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# Design of experiments in humanitarian logistics: Facility decision making in disaster preparedness

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**Abstract**

Facility planning is one of the critical decisions faced by humanitarian managers. Some managerial implications have been offered in the literature, but these are commonly derived from simple sensitivity analyses on individual instance characteristics and/or using a single case study, and as such can be misleading as they ignore important interactions between many disaster properties. We carried out a large experimental study that analyses the influence of different factors and their interactions on the choice of facility configuration for inventory pre-positioning in preparation for emergencies. On the one hand, the outcomes of the study provide insights on the effect of the most important factor interactions on the facility decision making. On the other hand, the findings also demonstrate that the simple analyses might provide guidelines which are not robust across different disasters, and as such promote better experimental designs in the field of humanitarian logistics.

*Keywords:* Humanitarian logistics; Facilities planning and design; Robustness and sensitivity analysis

## 1. Motivation and literature review

Natural and man-made disasters affect millions of people worldwide each year, and result in catastrophic loss of life, critical injuries, and debilitating economic impacts (Al Theeb and Murray, 2017), underscoring the importance of effective relief efforts. Humanitarian agencies play a key role in disaster response (e.g., procuring and distributing relief items to affected population, providing healthcare, assisting in the development of long-term shelters), and thus their efficiency is critical for a successful disaster response (McCoy, 2008).

The devastating effects of disasters has led to an an increasing interest in developing measures in order to diminish the possible impact of disasters, which gave rise to the field of disaster operations management (Galindo and Batta, 2013). Operations research has the potential to help relief agencies save lives and money, maintain standards of humanitarianism and fairness and maximize the use of limited resources amid post-disaster chaos (Luis et al., 2012; Van Wassenhove and Pedraza Martinez, 2012). The disaster management literature is abundant with mathematical models and solutions procedures that aim to optimize humanitarian supply chain (Altay and Green, 2006; Caunhye et al., 2012; Luis et al., 2012; Galindo

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and Batta, 2013; Anaya-Arenas et al., 2014; Hoyos et al., 2015; Özdamar and Ertem, 2015; Balcik et al., 2016; Habib et al., 2016). Although these optimization tools are necessary to study the problems arising in humanitarian logistics, the lack of mathematical background and/or computational infrastructure rarely allows practitioners to effectively use these tools (de Vries and Van Wassenhove, 2017). Most of the aforementioned literature surveys recognize the challenge of carrying theory into practice as an important future research direction. One way to do this is to pare down these models into simple guidelines that workers can use on the ground (Northwestern's McCormick School of Engineering, 2010), since managers most often prefer to rely on straightforward rules of thumb to guide their planning process (Cotts et al., 2009).

In this paper, we focus on the problem of advance procurement and pre-positioning of emergency supplies at strategic locations as a strategy to better prepare for a disaster. Disaster preparedness involves the activities undertaken to prepare a community to react when a disaster takes place (Altay and Green, 2006). Adequate preparedness can significantly improve disaster response activities. For instance, in India, a major cyclone in 1977 caused a death toll around 20,000 people. After an early warning system, meteorological radars and emergency plans were established, similar cyclones caused considerably lower death tolls (United Nations International Strategy for Disaster Reduction (UNISDR), 2009). Pre-positioning emergency inventory in selected facilities is commonly adopted to prepare for potential disaster threat (Ni et al., 2018). Humanitarian organizations typically purchase and stockpile the required relief items in strategic warehouses at pre-disaster and distribute them to affected areas in order to save lives immediately in the early post-disaster (Balcik and Ak, 2014). Hence, configuring a relief pre-positioning and distribution network in an effective and efficient way can play an essential role in mitigating negative impacts of potential disasters (Torabi et al., 2018). For a recent survey of pre-positioning in disaster operations management, see (Sabbaghtorkan et al., 2020).

So far in the literature on the pre-positioning problem, some managerial guidelines have been derived, but most often through a sensitivity analysis carried out on one or a few parameters, using a single case study (a common approach throughout humanitarian logistics literature). For example, Balcik and Beamon (2008) employ a case study focused on worldwide earthquake-caused disasters to investigate the sensitivity of facility location decision in humanitarian relief on the available budgets. The results show that the increase of pre-disaster budget for establishing distribution centres and procuring and stocking relief items yields a greater number of open distribution centres (with approximately the same capacities), whereas an increase in post-disaster funding for transportation decreased the number of distribution centres (and increased the capacity differences between the centres). A Hurricane Katrina case study is used by Bemley et al. (2013) to study the effect of supply amount and acquisition time on the ability of a port to quickly recover from disasters, that is measured by the number of aids to navigation (which help vessels and mariners with navigation through the waterways) to be repaired. The experimental results show that a decrease in supply amount results in a decline in the amount of aids to navigation repaired. Similarly, an increase in the supply acquisition time effectively reduces the amount of available time to repair the aids and therefore decreases the number of aids repaired, what helps to reinforce the need for coordination efforts well in advance of disaster events.

Noyan (2012) employs a case study focused on a hurricane threat in US Gulf Coast to study how the optimal pre-positioning location and allocation policies change with respect to the risk parameters. The study shows that increasing the level of risk aversion leads to a more risk-averse policy with higher positioning costs and lower expected (transportation, salvage and) shortage costs in general. The inventory level, however, does not necessarily increase for every commodity; whether the inventory level of a commodity increases or decreases depends on the associated shortage penalty cost. Manopiniwes et al. (2014) introduce a Thai flood case study to discuss the sensitivity of the pre-positioning facility and inventory decisions on different time and cost parameters, and thereupon derive managerial implications. The results suggest that an increase in the maximum response time at each demand location reduces the total operation cost (that remains unchanged beyond a certain maximum response time), implying that budget limitations can lead to a slow response system. In particular, with greater maximum response time, the opening cost of the facilities and the holding cost decrease, while the transportation cost increases. In other words, the more restrictive the time, the model responds by opening more warehouses (with lower level of utilization of facility capacity) in order to provide timely service for each demand location. The trade off between opening and transportation costs, however, has an impact on the choice between the far-located low-cost and near-located high-cost warehouses.

However, opportunities to derive good rules of thumb are missed by sensitivity analysis that focus on a single or a few parameters, if they ignore the influence of other factors that can completely reverse the patterns seen in individual analyses. For example, if opening few big facilities costs less than opening many small facilities, but offers a greater storage capacity, it might often be preferred. However, if the transportation budget is quite limited, or if the transportation network is severely damaged after a disaster, opening many small facilities can be a better facility configuration, as it allows to provide assistance to a greater number of demand locations. Studying only how the relationship between facility opening costs influences the facility decisions can thus lead to serious misunderstanding of how the facility decisions change with respect to this factor, as it does not investigate the interaction between facility opening costs and the transportation budget or level of network damage. The importance of considering the interaction between different parameters is notable in the aforementioned articles, e.g., interaction between risk aversion and shortage penalty costs (Noyan, 2012), or the interaction between maximum response time and opening and transportation costs (Manopiniwes et al., 2014). Deriving robust rules of thumb necessitates a more complex analysis that evaluates different parameters and investigates how they interact with each other.

In addition, the managerial implications are most often derived using a specific case study. Most of the instance characteristics therefore implicitly remain fixed throughout the analysis, such as the network and demand topology, or disaster type or scale. For different types of instances, the guidelines derived can therefore be misleading. Indeed, disasters vary in types and levels of intensity, each demanding a different response (Tomasini and Van Wassenhove, 2009). This was also explicitly acknowledged by the authors of the aforementioned articles as a limitation of their work, as they affirm that the policies could be improved and more insights could be gained with information from other disasters, i.e., with multiple case studies (Bemley et al., 2013; Manopiniwes et al., 2014). The consideration of additional instances enables to determine more robust strategies (Mejia-Argueta et al., 2018), what is a common practice in the general operations research literature that employs a benchmark set of diverse problem instances (e.g., for the vehicle routing problem).

To derive rules of thumb that avoid the aforementioned issues, we propose the following approach:

(1) Describe the problem instance with reasonably many factors (independent variables) $\mathcal{X}_1, \mathcal{X}_2, \ldots, \mathcal{X}_K$ that could have an influence on the response (dependant variable) $\mathcal{Y}$.

(2) Identify the most important factors and factor interactions, and investigate their effect on the response. For instance (assume that $K = 10$), we obtain that important main effects are $\mathcal{X}_2$, $\mathcal{X}_5$, $\mathcal{X}_9$, and interaction $\mathcal{X}_2 \times \mathcal{X}_5$. These findings provide the big picture, a "bird's-eye view" of the problem. The outcomes can, for example, provide recommendations on the definition and mathematical models of the problem (as they identify the crucial parameters that should be included in the problem formulation), but also guide the design of robust heuristics to solve the problem (as they provide an understanding of the effect of the crucial parameters and their interactions).

(3) Investigate the influence of one or a few selected factors (factors that are the most important or interesting for any other reason) on the response in greater detail, with the remaining factors fixed to some reasonable value. Here *it is crucial to take the findings from previous step into consideration*: the factors that are shown to interact with the selected factor must not remain fixed, but should explicitly be included in the analysis. In the example above, if we decide to study the influence of factor $\mathcal{X}_2$ in more detail (e.g., by considering more values of factor $\mathcal{X}_2$, or by describing the related information with multiple factors $\mathcal{X}_{21}, \mathcal{X}_{22}, \mathcal{X}_{23}$, whose interaction should also be investigated), it is important to consider different levels of factor $\mathcal{X}_5$. This type of analysis results in robust rules of thumb that are applicable across different disasters.

It is common in the literature, as explained above, to only perform a flawed variation of Step (3). This would, for instance, correspond to a sensitivity analysis of factor $\mathcal{X}_2$ (that might possibly also include an investigation of e.g., factor $\mathcal{X}_1$, or even an interaction $\mathcal{X}_2 \times \mathcal{X}_1$). This type of myopic analysis results in rules of thumb that cannot generalize to other disasters, i.e., to other problem instances with different values of $\mathcal{X}_5$. In this paper, we carry out the analysis from Step (1) and Step (2), that provides the motivation for some interesting further research directions, as described in Step (3).

More precisely, we carry out a large computational study that includes a comprehensive set of factors in order to answer the following questions about the problem of pre-positioning emergency supplies:

(RQ1) Which instance characteristics and/or their interactions have the largest influence on the facility decision making?
(RQ2) What is the effect of important interactions on facility planning?

To the best of our knowledge, this paper is the first such attempt in the domain of humanitarian logistics that we hope will gain more traction in the field. For this reason, we also include a few examples that demonstrate how the conclusions can be misleading if derived from an analysis of only the main effect of a parameter, or using a single case study.

The remainder of the paper is organized as follows. In Section 2, we describe the pre-positioning problem, and the matheuristic that we use to solve the problem. Section 3 introduces the instance characteristics and the response variables included in the study, and describes the experimental set-up. The experimental results provide information about the most important instance characteristics and their interactions, that are summarized in Section 4.1, and whose effect is studied Section 4.2. The experimental results are also used to provide some examples in Section 4.3 that illustrate how simple sensitivity analyses that ignore important interactions can yield conclusions that do not generalize to other disasters. The paper ends with a summary of the most important contributions, limitations and possibilities for future research in Section 5.

