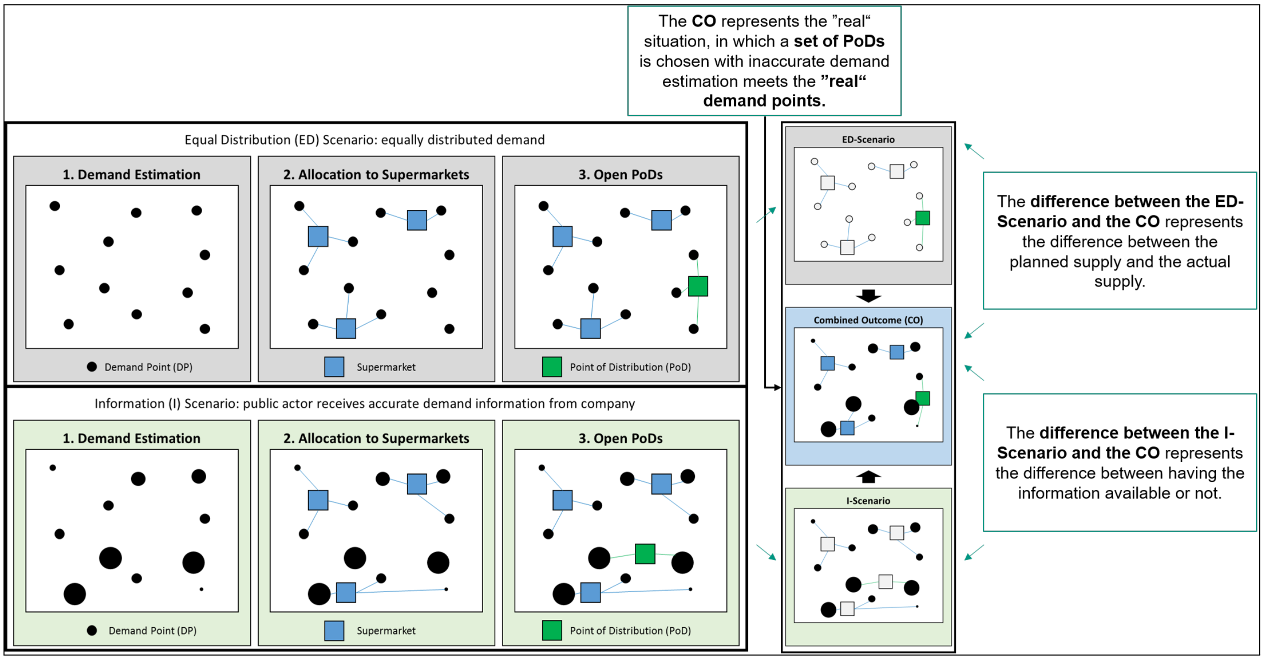

Figure 1: Overview of the framework.

and open up PoDs to support the population that is not supplied by the supermarkets (Wiens et al., 2018). These PoDs can, for instance, be public buildings, churches, or stadiums (DHS, 2006; PAHO, 2009; U.S. Department of Agriculture, 2017).

Second, we analyze the outcome, if the authorities had more accurate information with the same procedure as mentioned above. The chosen PoDs differ significantly from the opened PoDs selected with more accurate information (see "I"-Scenario; green boxes in Figure 1).

Third, the quantification of the value of information follows. This requires an additional Scenario, the "Combined Outcome" or CO-Scenario (see "CO"-Scenario; blue box in Figure 1). The CO results from the combination of PoDs chosen with theoretical, inaccurate demand information and the "real-world" DPs. It therefore represents the outcome of the plan in reality. Hence, the difference between CO and ED quantifies the planning error, while the difference between I and CO represents the value of the information.

In the following Subsections, we provide a brief overview of the main components of the framework, while the case study discussed in Chapter 4 highlights the power of the approach in practice. Moreover, potential extensions of the framework, e.g. regarding different time of interventions or different intervention intensities are discussed in Chapter 5.

3.3 Definition of Demand Points

DPs consist of two components - the location and the demand of a required good (or a combination of goods) at time t.

- The location of the DPs depends on the level of aggregation. While the highest level of detail results from a per capita analysis, aggregations on a house, block, or district level might be more feasible in terms of computation power and available data.
- The demand for a good depends on various factors such as the disaster context, individual preferences, or the physical constitution of the population. While certain minimum standards in disaster situations exist (see for instance Sphere (2018)), an assessment of the needs of the population is central.

3.4 Allocation of DPs to Supermarkets

The concrete formulation of the allocation model depends on the context of the disaster and many realizations are possible. An example of objective functions could be the minimization of PoDs required to offer a target service level (Charles et al., 2016), the minimization of total cost (Lin et al., 2012), or a multi-objective approach (Baharmand et al., 2019). Dependent on the quality of the available data and the specific context of the model, specifications such as customers' supermarket chain preferences could also be included.

