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Deriving rules of thumb for facility decision making in humanitarian operations

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Abstract

In this paper, we investigate the factors that have an impact on the choice of facility configuration for inventory pre-positioning in preparation for emergencies - a critical decision faced by humanitarian managers. Current research in the field is rich with mathematical models and solution algorithms for the problem of pre-positioning emergency supplies. However, due to a lack of a strong mathematical background and/or computational infrastructure, the decision makers rely on simpler rules of thumb to guide their planning. Some managerial implications have been offered in the literature, but these have been derived from sensitivity analyses focused on a single factor and using a single case study, and as such can be misleading as they ignore important interactions between many instance characteristics. We carried out a large experimental study that analyses the effect of different instance characteristics and their interactions on the facility decision making. On the one hand, the outcomes of the study help us identify the most important factors and factor interactions that are further used to yield policy recommendations for facility planning. On the other hand, this study also demonstrates the extent of erroneousness of the guidelines derived from simple analyses, and as such hopefully promotes better experimental designs in the field of humanitarian logistics.

1 Motivation and literature review

Each year, millions of people worldwide are affected by disasters [1], 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 [18].

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 [13]. 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 [16]. The disaster management literature is abundant with mathematical models and solutions procedures that aim to optimize humanitarian supply chain [2, 10, 16, 13, 3, 15, 22, 6, 14]. 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. 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 [20], since managers most often prefer to rely on straightforward rules of thumb to guide their planning process [11].

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 [2]. 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 [29]. Pre-positioning emergency inventory in selected facilities is commonly adopted to prepare for potential disaster threat [19]. 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 [4]. 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 [24].

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 a single parameter using a single case study (a common approach throughout humanitarian logistics literature). For example, in [5], the authors 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 in [8] 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.

In [21], the authors use 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. A Thai flood case study is introduced in [17] 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 on a single parameter, as they ignore the influence of other factors that can completely reverse the patters 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 in [21], or the interaction between maximum response time and opening and transportation costs in [17]. Deriving general 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. 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 [8, 17].

To avoid the aforementioned issues, we carry out a large computational study that includes a comprehensive set of factors in order to answer the following questions:

(1) Which instance characteristics and/or their interactions have the largest influence on the facility decision making?

(2) What are the best facility configurations for an instance with certain characteristics?

To the best of our knowledge, this paper is the first such attempt in the domain of humanitarian logistics that we hope becomes a standard practice 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 a single instance parameter, using a single case study.

The remainder of the paper is organized as follows. In Section 2, we describe the prepositioning 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, which is then used to derive some rules of thumb in Section 4.2. The experimental results are also used to provide some examples in Section 4.3 that illustrate how a simple sensitivity analysis on a single parameter and/or using a single case study can yield misleading conclusions. 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 procedure

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. A 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 M_q and opening cost A_q. We consider a set of different commodities $k \in \mathrm{K}$ (e.g., food, water, medicine, blankets, clothing) with unit volume V^k, unit acquisition cost B^k and unit transportation cost C^k. These commodities 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 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 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 $s \in \mathrm{S}$.

The aforementioned problem assumptions are an adapted version of the pre-positioning problem definition that was introduced in [23] and has since been widely adopted in the literature.

Table 1: Notation for the instance and solution of the pre-positioning problem.

Sets	
Q	set of facility categories
K	set of commodities
S	set of scenarios
V	set of vertices
E_s	set of edges in scenario $s \in \mathrm{S}$
Coefficients	
F_i	$\begin{cases} 1, & \text{if a facility (of any category) can be open at vertex } i \in \mathrm{V} \\ 0, & \text{otherwise} \end{cases}$
V_q	volume capacity of a facility of category $q \in \mathrm{Q}$ (m^3)
A_q	opening cost of a facility of category $q \in \mathrm{Q}$ (€)
V^k	unit volume of commodity $k \in \mathrm{K}$ (m^3)
B^k	unit acquisition cost of commodity $k \in \mathrm{K}$ (€)
C^k	unit transportation cost of commodity $k \in \mathrm{K}$ (€)
V	average speed (km/h)
P^s	probability of scenario $s \in \mathrm{S}$
D_i^{ks}	demand for commodity $k \in \mathrm{K}$ at vertex $i \in \mathrm{V}$ in scenario $s \in \mathrm{S}$
R_i^{Ks}	$\begin{cases} \text{proportion of pre-positioned commodity } k \in \mathrm{K} \text{ that remains usable at vertex } i \in \mathrm{V} \\ \text{ in scenario } s \in \mathrm{S}, \quad F_i = 1 \\ -1, \quad \text{otherwise} \end{cases}$
L_{ij}^s	$\begin{cases} \text{distance from vertex } i \in \mathrm{V} \text{ to vertex } j \in \mathrm{V} \text{ in scenario } s \in \mathrm{S} \text{ (km)}, & (i,j) \in \mathrm{E}_s \\ -1, \quad \text{otherwise} \end{cases}$
A	total budget for opening the facilities (€)
B	total budget for aid acquisition (€)
C	total budget for transportation (€)
Decision variables	
x_{iq}	$\begin{cases} 1, & \text{if a facility of category } q \in \mathrm{Q} \text{ is open at vertex } i \in \mathrm{V} \\ 0, & \text{otherwise} \end{cases}$
y_i^k	amount of commodity $k \in \mathrm{K}$ pre-positioned at vertex $i \in \mathrm{V}$
z_{ij}^s	$\begin{cases} 1, & \text{if the facility open at vertex } i \in \mathrm{V} \text{ fully meets the demands of vertex } j \in \mathrm{V} \\ & \text{in scenario } s \in \mathrm{S} \\ 0, & \text{otherwise} \end{cases}$

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 $i \in \mathrm{V}$ serves 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 notation for an instance and a solution of the pre-positioning problem is summarized in Table 1. An example of a small pre-positioning problem instance, and the mathematical formulation can be found in [26].

Since the pre-positioning problem becomes intractable for larger instances for commercial solvers such as CPLEX, we employ a matheuristic that is able to find good solutions in a very limited computation time, introduced in [28]. The matheuristic is based on the iterated local search procedure, with the aid distribution sub-problem intermittently solved by CPLEX. The experimental results in [28] suggest that a simple improvement of the matheuristic would be to let the matheuristic run for most of the given computation time, but to also allocate a very limited amount of time (only a few seconds) 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 set-up

In this section, we describe in detail the set-up of the extensive computational study that we carried out. As mentioned before, the first goal of the experiment is to identify the instance characteristics that have the most significant influence on the facility decision making, and to determine how these characteristics influence each other. The second goal of the experiment is to identify the rules of thumb for facility decision making in humanitarian operations.

As described in Section 2, to solve the pre-positioning problem is to make not only the facility decisions, but also the inventory and distribution decisions. We limit our study only to the analysis of the facility decisions, as they are the most critical. Indeed, it is shown in [28] 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 in [28] to find good inventory and distribution schemes.

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 [28]), deciding on the number and categories of facilities to be open seems more intricate. For the standard deterministic facility location problem in commercial logistics, the demands of every customer must be met so that the transportation cost or time needs to be minimized, and thus a good rule of thumb would be to open as many facilities as possible. For the pre-positioning problem, it is unrealistic to request that the demand must completely be met, and thus the objective is to provide service to the greatest number of people possible, as soon as possible (minimize unmet demand and response time in lexicographic order) such that the financial limitations are respected. This, combined with multiple facility categories and uncertainties about a number of aspects of a disaster, completely change the guidelines for the number and categories of facilities to open.

What a good facility configuration looks like for the pre-positioning problem instance therefore requires studying the influence of a number of instance characteristics. Before we describe each of them in detail, we give a general idea why they are important for this problem and illustrate the discussion with a small example.

Obviously, the available budgets have an important effect on the the facility decisions. If the inventory budget B is unlimited (i.e., very large), the demand of every vertex in every scenario can be met (except the isolated demand locations that cannot be reached from any potential facility location, or if there are insufficient number of potential facility locations), and therefore the only objective is to minimize the response time. If the facility budget is also unlimited, the best strategy is to open a facility of the largest category at every potential facility location. Even if the facility budget is limited, a simple rule of thumb in this case would be to open as many facilities (of the smallest category, as they are the cheapest) as the facility budget permits, in order to provide the service as soon as possible. However, the more restricted the inventory budget becomes, the greater is the focus on the primary objective of minimizing unmet demand. It might become more preferable to open less facilities (and of bigger capacity) in order to make better use the pre-positioned aid across different disaster scenarios. In addition, if the proportions of aid that would remain usable are very low for many potential facility locations, we might prefer to open fewer facilities (with a bigger capacity) where the proportion of aid that remains usable is high, as illustrated in the example below. On the other hand, if the transportation budget is also very limited or if the transportation network would be destroyed across many disaster scenarios, we would try to open more facilities in order to be able to reach many demand locations. This gives a better idea why the mentioned instance parameters, but also their interactions, might influence the facility decision making.

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.