## 2. Description of the problem and solution (algorithm)

Let V be the set of vertices representing the cities, villages or communities in the area that might be affected by the disaster. The subset of vertices $i \in \mathrm{V}$ with $F_i = 1$ are potential facility locations. At most one storage facility of any category $q \in \mathrm{Q}$ might be opened at any of these potential facility locations, while the facility budget $A$ is respected. The facility categories differ in volume capacity $V_q$ and opening cost $A_q$. Commodities $k \in \mathrm{K}$ (such as food, water, medicine, blankets, or clothing) with unit volume $V^k$, unit acquisition cost $B^k$ and unit transportation cost $C^k$ may be pre-positioned at open storage facilities if the facility capacity and acquisition budget $B$ are respected.

The pre-positioning facility and inventory decisions are made in the disaster preparedness phase, under uncertainty about if, or where, a disaster might occur. We consider uncertainties about demands, survival of pre-positioned supplies, and transportation network availability, and represent them with a set S of possible disaster scenarios, that can occur with given probabilities $P^s$. The proportion $R_i^{ks}$ of pre-positioned commodity type $k \in \mathrm{K}$ at vertex $i \in \mathrm{V}$ that remains usable (i.e., that is not destroyed) in a disaster scenario $s \in \mathrm{S}$ can be distributed via traversable links (i.e., roads that are not destroyed, covered with debris, or posing a security risk) with an average speed $V$ to the beneficiaries that are in need of assistance, as long as the transportation budget $C$ is not violated. The demand for commodity type $k \in \mathrm{K}$ at a vertex $i \in \mathrm{V}$ in disaster scenario $s \in \mathrm{S}$ is denoted by $D_i^{ks}$. The set of edges $\mathrm{E}_s$ represents the transportation links in scenario $s \in \mathrm{S}$, with the weight of an edge $(i, j)$ being the distance $L_{ij}^s$ from vertex $i \in \mathrm{V}$ to vertex $j \in \mathrm{V}$ in scenario $s \in \mathrm{S}$. These problem assumptions are an adapted version of the pre-positioning problem definition that was introduced by Rawls and Turnquist (2010) and has since been widely adopted in the literature. A toy example of a pre-positioning problem instance is given in the next section.

Given an instance of the pre-positioning problem described above, we want to determine the best possible strategy to pre-position the aid. To solve the pre-positioning problem is to develop a strategy that determines:

- the number, location and category of storage facilities to open, represented by binary variables $\mathbf{x} = [x_{iq}]$ that indicate whether a facility of category $q \in \mathrm{Q}$ is open at vertex $i \in \mathrm{V}$,
- the amounts $\mathbf{y} = [y_i^k]$ of commodity $k \in \mathrm{K}$ to pre-position at a facility open at vertex $i \in \mathrm{V}$, and
- the aid distribution strategy, represented by binary variables $\mathbf{z} = [z_{ij}^s]$ that indicate whether a facility open at vertex $i \in \mathrm{V}$ completely covers the demands of vertex $j \in \mathrm{V}$ in scenario $s \in \mathrm{S}$,

that provides assistance to the greatest number of people possible, as soon as possible, i.e., that minimizes the unmet demand and response time in lexicographic order.

The mathematical formulation can be found in Turkeš et al. (2019), that discusses the many modelling choices in great detail. For example, there is a number of different reasons why the aid distribution is modelled as an assignment problem (thus assuming that each vertex is assigned to at most one open facility in one disaster scenario), rather than as a network flow, routing or transportation problem. In addition, we stress that considering three separate budget constraints instead of a limitation on the total logistics cost can help guide fund-raising efforts, as it enables to carry out sensitivity analyses to identify the type of budgets that are the most crucial for improving the quality of emergency response. Similarly, consideration of the three budgets enables us to study how each of them influence the facility decisions in our experiment. Furthermore, it is often the case that different types of funding come from different sources and can be directed only to certain type of activities. Sometimes, the donations are not even monetary, but rather correspond to readily available warehouses, aid, or fuel.

Since the pre-positioning problem becomes intractable for larger instances for exact solvers such as CPLEX, we employ a matheuristic that is able to find good solutions in a very limited computation time, introduced by Turkeš et al. (2021). The matheuristic is based on the iterated local search procedure, with the aid distribution sub-problem intermittently solved by CPLEX. The experimental results in Turkeš et al. (2021) suggest that a simple improvement of the solution algorithm would be to let the matheuristic run for most of the given computation time, but to also allocate a limited amount of time for CPLEX. The final solution would of course be chosen as the better of the two solutions, yielded by the matheuristic and by CPLEX. Such a heuristic has the best of both worlds: it will identify the optimal solution for small instances which CPLEX can solve to optimality, find good solutions even for large instances, and avoid CPLEX numeric difficulties for any instance. To find a solution of any problem instance in our experiment, we therefore run the matheuristic for 60 seconds, and CPLEX for 30 seconds, and select the better of two as the final solution.

## 3. Experimental design

In this section, we describe the design of the extensive computational study that we carried out in order to investigate the relationship between different instance characteristics and facility decisions.

We start with a toy example to illustrate how some of the instance features and their interactions complicate the facility planning. Consider a small pre-positioning problem instance with 3 vertices, 1 facility category, 1 commodity type and 2 scenarios in Figure 1. Every vertex is a potential facility location, and vertices $i = 1$ and $i = 2$ are demand locations in both scenarios. If the inventory budget is unlimited, we would open a facility at both demand locations and pre-position $y_1^1 = \max\{\lceil\frac{100}{1}\rceil, \lceil\frac{30}{0.8}\rceil\} = 100$ and $y_2^1 = \max\{\lceil\frac{50}{0.7}\rceil, \lceil\frac{70}{0.7}\rceil\} = 100$, i.e., 200 units of aid in total. The demand vertices in each scenario would be served from a facility open at the demand location site, with zero total response time. However, if the inventory budget would allow acquiring only 150 units of aid, we would open only one facility at vertex $i = 1$ (where the proportion of aid that remains usable is higher) and pre-position

$y_1^1 = \max\{\lceil\frac{100+50}{1}\rceil, \lceil\frac{30+70}{0.8}\rceil\} = 150$ units of aid. In addition, even if the inventory budget would allow to acquire 200 units of aid, but if the proportion of aid that would remain usable at vertex $i = 2$ in both scenarios would be very low (e.g., $R_2^{11} = R_2^{12} = 0.2$), we would also only open a facility at vertex $i = 1$ and pre-position $y_1^1 = 150$ units of aid.

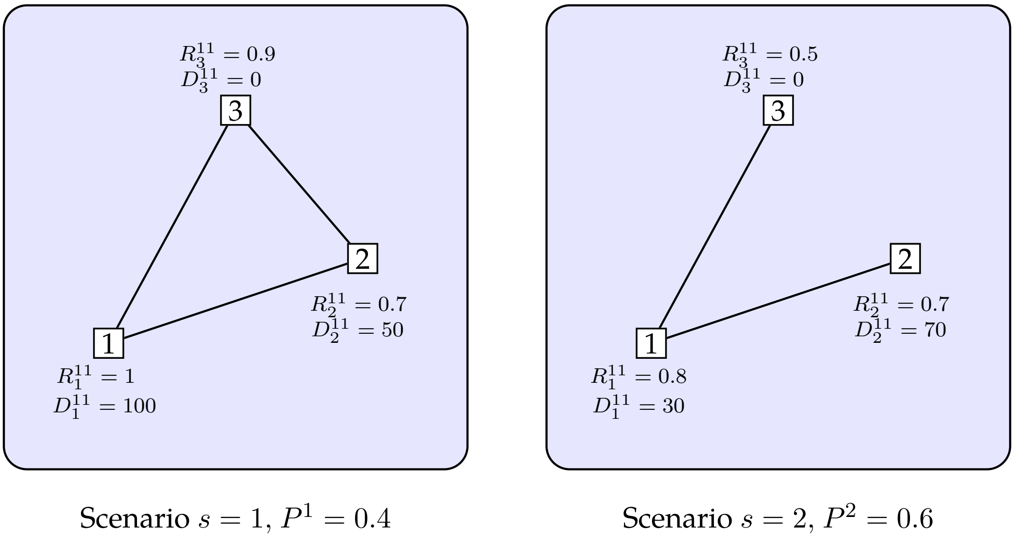


Figure 1: Graphs $G_1$ and $G_2$ represent three cities and the road network that connects them in two possible disaster scenarios. The scenarios occur with probabilities $P^1$ and $P^2$ respectively, and both are defined with the demand $D_i^{ks}$ and proportion of aid that remains usable $R_i^{ks}$ for every commodity $k \in \mathrm{K}$ and every vertex $i \in \mathrm{V}$, together with the availability of every edge that is indicated in the graph.

### *3.1. Definition of factors*

The example above discusses only some of the instance characteristics and their interactions that can have an influence on the facility decision making. In our study, we described each part of the instance information (Section 2) with a factor (Table 1). The demand graphs are publicly available on Mendeley (Turkeš, 2021), where we also motivate the choice of factors in greater detail, as we describe how each of them might be relevant for facility planning.

Note that the insights gained will depend on the choice of factor levels. For instance, if we would allow the transportation network to be significantly more destroyed (by, e.g., considering levels $\{0, 0.45, 0.9\}$ instead of $\{0, 0.25, 0.5\}$), it is to be expected that factor $L$ would turn out to be much more important. However, as we note in the detailed data description available on Mendeley (Turkeš, 2021), to define reasonable values of the factor levels, we took inspiration from the real case studies described in (Turkeš and Sörensen, 2019). Moreover, the findings that tell us something about the effect of the important factors and their interactions provide information about the trends in the behaviour of the response variables.

Table 1: In the computational study, we investigate how 10 different factors and their interactions influence the facility decision making.

| **Factor** | **Notation** | **Levels** | **Problem instance parameters** |
|---|---|---|---|
| Percentage of potential facility locations | $F$ | 0.1<br>0.5<br>1 | $100F\%$ of random vertices are potential facility locations. |
| Facility capacities | $QV$ | 2<br>4<br>6 | The capacity $V_1$ of a small facility is $QV$ times bigger than the volume of the average demand at a vertex in a scenario; $V_2 = 2V_1$. |
| Facility unit opening costs | $QAV$ | 0.5<br>0.75<br>1 | This factor represents the ratio between the unit opening cost between a big and a small facility, $QAV = (A_2/V_2)/(A_1/V_1)$. |
| Number of scenarios | $S$ | 5<br>10<br>20 | $S$ different disaster scenarios are considered, that occur with the same probability $\frac{1}{S}$. |
| Average proportion of aid that remains usable | $R$ | 0.5<br>0.75<br>1 | The proportions of pre-positioned aid that remains usable are drawn from the normal distribution $\mathcal{N}(R, 0.2)$. |
| Demand graphs | $D$ | `Chile1`<br>`Chile2`<br>`Chile3`<br>`Chile4`<br>`Random1`<br>`Random2`<br>`Random3`<br>`Senegal`<br>`Turkey`<br>`US1`<br>`US2`<br>`US3`<br>`US4`<br>`US5`<br>`US6` | This factor represents the network and demand topology that is defined from the case studies (focusing on disasters of different type and scale that occurred in different parts of the world) and diverse random instances introduced in (Turkeš and Sörensen, 2019)(Turkeš, 2021). The different levels of factor $D$ differ with respect to the number of vertices, number of demand vertices, range and distribution of demand values and distances, demand variance across vertices in a scenario and across disaster scenarios, commodity type and its unit volume, acquisition and transportation cost. |
| Transportation network damage | $L$ | 0<br>0.25<br>0.5 | In every disaster scenario, $100L\%$ of random edges is destroyed. |
| Facility budget | $AP$ | 0.5<br>0.75<br>1 | The facility budget is $100AP\%$ of an estimated facility budget necessary to meet the expected total demand. |
| Acquisition budget | $BP$ | 0.5<br>0.75<br>1 | The acquisition budget is $100BP\%$ of an estimated acquisition budget necessary to meet the expected total demand. |
| Transportation budget | $CP$ | 0.5<br>0.75<br>1 | The transportation budget is $100CP\%$ of an estimated transportation budget necessary to meet the expected total demand. |

### 3.2. *Experimental set-up*

We consider the full factorial experimental design, i.e., we consider all possible level combinations across all factors. Since a lot of instance information is defined randomly (the potential facility locations, choice of scenarios, proportions of aid that remain usable, and the destroyed edges), we construct three replicates for each of the level combinations. This results in an extensive computational study that involves

$$3 \times 3 \times 3 \times 3 \times 3 \times 15 \times 3 \times 3 \times 3 \times 3 \times 3 = 885\,735$$

experimental units, i.e., pre-positioning problem instances.