3.5 Facility Location Model

Similar to the allocation model mentioned above, the Facility Location Model (FLM) needs to be tailored to the disaster context. Since public actors are not profit-driven, the objective functions could for instance entail the minimization of the total walking distance between DPs and a number of PoDs (Görmez et al., 2011), the maximization of supply to the population (Balcik and Beamon, 2008), or the minimization of social costs (Loree and Aros-Vera, 2018). Furthermore, aspects such as differences in the suitability of a building to become a PoD, or specific types of buildings could be considered (PAHO, 2009).

4 Case Study: Tap Water Contamination in Berlin

The case study was inspired by the water contamination from the city of Heidelberg, Germany, where the drinking water was contaminated on February 7th, 2019, for a couple of hours (Heidelberg24, 2019).

We assume that the tap water system in the city of Berlin is contaminated. Even though it is still usable to flush, wash clothes, or to shower, it is not drinkable anymore. Moreover, it is known that the tap water will be drinkable again after one day, reducing the level of panic within the population. Due to the crisis, the demand for bottled waters increases significantly and companies try to cope with the sudden increase. To reduce complexity, we only focus on drinking water. Indirectly induced demands for products such as food or soap will not be regarded.

Public authorities realize that the supermarkets are not able to supply enough water to the population. Therefore, they decide to open PoDs. Due to a contract with a logistics service provider, transportation of water to these facilities is secured and does not need to be regarded in the model. Furthermore, we assume that only public schools are considered as locations for PoDs and that these schools are all equally suitable as a PoD.

4.1 Definition of Demand Points

As mentioned above, two key characteristics define DPs: the location and the demand.

4.1.1 Location of DPs

An aggregation level of an "on a house basis" offers a high resolution. Data acquired from the city of Berlin (Geoportal Berlin, 2019a)[1] is the basis for the location of the 387,083 buildings. However, not all of these buildings are inhabited. Since the city of Berlin provides information on the population density on a "per block" base (Geoportal Berlin, 2019b), we only select the buildings that lie within one of those defined blocks, reducing the numbers of buildings in the scope of our analysis to 372,629 (see also Figure 2). Following, the inhabitants per block are evenly distributed over the buildings that are located within this block. The number of people per house results. The way the demand for each house is determined will be described in Subsection 4.1.2 below. However, due to the extremely high computational effort that comes with the allocation of 372,629 buildings, the sum of the demand of the houses within one block is aggregated back on a block base to reduce computational complexity. A total of 14,759 DPs results.

4.1.2 Demand Estimation

According to the Sphere handbook, 15 liters of water per person and day are sufficient for short periods of time (Sphere, 2018). Moreover, the authors of the handbook consider $2.5 - 3$ liters of water per day as an adequate amount for "drinking and food" (Sphere, 2018). Therefore, we regard demand of 3 liters per day and person.

We define the two different scenarios for the demand based on the respective actor: While private actors can predict the demand due to their experience with demand fluctuations (*accurate information*), public actors cannot estimate the demand as accurately, especially under high time pressure. Therefore, they can only relate on immediately available data (e.g. census data; *inaccurate information*) or wait until the situation becomes more clear (for example, Comes et al. (2020) states that the Philippine army was unaware of the concrete impact of Typhoon Haiyan until it was covered by international media).

[1] Data licence Germany – attribution – Version 2.0

Since private actors' success depends heavily on their market knowledge, this information is not publicly available, and we need to determine an approximation for our case study with the help of proxy data. Even though this data is free to access, the data analysis and manipulation process is extremely time consuming and cannot be done efficiently by authorities right after the disaster occurred.

We base our estimation on the assumption that, due to the short time of the crisis, only the part of the population, which did not store bottled water at home, requires water. Following, the demand per person we regard in the case study results from the required amount of water (3 liters) reduced by the stockpiled amount.[2]

According to a recent study by Sandholz (2019), where the authors conducted a representative survey of the stockpiling of 1,109 households in a major German city, 66.8% of the population stockpiles water for more than five days. Therefore, the stockpiling amount of 33.2 % of the population is 0.

In the case of inaccurate information, we assume that authorities only know the number of people living at each DP and the average amount of water stockpiled per person. Consequently, the demand for each person is reduced by 66.8% for the ED-Scenario, while the demand in the I-Scenario is 0 liters for 66.8% and 3 liters for 33.2% of the population.

Regarding the approximation for the accurate demand information, we regard three indicators for the number of goods stockpiled at home: the available space in the apartment (Bell and Hilber, 2006), the financial or social status of the person (Havranek et al., 2017), or the distance to the closest supermarkets (Jiao et al., 2016). Even though we acknowledge that multiple additional indicators influence the stockpiling, we only regard these three characteristics for each house for the sake of simplicity. After all, the objective of this study is not to provide an improved estimation of stockpiling behavior but to show how information sharing can improve decisions.