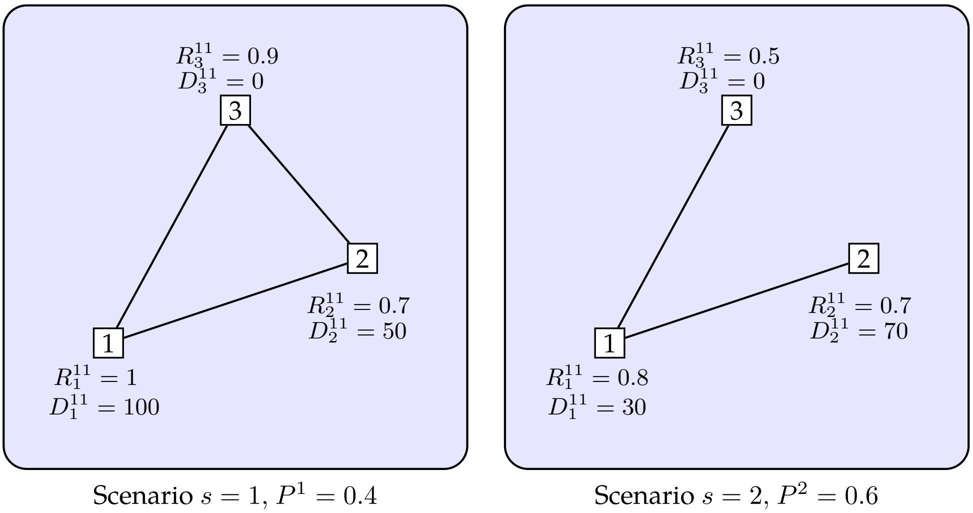


Figure 1: Graphs G_1 and G_2 represent three cities and the road network that connects them in two possible disaster scenarios. The scenarios occur with probabilities P^1 and P^2 respectively, and both are defined with the demand D_i^{ks} and proportion of aid that remains usable R_i^{ks} for every commodity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

The discussion and example above describe 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 (Table 1) with a factor. The complete list of factors that included in the experiment is given in Table 2. In the remainder of this section, we describe each factor in greater detail, and in the final subsection we describe how each experimental unit is evaluated.

3.1 Percentage of potential facility locations

The first instance characteristic that might influence the best facility configuration for a problem instance is the percentage of vertices that are potential facility locations. This factor can become important for instances whose good solutions correspond to many open facilities at the majority of potential facility locations, with total facility capacity that is much lower than the total demand volume (Section 3.2, $QV = 2$). Indeed, increasing the percentage of potential facility locations for such instances can change the best facility configuration by opening more facilities to allow to pre-position more aid that is able to serve more de-

Table 2: In the computational study, we investigate how different instance parameters and their interactions influence the facility decision making.

Factor	Notation	Levels	Description of levels
Percentage of potential facility locations	F	0.1 0.5 1	$100F\%$ of random vertices are potential facility locations.
Facility capacities	QV	2 4 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 0.75 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 10 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 0.75 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`
		`Chile2`
		`Chile3`
		`Chile4`
		`Turkey`
		`Senegal`
		`US1`
		`US2`
		`US3`
		`US4`
		`US5`
		`US6`
		`Random1`
		`Random2`
		`Random3`
			This factor represents the network and demand topology that is defined from the case studies and random instances introduced in [27], as explained in Section 3.6.

Transportation network damage	L	0 0.25 0.5	In every disaster scenario, $100L\%$ of random edges is destroyed.
Facility budget	AP	0.5 0.75 1	The facility budget is $100AP\%$ of an estimated facility budget necessary to meet the expected total demand.
Acquisition budget	BP	0.5 0.75 1	The acquisition budget is $100BP\%$ of an estimated acquisition budget necessary to meet the expected total demand.
Transportation budget	CP	0.5 0.75 1	The transportation budget is $100CP\%$ of an estimated transportation budget necessary to meet the expected total demand.

mand vertices. Even if the total number of facilities in the best found facility configuration is small relative to the total number of potential facility locations, increasing the percentage of potential facility locations can influence the facility decision making. Indeed, if all initial potential facilities are all located within one region (with many demand vertices outside this region), and the transportation network is severely damaged (Section 3.7, $L = 0.5$) and/or the transportation budget is very limited (Section 3.10, $CP = 0.5$), opening facilities at new potential facility locations can improve the facility configuration. This demonstrates not only the effect of the number of potential facility locations, but the interaction between this and a few other factors, such as the facility capacities and transportation network damage or transportation budget.

We therefore consider the percentage of vertices that are potential facility locations as a factor in our experiment, with 3 different levels that correspond to $10, 50$ and 100% of random vertices as the potential facility locations. The minimum level needs to be greater than zero, since no facilities can be open (and therefore no non-trivial solutions exist) if there are no potential facility locations. The maximum level is set to 100%, as it might be possible that a facility can be open at any location (which is the case, e.g., for the US case study introduced in [23] and described in [27]).

3.2 Facility capacities

For each problem instance, we consider that facilities of two different categories can be open, a small facility $q = 1$, or a big facility $q = 2$. The relative capacities of these facility categories influences the facility decision making, at least with regards to the number of open facilities. Indeed, the smaller the capacities, the greater number of facilities is necessary to store the total demand volume. However, if the inventory budget is limited (Section 3.9, $BP = 0.5$), the number of open facilities in the best found solution (with a high unmet demand) might also remain small even if the facility capacities are small.

We consider three different levels for the factor QV representing the facility capacities. The factor levels $QV = 2$, $QV = 4$ and $QV = 6$ mean that the facility capacity of a small facility V_1 is 2, 4 or 6 times the volume of the average demand at a vertex (that is calculated from the demands given in Section 3.6, when the complete set of 20 scenarios is considered, so that the facility capacities remain the same for different levels of factor S, in order to properly assess the effect of S). In all cases, we consider that the capacity of a big facility is 2 times larger than the capacity of a small facility, $V_2 = 2V_1$. To define these capacities, we took inspiration from the case studies described in [27].

3.3 Facility unit opening costs

Another factor that obviously has a strong influence on the facility decision making are the facility opening costs.

For example, if opening 3 small and 2 big facilities yield the same total opening cost, big facilities might be preferred for many instances, as this facility configuration would ensure a greater total storage capacity (Section 3.2, $V_2 = 2V_1$ throughout the study) and thus allow pre-positioning a greater volume of aid.

In practice, due to the economies of scale, it is to be expected that the unit opening cost of a big facility is lower than the unit opening cost of a small facility. If, however, the unit cost of a big facility is only 75% of the unit facility cost of a small facility (as in the aforementioned example), opening small facilities might still be better for some instances, but this can change if the unit cost of a big facility is 50% of the opening cost of a small facility. This is why it is important to consider different levels of this ratio between the unit opening costs.

The third factor QAV that we included in the experiment represents the ratio between the unit opening costs between a big and a small facility, $QAV = (A_2/V_2)/(A_1/V_1)$. We consider 3 different levels $QAV \in \{0.5, 0.75, 1\}$ that mean that the unit opening cost of a big facility is respectively $50, 75$ and 100% of the unit opening cost of a small facility. In other words, since the capacity of a big facility V_2 is 2 times greater than the capacity V_1 of a small facility for any problem instance ($V_2 = 2V_1$, Section 3.2), this means that the opening cost A_2 of a big facility is 1, 1.5 and 2 times greater than the opening cost A_1 of a small facility.

For every problem instance, we consider that the unit opening cost of a small facility $A_1/V_1 = 10$ €/m^3 and therefore calculate the opening cost of a small facility as $A_1 = 10V_1$. The unit opening cost $QAV \times 10$ of a big facility can therefore be 5, 7.5 or 10 €/m^3, and the opening cost of a big facility is $A_2 = QAV \times 10 \times V_2$. To define these unit opening costs, we took inspiration from the case studies described in [27].

3.4 Number of scenarios

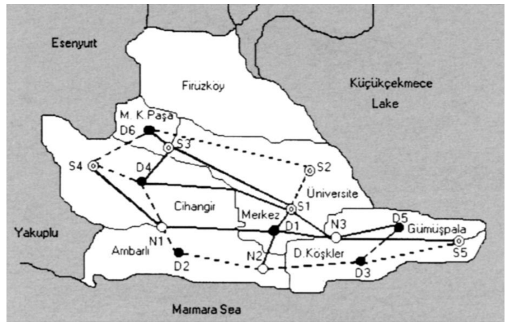
As explained in the small example in the first part of this section (Figure 1), the number of scenarios might also have an influence on the facility decision making. We therefore consider the number of scenarios S as a factor, with three different levels $S \in \{5, 10, 20\}$. The scenario probabilities are all equal, $P^s = \frac{1}{S}$.

3.5 Proportion of aid that remains usable

In the example in the first part of this section (Figure 1), we also described how the proportions of aid that remain usable at the potential facility locations can also have an influence on the facility decision making, and have therefore included them as a factor in the experiment.

The factor R that represents the proportions of aid that remains usable has three levels, $R \in \{0.5, 0.75, 1\}$. If $R = 0.5$, the proportion of aid that remains usable at every potential facility location in every scenario is a random number drawn from a normal distribution $\mathcal{N}(0.5, 0.2)$ with the mean $\mu = 0.5$ and variance $\sigma^2 = 0.2$, so that the average proportion is 0.5. If $R = 0.75$, the proportions are drawn from a normal distribution $\mathcal{N}(0.75, 0.2)$. Whenever the proportion is smaller than zero, we set it to zero, and whenever the proportion is greater than one, we define it to be one. Finally, if $R = 1$ every proportion is set to one, i.e., no aid would be destroyed.

(a) `case-study-47-1-4-1`



(b) `case-study-14-1-1-9`

(c) `case-study-30-1-1-10`

(d) `case-study-30-3-3-51`

Figure 2: Network graphs $G_1 = (V, E_1)$ of the 4 base case studies that inspired the generation of the 30 case studies: (a) Chile 2010 earthquake and tsunami (b) Turkey 1999 earthquake (c) Senegal Mboro region disaster threat (d) US Gulf Coast hurricane threat.