To reduce the number of observations and therefore the computation time of the experiment, it is possible to consider other experimental designs. However, full factorial experiments are the most straightforward due to their orthogonality: there is a zero correlation between any variable or interaction effects, i.e., the effects of any factor balance out (sum to zero) across the effects of the other factors. The disadvantage of unbalanced designs is that the main effects are not independent (orthogonal) to the interactions of which they are apart. The concept of orthogonality is important in the design of experiments, since effect of one variable may otherwise be masked or confounded with another variable or interaction, making it difficult to determine which variables actually cause the change in the response and consequently casting a doubt on the conclusiveness of the results.

The folder with the pre-positioning problem instances is too large to share, but a detailed explanation of how the instances are defined according to the factor levels can be found in the description of experimental data made available on Mendeley (Turkeš, 2021) (summarized in Table 1). We briefly note here that, when constructing an instance, each instance characteristic under study is defined only according to the levels of one factor and the underlying demand graphs, while the values of other factors are ignored. In this way, we ensure that changes in one factor only influence the corresponding part of instance information, while the remainder of the instance remains constant, in order to properly evaluate the influence of that factor. For example, we ignore the proportions of aid that remain usable when defining the inventory budgets, although more resources are needed if a lot of pre-positioned aid is expected to be destroyed. In other words, the inventory budget $B$ remains constant for different levels of factor $R$, so that a proper analysis of the effect of $R$ can be carried out. Otherwise, a change in the facility configuration from $R = 0.5$ to $R = 1$ might be a consequence of the change in the inventory budget, rather than in the change in aid availability.

### 3.3. *Response variables*

The matheuristic introduced in (Turkeš et al., 2021) and described in Section 2 is employed to look for promising pre-positioning strategies (i.e., facility, inventory and distribution decisions $\mathbf{x} = [x_{iq}], \mathbf{y} = [y_i^k], \mathbf{z} = [z_{ij}^s]$) for every problem instance.

We limit our study only to the analysis of the facility decisions, as they are the most critical. Indeed, Turkeš et al. (2021) show that it is the facility optimization part of the matheuristic that yields the most significant improvements of the solution quality. Besides, if the facility decisions are made, the matheuristic provides a very good rule of thumb for the inventory and distribution decisions: the greedy assignment of vertices with simultaneous inventory increase (that can easily be done manually) is shown to find good inventory and distribution schemes (Turkeš et al., 2021).

Actually, in our experimental study, we will only focus on the number and the categories of the facilities to open, without saying anything about the facility locations. While the location decisions seem to be pretty straightforward (choose for locations where a high percentage of pre-positioned aid remains usable, and in the neighbourhoods with high demand, as in the greedy heuristic described in (Turkeš et al., 2021)), deciding on the number and categories of facilities to be open seems more intricate.

For each problem instance, we consider that facilities of two different categories can be open, a small facility $q = 1$, or a big facility $q = 2$. We are primarily interested to learn if it is better to open small or big facilities and to what extent, i.e., we are interested in the percentage $X_1/X$ of the open facilities which are of small capacity. For further insights, we also record the numbers $X_1$ and $X_2$ of respectively small and big open facilities in the best found solution (Table 2). The table that stores the responses for each combination of factor levels is publicly available (Turkeš, 2021).

Table 2: In the computational study, we investigate how different instance characteristics and their interactions influence the facility decisions in the best found pre-positioning emergency strategy.

| Response variable | Notation |
|---|---|
| Percentage of open facilities which are small ($\in [0, 100]$) | $\frac{X_1}{X} = \frac{X_1}{X_1+X_2}$ |
| Number of small open facilities | $X_1$ |
| Number of big open facilities | $X_2$ |

## 4. Experimental results

Using the experimental data, our first goal is to identify the instance characteristics and their interactions that have the highest impact on facility decisions (Section 4.1). The second goal is to use investigate the effect of the most important interactions on the facility planning (Section 4.2). The section ends with some examples that illustrate how simplified analyses can lead to insights which are not robust across disasters (Section 4.3).

### *4.1. Identifying the most important factors and interactions*

To address the first research question, we estimate 6 standard least squares linear regression models with the purpose of quantifying the relationship between the 10 instance characteristics (factors, or independent variables) listed in Table 1 and the 3 responses (dependant variables) listed in Table 2. We first consider 3 initial models for the percentage $X_1/X$ of small open facilities and numbers $X_1$ and $X_2$ of open small and big facilities, that involve main effects only. We later extend these models by including interaction effects between every pair of factors, to increase their explanatory power. For continuous factors, the models with main effects would take the following form:

$$\frac{X_1}{X} = \beta_0^0 + \beta_1^0 F + \beta_2^0 QV + \cdots + \beta_{10}^0 CP + \varepsilon_0$$

$$X_1 = \beta_0^1 + \beta_1^1 F + \beta_2^1 QV + \cdots + \beta_{10}^1 CP + \varepsilon_1$$

$$X_2 = \beta_0^2 + \beta_1^2 F + \beta_2^2 QV + \cdots + \beta_{10}^2 CP + \varepsilon_2,$$

and the regression including interactions could be written as:

$$\frac{X_1}{X} = \beta_0^0 + \beta_1^0 F + \beta_2^0 QV + \cdots + \beta_{10}^0 CP + \beta_{1,2}^0 F \times QV + \beta_{1,3}^0 F \times QAV + \cdots + \beta_{9,10}^0 BP \times CP + \varepsilon_0$$

$$X_1 = \beta_0^1 + \beta_1^1 F + \beta_2^1 QV + \cdots + \beta_{10}^1 CP + \beta_{1,2}^1 F \times QV + \beta_{1,3}^1 F \times QAV + \cdots + \beta_{9,10}^1 BP \times CP + \varepsilon_1$$

$$X_2 = \beta_0^2 + \beta_1^2 F + \beta_2^2 QV + \cdots + \beta_{10}^2 CP + \beta_{1,2}^2 F \times QV + \beta_{1,3}^2 F \times QAV + \cdots + \beta_{9,10}^2 BP \times CP + \varepsilon_2.$$

Typically, regression coefficients $\beta$ are used to quantify the strength of the relationship between the response variable and the factors. For example, $\beta_1^0$ is the expected change in the percentage of small open facilities $X_1/X$ for a one-unit change in the percentage of potential facility locations $F$, when all the other factors remain fixed. Since the factors are measured on different scales (e.g., recall that $S \in \{5, 10, 20\}$ and $R \in \{0.5, 0.75, 1\}$), one way to gain insights into the most influential characteristics on the best facility configuration would be to use the standardized parameter estimates, which represent the change in standard deviations of the response for 1 standard deviation change of the factor. However, a change of 1 standard deviation in one variable is equivalent to the change of 1 standard deviation in another variable only if the shapes of the distributions of the two variables resemble one another, but the meaning of a standard deviation varies greatly between non-normal (e.g., skewed or otherwise asymmetrical) distributions. Indeed, standardized regression coefficients are known to be easily subject to misinterpretation (Greenland et al., 1986, 1991; Criqui, 1991). Furthermore, the $p$-values of the statistical tests (of the null hypothesis that the parameter estimate is equal to zero, i.e., that the factor has no effect on the response) do not properly determine the significance of each term in the model since in our experiment the residuals cannot be assumed to be normally distributed with equal variance. Moreover, the $p$-values on their own cannot be used to compare the impact of each term on the response variables, as even very small differences in performance may be highly statistically significant.

To compare the effect of the factors and their interactions in a straightforward manner, we therefore code each instance characteristic as a categorical factor (represented internally as continuous indicator variables that assume values 1, 0, -1), and examine the regression model parameter estimates of the indicator variables corresponding to each of the levels of every factor (interaction). These parameters represent the difference between the mean response for that level and the average response across all levels. For instance,

$$\beta_1^0(F=0.1) = \text{mean}\left(\frac{X_1}{X} \mid F=0.1\right) - \text{mean}\left(\frac{X_1}{X}\right)$$

$$\beta_1^0(F=0.5) = \text{mean}\left(\frac{X_1}{X} \mid F=0.5\right) - \text{mean}\left(\frac{X_1}{X}\right)$$

$$\beta_1^0(F=1) = \text{mean}\left(\frac{X_1}{X} \mid F=1\right) - \text{mean}\left(\frac{X_1}{X}\right).$$

The further the parameter values are from zero, the higher is the influence of the corresponding factor (interaction). For a given factor, it is sufficient to have at least one parameter estimate that is far from zero to consider it important, as this implies that a change in the factor can yield a significant change of the response.

The models with main effects only, for estimating $X_1/X$, $X_1$ and $X_2$, have adjusted coefficients of determination $R^2$ equal to 0.36, 0.41 and 0.61 respectively. In other words, the models are able to explain 36, 41 and 61% of the response variables' variability by taking into account the instance characteristics individually. Figure 2 shows the values of the regression model parameters estimated for each factor in the main-effects models. The three response variables are plotted together despite their difference in magnitude ($X_1/X$ is a percentage, whereas the $X_1$ and $X_2$ are absolute numbers of open small and big facilities), since we evaluate the importance of factors separately for each response. The factors that have the strongest impact on the facility decisions are $D$, $QV$ and $F$, which respectively represent the demand topology, the facility capacities and the number of potential facility locations, but they are also influenced by the remaining factors.

Table 3: The (adjusted) coefficients of determination $R^2$ increase significantly if the interaction effects between the instance characteristics are considered, and therefore, they play an important role in facility decision making.

| **Response variable** | $\mathbf{R^2}$ | |
|---|---|---|
| | Main effects | Main and interaction effects |
| Percentage of small open facilities $X_1/X$ | 0.36 | 0.54 |
| Number of small open facilities $X_1$ | 0.41 | 0.69 |
| Number of big open facilities $X_2$ | 0.61 | 0.82 |

The extended models including both the main and the interaction effects, for estimating $X_1/X$, $X_1$ and $X_2$, have coefficients of determination $R^2$ equal to 0.54, 0.69 and 0.82 respectively. This means that the models are able to explain an additional 18, 28 and 21% of the variability in the response variables by including the interactions between the instance characteristics (Table 3).

