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An Empirical Comparation of Several Anticipative Formulations for Planning Aid Distribution on the Verge of a Natural Disaster

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Abstract. Two-stage stochastic models are one of the most frequent approaches to handle uncertainty in problems related to emergency response. In such models, decision variables are separated into two sets: decisions made before and after the realization of an uncertain event. Although the categorization for each variable seems to be straightforward in the literature, in practice not all the information are revealed at a single moment, and not all the decisions are made at two given epochs, so managers organize their decision-making processes according to more flexible strategies. To demonstrate the relevant impact of the modeling approach choice on the solution's performance, we propose and compare five variants of a two-stage stochastic model designed to solve the logistics problem faced by an aid distribution organization on the verge of a natural disaster. Inspired by the real case study of a Mexican food bank organization, we generated a large set of instances to empirically compare the performance of the proposed models under different scenarios of supply variability. Instances were solved using the well-known sample average approximation. Our experiments confirm that different choices of decision-making timeframes and segmentation of decisions to be made before and after certainty have a rather important impact on the results that must be taken into account by managers when planning relief distribution in response to a sudden natural disaster.

Keywords: Aid distribution, two-stage stochastic programming, anticipative decisions, reactive decisions, humanitarian logistics, food banks.

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1. Introduction

The unceasing increase in the frequency and scope of disasters has become a major threat to supply chain managers [1]. Resilience, defined as "the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events" [2], is a must for humanitarian organizations whose mission aligns with the reduction of human suffering. A decision-making strategy to cope with the uncertainty is a key element for a resilient supply chain, especially in the case where organizations must deal with disasters. Disaster decision-making strategies can be classified into two broad categories, namely, anticipative and reactive, depending on the moment the decisions are made. Anticipative decisions are made before the event and therefore under uncertainty, whereas reactive decisions are made after the event. This study considers both strategies under information uncertainty or certainty, depending on whether they are made before or after a disaster. Although reactive strategies have been the most studied to date [3], anticipative models have also been successfully used to bring robustness and resilience to commercial and disaster-oriented supply chains alike [4–6]. Some authors argued the necessity to simultaneously consider anticipative and reactive strategies to ensure a resilient system [7,8]. To this end, two-stage stochastic modeling frameworks, wherein the first-stage focuses on proactive decisions that feed the later reactive second-stage, seek to integrate the anticipative and reactive approaches. In most of these studies the classification of decisions according to their stage is assumed to be given or straightforward and little or no discussion on such decisions is provided. However, the allocation of resources can be done under both certainty and uncertainty, generating different modeling strategies that can have a relevant impact on the outcomes.

This study focuses on the significance of selecting adequately the decision-making timeframe in two-stage stochastic models. Furthermore, it quantifies the extent to which the use of "here and now" rather than "wait and see" strategies in the supply chain planning under uncertain offer leads to more effective solutions. To this end, we are inspired by the case of Bancos de Alimento de México (BAMX), a Mexican network of food banks that plans a logistic response on a disaster, in particular, a hurricane strike. We propose five optimization models that separate the supply chain decisions into two stages (anticipative and reactive) based on whether they are fixed before or after the information on the donations becomes certain, considering uncertainty in the quantity and mixture of delivered food by donors to the banks. We performed a set of numerical experiments that seek to assess the effectiveness and efficiency of each decision-making strategy under different supply availability scenarios. Lastly, we suggest some managerial insights into the adaptation of humanitarian organizations' logistic operations for emergency response.

This document is organized as follows: Section 2 presents a brief review of relevant works. Section 3 introduces the case of BAMX. Section 4 presents five decision-making timeframes: anticipative, reactive, adaptative–reactive, anticipative–reactive, and detached. Section 5 includes mathematical formulations modeling BAMX's response to a disaster. Section 6 describes the solution method used for the stochastic programming models. Section 7 empirically evaluates the models' results to instances inspired on the impact of the 2018 Hurricane Willa in México, considering hypothetical scenarios of supply availability. Finally, Section 8 provides the conclusions, limitations, and future research recommendations.