3.6 Demand graphs

Probably one of the most important factors that influence the facility decision making is the actual demand for commodities. We limit our study to a single commodity type, $|K| = 1$. In [27], a number of case studies and a random instance generator for the pre-positioning problem are introduced. The case studies are inspired from the 4 case studies collected from the literature [9, 7, 25, 23], that focus on disasters of different type and scale that occurred in different parts of the world (Figure 2). The random instance generator employs research about the nature of disaster propagation to define reasonable random instance of any size. We use these case studies and random instance generator to define 15 different levels of the factor D that represents the demand graphs, what we explain in detail in the remainder of this subsection. For each of the 15 levels, we define 20 demand graphs that correspond to 20 different disaster scenarios, what is the maximum number of scenarios considered in the experiment (Section 3.4, $S = 20$). Whenever $S = 5$ or $S = 10$ in the experiment, we consider the subset of 5 or 10 randomly chosen disaster scenarios, i.e., demand graphs.

Next to the demand information, the factor D contains the information about the number of vertices, the network topology and the distances between the vertices (hence the name, demand *graphs*). The number of (demand) vertices, the network and demand topology vary greatly across the 15 different levels of factor D. Since these instance features are expected to have a strong influence on the facility decision making, it could be worthwhile to include them as separate factors in our experiment. However, this would mean that the demands would have to be randomly defined for each of the factor levels. We do not proceed in this manner in order to exploit the rich network and demand data that is contained in the case studies that focus on real disasters. The alternative approach is discussed further in the concluding section as a possible direction for future work.

Note that the factor D also includes the information about the commodity (unit volume V^k, unit acquisition cost B^k and unit transportation cost C^k). We adopt this information from the case studies, rather than considering them to be constant, as the actual values of demand are relative to this information. For example, extremely high values of demands for a commodity indicates that the unit volume is probably very small (e.g., water bottle), where lower demands indicate that the unit volume is larger (e.g., pallet of water bottles), see [27].

The factor levels $D \in \{\texttt{Chile1, Chile2, Chile3, Chile4}\}$ are defined using the base pre-positioning problem case study `case-study-47-1-4-1` with 47 vertices, 1 facility category, 4 commodity types and 1 scenario. This problem instance describes a magnitude-8.8 earthquake that occurred in Chile in 2010, and is inspired from a case study introduced in [9]. The demands for each region are based on the Richter scale of the earthquake and the level of damage and population size in each region, and are defined by analysing several sources of information, such as press notes, National Emergency Office, Red Cross, etc. [9]. In the base case study `case-study-47-1-4-1`, the only three potential facility locations are Lima, La Paz and Buenos Aires in the three neighbouring countries Peru, Bolivia and Argentina. In our experiment, however, we investigate the effect of the percentage F of potential facility (random) locations (Section 3.1), and therefore remove these three vertices outside of Chile from the network graph, considering a given percentage of demand locations within Chile to be potential facility locations. In addition, the base case study `case-study-47-1-4-1` considers 4 different commodity types (water, food, personal products and medicine) which allows us to consider 4 different sets of demand graphs for each of the commodities (since we have fixed the number of commodity types |K| to one throughout the experiment). To define the 20 demand graphs that correspond to 20 different disaster scenarios, we multiply the demand of every vertex by a random number generated from a probability distribution $\mathcal{N}(\mu, \sigma^2)$ with the mean $\mu \in \{0.5, 0.75, 1, 1.5, 2\}$ and $\sigma^2 \in \{0.1, 0.2, 0.3, 0.4\}$. Whenever this random number is negative, we define the demand to be zero. The four different levels of the factor D therefore each correspond to 20 demand graphs with 44 vertices.

The factor level $D = \texttt{Turkey}$ is defined using the base pre-positioning problem case study with 14 vertices, 1 facility category, 1 commodity type and 9 scenarios, `case-study-14-1-1-9`. This problem instance describes a magnitude-7.6 earthquake that occurred in Turkey in 1999, and is inspired from a case study introduced in [7]. In the original paper, the expected demands are defined using [12], which are then perturbed with certain percentages to define the demands in 9 disaster scenarios [7]. We proceed in the same manner to define the 20 demand graphs for our experiment, by multiplying the expected demands by 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4, 2.6, 2.8, 3, 3.2, 3.4, 3.6, 3.8, 4, 4.2, 4.5, 4.6 and 4.8 respectively. The factor level $D = \texttt{Turkey}$ therefore corresponds to 20 demand graphs with 14 vertices.

The factor level $D = \texttt{Senegal}$ is defined using the base pre-positioning problem case study with 30 vertices, 1 facility category, 1 commodity type and 10 scenarios, `case-study-30-1-1-10`. This problem instance is inspired from a Senegal case study introduced in [25]. In the original paper, the authors define the demand of a vertex in a scenario as the population size of the vertex multiplied by an uncertainty factor, where this uncertainty factor is a sum or a random baseline term that is common for the whole region, and a correction term that is specific for the given vertex. To define the 20 demand graphs, we adopt the same approach and thus define the demand D_i^{1s} at vertex $i \in \mathrm{V}$ in scenario $s \in \mathrm{S}$ as

$$D_i^{1s} = P_i \times (\xi_s + \xi_i^s),$$

where P_i is the population size of the vertex i, and ξ_s and ξ_i^s are random numbers generated from the uniform distribution on the interval $[0, 1]$. The factor level $D =$ `Senegal` therefore corresponds to 20 demand graphs with 30 vertices.

The factor levels $D \in \{$`US1, US2, US3, US4, US5, US6`$\}$ are defined using the base pre-positioning problem case study `case-study-30-3-3-51` with 30 vertices, 3 facility categories, 3 commodity types and 51 scenario. This problem instance focuses on hurricane threat in the Gulf Coast area of the United States, and is inspired from a case study introduced in [23]. The case study is constructed using historical records from a sample of fifteen hurricanes, obtained from the National Oceanic and Atmospheric Administration research facility Atlantic Oceanographic and Meteorological Laboratory. Since the base case study `case-study-30-3-3-51` considers 3 different commodity types (water, food, and medicine), we can consider 3 different sets of demand graphs for each of the commodities (since we have fixed the number of commodity types $|\mathrm{K}|$ to one throughout the experiment). In addition, since the base case study `case-study-30-3-3-51` considers 51 different scenarios, and in our experiment we limit the number of scenarios to 20 (Section 3.4), we use this base case study to define two groups of 20 demand graphs, that correspond to scenarios $s = 1$ to $s = 20$, and $s = 31$ to $s = 50$. The six different levels of the factor D therefore each correspond to 20 demand graphs with 30 vertices.

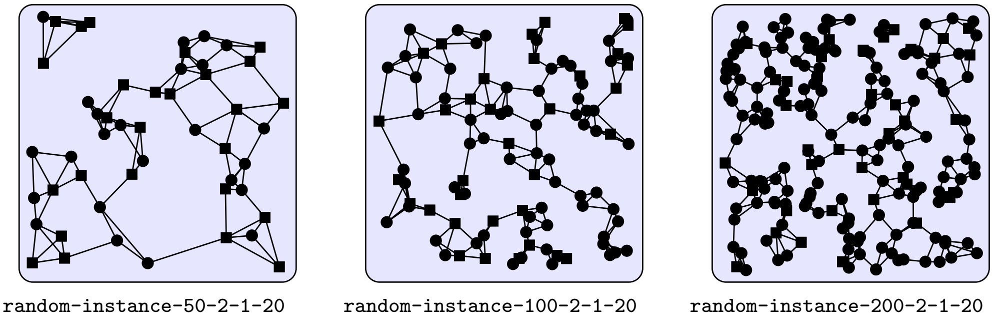


Figure 3: Network graphs $\mathrm{G}_1 = (\mathrm{V}, \mathrm{E}_1)$ of the 3 random instances that were used to generate the demand graphs that correspond to levels $D \in \{$`Random1`, `Random2`, `Random3`$\}$.

Finally, the factor levels $D \in \{$`Random1, Random2, Random3`$\}$ are defined using the random instance generator introduced in [27]. The instance generator is used to construct three random pre-positioning problem instances with 50, 100 and 200 vertices (and 2 facility categories, 1 commodity type and 20 scenarios) whose demand graphs correspond to three different levels of factor D (Figure 3).

3.7 Transportation network damage

The more the transportation network is damaged, the more facilities would likely need to be open in order to reach the demand locations. For this reason, we also include the level of transportation network damage L in our experiment, with three different levels $L \in \{0, 0.25, 0.5\}$. If $L = 0$, this means that no edges are destroyed, i.e., the distance matrices correspond to the distances defined in Section 3.6. If $L = 0.25$, 25% of random edges are destroyed in every disaster scenario, and if $L = 0.5$, the percentage of random edges that are removed is 50%.

3.8 Facility budget

Finally, the budgets obviously play an important role in the facility decision making. Factor AP corresponds to the total available budget A for opening the storage facilities, that is calculated as a percentage of an estimated facility cost necessary to meet the expected total demand. Since the unit opening cost of a small facility is 10€/m^3 (what is also the greatest possible unit opening cost of a big facility, Section 3.3), a reasonable estimate of the facility budget necessary to store the volume V_D of expected total demand could be $10 \times V_D$. However, different disaster scenarios that represent the uncertainties inherent to the pre-positioning problem, imply that the facility capacities are rarely completely utilized across all disaster scenarios. In addition, some pre-positioned aid might be destroyed, so that the volume of aid that is pre-positioned at the facilities might be greater than the volume of aid distributed to the beneficiaries. We therefore set the facility budget to $A = AP \times 2 \times 10 \times V_D$, considering three different levels of the factor $AP \in \{0.5, 0.75, 1\}$. Note that the volume V_D of the expected total demand is calculated from the demands given in Section 3.6, when the complete set of 20 scenarios is considered, so that the facility budget remains the same for different levels of factor S, in order to properly assess the effect of S (and the same is true when the acquisition budget is defined in Section 3.9). The choice of factor levels (also for the factors corresponding to the acquisition and transportation budgets in the next subsections) is based on the case studies described in [27].