To determine the stockpiling, we rank the DPs in terms of these indicators and sum up the individual ranks to attain a merged rank.[3] Finally, the best ranked 66.8% of the population is regarded with a demand of 0 liters. Furthermore, the demand for each DP (each block) results from the aggregation of each building within this block.

Size of the apartment

We use the population density per block as a proxy for the size of the apartment (see also Figure 2). Each building receives the density value of the block it is located in.

[2] Even though a person that stockpiles a limited amount of water could still try to buy additional water, we do not regard this "exceeding" demand further.

[3] In case of equal values, each of the related buildings receives the highest value.

Figure 2: Extract from map of Berlin with the population density highlighted on a per block basis [in ppl per hectar] (Geoportal Berlin, 2019b)

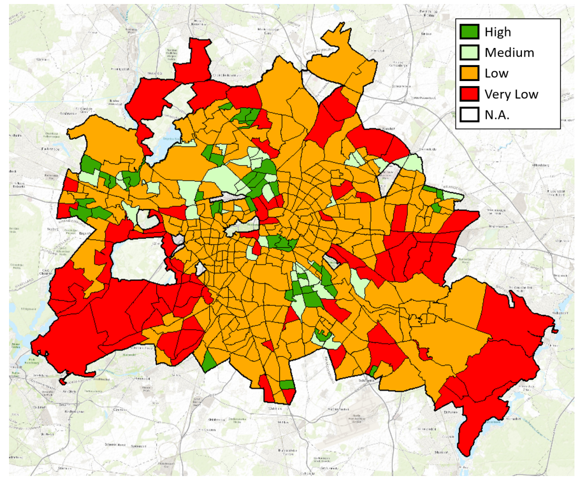

Figure 3: Map of Berlin with 447 PRs and their social status index (Geoportal Berlin, 2019c).

Financial situation

We estimate the financial situation with the help of the local "Status Index" (SI), which is based on the current and long term unemployment rates, the child poverty rate, and the "proportion of not-unemployed recipients of transfer payments" (Berlin.de, 2019a). The SI is defined on the level of the so-called "Planungsräume" (PRs, see also Figure 3) - 447 geographically defined areas dividing Berlin into segments of similar social and demographic characteristics (Berlin.de, 2019b).[4] Consequently, we allocate the SI of the related PR to each building.

Distance to supermarkets

The average distance between each building and the five closest supermarkets was calculated with ArcGIS Desktop 10.6.1. and represents the distance to the supermarkets. Afterward, the buildings were ranked accordingly.

Determination of stockpiled amount

As mentioned above, the individual ranks for each building were summed up to determine an overall ranking. We combine these overall ranks with stockpiling data obtained from Sandholz (2019) to determine the demand per DP. The allocation of DPs to supermarkets follows.

[4]Since January 1st, 2019, the city of Berlin slightly changed the structure and now defines 448 PRs. As the statistical data available refers to 447 PRs, we will keep using the "old" classification of the PRs without the minor adaptions.

4.2 Supermarket Allocation

The model for allocating the DPs to supermarkets is a maximum covering model (Farahani et al., 2012). With the binary decision variable x_{ij} (indicating if $DP\ i$ is allocated to supermarket j), a demand of b_i per DP, a supply of a_j per supermarket, a distance d_{ij} between DP_i and supermarket j, and a maximum walking distance of r, we define the model as follows:

$$\max \quad \sum_{i \in I} \sum_{j \in J} x_{ij} * b_i \tag{1}$$

$$s.t. \quad \sum_{i \in I} x_{ij} * b_i \leq a_j \qquad \forall j \in J \tag{2}$$

$$x_{ij} * d_{ij} \leq r \qquad \forall i \in I, \quad \forall j \in J \tag{3}$$

$$\sum_{j \in J} x_{ij} \leq 1 \qquad \forall i \in I \tag{4}$$

$$x_{ij} \in \{0; 1\} \qquad \forall i \in I, \quad \forall j \in J \tag{5}$$

While Eq.(1) defines the objective to maximize the allocated amount of water from all supermarkets j to all DPs i, Eq.(2) ensures that the capacity limit of each supermarket is not exceeded. To compute our calculations, we use supermarket data obtained from the Berlin Senate Department for Urban Development and Housing (Berlin Senate Department for Urban Development and Housing, 2016). Since this data only contained GIS coded data about 1062 supermarket locations and the corresponding size of the sales area, we needed to determine the capacity per supermarket by approximation: we broke down the amount of bottled water sold in Germany per year (VDM, 2019) on a per-day and capita base and multiplied it with Berlin's population to calculate the daily sales of bottled water in Berlin (in our case: 1.77 million liters per day). Following, we divided this number by the total sales area to determine the water capacity per m^2 of sales area (in our case: 1.63 liters per m^2). The capacity per supermarket follows by the multiplication with the size of the corresponding sales area.