2. Literature review

Mathematical tools for analyzing and supporting supply chain decision-making are a key part of humanitarian logistics. Within this cast field, humanitarian logistics models that consider uncertainty on supply availability are still scarce [3,9–11]. Donor-reliant organizations, like food banks, are excellent examples of supply uncertainty. Although food banks are not profit-driven, the donors acting as their suppliers are profit-driven, making their contributions unpredictable. This problem is stressed in a disaster situation, where donors react effusively but inconsistently [12], thereby frequently offering goods that are difficult to transport or do not contribute to fulfilling people's basic needs and reducing food insecurity [13,14]. Therefore, this literature review focuses on the relief distribution supply chain resilience, and the consideration of uncertainty on supply availability, two specific topics which converge at the arrival of a sudden disaster and that constitute the pillar of this research.

2.1. Resilient disaster relief supply chains

Natural and artificial disasters are considered main causes of major supply chain disruptions. Donadoni et al. [15] investigated managers' understanding of disruptions and resilience and how they measure these constructs. The problem of material convergence is a common disruptor of disaster relief supply chains [16]. Christopher and Peck [17] identified different supply chain risks to be considered in designing a resilient supply chain. Meanwhile, Mu et al. [18] defined resilient food supply chains in the context of food safety and a procedure to assess food safety resilience. Furthermore, Jia et al. [19] studied social capital emanating from supply chain partners as an external factor building organizational resilience. Most strategies used to prevent supply chain disruptions can be roughly classified into *proactive* and *reactive* strategies, based on the timing of the decisions.

2.1.1. Reactive strategies

Anaya-Arenas et al. [20] studied the literature for distribution networks for disaster relief distribution. Heckmann et al. [21] analyzed the meaning of supply chain risk in literature and reactive mathematical models and identified a lack of quantification of risk in supply chains. Meanwhile, Zobel and Khansa [22] proposed a resilience evaluation model for a multi-disaster event that compares the recovery time in various scenarios generated for illustration. Moreover, Zahiri et al. [23] proposed an integrated supply chain network multi-objective model addressing sustainability and resiliency aspects for the pharmaceutical industry. Anaya-Arenas et al. [24] discussed the importance of fairness in the relief distribution and how it can be defined, especially in a context where the delivery of essential items must be ensured periodically. They also proposed some performance indicators to measure fairness, which can be useful to organizations that are held accountable for the impartiality of their decisions. Furthermore, Maghfiroh and Hanaoka [25] proposed a multi-modal relief distribution model using a three-level chain composed of supply nodes, logistics operational areas, and affected areas while considering multiple trips for disaster response operations. Finally, for use in the disaster response domain, Jayawardene et al. [26] revised and consolidated extant definitions of data and information quality.

2.1.2. Anticipative/proactive strategies

Most proactive strategies proposed so far revolve around supplier selection and preventive disruption frameworks. Huang and Song [27] proposed a distribution model for unexpected events considering demand and lead-time as a function of experts' judgment. Meanwhile, Burkart et al. [28] used various methods to anticipate demand and proposed distribution models for different situations. Moreover, Huang et al. [29] proposed logistics and distribution models considering probabilistic parameters. With regard to aid distribution planning in emergency response, several studies lay on two-stage or two-level approaches decomposing the problem into a location planning phase that informs a subsequent transportation phase [30]. Furthermore, the most frequent objectives pursued are cost and unmet demand minimization (approx. 75%) [31,32]. Therefore, we use these objectives in our analysis.

A two-stage stochastic programming is a framework for cases where parameter uncertainties, like supply quantity, are decision-independent. In stochastic models, uncertain parameters are explicitly represented by a set of scenarios. Each scenario corresponds to one possible realization of the uncertain parameters according to a probability distribution. Such schemes aim to optimize the expected value of the objective function over the full set of scenarios, subject to the implementation of common decisions at the beginning of the planning horizon. When developing these models, which decisions are "here and now" type and which ones are set as the later "wait and see" type must be established [33]. Some studies evidenced that combining these two kinds of decisions improves the resilience of supply chains [6,7,34,35]. Meanwhile, Hosseini et al. [36] presented a systematic review of the literature on quantitative modeling of supply chain resilience and argued that two-stage stochastic programming is one of the most appropriate ways to deal with uncertainty originating from the disruption.

Kamalahmadi and Parast [37] assessed the effectiveness of incorporating three types of redundancy practices (pre-positioning inventory, backup suppliers, and protected suppliers) into a firm's supply chain exposed to two types of risks: supply risk and environmental risk. They developed a two-stage mixed-integer programming model to address the problem of supplier selection and order allocation under supplier dependencies and disruption risks. Kaur and Singh [7] proposed a resilient procurement framework involving supplier selection and two mathematical models for resilient disaster procurement in proactive and reactive situations.