Another possibility would be to estimate the facility cost as the average between facility cost of opening only small or only big facilities that are sufficient to store the expected total demand volume. In this case, the facility budget A would change with respect to changes in the factor QAV that corresponds to the ratios between different facility opening costs (Section 3.3) and would therefore hinder the investigation of the effect of factor QAV on the facility decisions (or its interaction with factor AP).

3.9 Acquisition budget

It is to be expected that the budget B for procurement of the humanitarian aid has a strong effect on the facility decision making. Similarly to the facility budget definition in Section 3.8, for three different levels $BP \in \{0.5, 0.75, 1\}$, we define the acquisition budget B to be $50, 75$ or 100% of double the acquisition cost of the expected total demand.

3.10 Transportation budget

Three different levels of the factor $CP \in \{0.5, 0.75, 1\}$ indicate that the transportation budget C is $50, 75$ or 100% of an estimate of the transportation cost necessary to meet the expected total demand. To find this estimate, we first calculate the total cost of transporting the required amount of aid to every demand location $i \in \mathrm{V}$ over the average distance from every vertex $j \in \mathrm{V}$ connected with $i \in \mathrm{V}$, to the demand vertex $i \in \mathrm{V}$. Since the demand is rarely completely met, and since the vertices are most often served from close-by open facilities rather than from an average distance to the vertex, we define the transportation budget as half the aforementioned transportation cost.

3.11 Experimental design and response variables

In the experiment, we consider all possible level combinations across all characteristics (full-factorial experimental design). 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.

We 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 base instance, 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, the facility capacities and the available budgets are defined using the average and expected demand volumes and shortest path distances obtained from the 20 demand graphs in the underlying base instance, so that these values remain constant with different number of scenarios S and that the impact of factor S can be properly evaluated.

Similarly, if the transportation budget C were defined according to the shortest paths of the respective instance, the budget C would change with changes in the level of transportation network damage L, what would make it difficult to study the effect of L (as we would not know if a change in the facility configuration was yielded by the changes in the transportation network availability, or a change in the budget). Furthermore, we consider the distances from every vertex to the demand locations, rather than only considering the distances from potential facility locations when defining the transportation budget C (Section 3.10), in order to properly analyse the effect of factor F. It is for the same reason that we ignored the relationship between facility unit opening costs or proportions of aid that remain usable when defining the facility and inventory budgets, so that e.g., the inventory budget B remains constant for different levels of factor R and a proper analysis of the effect of R can be carried out.

The folder that contains all the instances is very large (68GB), and we therefore publish only the 15 instances that correspond to the 15 different levels of the demand factor D. Each of the 15 instances contains the information about 20 demand graphs that represent 20 disaster scenarios (demands, distances, commodity information, Section 3.6), but does not define the potential facility locations, facility capacities and opening costs, scenario probabilities, proportions of aid that remains usable and the available budgets, i.e., $F_i = 0$, $V_q = A_q = 0$, $P^s = 0$, $R_i^{ks} = 0$ and $A = B = C = 0$ for every $i \in$ V, $q \in$ Q, $k \in$ K, $s \in$ S. However, this data is sufficient to replicate the experiment, as the remaining instance information can be defined according to the rules listed in Table 2. The 15 instances are available for download from the following webpage:

`http://antor.uantwerpen.be/members/renata-turkes/.`

The matheuristic introduced in [28] and described in Section 2 is employed to look for promising facility decisions $\mathbf{x} = [x_{iq}]$ for every problem instance. 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 3: In the computational study, we investigate how different instance parameters and their interactions influence the facility decisions in the best found pre-positioning emergency strategy. We are mainly interested in the categories of facilities to be open (represented by the percentage of small open facilities X_1/X, or analogously, percentage of big open facilities), but we also keep track of the numbers of small and big open facilities, represented respectively by response variables X_1 and X_2.

Response variable	**Notation**
Percentage of open facilities which are small	$\frac{X_1}{X} = \frac{X_1}{X_1+X_2}$
Number of small open facilities	X_1
Number of big open facilities	X_2

Next to the instances, a summary of the experimental results (a single, easy to read .csv file) is also freely available at

`http://antor.uantwerpen.be/members/renata-turkes/.`

In addition to X_1/X, X_1 and X_2, for every pre-positioning problem instance we register a lot of instance and solution information, such as the number of (demand) vertices, coefficient of demand volume variation across scenarios, the maximum number of small and big facilities that the facility budget allows to be open, the total capacity open, the unmet demand and response time, the average percentage of facility capacity, pre-positioned aid and the budgets that are actually utilized. The rich experimental data can therefore be used to gain further insights into the pre-positioning problem, e.g., into the effect of different instance characteristics and their interactions on the quality of emergency strategy (i.e., unmet demand and response time).

4 Experimental results and managerial implications

Using the experimental data, our first goal is to identify the instance characteristics that have the highest impact on facility decisions. To this end, we estimate a number of linear regression models with the purpose of quantifying the relationship between the instance characteristics and the response variables described in Section 3. 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. The second goal is to use these findings to derive rules of thumb for facility decision making.

In Section 4.1, we examine the parameters of the 6 regression models and discuss the most important instance characteristics and their interactions. Further analysis of the relationship between these important instance characteristics and their interactions and the facility decisions allows us to derive some policy recommendations in Section 4.2. The section ends with some examples that illustrate how simplified analyses can lead to misleading conclusions in Section 4.3.

4.1 Identifying the most influential instance characteristics and their interactions

To compare the effect of the factors and their interactions in a straightforward manner, we code each instance characteristic as a categorical factor 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. The further the parameter values are from zero, the higher the influence of the corresponding factor (interaction) is. This approach allows to gain insights into the most influential characteristics on the best facility configuration that is more appropriate that simply considering the p-values. Indeed, since in our experiment the residuals cannot be assumed to be normally distributed with equal variance, the p-values of the statistical tests do not properly determine the significance of each term in the model. 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.

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 4 shows the values of the regression model parameters estimated for each factor in both main-effects models. 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.

The extended models including 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 4).

Figure 5 shows the values of the regression model parameters estimated for each interaction in the extended models. The coefficient values of the individual factors are not included since they are equal to those shown in Figure 4. This property follows from the fact that the data used to estimate the models comes from the experiment described in Section 3. Such an experiment was designed as a full factorial experiment (in which all possible factor combinations are evaluated). Therefore, all main effects and all interaction effects can be estimated independently.

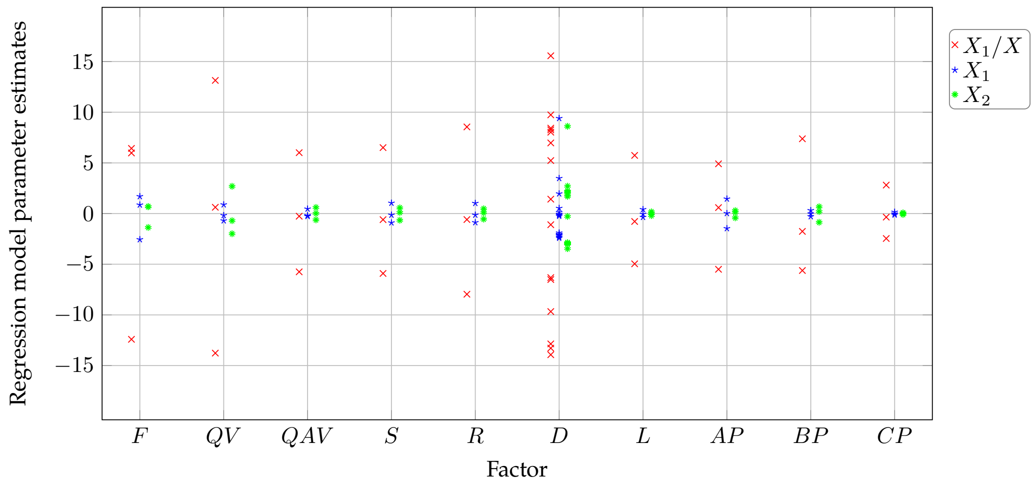


Figure 4: The demand topology D, the facility capacities QV and the number of open facilities F have the strongest influence on the facility decision making. In addition, the survivability R of pre-positioned aid, availability L of the transportation network, the ratio QAV between facility unit opening 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.

Table 4: The (adjusted) coefficients of determination R^2 increase significantly if the interaction effects between the instance characteristics are considered: the models that include the interactions explain additional 18, 28 and 21% of the variability in the percentage of small open facilities, and numbers of small and big open facilities, and thus 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

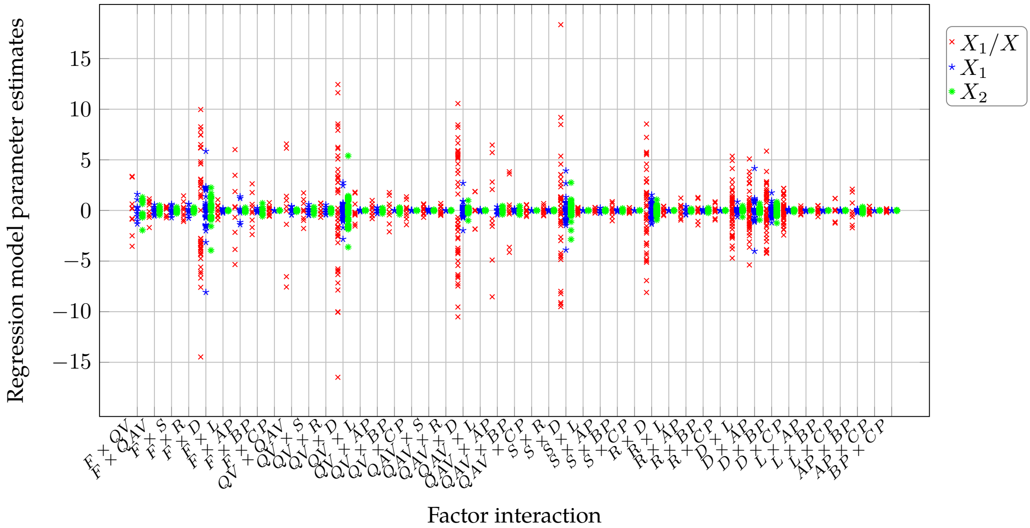


Figure 5: The interaction between the factor D and the remaining factors play the most important role in the facility decision making. The facility decisions are also strongly influenced by the interactions between the number F of potential facility locations and the facility capacities QV, or with the 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.