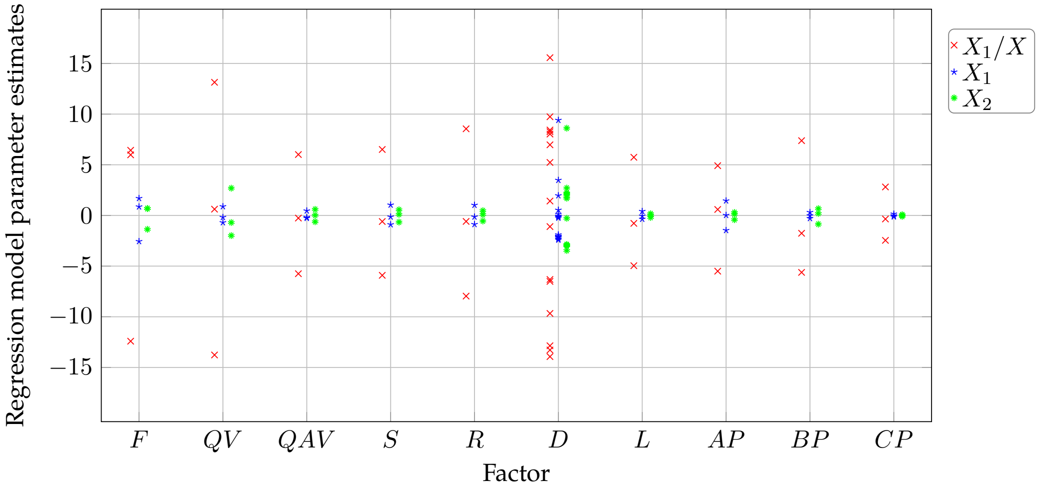


Figure 2: The demand topology $D$, the facility capacities $QV$ and the number of open facilities $F$ have the strongest influence on the facility decision making. In addition, the survivability $R$ of pre-positioned aid, availability $L$ of the transportation network, the ratio $QAV$ between facility unit opening costs, the number $S$ of scenarios and the facility and acquisition budgets $AP$ and $BP$ have a great impact on at least the percentage $X_1/X$ of small open facilities, or the numbers $X_1$ and $X_2$ of small and big open facilities in the best found solution.

Figure 3 shows the values of the regression model parameters estimated for each interaction in the extended models. The estimates for the individual factors are not included as they are equal to those in Figure 2. This is a consequence of the orthogonality of the full factorial experimental design (Section 3.2), which evaluates all possible factor combinations. Therefore, all main effects and all interaction effects can be estimated independently.

Observe that there are several interaction effects whose parameter values show large deviations from zero, i.e., there is a number of interactions that have a significant influence on the facility decisions (Figure 3). The interactions between the demand topology, represented by the factor $D$ and the remaining factors, are clearly the most influential, as their coefficient values are widely spread. The interactions between the number of potential facility locations $F$ and the facility capacities $QV$, the facility budget $AP$, and the acquisition budget $BP$ also have a strong impact on the response variables. In addition, the facility decisions are also influenced by the interactions between the facility and acquisition budgets $AP$ and $BP$ and the ratio $QAV$ of facility unit opening costs, and the interaction between those budgets.

Note that all parameter estimates remain unchanged if the less important factors or interactions are removed from the regression models - this is again a consequence of the orthogonality of the full factorial experimental design.

The unexplained variability comes from the fact that the ten factors included in our experimental study define a problem instance to a certain extent, but do not describe it completely. Indeed, many instance coefficients are defined randomly under some assumptions defined by the factor levels. For example, even though two problem instances can be defined for the same levels of each of the factors, factor $F = 0.1$ only implies that 10% of vertices are potential facility locations, so that the two instances can have very different sets of locations where aid can be pre-positioned. Although $S = 5$ assures that 5 scenarios are chosen from the given 20 in the underlying base problem instance (Turkeš, 2021), these scenarios are chosen randomly and can thus differ from instance to instance. $R = 0.75$ implies that the average proportion of aid that remains usable at a potential facility location is 75%, but it could be very low at the

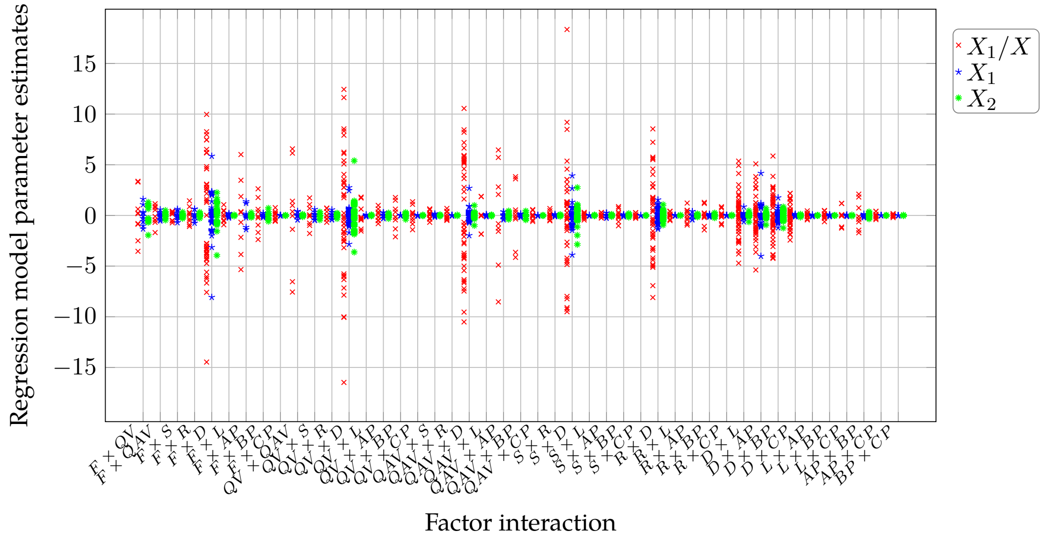


Figure 3: The interaction between the factor $D$ and the remaining factors play the most important role in the facility decision making. The facility decisions are also strongly influenced by the interactions between the number $F$ of potential facility locations and the facility capacities $QV$, or with the available facility and acquisition budgets $AP$ and $BP$, the interaction between those budgets, or the budgets with the ratio $QAV$ of facility unit opening costs.

most strategic locations for one problem instance, but (close to) 100% for another, with the same levels of $R$ and the remaining factors. Finally, if $L = 0.25$, then 25% of transportation links is destroyed, but these are also chosen in a random manner, and can therefore vary from the most crucial edges in the network, to the less relevant ones.

### 4.2. *Effect of the most important factor interactions*

In the previous subsection, we identified *which* instance characteristics and their interactions have the greatest influence on promising facility configurations. In this subsection we describe a more detailed analysis of the experimental results to identify *how* these instance characteristics influence the facility decision making. For the purpose of simplicity and clarity, we restrict our analysis to the average of a response variable for a given value of a factor, but other statistics could also easily be calculated from the data (Turkeš, 2021). For instance, the supplemental file includes the box plot for each response and factor level, showing the median, first and third quartile, and 1.5x the inter-quartile range, providing more detailed information about the results plotted in this subsection. The variation for any factor level is never that large to often enough allow for a change in how a factor influences the response, implying that the analysis of the average responses provides good insights about the relationships of interest in our experiment.

As can be seen in Figure 3, the interaction between the demand topology, represented by the factor $D$, and the other factors, has a strong influence on the facility decisions in the best found pre-positioning emergency strategy. We therefore study these interactions one by one, and provide further information about some related interactions if they were indicated as important in Figure 3.

#### 4.2.1. *Important interactions with the percentage of facility locations $F$: $F \times D$, $F \times QV$, $F \times AP$, $F \times BP$*

Across different disaster types and scales (represented by the factor $D$), the percentage $X_1/X$ of small open facilities increases if more potential facility locations (represented by the factor $F$) become available, as both the number $X_1$ and $X_2$ of small and big open facilities increase, but the latter increase at a lower rate (Figure 4). Indeed, if there is only a few potential facility locations, it seems reasonable to focus on opening big facilities in order to ensure more storage capacity and therefore pre-position as much aid as possible. The effect is much stronger when $F$ changes from $F = 0.1$ to $F = 0.5$, compared to the change from $F = 0.5$ to $F = 1$, since $F = 0.5$ already offers a great number and variety of potential locations to open the facilities. We note that the effect of $F$ is not as strong when $D$ corresponds to the Turkey or US demand graphs, since even the smallest number of potential facility locations ($F = 0.1$) comes very close to the number of demand vertices for these case studies. Indeed, the expected number of demand vertices in a scenario for Turkey and US is approximately 6 or 8, whereas the number of vertices is 14 and 30 respectively (and the number of potential facility locations is defined as the percentage of the total number of vertices, see Table 1). For these case studies, only one or a few small facilities are often sufficient to pre-position the volume of total demand in a scenario, and it can even happen that the facility budget does not allow any big facilities to be open. The number of demand vertices is closer to the total number of vertices (which are also greater) in the other demand graphs, so that a greater number of potential facility locations can significantly change the best facility configuration.

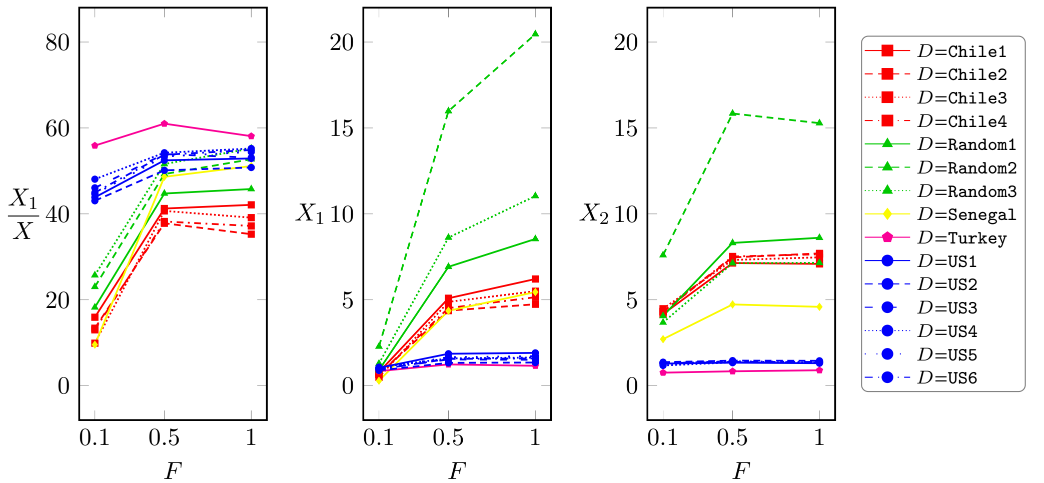


Figure 4: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities typically increases with an increase in the number of potential facility locations $F$, with the increase being particularly strong when the percentage of vertices which are facility candidates changes from $F = 0.1$ to $F = 0.5$. The number $X_1$ of small open facilities increases, whereas the number $X_2$ of big open facilities increases somewhat or remains unchanged.

Figure 3 shows that the interaction between factor $F$ and factors $QV$, $AP$ and $BP$, corresponding to the facility capacities, facility and acquisition budget, also play an important role in facility decision making. As expected, the numbers $X_1$ and $X_2$ of small and big open facilities increases at a greater rate when facility capacities are relatively small, i.e., when $QV = 2$ (Figure 5). When more facility or acquisition budget becomes available, represented by a greater $AP$ and $BP$, the influence of the factor $F$ is more strongly pronounced, but in opposite directions. Indeed, it is primarily the number $X_1$ of small open facilities that increases at a greater rate with an increase in $F$ when the facility budget is large ($AP = 1$), i.e., when there is sufficient facility budget to actually open additional facilities (Figure 6). On the other hand, the number $X_2$ of big open facilities increases faster with an increase in $F$ when the inventory budget is large ($BP = 1$), since it is then when the additional storage capacity can actually be used to pre-position more goods (Figure 7). For these reasons, the increase in the percentage $X_1/X$ with greater $F$ is typically more pronounced with a sufficient facility budget, or a limited acquisition budget.