A relatively small number of studies take the approach of decomposing the modeled system into more than two stages. In some relevant examples, Escudero et al. [38] proposed a three-stage optimization model for resource allocation, warehouse location, and disaster relief capacity. They considered two types of uncertainties: exogenous and endogenous. Exogenous uncertainty arises due to the lack of full knowledge of the disaster characteristics, whereas endogenous uncertainty is based on the decision-maker investment to obtain accurate information. Zhan et al. [39] employed a decision-making framework where the traditional disaster relief logistics actions are replaced by periodic, sequential actions involving demand points location and assignment. The sequential approach allows the decision-maker to decide whether to locate and assign it to relief suppliers immediately or later, which influences the decision in the next period.

Although the anticipative approach has been tested with the main objective of minimizing operational costs, some authors have suggested that cost-minimizing models applied to disaster response ignore human suffering or force the decision-makers to assign an economic value to it, degrading the quality of the aid [40]. Therefore, further research must evaluate the applicability of anticipative decision-making approaches in contexts where the minimization of deprivation is pursued as primary goals.

2.2. Considering uncertainty in supply

Uncertainty affects supply along three dimensions (i.e., timing, quantity, and purchase price) [41]. Relevant studies in uncertain supply quantities present strategies that address yield uncertainty or supply interruptions from production, procurement, or sourcing perspectives [42]. Alem et al. [43], Falasca and Zobel [44], and Cook and Lodree [45] proposed models with stochastic supply and demand. In particular, Alem et al. [43] defined discrete levels of demand based on historical data. Then, three possible values for supply are generated: one level lower than demand, the same level as demand, and one level higher than demand. Meanwhile, Falasca and Zobel [44] and Cook and Lodree [45] modeled stochastic variables with a triangular distribution and a Poisson distribution, respectively, assuming in both cases arbitrary values for the parameters of the distributions.

To the best of our knowledge no other work in the literature has explicitely assessed the importance of decisions' timing in two-stages stochastic programming. Indeed, whereas previous works assume a sharp separation of decisions before and after certainty, this paper explores how the choice of making a decision before or after certainty impacts the model performance. Moreover, the paper considers a foodbank's network logistics, but instead of studying regular day-to-day operations, it investigates how the network adapts to cope with the consequences of a natural disaster. Third, the proposed models simultaneously consider donation supply uncertainty and food mixture constraints. Altogether, these features make this problem very interesting from both scientific and practical standpoints.

3. Food bank disaster response planning: The BAMX case

BAMX is a Mexican non-profit civil organization, and a co-founder and member of the Global FoodBanking Network. With more than 50 food banks distributed across the country, BAMX is the only food bank network in México and the second largest in the world. More than 1.137 million Mexicans in food poverty received support from BAMX in 2018 [46].

3.1. Foodbank network structure in the day-to-day operation

BAMX's supply chain encompasses three entities: (i) suppliers (donors and retailers), (ii) food banks, and (iii) communities. Donors–the start of BAMX supply chain–are assigned to specific banks, and each bank covers the needs of a geographical region. Donor-to-bank assignments have been set according to their distance, regions' demand, and banks' logistic capabilities. The bank handles the donor's products and returns to the donor reports and acknowledgments of the goods they have received.

Being responsible for the demand region, each bank organizes and coordinates with the communities to ensure the deliveries to individuals in need. Notice that the representatives of the communities are in charge of the aid's last-mile delivery and work in an agreed schedule. Unlike donors that can collaborate with the entire food bank network, local representatives cooperate only with the bank of their region.

Each bank produces forecasts of its region's needs and receives a budget from the headquarters to ensure its operations. Since labor is provided mostly by volunteers, the budget is almost entirely spent on logistics (warehouse, transportation, and managing). However, the volume and the nature of the products supplied by each donor vary greatly; thus, a donor-to-bank assignment cannot match the supply and demand perfectly. Moreover, BAMX seeks to deliver a balanced proportion of macronutrients and micronutrients to prevent malnutrition; thus, the acquisition of basic supplies that are not commonly donated is needed. The purchased food represents approximately 5% of the total aid delivered by each bank.