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 5). 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.

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, 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 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 Rules of thumb for pre-positioning facility planning

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, in order to derive some rules of thumb for the facility planning in disaster preparedness.

As can be seen in Figure 5, 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 5.

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 6). 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 Section 3.1). 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. This difference in the number of demand vertices also greatly explains the difference in the response variable across different levels of factor D.

Figure 5 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 7). 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 there is sufficient facility budget available, i.e., when there is sufficient facility budget to actually open additional facilities (Figure 8). On the other hand, the number X_2 of big open facilities increases faster with an increase in F when there is sufficient acquisition budget available, since it is then when the additional storage capacity can actually be used to pre-position more goods (Figure 9). For this reason, the increase in the percentage X_1/X with greater F is more pronounced when there is more facility budget, or when the acquisition budget is limited.

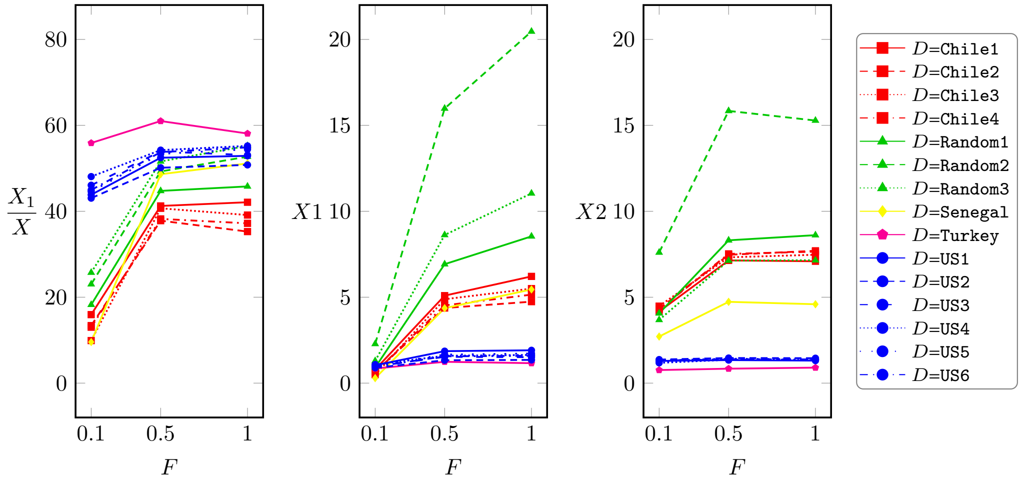


Figure 6: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities typically increases with an increase in the number of potential facility locations F, with the increase being particularly strong when the percentage of vertices which are facility 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.

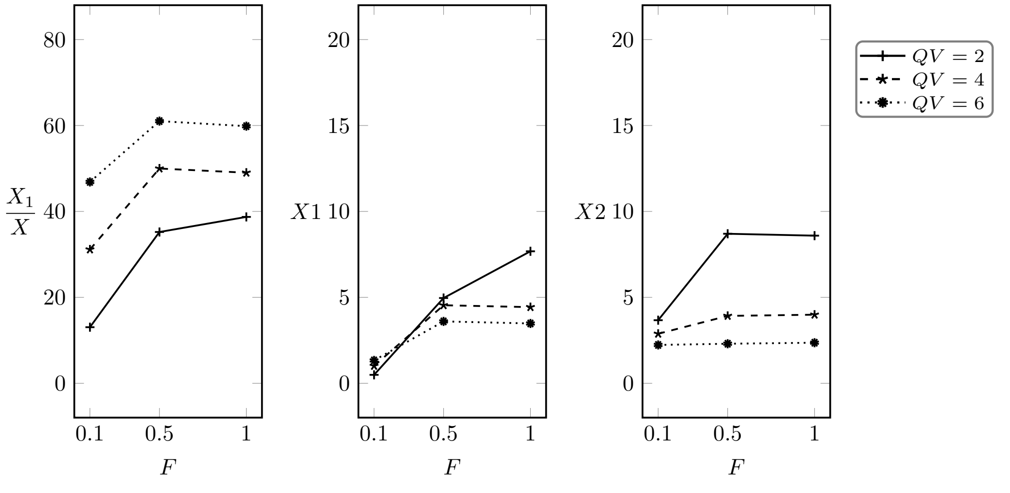


Figure 7: The effect of the number of potential facility locations, represented by factor F, on the facility decision making, is greater when the facility capacities are smaller ($QV = 2$).

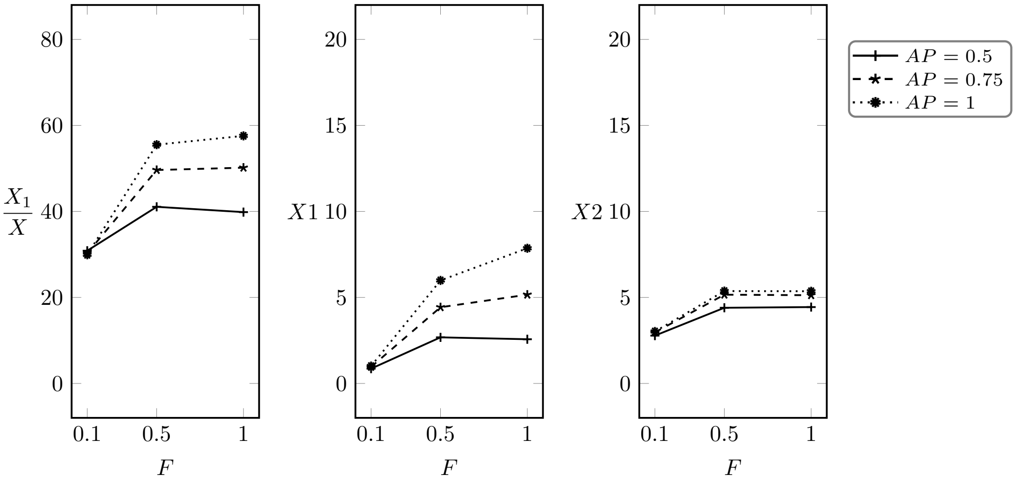


Figure 8: The effect of the number of potential facility locations, represented by factor F, on the facility decision making, is greater when there is more facility budget available ($AP = 1$).

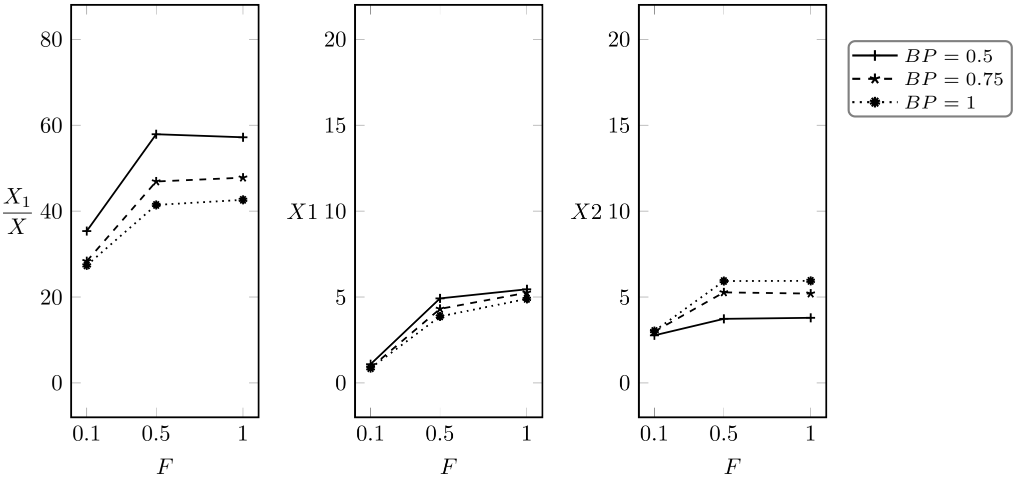


Figure 9: The effect of the number of potential facility locations, represented by factor F, on the facility decision making, is greater when there is more acquisition budget available ($BP = 1$).

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 10). 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.