Eq.(3) ensures that a DP is only assigned to a supermarket ($x_{ij} = 1$) if the geodesic distance between DP and supermarket is within walking distance of the DP. In the context of our case study, we follow the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety and define the maximum walking distance as 1,000 meters (BMUB, 2014). Moreover, Eq.(4) ensures that no DP is allocated to more than one supermarket to reduce the complexity to collect the goods for the population. Finally, Eq.(5) defines x_{ij} as a binary variable.

4.3 Location Selection for PoDs

The remaining demand after the allocation to the supermarkets is considered as the input-demand for the PoD location selection. We assume that the authorities are only able to open a limited amount of schools as PoDs and that each of these PoDs has a capacity of 60,000 liters per day (roughly five trucks with a load of 12 tons). This capacity would furthermore be in line with the recommendations of the World Food Programme, who recommend limiting the number of people per distribution site to 20,000 (WFP, 2002). Regarding potential schools to open, we use data received from the Berlin Senate Department for Education, Youth and Sport (Berlin Department for Education, Youth and Sport, 2019) that included GIS data for all public schools in Berlin. After data editing and preparation, the pool of potential PoD locations included 631 schools.

The following model decides, which of the schools k should be opened as PoD ($y_k = 1$), and which DP is allocated to which school ($x_{ik} = 1$) if a total number of L schools can be opened ($L \leq |K|$):

$$\max \quad \sum_{i \in I} \sum_{k \in K} x_{ik} * b_i \tag{6}$$

$$s.t. \quad \sum_{i \in I} x_{ik} * b_i \leq a_k \qquad \forall k \in K \tag{7}$$

$$x_{ik} * d_{ik} \leq r \qquad \forall i \in I, \quad \forall k \in K \tag{8}$$

$$\sum_{k \in K} x_{ik} \leq 1 \qquad \forall i \in I \tag{9}$$

$$x_{ik} \leq y_k \qquad \forall i \in I, \quad \forall k \in K \tag{10}$$

$$\sum_{k \in K} y_k \leq L \tag{11}$$

$$x_{ik}, y_k \in \{0; 1\} \qquad \forall i \in I, \quad \forall k \in K \tag{12}$$

Note that, even though I refers to the same set of DPs, the demand of the DPs of the second model differs (whenever a DP x was allocated to a supermarket within the supermarket allocation model, the demand of this DP x in the school allocation model is 0). Eq.(6-9) are equivalent to the supermarket allocation model mentioned above, with the objective of maximizing the allocation to the population. Eq.(10) ensures that an allocation is only possible, if a school k is open. Eq.(11) accounts for the maximum number of schools to open (L), while Eq.(12) defines y_k and x_{ik} as a binary variable.

5 Results

5.1 Demand Points

The calculation of ranks and the allocation of demand to the DPs was conducted using Microsoft Excel (16.0.4849.100 64-bit) and ESRI ArcGIS Desktop 10.6.1. A total demand for 3,720,554 liters results. Since the information about potentially vulnerable blocks is very sensitive, we avoid highlighting the assessment on a per-block base and aggregate the demand for each DP on the level of the PR (see Figure 4 and 5).

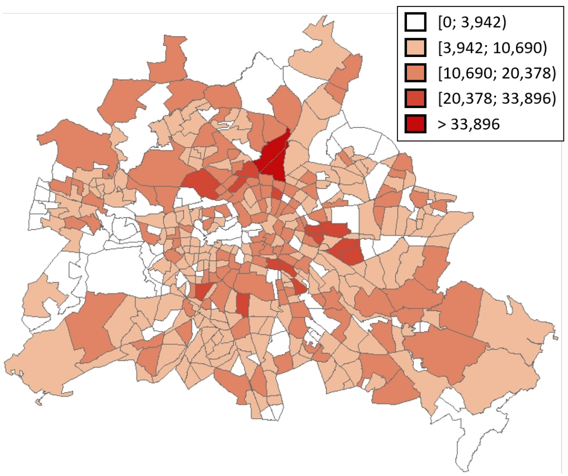

Figure 4: Visualization of the demand per PR assuming evenly distributed stockpiling estimation [in l per PR].

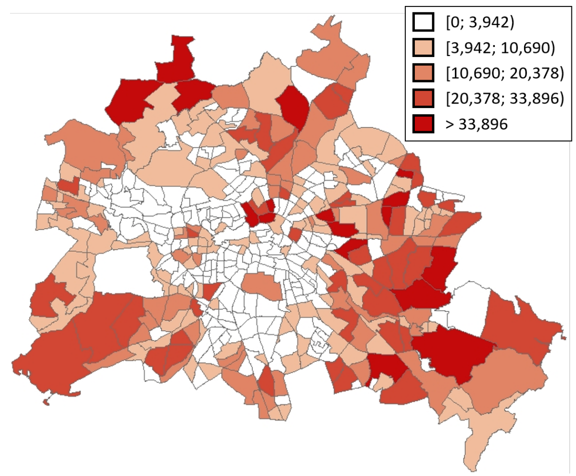

Figure 5: Visualization of the demand per PR highlighting the accurate demand stockpiling estimation [in l per PR].