Finally, supply is generally insufficient to cope with the demand; therefore, decision-making models for aid distribution usually seek to simultaneously improve the distribution's effectiveness and equity. Effectiveness refers to the ability to distribute the maximal amount of aid available, whereas equity addresses the ability to distribute the aid among the individuals suffering from food insecurity fairly [47].

3.2. Foodbanks' disaster response planning

The arrival of a natural or a man-made disaster increases the number of people in need and the relief requested. At the other end of the supply chain, solidarity and generosity increase the number and volume of donations, which paradoxically causes managerial challenges. Compared to regular donations, extraordinary donations are unpredictable, and their precise characteristics are known only once they are delivered at the banks. This unreliable supply behavior can cause a sudden overflow of managerial requirements and expenses at individual banks. Uncertainty is further complicated by the phenomenon of material convergence [16], where well-meaning donors supply goods having low or no use to fulfill people's basic needs that can clog the supply chain.

BAMX's central logistics management office must make quick decisions to harmonize the surging supply and demand in such challenging situations. However, according to the organization's managers, specialized protocols for such situations do not exist. Indeed, although each bank is willing to cooperate with the network, the arrival of a disaster triggers a rather unstructured process where proactive banks contact other banks or make available part of their resources, and reactive banks wait to see how the help is specifically requested. The timeframe for BAMX to draw up a logistic plan should respect the day-to-day operation cycle, which can be segmented into two phases: before and after donations are grabbed.

4. Decision-making timing strategies: anticipative versus reactive

Without loss of generality, we consider a distribution network, inspired by BAMX, which requires help because of problems caused by the disaster while keeping its regular humanitarian operations. Thus, we consider the problem of re-defining the logistic plans of a single operation cycle of the network–collection, handling, and distribution–to cope with the rise of demand and supply. The operation cycle is divided into two stages in which decisions can be made. The level of information available distinguishes stages into (i) supply uncertainty (stage 1) and (ii) supply certainty (stage 2). Supply certainty is assumed to occur once the donations have been received and handled at the banks. The supply for the day-to-day operation of the network is assumed to be constant and known. Thus, the source of uncertainty is the emergency supply offered by the donors in response to the disaster.

We assume three types of decisions: (1) re-assigning of donors to banks, 2) purchasing food from retailers, and 3) transshipping food between banks. These decisions can be made before and after supply certainty.

Decisions made under uncertainty can be considered as fixed or as adjustable later, during the certainty stage, where all decisions are considered fixed. These decision-making timeframes create a Stackelberg setting where the asymmetry of the information defines the hierarchy. Adopting the terminology of Schneeweiss [48], we refer to the decision-making under supply uncertainty as *anticipation*, the resulting decisions as *instruction*, and the decision-making under information certainty as *reaction*. By allowing different sets of decisions to be or not reconsidered in the certainty stage, the following four anticipative models and one reactive model, which will be used as a baseline, were proposed.

Anticipative–adaptative decision-making model (AADM). This model generates an anticipative solution to the allocation of donations and food purchases while trying to anticipate how the network will adapt once the supply is known (certainty stage). This means that, although the anticipation considers all the possible decisions available for the network, decisions that can be changed after Stage 1 are assumed to depend on the actual supply provided by the donors. Hence, first-stage fixed decisions are optimized with the feedback of the second-stage decisions' expected value (Figure 1). The anticipative–adaptative decision-making (AADM) model aims to offer a robust optimization of the supply chain's upstream and reduce response time by allowing an earlier purchase of goods. From a practical viewpoint, AADM offers the highest flexibility among the proposed models at the cost of being the most complex and computationally expensive, which may make it unsuitable for tackling large networks or short operation cycles.