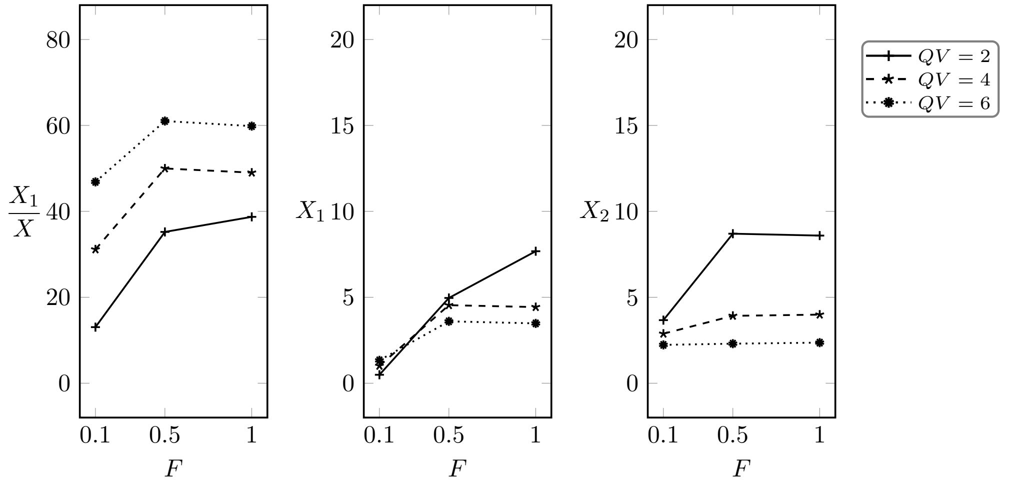


Figure 5: The effect of the number of potential facility locations, represented by factor $F$, on the facility decision making, is greater when the facility capacities are smaller ($QV = 2$).

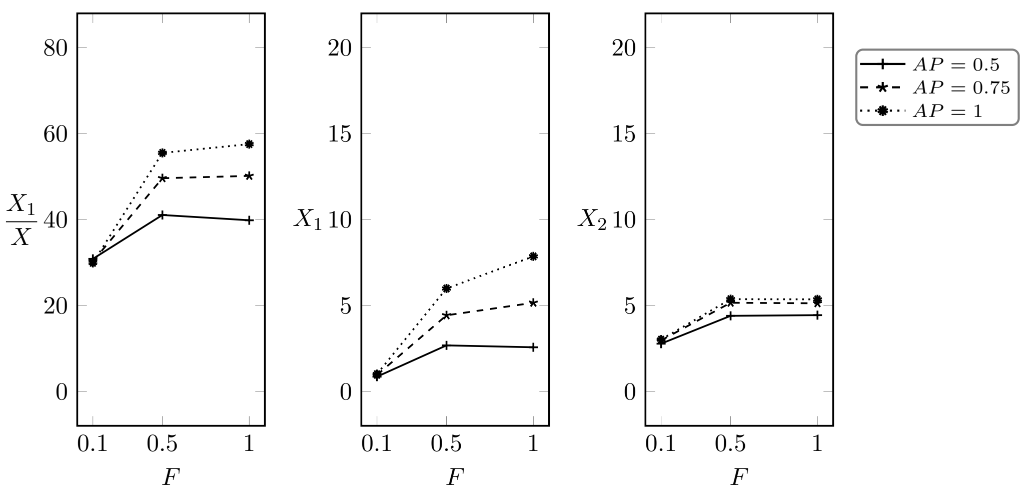


Figure 6: The effect of the number of potential facility locations, represented by factor $F$, on the facility decision making, is greater when there is more facility budget available ($AP = 1$).

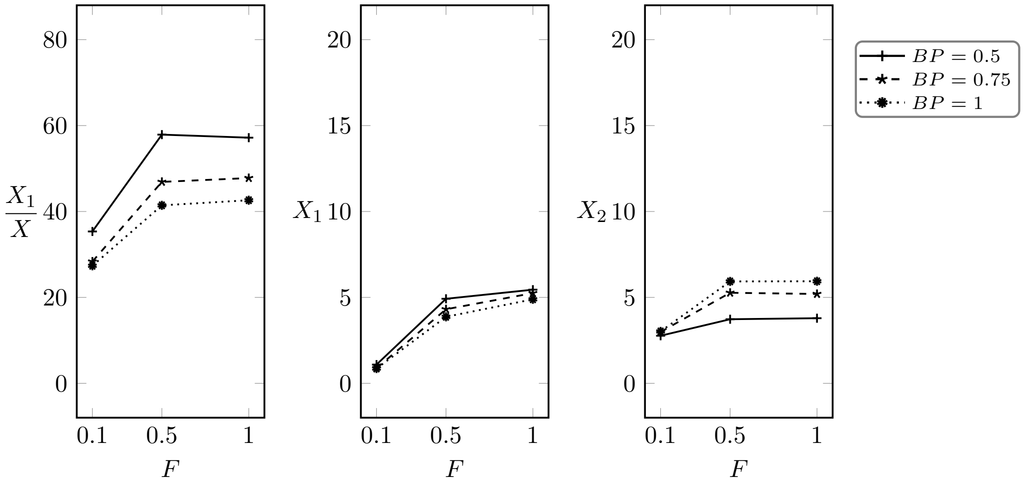


Figure 7: The effect of the number of potential facility locations, represented by factor $F$, on the facility decision making, is greater when there is more acquisition budget available $(BP = 1)$.

*4.2.2. Important interactions with the facility capacities $QV$: $QV \times D$*

With greater relative capacity of the facilities, represented by the factor $QV$, the percentage $X_1/X$ of small open facilities increases for any level of the factor $D$ (Figure 8). Indeed, if the facility capacities are relatively large, small facilities can often provide sufficient storage capacity. On average, the percentage of small open facilities increases from $29\%$ for $QV = 2$ to $55.90\%$ for $QV = 6$. Both the numbers $X_1$ and $X_2$ of small and big open facilities decrease when the facility capacities are greater (as both their capacities, but also opening costs increase), but the latter decrease at a more pronounced rate.

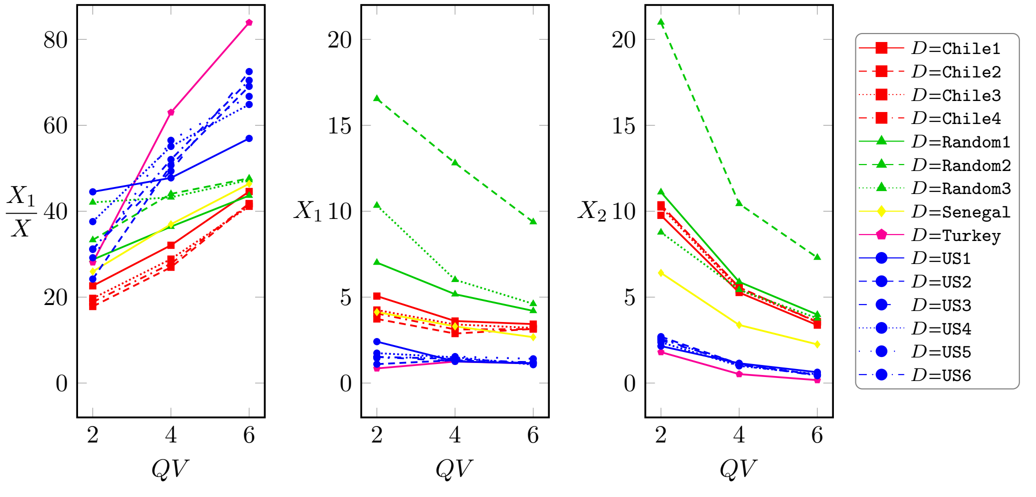


Figure 8: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities increases strongly with an increase in the facility capacities $QV$. Both the number $X_1$ and the number $X_2$ of small and big open facilities decrease, but the decrease in $X_2$ is more pronounced.

*4.2.3. Important interactions with the facility unit opening costs $QAV$: $QAV \times D$*

As expected, the greater the unit opening cost of a big facility is compared to the unit opening cost of a small facility (represented by greater $QAV$), the greater is the percentage $X_1/X$ of small open facilities, across different demand topologies $D$ (Figure 9). In other words, the more expensive the big facilities are, the more we prefer small facilities. Moreover, Figure 3 shows that the interaction between the factor $QAV$ and the available facility and acquisition budgets, plays an important role in the facility decision making. As we will see later in Figures 14 and 17, the effect of $QAV$ is more prominent if the facility budget is strict and if the acquisition budget is less restrictive. Indeed, if $QAV = 0.5$ or $QAV = 0.75$, opening big facilities yields greater total storage capacity for the same amount of facility budget, compared to opening small facilities. The importance of greater storage capacity is of particular significance when the facility budget for ensuring enough capacity is strict, or when there is sufficient acquisition budget that can be used to procure and store the relief items in that capacity.

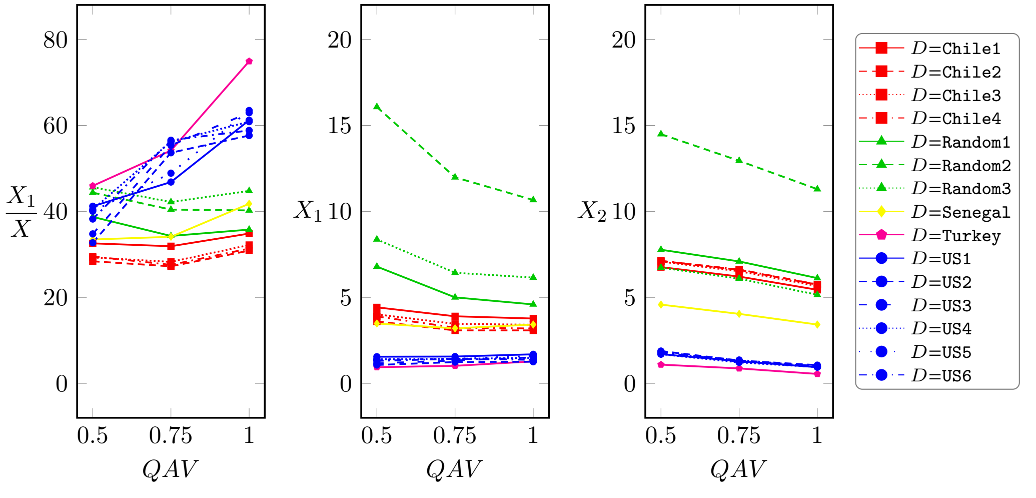


Figure 9: Across the majority of disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is greater when the big facilities are more expensive (represented by a larger $QAV$), as a consequence of a lower number $X_2$ of big open facilities.

*4.2.4. Important interactions with the number of disaster scenarios $S$: $S \times D$*

Figure 10 shows that the percentage $X_1/X$ of small open facilities decreases if the number $S$ of disaster scenarios is greater, for any level of factor $D$ (Figure 10). Indeed, when there are more disaster scenarios, i.e., where there is more uncertainty about how the disaster might affect a region, it makes more sense to focus on opening big facilities (so that the number $X_2$ of big open facilities is larger, and the number $X_1$ of small open facilities is smaller), as such emergency plans are more flexible and enable to better utilize the pre-positioned supplies across possibly very different disaster scenarios.