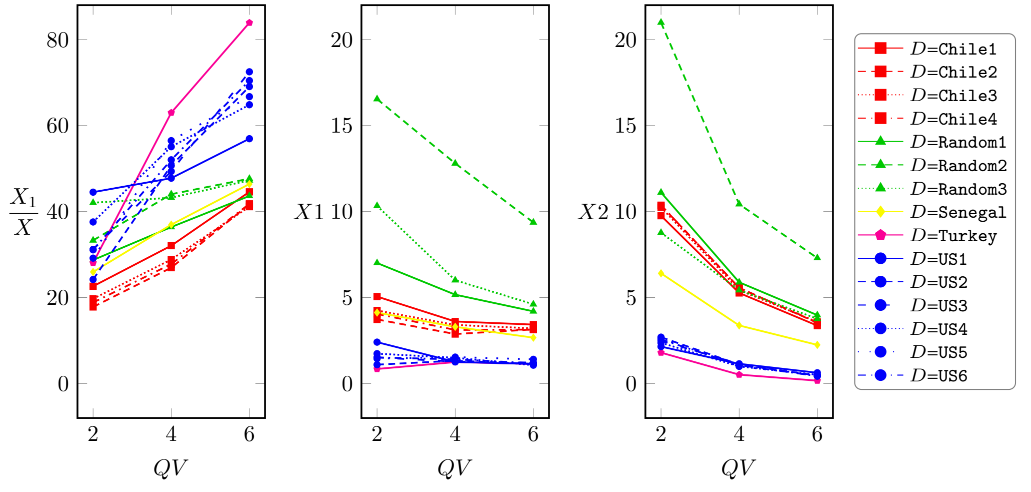


Figure 10: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities increases strongly with an increase in the facility capacities QV. Both the number X_1 and the number X_2 of small and big open facilities decrease, but the decrease in X_2 is more pronounced.

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 11). In other words, the more expensive the big facilities are, the more we prefer small facilities. Moreover, Figure 5 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 16 and 19, 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 12 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 12). 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.

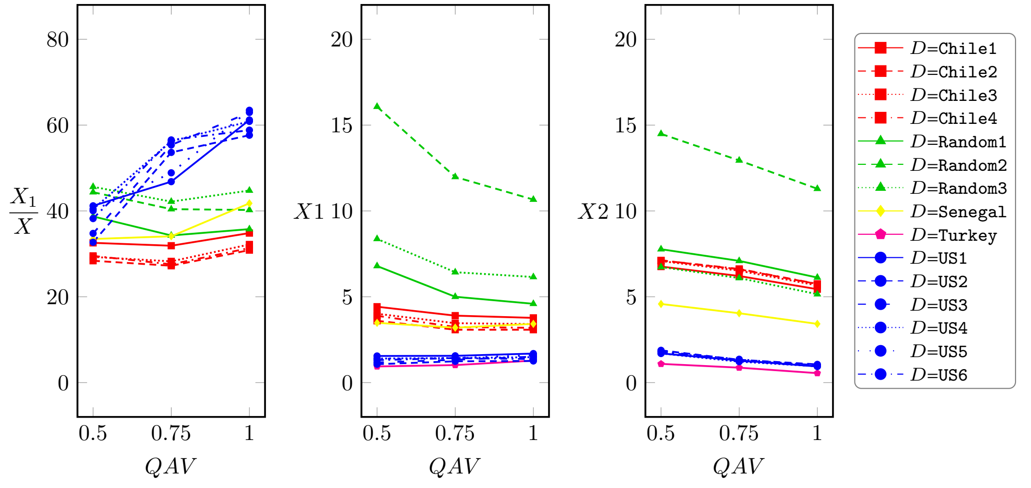


Figure 11: Across the majority of disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is greater when the big facilities are more expensive (represented by a larger QAV), as a consequence of a lower number X_2 of big open facilities.

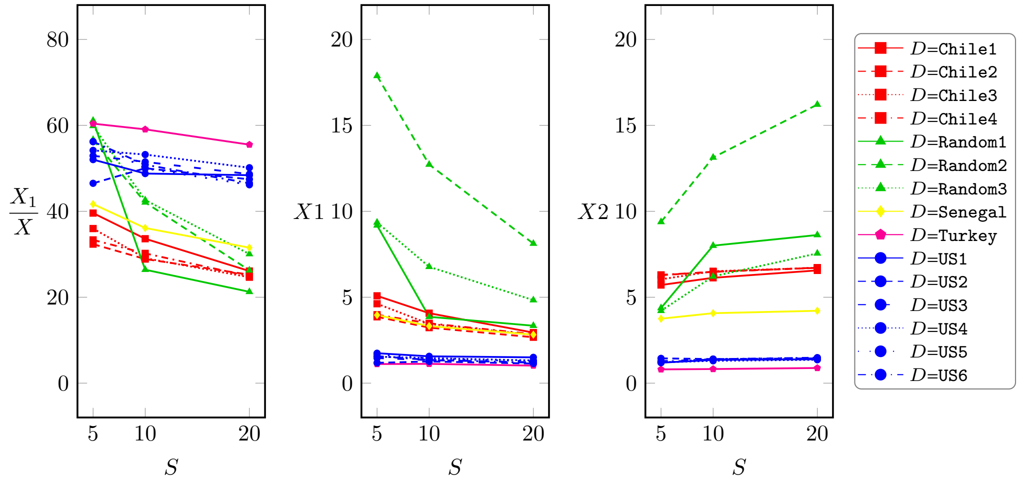


Figure 12: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is lower if the number S of disaster scenarios is greater. The number X_1 of small open facilities decreases, whereas the number X_2 of big open facilities increases.

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 13). 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 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.

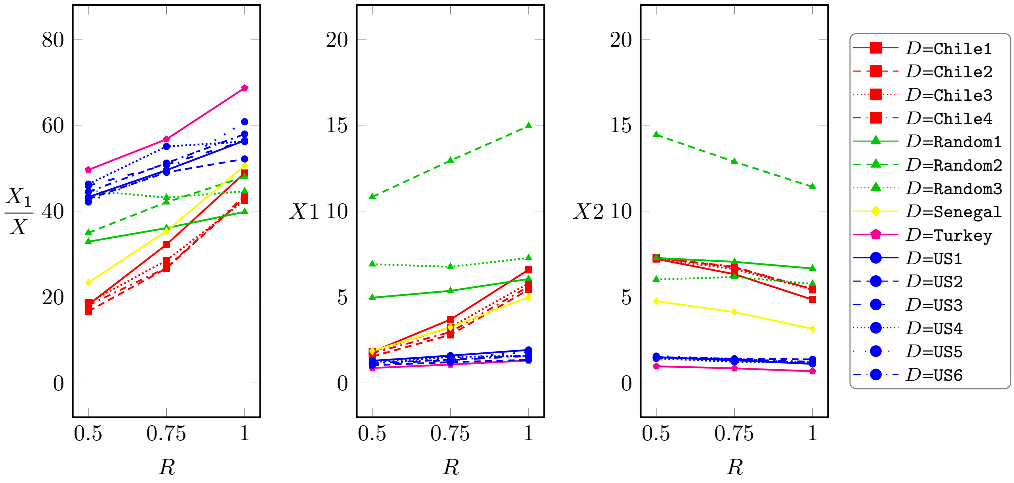


Figure 13: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is greater if greater proportions of aid remain usable after the disaster, represented with a greater value of factor R. The number X_1 of small open facilities increases, whereas the number X_2 of big open facilities decreases, with an increase in R.

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 14). This seems reasonable, as more facilities are necessary in order to reach the beneficiaries.

Figure 15 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. As we can see from Figure 8, 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 5 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 (when $QAV = 0.5$) (Figure 16). 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 there is less acquisition budget is available $(BP = 0.5)$, as it is then of lesser importance to open more big facilities in order to ensure sufficient storage for the acquired emergency supplies (Figure 17).

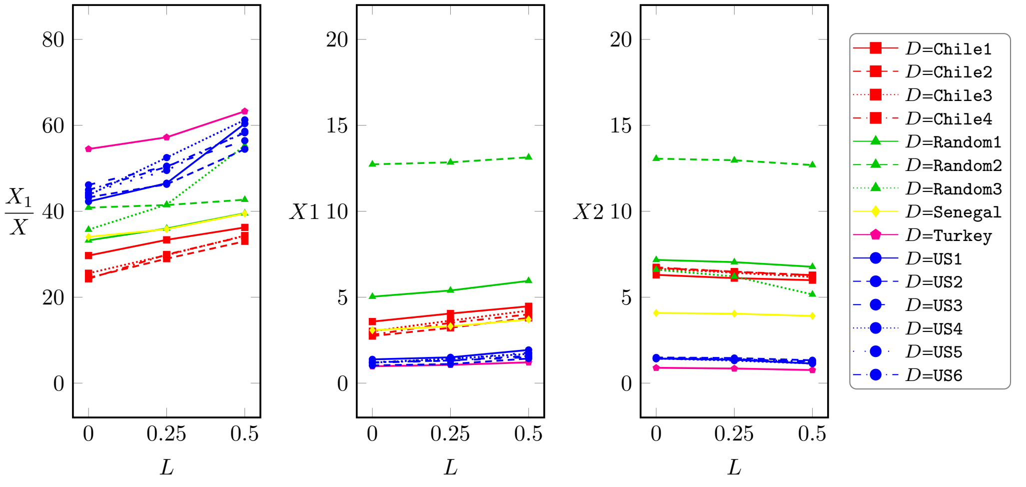


Figure 14: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is greater if the transportation network is severely damaged, represented with a greater value of factor L. The number X_1 of small open facilities increases, whereas the number X_2 of big open facilities decreases, with an increase in L.