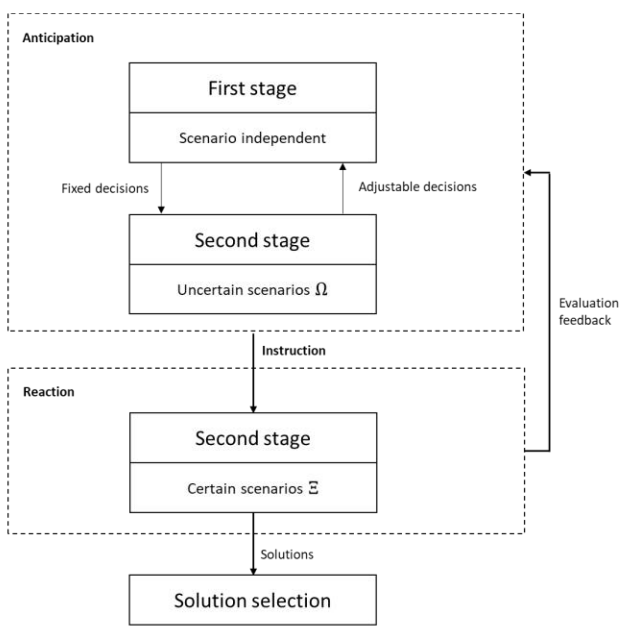

Figure 1 Two-stage decision-making models and the relations between their levels

Anticipative–reactive decision-making model (ARDM). Unlike AADM, the anticipative–reactive decision-making model excludes adaptative decisions (scenario dependent). This two-stage anticipative strategy obtains the solution of the first-stage decisions while assuming the second-stage decisions are fixed, and later adjusts the second-stage decisions using the reactive model. The set of fixed decisions that constitute the instruction for the reaction is the same as in AADM. By including fewer variables, ARDM is less complex than AADM but potentially less robust.

Detached decision-making model (DDM). The detached decision-making model addresses the first- and second-stage decisions as separate models. Therefore, DDM is not a real two-stage anticipative strategy. In the DDM model, the anticipation solves the response planning problem of food bank network disaster solely by the allocation of donations and early purchase by the banks, which is then used as "inputs" (instruction) for the reaction phase. The DDM model can be considered a further simplification of AADM, compared to ARDM.

Anticipative decision-making model (ADM). The single-stage anticipative decision-making model contemplates making all decisions before starting the donations' collection (under supply uncertainty). Given that only the anticipation is considered, the instruction becomes the new logistic plan. This stochastic model may seem to offer no advantage because it does not optimize the reaction once supply certainty is reached. Nevertheless, ADM seems valuable, particularly from a managerial standpoint because an early and unique logistic plan may be easier to negotiate, agree, and deploy than one that assumes different decision-making stages and updates.

Reactive decision-making approach (RDM). The reactive decision-making model is the one closest to BAMX's operations. All decisions are made under information certainty in what is also known as "wait and see." Having certain information makes it easier to negotiate with the involved stakeholders. However, decisions are delayed, resulting in the incapacity to adjust the logistic network flow timely.

Figure 2 summarizes and illustrates what decisions are made before (Stage 1) of after certainty (Stage 2) as well as the activities performed. The unload and handling at the banks of the goods previously collected at the donors' sites, makes the supply information certain, thus separating the first and second stages. For each model, decisions are separated into "Decisions to execute" (once taken, they cannot be reconsidered), and "Anticipated" decisions that might be adjusted later.