*4.2.5. Important interactions with the aid survivability $R$: $R \times D$*

The greater the average percentage $R$ of aid that remains usable, the greater is the percentage $X_1/X$ of small open facilities, since the number $X_1$ of small open facilities typically increases, whereas the number $X_2$ of big facilities decreases (Figure 11). The total number of facilities open is lower when a considerable proportion of aid might be destroyed. Indeed, using a small example in Section 3, we explain how it might be better in such a case to open fewer facilities where the proportion of aid that remains usable is the greatest. In order to ensure the sufficient storage capacity, there is a preference for big open facilities.

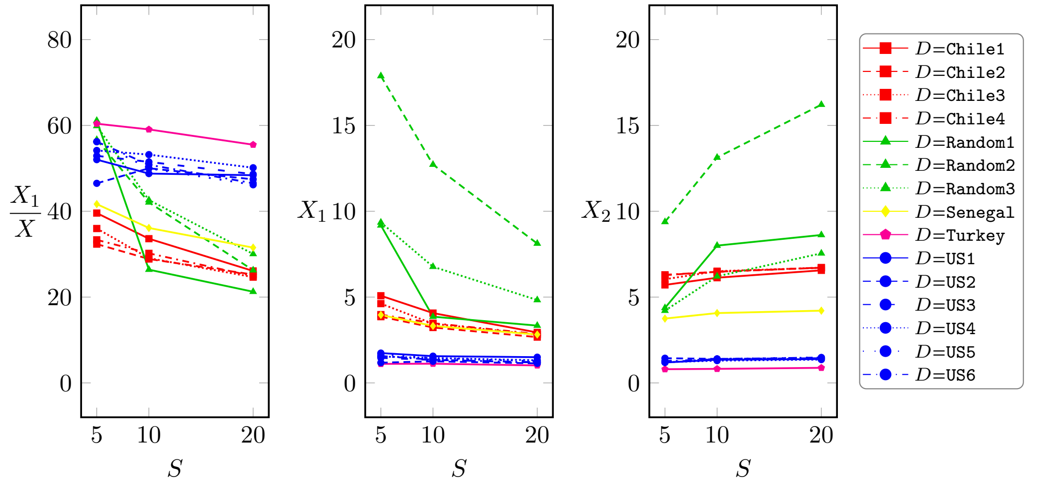


Figure 10: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is lower if the number $S$ of disaster scenarios is greater. The number $X_1$ of small open facilities decreases, whereas the number $X_2$ of big open facilities increases.

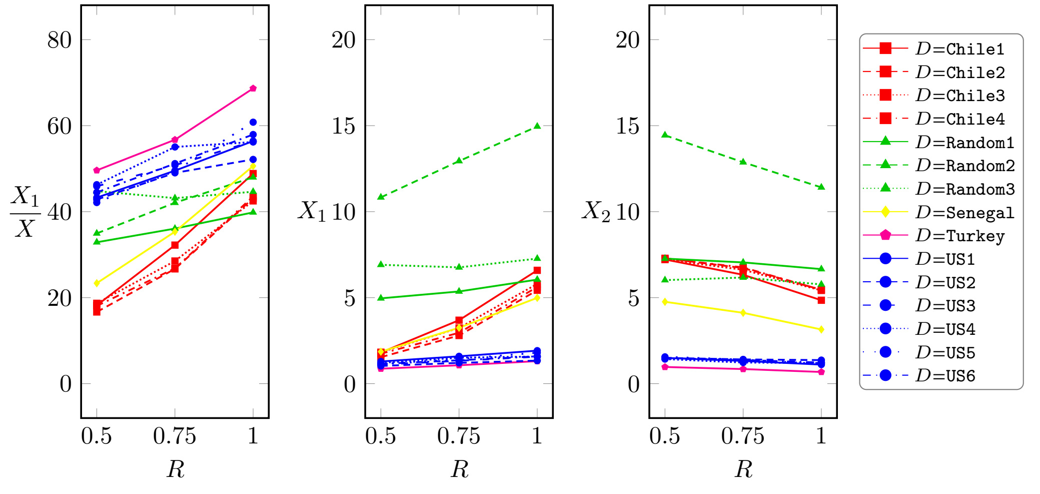


Figure 11: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is greater if greater proportions of aid remain usable after the disaster, represented with a greater value of factor $R$. The number $X_1$ of small open facilities increases, whereas the number $X_2$ of big open facilities decreases, with an increase in $R$.

#### *4.2.6. Important interactions with the transportation network damage L: L × D*

Irrespective of the demand topology $D$, the percentage $X_1/X$ of small open facilities increases with greater level $L$ of transportation network damage, since the number $X_1$ of small open facilities increases, and the number $X_2$ of big open facilities decreases (Figure 12). This seems reasonable, as more facilities are necessary in order to reach the beneficiaries.

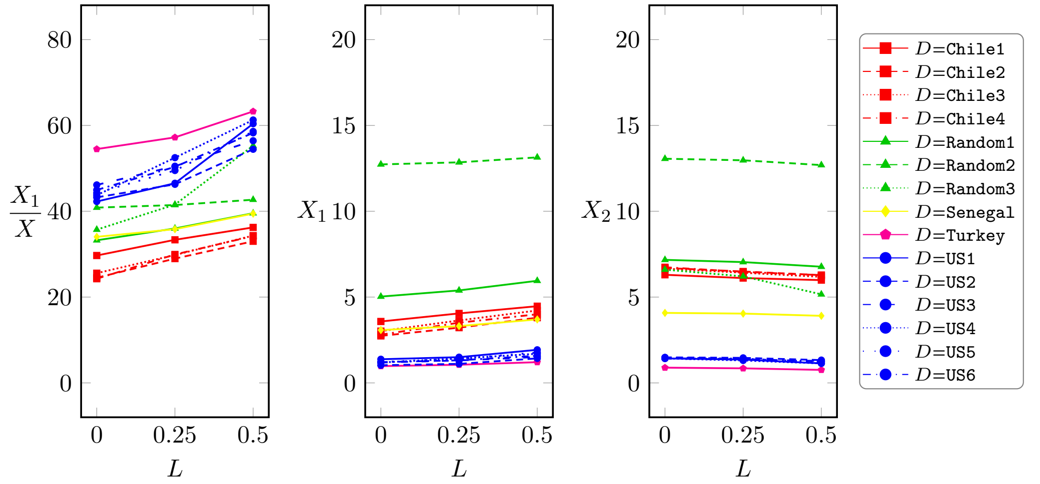


Figure 12: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is greater if the transportation network is severely damaged, represented with a greater value of factor $L$. The number $X_1$ of small open facilities increases, whereas the number $X_2$ of big open facilities decreases, with an increase in $L$.

#### 4.2.7. *Important interactions with the facility budget $AP$: $AP \times D$, $AP \times QAV$, $AP \times BP$*

Figure 13 shows that the percentage $X_1/X$ of small open facilities increases with greater facility budget, represented by the factor $AP$, for any demand graph $D$. Both the numbers of small and big facilities $X_1$ and $X_2$ typically increase when more facility budget is available, but the former increase at a greater rate or more often.

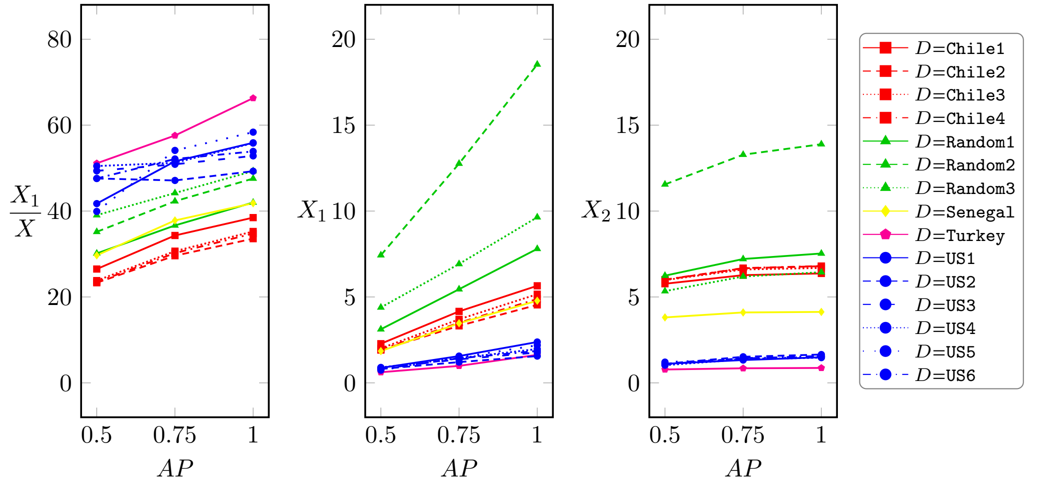


Figure 13: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is greater if there is more facility budget $AP$ available. Both the number $X_1$ and the number $X_2$ of small and big open facilities increase with greater $AP$, but the increase in $X_1$ is more pronounced.

As we can see from Figure 6, the effect of the facility budget $AP$ is stronger when there are more potential facility locations (where the greater number of facilities can actually be open). Figure 3 indicates that the effect of the interaction between the facility budget $AP$ and the ratio $QAV$ of the unit opening costs, and the acquisition budget $BP$, also has a strong influence on the facility decision making. The effect of $AP$ on $X_1/X$ is more pronounced when the unit opening cost of big facilities is smaller than of the small facilities ($QAV = 0.5$) (Figure 14). Indeed, the stricter the facility budget, the greater is the focus on big facilities which can ensure sufficient storage capacity, in particular if the unit opening cost of big facilities is smaller than the cost of small facilities. This effect of $AP$ is also more pronounced when the acquisition budget is limited ($BP = 0.5$), as it is then of lesser importance to open more big facilities in order to ensure sufficient storage for the acquired emergency supplies (Figure 15).

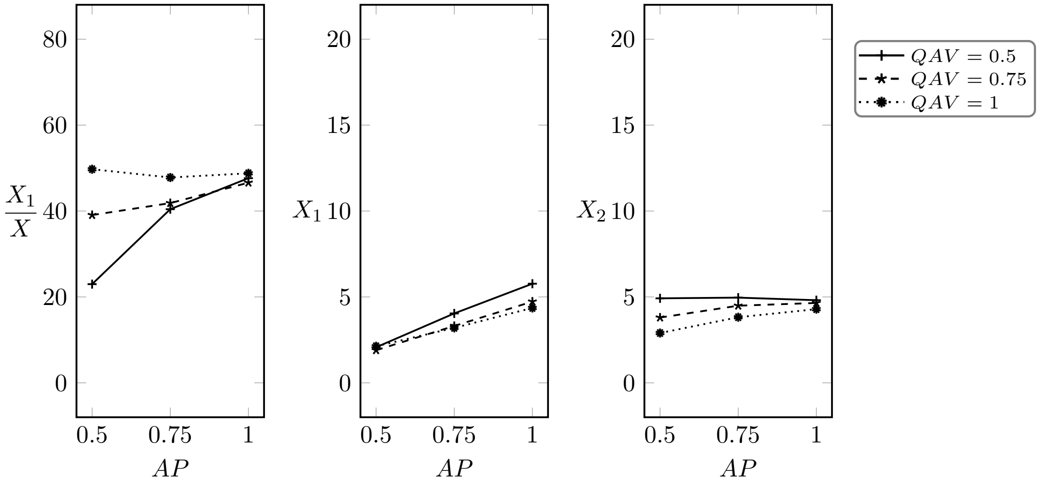


Figure 14: The effect of the facility budget $AP$ on the facility decisions is influenced by the ratio $QAV$ between facility unit opening costs. When big facilities are less expensive ($QAV = 0.5$), a considerable number $X_2$ of them can already be open even for a more limited facility budget, so that it remains unchanged if more budget becomes available, and therefore an increase in the number $X_1$ of small open facilities implies also a greater increase in the percentage $X_1/X$ of small open facilities.