Therefore, accurate information helps to identify potentially critical regions since the demand in different regions of Berlin varies stronger than in the case of equal distribution. Following, it is possible to prioritize regions more efficiently.

5.2 Allocation to Supermarkets

The model to allocate DPs to supermarkets was implemented in GAMS and solved using the CPLEX Solver (on an Intel Xeon CPU E7-4850, 2.00 GHz, 256 GB RAM). It took approximately 45 minutes to solve the problem with a relative MIP-gap of 0.5%, resulting in a total supply from the supermarkets of 1,734,812 liters and capacity utilization of 98%. Consequently, the exceeding demand results in 1,985,742 liters.

5.3 Location Selection for PoDs

Regarding the number of PoDs to open, we distinguish between two cases - 10 schools and 33 schools. Thirty-three schools were chosen since this number ensures that the capacity of supermarkets and schools matches the demand. On the other hand, the significant operational effort required to open 33 PoDs cannot be neglected. Therefore, we also regard 10 PoDs as a more feasible number of schools to open. This number is further supported by the blackout in Berlin Koepenick in February 2019, in which five schools were opened (RBB, 2019). Since Koepenick only represents a small part of Berlin, a safety cushion of 100% was chosen.

The PoD location model was implemented in GAMS and solved using the CPLEX Solver (on an Intel Xeon CPU E7-4850, 2.00 GHz, 256 GB RAM). It took on average 9 minutes to solve the problem with a relative MIP-gap of 0.5%, resulting in a total supply of 416,321 liters from 10 schools and 947,518 from 33 schools. Therefore, public authorities are able to estimate that opening ten schools lead to a total supply of 2,151,133 liters of water (equivalent to 58% of the total demand of the population), while 2,682,330 liters could be distributed with 33 schools (equivalent to 72% of the total demand). Therefore, it can be followed that 28% of the capacities are unused due to the distance restriction if 33 schools are considered.

5.4 Quantification of the Planning Error

As discussed in Chapter 3, the planning error results from the difference of the CO- and the ED-Scenario. Furthermore, the CO is determined by an additional run of the location selection model with the additional restriction:

$$y_j = 1 \qquad \forall\, j \in \{\text{Locations selected in ED-Scenario}\} \tag{13}$$

It follows that the results planned do not reflect potential outcomes since the chosen locations only lead to a supply of 120,586 liters from 10 schools and 396,843 liters from 33 schools. Consequently, authorities would overestimate the outcome of their intervention by up to 71%. This can have severe consequences. If, for instance, a mayor of a city planned to supply goods for 10,000 people, aid would, in fact, only reach less than 3,000 people. This effect is furthermore underlined by the fact that only 23 of 33 open schools actually distribute goods, while 10 are left with all of their goods and nobody around to pick them up.

5.5 Quantification of the Value of Information

The value of information results from the comparison of the I-Scenario and the CO-Scenario described in Section 5.4 above. If the state possessed all information before making its decision, the supply to the population would result in 496,608 liters from 10 schools and 1,092,457 liters from 33 schools. Therefore, public actors benefit significantly from the exchange of information, leading to an increase in supplies of up to 412%.

Figures 6 - 8 furthermore highlight the results, presenting the 33 locations chosen for the ED-, the CO-, and the I-Scenario. It follows that authorities would rather open schools in the center of Berlin, even though schools more towards the outskirts of the city are better if the real demand is considered.

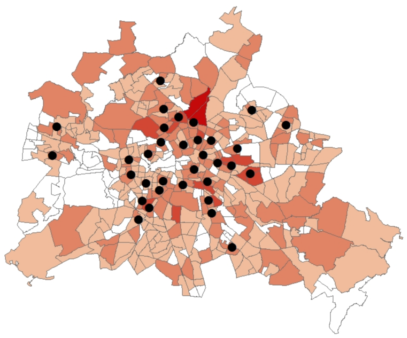

Figure 6: 33 schools opened in the ED-Scenario.

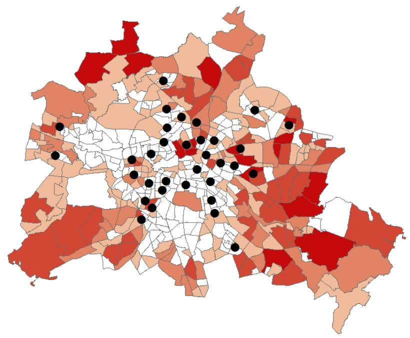

Figure 7: 33 schools opened in the CO-Scenario.