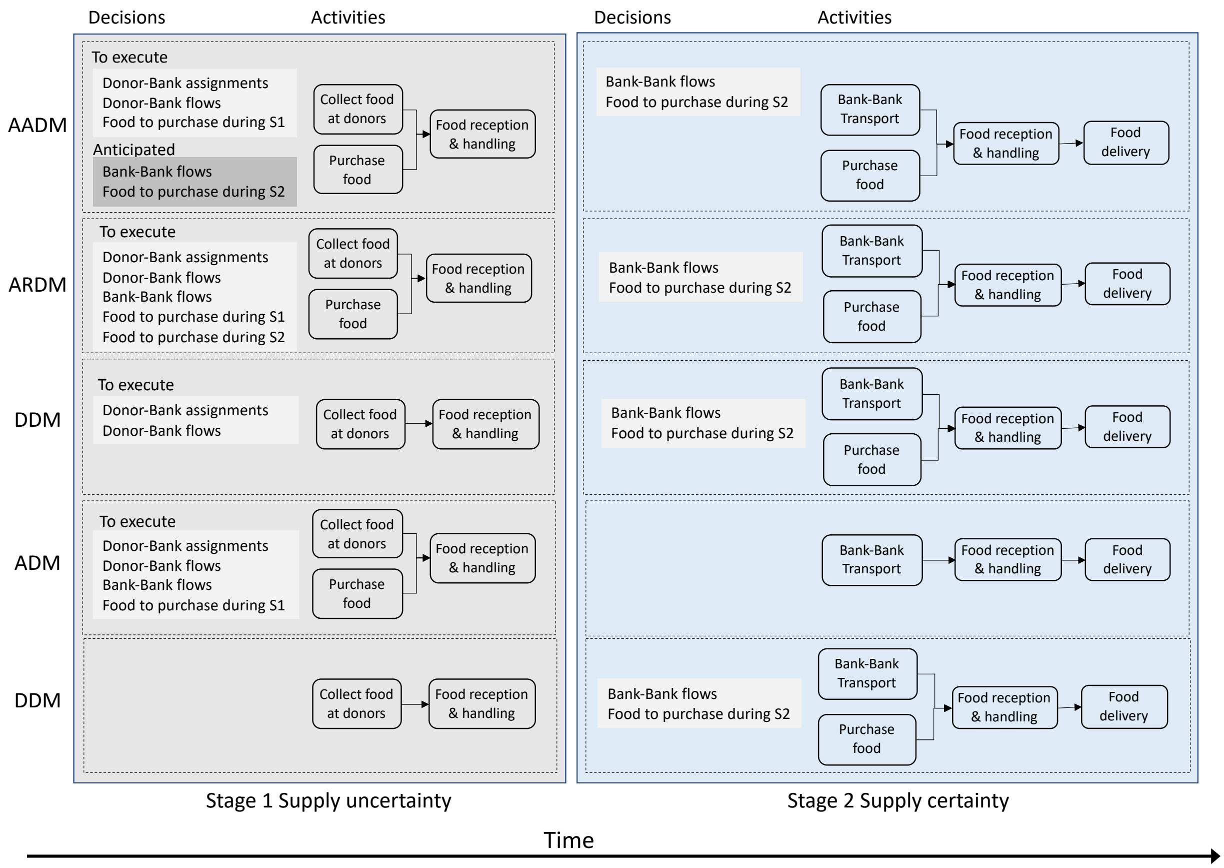

Figure 2 Logistics decisions for the emergency response plan of food bank network and their timing according to the proposed anticipative and reactive models.

5. Mathematical formulations

This section proposes mathematical formulations for each of the five models presented in the previous section. We first present the most general two-stage formulation containing all the potential decision variables, and then the formulation is reduced by dropping variable sets or entire phases to obtain the other models' formulations. Parameters and variables are classified according to the timeframe to which they are subjected. In the case of variables, this leads to the three following categories: *scenario-independent variables* representing decisions made in the first-stage and kept during the second; *uncertain-scenario-dependent variables* representing decisions made in the first-stage that can be reconsidered or adjusted during the second-stage; and *certain-scenario-dependent variables* representing decisions made during the second-stage (i.e., after the realization of the supply availability). The same notation applies to the parameters.

Indices or Sets

$d \in D$	Index and set of donors
$b \in B$	Index and set of food bank
$f \in F$	Index and set of food types
$\omega \in \Omega$	Index and set of anticipative (uncertain) scenarios
$\xi \in \Xi$	Index and set of reactive (certain) scenarios
M	Set of arcs connecting nodes (d, b): $(d \in D, b \in B)$
N	Set of arcs connecting nodes (i, j): $(i \in B, j \in B, i \neq j)$
A	Set of arcs used to transport from donors to banks in the day-to-day operation $A \in M$

Scenario-independent variables

x_{fdb}	Kilograms of food type f planned to be shipped from donor d to bank b
y_{fij}	Kilograms of food type f shipped from bank i to bank $j \mid (i, j) \in N$
z_{fb}	Kilograms of food type f purchased by bank b in the first-stage
αx_{db}	Takes value 1 if food is shipped from donor d to bank $b \mid (d, b) \in A$, 0 otherwise
αy_{ij}	Takes value 1 if food is shipped from bank i to bank $j \mid (i, j) \in N$, 0 otherwise
αz_b	Takes value 1 if food is purchased in the first-stage by bank $b \in B$, 0 otherwise
k_b	Consolidation time of food at bank $b \in B$ in stage one
k'_b	Consolidation time of food at bank $b \in B$ in stage two
r_{fb}	Kilograms of food f that are shipped to communities from bank b
u_b	The proportion of unmet demand at bank b
eb_b	Excess budget spent by bank b
et_b	Excess delivery time by bank b