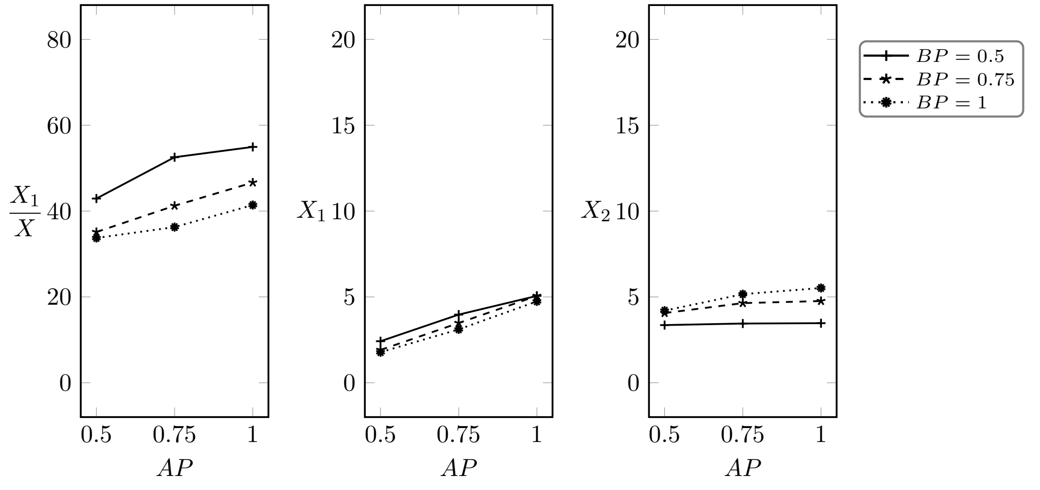


Figure 15: The effect of the facility budget $AP$ on the facility decisions is influenced by the acquisition budget $BP$. When the acquisition budget is greater ($BP = 1$), it becomes more beneficial to ensure a larger storage capacity to pre-position the additional goods, so that the number $X_2$ then also increases, and as a consequence, the increase in the percentage $X_1/X$ of small open facilities is somewhat less pronounced.

*4.2.8. Important interactions with the inventory budget $BP$: $BP \times D$, $BP \times QAV$*

When more acquisition budget becomes available, represented by a greater $BP$, the percentage $X_1/X$ of small open facilities decreases, since the number $X_1$ of small open facilities typically decreases, and the number $X_2$ of big open facilities increases (Figure 16). Indeed, as already mentioned, big facilities become more important when there is actually sufficient acquisition budget available, as they can ensure sufficient storage capacity for the acquired emergency supplies. As expected, this effect is pronounced even more when the unit cost of big facilities is smaller than the unit cost of small facilities, i.e., when $QAV$ is smaller (Figure 17).

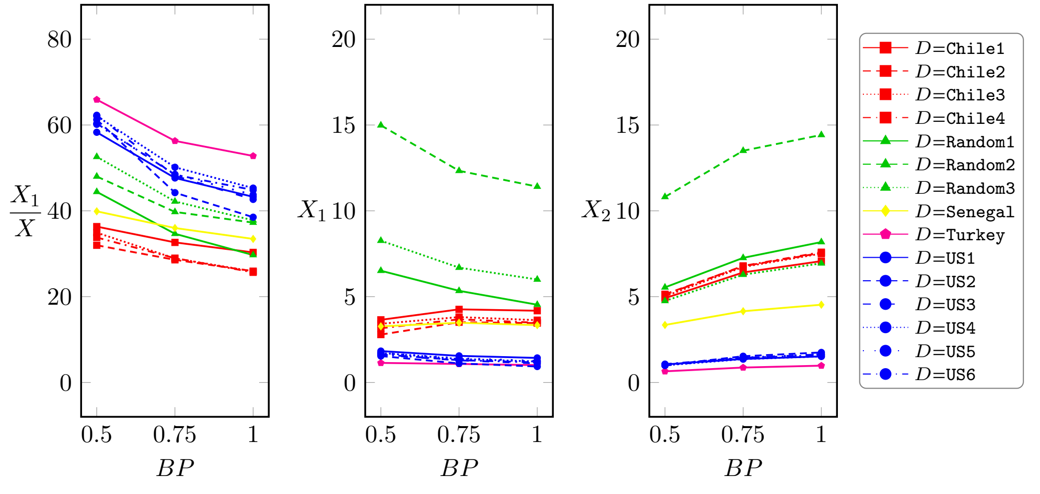


Figure 16: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is lower if there is more acquisition budget $BP$ available. The number $X_1$ of small open facilities decreases, whereas the number $X_2$ of big open facilities increases with greater $BP$.

*4.2.9. Important interactions with the transportation budget $CP$: $CP \times D$*

For any demand graph $D$, the percentage $X_1/X$ of small open facilities decreases with greater transportation budget, represented by the factor $CP$ (Figure 18). Indeed, if the transportation budget is limited, it is of greater importance to open more (and thus more small) facilities.

*4.3. Ignoring important interactions can yield misleading conclusions*

In Section 1, we motivated our large computational study as a method that can help gain robust insights into the pre-positioning facility decision making, that are often missed by simplified analyses that are more common in the humanitarian logistics literature.

The first simplification that is common in the literature is an investigation of only the main effects of one or multiple factors. Figure 19 demonstrates how such a simplified analysis can yield misleading conclusions. Indeed, Figure 19 shows the effect of the factor $AP$ that represents the facility budget, on the facility decision making, where it seems that the percentage $X_1/X$ of small open facilities increases when there is more facility budget available, as the number of $X_1$ of small open facilities increases, whereas the number $X_2$ of big open facilities does not significantly change.

However, we have seen in the Section 4.2 that this is not always the case. For example, if the facility budget is limited ($AP = 0.5$), and the unit opening cost of big facilities is as large as the unit cost for small facilities ($QAV = 1$), the number $X_2$ of big open facilities is limited, so that an increase in the facility budget can in this case yield an increase in the

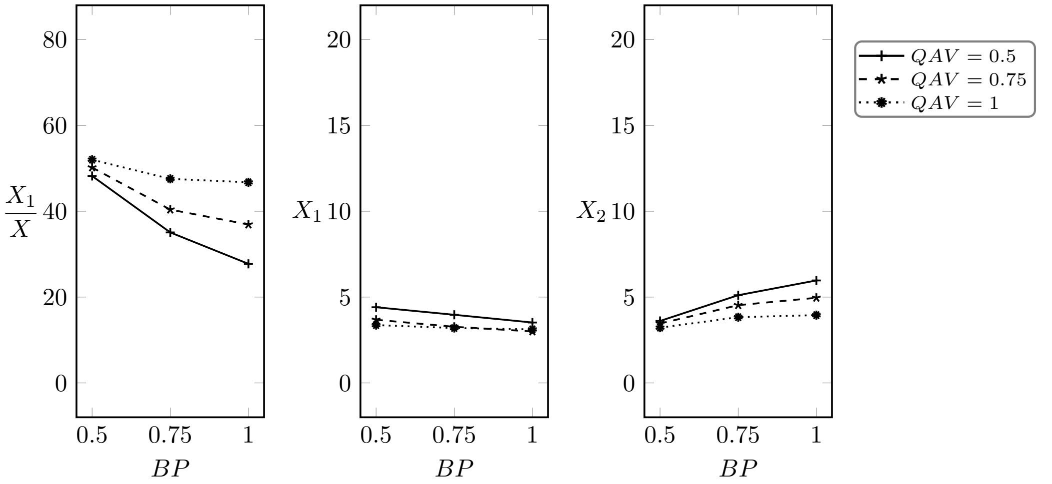


Figure 17: The effect of the acquisition budget $BP$ on the facility decisions is influenced by the ratio $QAV$ between facility unit opening costs. When big facilities are less expensive ($QAV = 0.5$), it is also possible to open a greater number $X_2$ of them in order to benefit from more storage for pre-positioning the additional goods obtained with greater $BP$; consequently, the the decrease in the percentage $X_1/X$ of small open facilities is more pronounced.

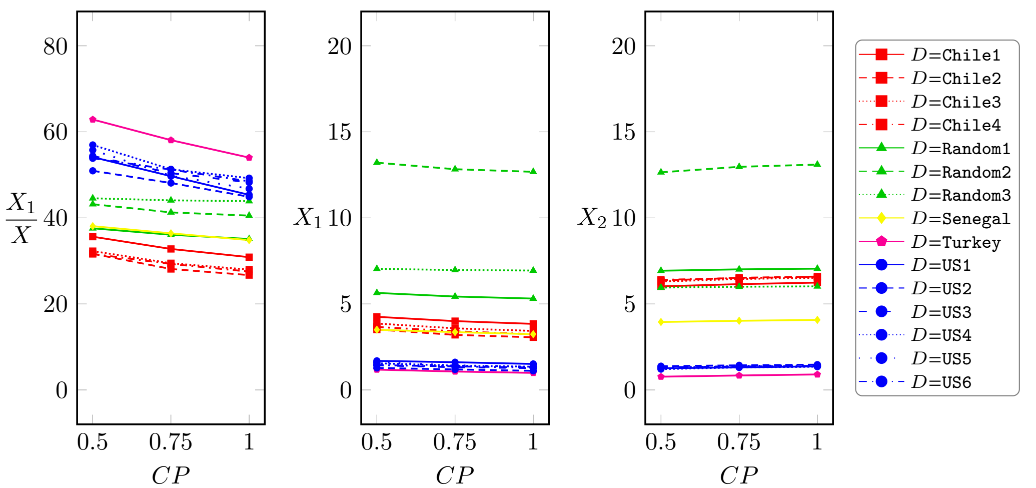


Figure 18: Across different disaster types, scales and demand topologies $D$, the percentage $X_1/X$ of small open facilities is lower if there is more transportation budget $CP$ available. The number $X_1$ of small open facilities decreases, whereas the number $X_2$ of big open facilities increases with greater $CP$.

number of big open facilities (Figure 14). In this case, the percentage of $X_1/X$ on average remains the same, whereas the number $X_2$ of big open facilities increases with greater $AP$, contrary to what we can see when only investigating the main effect of the facility budget $AP$ (Figure 19). In addition, Figure 15 shows that the number $X_2$ of big open facilities is strongly influenced by the interaction between the facility and acquisition budget, represented by factors $AP$ and $BP$: if there if sufficient acquisition budget available, it becomes important to also open additional big facilities when the facility budget increases, in order to ensure a greater storage capacity to pre-position the acquired supplies. Finally, we can also see in

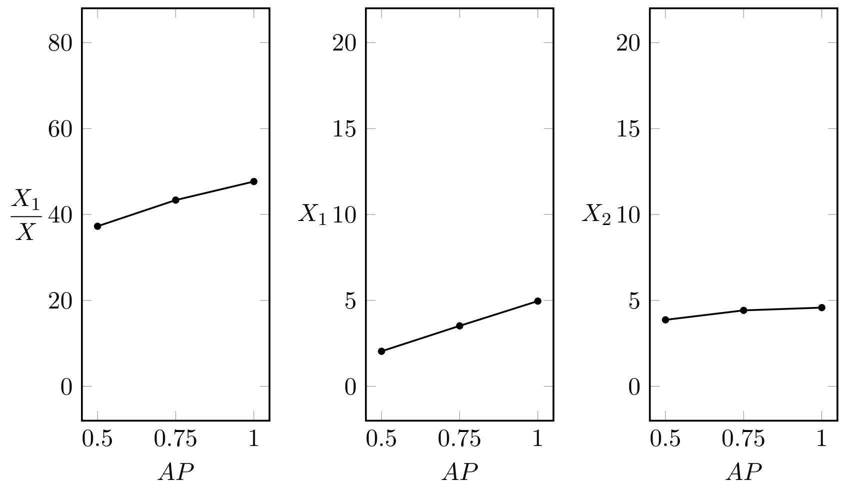


Figure 19: This example shows how studying the factors individually can lead to misleading conclusions and policy recommendations. Simply analysing the influence of the factor $AP$ that represents the facility budget, it seems that the percentage $X_1/X$ of small open facilities, as well as the numbers $X_1$ and $X_2$ small and big open facilities, increase with an increase in the available budget. However, earlier analysis revealed that this behaviour is strongly influenced by the interaction of the factor $AP$ with the percentage of facility locations, ratio between facility unit opening costs, and the acquisition budget, represented respectively with factors $F$, $QAV$ and $BP$.