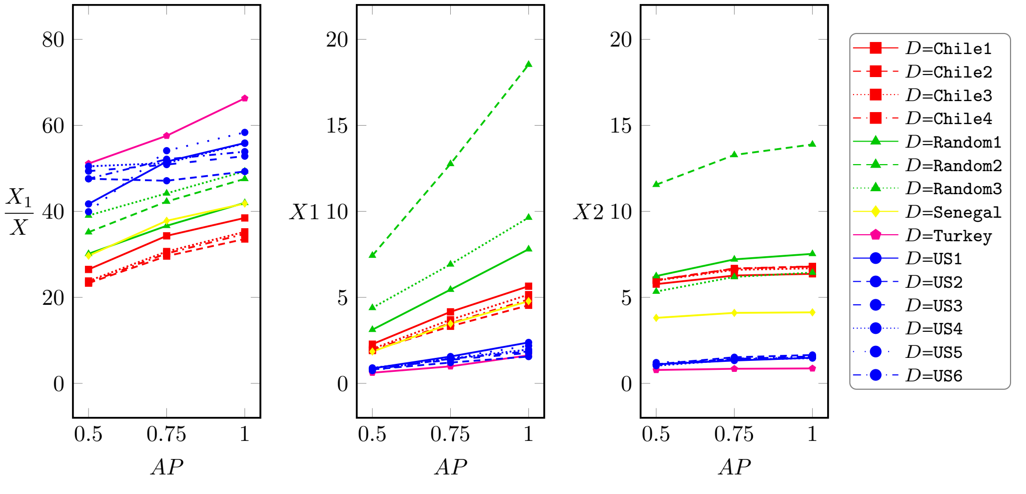


Figure 15: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is greater if there is more facility budget AP available. Both the number X_1 and the number X_2 of small and big open facilities increase with greater AP, but the increase in X_1 is more pronounced.

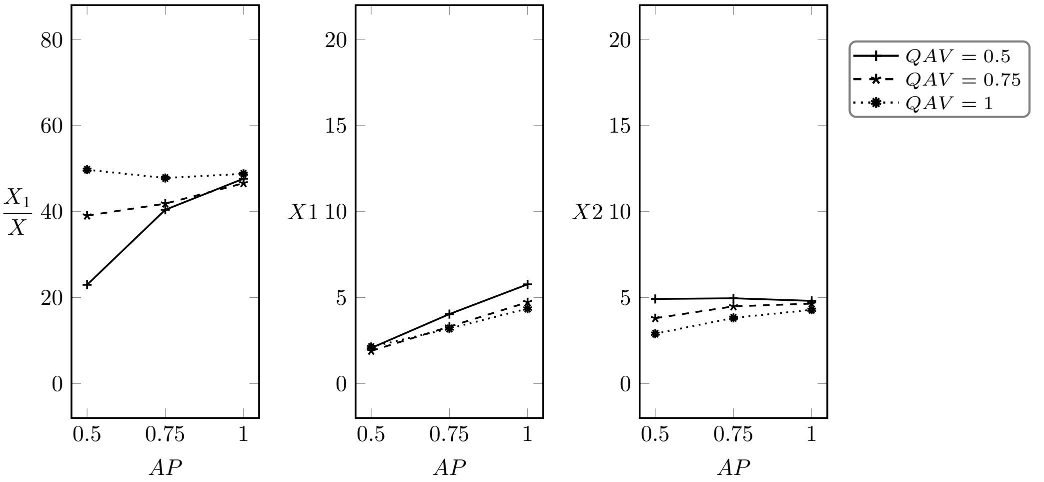


Figure 16: The effect of the facility budget AP on the facility decisions is influenced by the ratio QAV between facility unit opening costs. When big facilities are less expensive ($QAV = 0.5$), a considerable number X_2 of them can already be open even for a more limited facility budget, so that it 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.

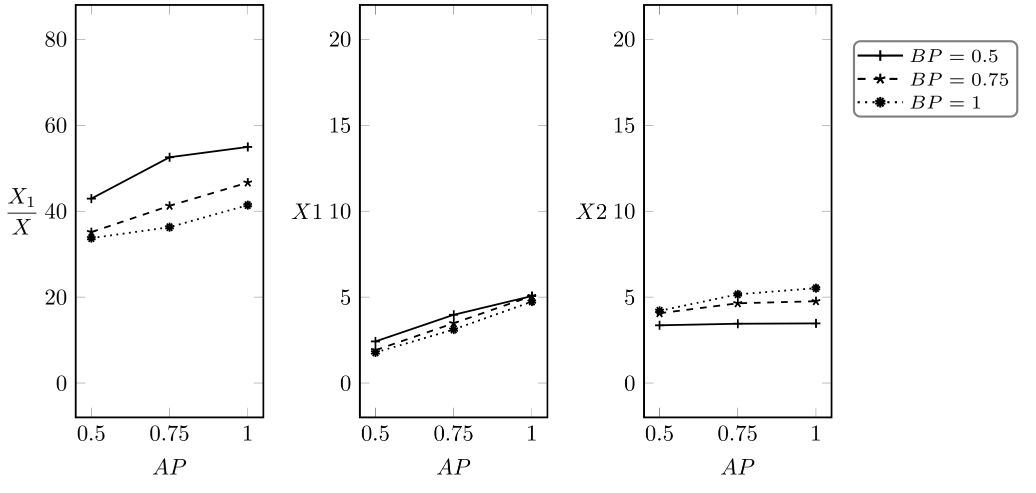


Figure 17: The effect of the facility budget AP on the facility decisions is influenced by the acquisition budget BP. When the acquisition budget is greater ($BP = 1$), it becomes more beneficial to ensure a larger storage capacity to pre-position the additional goods, so that the number X_2 then also increases, and as a consequence, the increase in the percentage X_1/X of small open facilities is somewhat less pronounced.

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 18). 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 19).

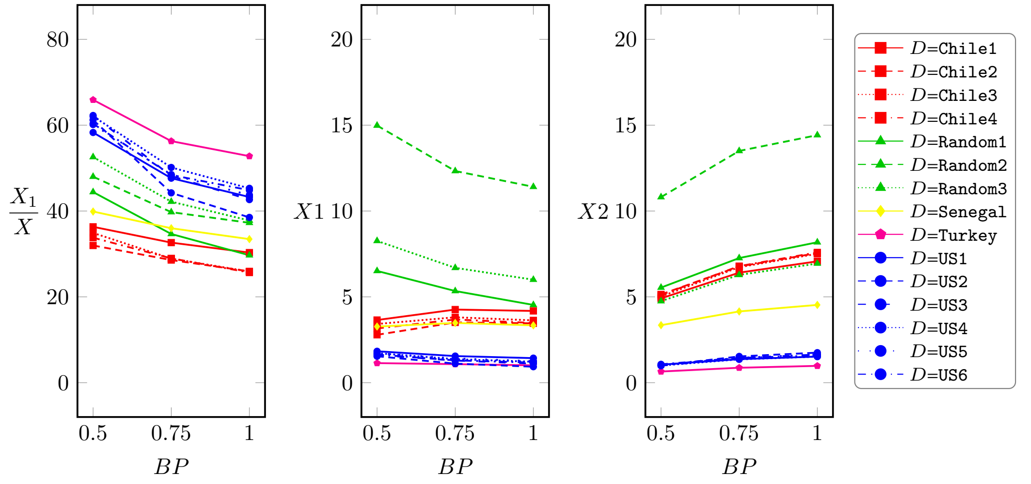


Figure 18: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is lower if there is more acquisition budget BP available. The number X_1 of small open facilities decreases, whereas the number X_2 of big open facilities increases with greater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

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 20). Indeed, if the transportation budget is limited, it is of greater importance to open more (and thus more small) facilities.

4.3 Analysis simplifications can yield misleading conclusions

In Section 1, we motivated our large computational study as a method that can help gain better 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 humanitarian logistics literature is an investigation of only the main effects of one or multiple factors. Figure 21 demonstrates how such a simplified analysis can yield misleading conclusions. Indeed, Figure 21 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.

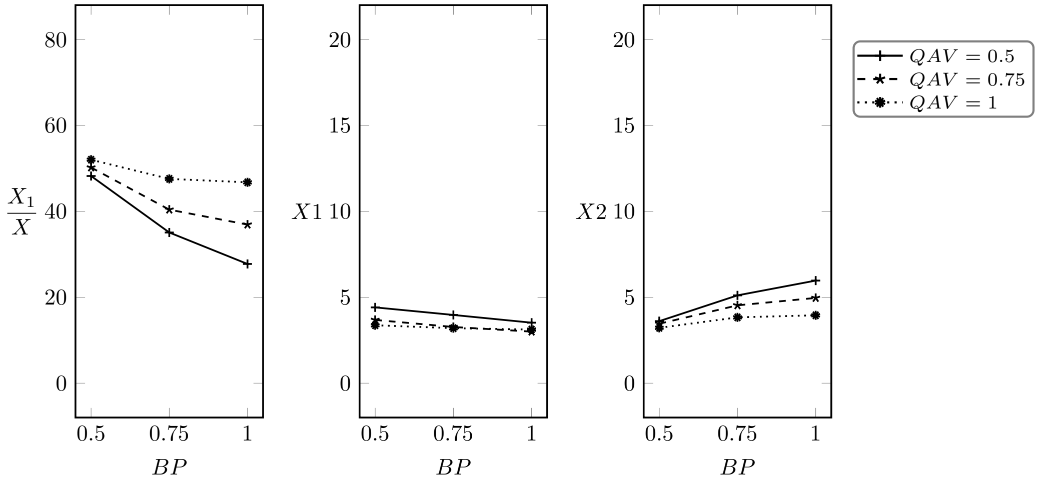


Figure 19: The effect of the acquisition budget BP on the facility decisions is influenced by the ratio QAV between facility unit opening costs. When big facilities are less expensive ($QAV = 0.5$), it is also possible to open a greater number X_2 of them in order to benefit from more storage for pre-positioning the additional goods obtained with greater BP; consequently, the the decrease in the percentage X_1/X of small open facilities is more pronounced.