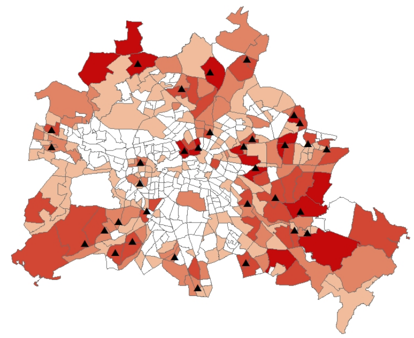

Figure 8: 33 schools opened in the I-Scenario.

6 Discussion and Further Analysis

The presented framework allows for a precise determination of the planning error and the value of information. Therefore, it provides crucial insights for decision-makers in disaster management. They can, for example, use the planning error from this study as an outcome estimation indicator in cases of high uncertainty. Furthermore, it highlights the impact of an increase in information accuracy and provides an understanding of how much the quality of disaster relief can be improved by higher information quality. However, it remains questionable if private actors are willing to share information.

Moreover, the exchange of information is challenging, even if a company is willing to collaborate. For example, agreeing on appropriate data-types, interfaces for the data-exchange, or update-cycles can - together with the time it takes to find a partner to collaborate - take a long time. Therefore, relief can significantly speed up if public and private actors agree on the specific collaboration parameters before the crisis. Moreover, PoDs chosen in the model can be regarded as designated disaster sites in disasters, reducing the communicational and planning effort in the direct aftermath of the disaster drastically (similar to Dekle et al. (2005) who identified designated relief sites in the US).

To gain a better understanding of the importance of time, we compare the decision in the case study above with an alternative, accelerated decision where schools open up at the same time as the supermarkets. Therefore, beneficiaries have more opportunities to receive goods while supermarkets might sell less.

6.1 A Comparison of Different Times to Start the Intervention

While market interference was implicitly excluded due to the dime lag between the start of the crisis and the start of public actors' intervention, it is also possible to analyze the consequences of an earlier intervention of public actors. Earlier intervention in this context refers to opening the PoDs at the same time as the supermarkets open (see Table 1). Hence, parts of the population that were expected to go to supermarkets in the Scenario above could go to schools. Therefore, earlier intervention leads to market interference.

This Subscenario ”B” is calculated similarly to the CO-Scenario described in Section 5.4: after the selection of PoDs to open, an additional run of the supermarket allocation model follows, in which the opened PoDs are included as additional distribution points.

Subscenario B leads to an increase in total supply (see Table 2). While total deliveries increase in each Scenario analyzed, the overall effects are rather small, ranging from a 2% increase in the I-Scenario for 10 schools up to an increase of 12% in the ED-Scenario for 33 schools.

Table 1: Overview of the different Subscenarios.

Name of Subscenario	**A Benchmark w/o market interference**	**B Simultaneous w/ limited market interference**	**C Simultaneous w/ market interference**
Relevant demand for public actors	Unmet demand after the population is allocated to supermarkets.	Expected unmet demand after supermarkets ran out of goods.	Total demand of the population.
Time information is shared and public actors become active	After supermarkets are out of capacity.	At the beginning of the crisis.	At the beginning of the crisis.
Narrative description / Interpretation of strategy	Public actors wait until supermarkets run out of capacity before they receive the information and can start to supply goods to people without water.	Public actors estimate the demand that will be left when the supermarkets run out of goods and choose the best locations to fulfill this demand. Each person can either go to one of the supermarkets or one of the PoDs that are open.	Public actors choose PoDs so that the total demand can be supplied best. There, PoDs are in direct competition to supermarkets for the demand that could have been met without public intervention.

The implications of public interventions on private supply chains cannot be neglected and should be considered carefully before intervening. In Subscenario B, public actors implicitly tried to reduce the impact of their interventions by only focusing on the demand that cannot be supplied for by the market. However, public actors could also try a more holistic approach and consider the total demand. Hence, the impact on supermarkets is expected to be more significant. In the following Subsection, we analyze this Subscenario C.

6.2 A Comparison of Different Intervention Intensities

In the context of this case study, we define the difference in intervention intensity by the demand regarded in the public actors’ optimization model (see also Table 1). In the case of a less severe intervention (Subscenario B), authorities only consider the demand that would not be fulfilled by the supermarkets if the supermarkets were to distribute goods by themselves. In the case of a stronger market intervention (Subscenario C), public authorities consider the total demand of the population. Consequently, Subscenario C can be interpreted as the population's favorite Subscenario since the best possible supply results, in which the allocation to supermarkets and the facility decision for schools occurs at the same time.