Certain-scenario-dependent variables

$y_{fij}(2, \xi)$	Kilograms of food type f shipped from bank i to bank $j \mid (i, j) \in N$
$z'_{fb}(2, \xi)$	Kilograms of food type f purchased by bank b in the second-stage
$\alpha y_{ij}(2, \xi)$	Takes value 1 if food is shipped from bank i to bank $j \mid (i, j) \in N$, 0 otherwise
$\alpha z'_b(2, \xi)$	Takes value 1 if food is purchased by bank $b \in B$ in the second-stage, 0 otherwise
$k'_b(2, \xi)$	Consolidation time of food at bank $b \in B$ in stage two
$r_{fb}(2, \xi)$	Kilograms of food f that are shipped to communities from bank b
$u_b(2, \xi)$	The proportion of unmet demand at bank b
$eb_b(2, \xi)$	Excess budget spent by bank b
$et_b(2, \xi)$	Excess delivery time by bank b
$I_{fb}(2, \xi)$	Available inventory of food f used by bank b

Uncertain-scenario-dependent variables

s^{ω}_{fdb}	Kilograms of food type f shipped from donor d to bank b under scenario ω
y^{ω}_{fij}	Kilograms of food type f shipped from bank i to bank $j \mid (i, j) \in N$ under scenario ω
z'^{ω}_{fb}	Kilograms of food type f purchased by bank b in the second-stage under scenario ω
αy^{ω}_{ij}	Takes value 1 if food is shipped from bank i to bank $j \mid (i, j) \in N$ under scenario ω, 0 otherwise
$\alpha z'^{\omega}_b$	Takes value 1 if food is purchased in the second-stage by bank $b \in B$ under scenario ω, 0 otherwise
k^{ω}_b	Consolidation time of food at bank $b \in B$ in stage one under scenario ω
k'^{ω}_b	Consolidation time of food at bank $b \in B$ in stage two under scenario ω
r^{ω}_{fb}	Kilograms of food f that are shipped to communities from bank b under scenario ω
u^{ω}_b	The proportion of unmet demand at bank b under scenario ω

eb_b^ω	Excess budget assigned to bank b under scenario ω
et_b^ω	Excess delivery time required by bank b under scenario ω

Scenario-independent Parameters

Don_{fd}	Kilograms of food type f supplied by donor d for the day-to-day operation
ΔDon_{fd}	Kilograms of food type f offered by donor d in response to the disaster
H_b	Historic unmet demand at bank b in the day-to-day operation
$Bcap_b$	Capacity in kilograms of food that bank $b \in B$ can process
Fu_f	The maximum proportion of food type $f \in F$ a bank can deliver
Fl_f	The minimum proportion of food type $f \in F$ a bank can deliver
Vsp	Mean transportation speed
Dem_b	Demand in kilograms of food at bank $b \in B$
ΔDem_b	Increase in demand (in kilograms) of food at bank $b \in B$ due to the disaster
Td_{db}	Distance (km) between donor d and bank $b \mid (d, b) \in A$
Tb_{ij}	Distance (km) between bank i and bank $j \mid (i, j) \in N$
Tk_b	Distance (km) between bank b and their communities
Tl_b	Lead-time for purchases made by bank $b \in B$
Tp_b	Processing time of a kilogram of food at bank $b \in B$
$Tmax$	Latest arrival time allowed in the network for food delivery to a community
Bud_b	The available budget for bank $b \in B$
Tc_{ofb}	Transportation cost of a kilogram of food type $f \in F$ per kilometer for bank $b \in B$
Pc_{fb}	Cost of purchasing one kilogram of food $f \in F$ for bank $b \in B$
β	The factor of excess budget and time penalization

Uncertain-scenario-dependent parameters

$\widetilde{\Delta Don}_{fd}^{\omega}(1, \omega)$	Random amount of ΔDon_{fd} delivered by donor d under scenario ω

Certain-scenario-dependent parameters

$X_{fdb}(1, \xi)$	Kilograms of food type f shipped from donor d to bank b in stage one
$Z_{fb}(1, \xi)$	Kilograms of food type f purchased by bank b in the first-stage
$\Delta Don_{fd}(2, \xi)$	A realization of $\widetilde{\Delta Don}_{fd}^{\omega}(1, \omega)$
$S_{fb}(1, \xi)$	Kilograms of food type f that were shipped in stage one to bank b under scenario ξ
$K_b(1, \xi)$	Consolidation time of food at bank $b \in B$ in stage one