Figure 6 that the numbers of small and big open facilities do not increase with greater facility budget $AP$ if there is not sufficiently many potential facility locations ($F = 0.1$). The insights obtained from the analysis of the main effect of the factor $AP$ therefore do not generalize when $F = 0.1$, $QAV = 1$ or $BP = 1$.

Similarly, a simplified analysis that employs a single case study (i.e., that ignores the interaction with factor $D$) might not generalize to other disasters. This is demonstrated in Figure 20 that shows the effect of the number of potential facility locations, represented by the factor $F$, on the facility decisions for the Turkey case study ($D = \texttt{Turkey}$).

It seems that the numbers $X_1$ and $X_2$ of small and big open facilities remain the same, regardless the changes in the number of facility candidates. However, we have seen in the Section 4.2 that the facility decisions change significantly when there are more potential facility locations. Indeed, Figure 4 shows that that the percentage $X_1/X$ of small open facilities, and the numbers $X_1$ and $X_2$ all increase with an increase in $F$, for any other case study, i.e., for other levels of factor $D$ (and further analysis, in Figures 5, 6 and 7, shows that the increase rate is strongly influenced by facility capacities, facility and acquisition budget, represented respectively by factors $QV$, $AP$ and $BP$). In other words, an analysis relying on a single case study does not yield findings which are robust across disasters.

## 5. Conclusions, limitations and future research

Facility decision making is a crucial aspect of the pre-positioning disaster planning. Good facility configurations can be found by employing mathematical models and solution procedures, but humanitarian workers rarely use these tools in practice and rather rely on simpler rules of thumb to guide their planning. The best facility configurations are highly dependant on the instance characteristics and therefore a thorough investigation of the impact of these characteristics is necessary to obtain meaningful policy recommendations. The common practice in the literature to derive managerial implications is sensitivity analysis on one or a few

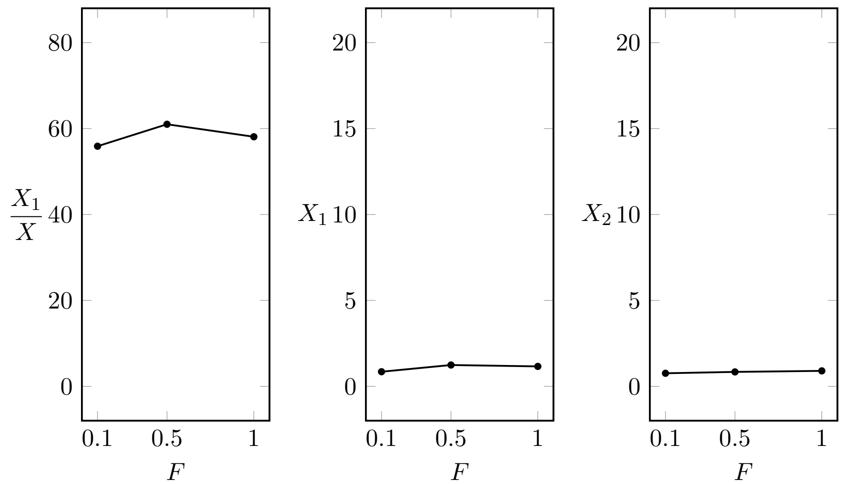


Figure 20: This example shows that studying the pre-positioning facility decisions using a single case study can lead to misleading conclusions and policy recommendations. The graph shows the influence of the number of potential facility locations, represented by the factor $F$, on the percentage $X_1/X$ of small open facilities, and the numbers $X_1$ and $X_2$ of small and big open facilities for the Turkey case study. From this analysis, it seems that the number of potential facility locations does not have a strong impact of the facility decisions. However, earlier analysis which includes other case studies focusing on disasters of different type and scale (i.e., the interaction with the factor $D$ representing demand topologies), revealed that $X_1/X$, $X_1$ and $X_2$ increase significantly when there are more facility candidate locations.

instance characteristics, carried out separately and using a single case study. However, such simple analyses provide no guarantee of the robustness of the derived rules of thumb (or any insights about the problem) across different disaster properties, as the findings might not generalize to a new disaster if the analysis ignores important interaction effects.

In this paper we describe the extensive computational study that we carried out in order to analyse the importance of a comprehensive set of instance characteristics and their interactions on the facility decision making. The main contributions lie in the outcome of the study that answers the two research questions introduced in Section 1, i.e., it identifies *which* factors and their interactions have the greatest influence on the facility decisions, and *how* they influence the facility planning, summarized below.

(1) Each of the considered factors has an influence on the facility decision making, in the following order: demand topology, facility capacities, number of potential facility locations, proportions of aid that remains usable, acquisition and facility budget, number of scenarios, ratio between facility unit opening costs, level of transportation network damage, transportation budget; and many interaction effects are more important than some of the main effects.

(2) Across different types of disasters considered, there is typically a stronger preference for small facilities when:
- facility capacities are large
- there are many available facility candidate locations
- most of the pre-positioned aid remains undestroyed
- facility budget is not very limited
- acquisition or transportation budget is restricted
- there is less uncertainty about the disaster
- unit opening cost of a big facility is close to the unit cost for small facility
- transportation network is severely damaged.

Next to the practical implications, the outcomes of the study also demonstrate the importance of such elaborate computational studies and thereby constitute a methodological contribution of the work. The experimental results show that including interactions between instance characteristics significantly increases the explanatory power of the regression models. In particular, we also offer some examples that show how simplified analysis of only the main effects and/or using a single case study (typical in the literature) can lead to insights that do not generalize to other disasters. Hopefully, these results will motivate better experimental designs in the field of humanitarian logistics, that ensure that the findings are robust across different disaster properties.

Furthermore, by emphasizing the importance of some of the instance characteristics, the outcomes of the study can also be beneficial in the discussion on the standard pre-positioning problem definition, what has been identified as an important future research direction in a survey of pre-positioning problem literature (Balcik et al., 2016). The authors recognize that there are several problem aspects that are considered by some studies and ignored by others, so that it would be of interest to investigate whether and how the facility and inventory decisions are affected if these problem aspects are included. For example, a literature review in (Turkeš and Sörensen, 2019) or (Sabbaghtorkan et al., 2020) shows that the pre-positioning problem definitions often ignore the uncertainties in the aid and/or transportation network survivability. Our experimental results, however, show that the best facility configuration changes greatly with respect to the average proportion of aid that remains usable and the level of transportation network damage, represented by the factors $R$ and $L$. These factors play a significant role in the facility decision making and therefore need to be incorporated into the definition of the pre-positioning problem.

In addition, the insights gained can be used to design better heuristics for the pre-positioning or related problems by incorporating the problem specific knowledge into heuristic elements. For instance, starting from an initial solution, we can change the facility configuration (by closing or opening small or big facilities, or by changing the facility categories) according to the values of different important instance characteristics identified in this paper, for the given problem instance.

Finally, the experimental data and summary of results are made publicly available on the Mendeley (Turkeš, 2021), in order to allow to replicate the study and/or gain a better understanding of the pre-positioning problem. Next to the information about the best found facility configuration (i.e., the percentage of small open facilities, and the numbers of small and big open facilities), the summary of results also records information about the quality of emergency strategy (unmet demand and response time) and other properties of the solution for every pre-positioning problem instance. The results can therefore be immediately employed to, for example, investigate the impact of the instance characteristics on the quality of pre-positioning strategy. A first look at the main effects implies that it is most crucial to ensure sufficient number of potential facility locations, to invest in the availability of the transportation network, and in preventing the aid from being destroyed after the disaster (Turkeš, 2021), but a thorough investigation of the interaction effects can help to gain other valuable insights into the problem.

Our study shows that factor $D$, representing the demand graphs, has a very strong influence on the facility decision making (what further supports the importance of considering multiple case studies). An important limitation of our experimental design is that is does not answer what are the key properties of these demand graphs, and how do they influence the choice of the best facility configuration. We chose to exploit the rich and realistic network and demand information from the case studies available in the literature, and therefore preserved this information in a single factor. It might be worthwhile to rather consider a set of separate factors to be included in future experimental studies. Some of the factors that could be considered are the number of vertices, the size of geographical area (reflecting the disaster scale), the number of demand vertices, demand distribution (e.g., random or clustered, reflecting localized and dispersed disasters), demand variance across vertices in a single scenario and across different disaster scenarios. The outcomes of our experiment already give an idea that there is a strong relationship between the number of demand vertices, the coefficient of demand volume variance across disaster scenarios (ratio of the standard deviation to the mean) and the best facility configuration (Turkeš, 2021), and a deeper look at these dependencies might yield further valuable insights. The main challenge with this alternative experimental set-up is a reasonable definition of demands for each of the factor level combinations.

The experimental results also motivate in-depth analyses of other factors, that could derive more precise rules of thumb for facility planning. For example, the availability $R$ of pre-positioned goods was identified as one of the important factors. However, our definition of factor $R$ only gives information about the proportion of available aid averaged across different facility candidates, but it might be worthwhile to investigate the standard deviation between these proportions (i.e., there is a difference if the proportion of aid that remains usable at two different facilities is 50%, or if it is 20% at one, and 80% at another facility). As another example, the factor $F$ only gives information about the number of open facilities, but more precise managerial implications could be derived if we look at how facility candidates are spread out (average distance between facility locations), or how distant they are from demand regions. For an in-depth analysis of factor $F$, our results show that it is important to consider different values of the relative facility capacities, facility and inventory budget.

The applicability of the findings obtained is also limited by the underlying problem assumptions. For example, the best facility configuration is defined by the choice of the objective function, and therefore different rules of thumb might apply if the lexicographic order between unmet demand and response time was relaxed or if logistics cost were to be minimized. The same is true if a multi-echelon, multi-period or multi-modal formulation of the pre-positioning problem would be considered. Interesting potential future research directions might thus be directed towards designing similar experiments for other problem formulations and other problems in humanitarian logistics.

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