From a mathematical perspective, we implemented this Subscenario as an extended location selection model with $M = \mathrm{I} \cup \mathrm{J}$. Furthermore, we set $y_m = 1 \,\forall\, m \in \mathrm{I}$. Consequently, the constraint that controls the number of opened PoD (Eq. (11)) is adapted to include the 1,062 additionally opened PoDs:

$$\sum_{m \in M} y_m \leq L + 1,062 \tag{14}$$

Subscenario C leads to a better supply to the population than the baseline (A) and the less severe intervention (B, see Table 2).[5]

Table 2: Overview of the results of the different Subscenarios.

#Schools	**10**			**33**		
Distribution Strategy	**A**	**B**	**C**	**A**	**B**	**C**
Equally Distributed Scenario						
Total Deliveries to Population	2,151,133	2,289,701	2,303,329	2,682,330	2,991,653	3,071,427
Utilization of Total Capacities	0.91	0.97	0.97	0.71	0.80	0.82
Proportion of Total Demand supplied	0.58	0.62	0.62	0.72	0.80	0.83
Deliveries from Supermarket	1.734,812	1,733,508	1,714,781	1,734,812	1,541,330	1,679,129
Utilization of Supermarket Capacities	0.73	0.98	0.97	0.73	0.87	0.95
Deliveries from Schools	416,321	556,192	588,548	947,518	1,450,323	1,392,297
Utilization of School Capacities	0.69	0.93	0.98	0.48	0.73	0.70
Combined Outcome Scenario						
Total Deliveries to Population	1,562,120	1,584,712	1,593,988	1,838,377	1,904,606	1,884,325
Utilization of Total Capacities	0.66	0.67	0.67	0.49	0.51	0.50
Proportion of Total Demand supplied	0.42	0.43	0.43	0.49	0.51	0.51
Deliveries from Supermarket	1,441,534	1,408,424	1,369,340	1,441,534	1,256,422	1,279,380
Utilization of Supermarket Capacities	0.81	0.79	0.77	0.81	0.71	0.72
Deliveries from Schools	120,586	176,289	224,648	396,843	648,184	604,945
Utilization of School Capacities	0.20	0.29	0.37	0.20	0.17	0.31
Information Scenario						
Total Deliveries to Population	1,938,142	1,977,576	1,982,790	2,533,991	2,705,482	2,709,825
Utilization of Total Capacities	0.82	0.83	0.84	0.68	0.72	0.72
Proportion of Total Demand supplied	0.52	0.53	0.53	0.68	0.73	0.73
Deliveries from Supermarket	1,441,534	1,397,066	1,408,249	1,441,534	1,290,523	1,361,218
Utilization of Supermarket Capacities	0.81	0.79	0.79	0.81	0.73	0.77
Deliveries from Schools	496,608	580,510	574,541	1,092,457	1,414,959	1,348,607
Utilization of School Capacities	0.83	0.97	0.96	0.55	0.71	0.68

However, the proportion of the supply that is taken care of by the private sector remarkably deviates from the intuitively expected outcome since supermarkets lose, on average, a higher share of sales in the case of weak intervention than in the case of strong intervention. A reason for this is the increased flexibility of public actors regarding potential beneficiaries and the implicit division of the population between the two actors that results from the holistic optimization approach. Consequently, supermarkets have an incentive to collaborate closely with public actors in case they expect any kind of intervention. However, it is not possible

[5]It has to be mentioned that due to the increased complexity of the problem, we had to increase the allowed relative MIP-gap to 3%.

to eliminate crowding-out effects if public and private actors are active at the same time.

6.3 Effects of Different Subscenarios on Supermarket Chains

Since it is not possible to eliminate crowding-out effects, we further analyze the consequences of the different intervention strategies on supermarket chains. Therefore, we aggregate the supply from the individual supermarkets on a "per-corporate-group" level. In line with Kaufda (2019), we consider the following groups: Aldi, Edeka, Metro, Norma, Rewe, Schwarz, and "others".

Figure 9 highlights the distribution per chain in the different Subscenarios.[6] For example, group 7 is highly affected by Subscenario B_CO_33, while the sales of group 3 change significantly less due to the intervention. Consequently, crowding-out affects different chains with different intensities. Therefore, public actors need to be very careful to make sure that they do not "pick winners" and have significant long term consequences on the competition in the market.