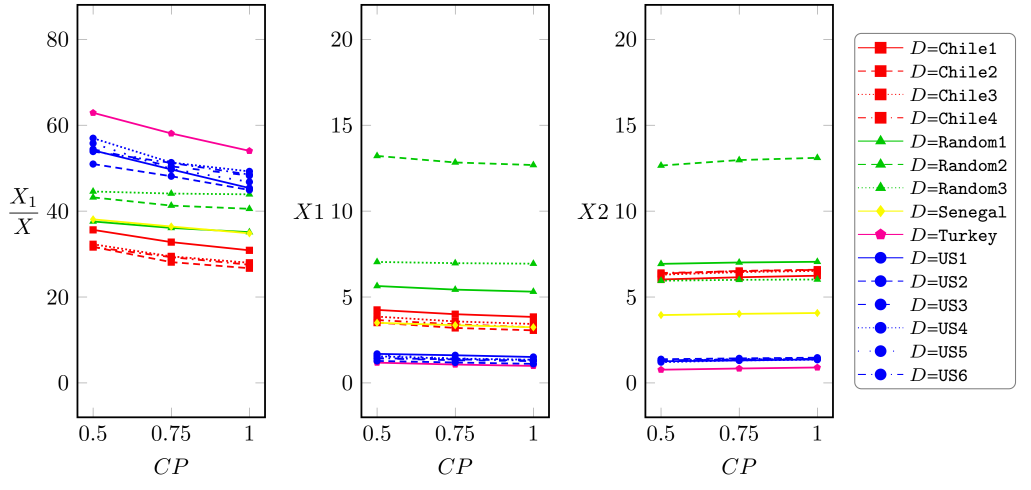


Figure 20: Across different disaster types, scales and demand topologies D, the percentage X_1/X of small open facilities is lower if there is more transportation budget CP available. The number X_1 of small open facilities decreases, whereas the number X_2 of big open facilities increases with greater CP.

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 number of big open facilities (Figure 16). 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 21). In addition, Figure 17 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 8 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 ($F = 0.1$).

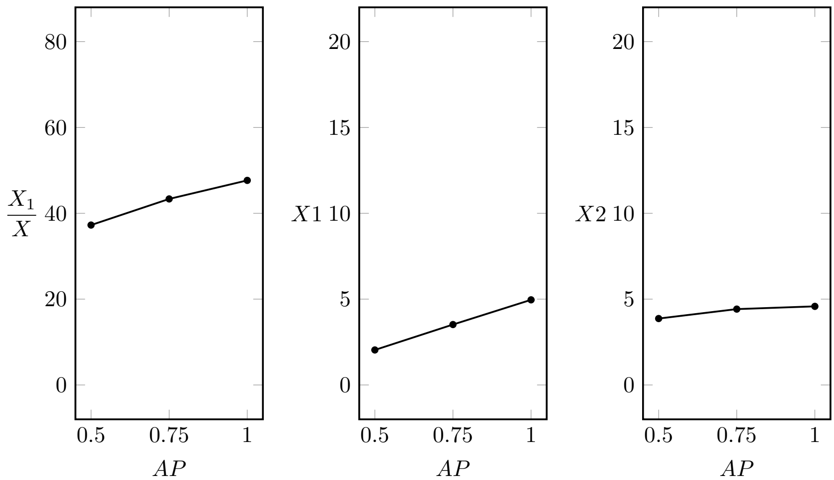


Figure 21: This example shows how studying the factors individually can lead to misleading conclusions and policy recommendations. Simply analysing the influence of the factor AP that represents the facility budget, it seems that the percentage X_1/X of small open facilities, as well as the numbers X_1 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 ratio between facility unit opening costs, and the acquisition budget, represented respectively with factors QAV and BP.

Similarly, a simplified analysis that employs a single case study (i.e., that ignores the interaction with factor D) can yield misleading conclusions. This is demonstrated in Figure 22 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 ($D =$ `Turkey`, Section 3.6).

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, Figures 6 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 7, 8 and 9, shows that the increase rate is strongly influenced by facility capacities, facility and acquisition budget, represented respectively by factors QV, AP and BP).

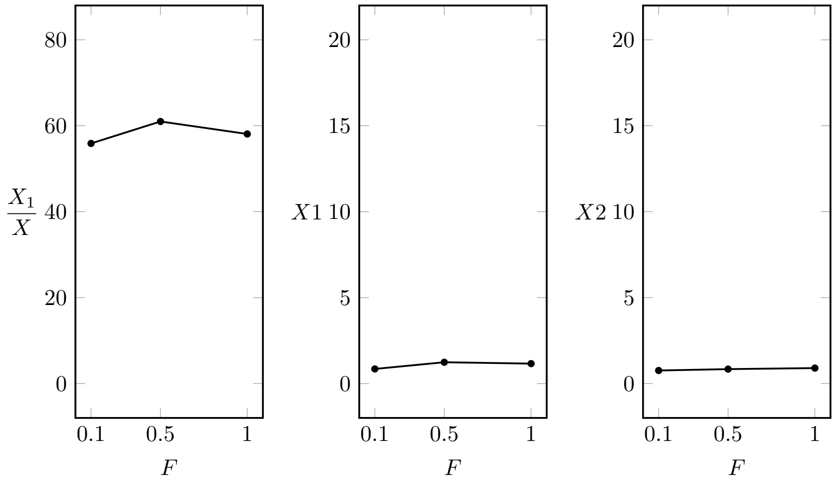


Figure 22: This example shows that studying the pre-positioning facility decisions using a single case study can lead to misleading conclusions and policy recommendations. The graph shows the influence of the number of potential facility locations, represented by the factor F, on the percentage X_1/X 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.

5 Conclusions, limitations and future research

Facility decision making is the 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 instance characteristics, carried out separately and using a single case study. Conclusions obtained through such simplified observations are of low reliability and can often be misleading.

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. The most important factors and their interactions are listed in Section 4.1; an investigation of their effect on the best facility configuration helped us to derive some rules of thumb for facility planning in Section 4.2. The main insights that can help the practitioners to make better facility decisions are the following.

(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, facility and transportation budget, number of scenarios, ratio of facility unit opening costs, level of transportation network damage; and the interactions between these factors explain up to 28% of the variability in facility decisions.

(2) There is a stronger preference for small facilities when the facility capacities are large, when there is more facility candidates available, when the aid survivability is greater, when the acquisition or transportation budget is restricted and when there is more facility budget available, when there is less uncertainty about the disaster, when the unit opening cost of a big facility is closer to the unit cost for a small facility, or when the transportation network is more severely damaged; and these effects can be particularly pronounced or changed when the interactions between these effects are considered.

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 can lead to erroneous conclusions. Hopefully, these results will motivate better experimental designs in the field of humanitarian logistics.

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 example, the experimental results show that the best found facility configuration does not necessarily completely utilize the available facility budget (although more facilities could be open), and therefore a good heuristic needs to consider the facility decisions where less than a maximum number of facilities is open. The total number of open facilities in the best found solution can vary significantly even for small changes in some of the instance parameters, and thus a local search that always closes one, and opens another facility is not sufficient to find the best facility configurations. 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 the values of different important instance characteristics identified in this paper, for the given problem instance.

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 the recent survey of pre-positioning problem literature [6]. 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 [27] 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.

Finally, the experimental data and summary of results are made publicly available on the following website:

`http://antor.uantwerpen.be/members/renata-turkes/,`

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 data shows that the most important factors that influence the unmet demand the number of potential facility locations available, the level of transportation network availability, the proportions of aid that remain usable, and the available budgets (Figure 23). A more thorough investigation of the effects of these characteristics and their interactions can help to gain valuable insights into the problem and to obtain some managerial implications. For instance, Figure 23 suggests to focus on ensuring sufficient number of potential facility locations, or that it is worthwhile to invest in the availability of the transportation network, and in preventing the aid from being destroyed after the disaster.

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 set-up 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 available case studies and therefore preserved this information in a single factor. As mentioned earlier in Section 3.6, 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, 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.

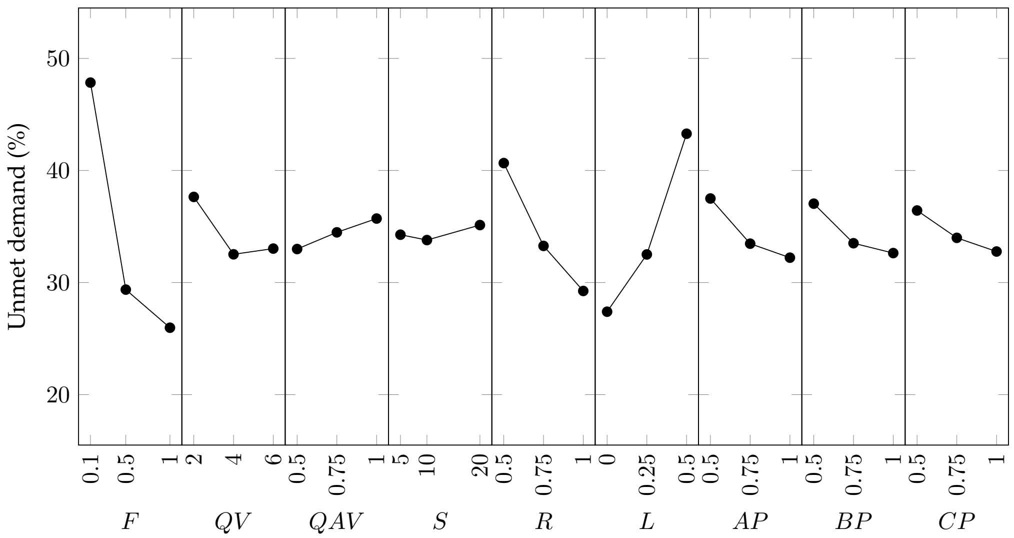


Figure 23: The factors that have the greatest main effect on the percentage of unmet demand are the number of potential facility locations, the level of transportation network damage, the proportions of aid that remain usable, and the available budgets, represented by factors F, L, R, AP, BP and CP respectively.

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.

Acknowledgments

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