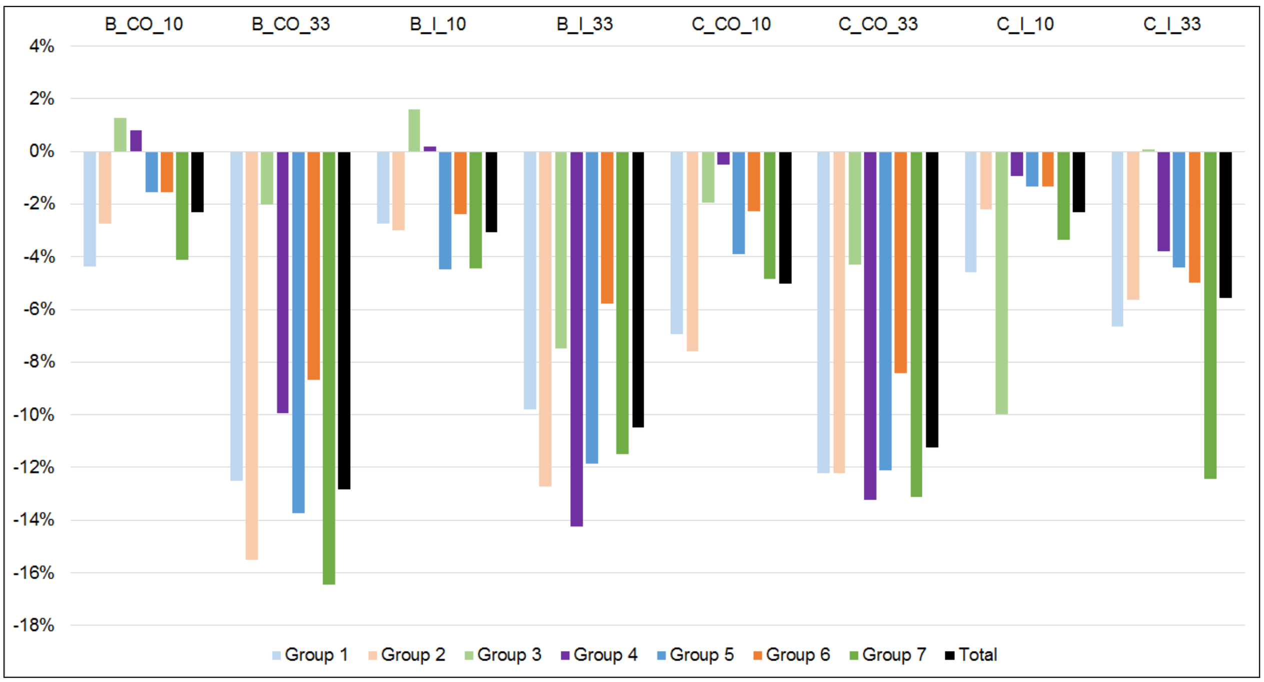

Figure 9: Overview of the lost sales per group compared to no intervention (A).

7 Conclusion

Public actors strategies strongly depend on accurate demand information during crisis intervention. Within the realm of our case study, inaccurate information can result in planning errors of up to 71%. At the same time, the impact of the intervention can increase by up to 412%, if decision-makers receive accurate

[6] Due to reasons of confidentiality, we do not link the names of the groups to the data and generalize them as group 1-7.

information. Moreover, the earlier public actors become active also has a positive effect, even though this effect is comparably small. Furthermore, we were able to show that severe market intervention results in better exploitation of supermarkets than a less severe market intervention. Consequently, private actors should seek for collaboration in cases they are afraid that public actors would become active individually otherwise.

However, additional research is necessary to gain a deeper understanding of the crisis mechanisms. First, we did not consider the legal implications of the different Scenarios. We were able to show that the effects of the interventions on supermarket groups differ significantly. Since authorities are not allowed to pick "winners", it remains critical if addition in total supply justifies different decisions.

Moreover, we did not consider crisis dynamics. The objective of this article was to quantify the value of a current level of information in contrast to an alternative set of information. Therefore, we did not consider dynamic effects, even though additional information might change the assessment (for an overview of humanitarian logistics models that include real-time data, see, for example, Yagci Sokat et al. (2016)). Therefore, the approach could, for instance, be combined with dynamic optimization approaches such as the work from Paterson et al. (2019), who developed a work-in-progress approach for updating stochastic models of human-centric processes in disaster management through unstructured data streams and encoded information.

Furthermore, we treated every DP equally. Even though this is reasonable within an analysis of system capacities, a prioritization of vulnerable parts of the population could help to make the results more applicable for practice.

Closely connected is the definition of the next steps if authorities were to implement ways to receive information in crises. This could include defining DPs together, to agree on the format of the data sent (e.g. as an Excel, or as GEO-Coded files), or to discuss the way authorities can process the data.

Despite the challenges discussed above, the framework proved to quantify the value of information in disasters efficiently. Therefore, it can establish itself as a powerful tool to improve disaster resilience.

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Working Paper Series in Production and Energy

recent issues

Impressum

Karlsruher Institut für Technologie

Institut für Industriebetriebslehre und Industrielle Produktion (IIP)
Deutsch-Französisches Institut für Umweltforschung (DFIU)

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KIT – Universität des Landes Baden-Württemberg und
nationales Forschungszentrum in der Helmholtz-Gemeinschaft

Working Paper Series in Production and Energy
No. 51, December 2020

ISSN 2196-7296