5.1 Anticipative–adaptative decision-making

We formulate the AADM model as follows:

Anticipation

$$\min f(U) \;=\; E_{\Omega}[\Pi(U,\omega)] + \frac{\beta}{|B|}\sum_{b\in B}\frac{1}{Bud_b}\sum_{d\in D}\sum_{f\in F}(Tc_{fb} * Td_{db} * x_{fdb} + Pc_{fb} * z_{fb}) \qquad (1)$$

where $E_{\Omega}[\Pi(U,\omega)]$ is computed as:

$$\Pi(U,\omega) \;=\; \frac{1}{|B|}\sum_{b\in B}(u_b^{\omega} - H_b) + max_b\{u_b^{\omega} - H_b\} + \frac{\beta}{|B|}\sum_{b\in B}\left[\frac{eb_b^{\omega}}{Bud_b} + \frac{et_b^{\omega}}{Tmax}\right] \qquad (1')$$

subject to:

$$s_{fdb}^{\omega} \le x_{fdb} \qquad \forall\, f \in F, d \in D, b \in B, \omega \in \Omega \qquad (2)$$

$$s_{fdb}^{\omega} \le Don_{fd} + \widetilde{\Delta Don}_{fd}^{\omega}(1,\omega) \qquad \forall\, f \in F, d \in D, b \in B, \omega \in \Omega \qquad (3)$$

$$\sum_{j\in B} y_{fbj}^{\omega} \le \sum_{d\in D} s_{fdb}^{\omega} \qquad \forall\, f \in F, b \in B, \omega \in \Omega \qquad (4)$$

$$\sum_{f\in F} x_{fdb} \le Bcap_b * \alpha x_{db} \qquad \forall\, (d,b) \in A \qquad (5)$$

$$\sum_{f\in F} y_{fij}^{\omega} \le Bcap_j * \alpha y_{ij}^{\omega} \qquad \forall\, (i,j) \in N, \omega \in \Omega \qquad (6)$$

$$\sum_{f\in F} z_{fb} \le Bcap_b * \alpha z_b \qquad \forall\, b \in B \qquad (7)$$

$$k_b^{\omega} \ge \frac{Td_{db}}{Vsp} * \alpha x_{db} + \sum_{f\in F}\sum_{d\in D}\frac{Tp_b}{1000} * s_{fdb}^{\omega} \qquad \forall\, b \in B \qquad (8)$$

$$k_b'^{\omega} \ge \frac{Tb_{ib}}{Vsp} * \alpha y_{ib}^{\omega} + k_b^{\omega} \qquad \forall\; b \in B, (i,b) \in N, \omega \in \Omega \qquad (9)$$

$$k_b'^{\omega} \ge Tl_b * \alpha z_b \qquad \forall\; b \in B, \omega \in \Omega \qquad (10)$$

$$k_b'^{\omega} \le Tmax + et_b^{\omega} \qquad \forall\; b \in B, \omega \in \Omega \qquad (11)$$

$$u_b^{\omega} \;\ge\; \frac{1}{Dem_b + \Delta Dem_b}(Dem_b + \Delta Dem_b - \sum_{f\in F} r_{fb}^{\omega}) \qquad \forall\, b \in B, \omega \in \Omega \qquad (12)$$

$$\sum_{b\in B} \alpha x_{db} \le 1 \qquad \forall\, d \in D \qquad (13)$$

$$\sum_{f\in F}\sum_{d\in D} s_{fdb}^{\omega} + \sum_{f\in F}\sum_{j\in B} y_{fjb}^{\omega} + \sum_{f\in F} z_{fb} + \sum_{f\in F} z_{fb}'^{\omega} - \sum_{f\in F}\sum_{j\in B} y_{fbj}^{\omega} \le Bcap_b \qquad \forall b \in B, \omega \in \Omega \qquad (14)$$

$$r_{fb}^{\omega} \le Fu_f * (\sum_{i\in F}\sum_{d\in D} s_{idb}^{\omega} + \sum_{i\in F}\sum_{j\in B} y_{ijb}^{\omega} + \sum_{i\in F} z_{ib} + \sum_{i\in F} z_{ib}'^{\omega} - \sum_{i\in F}\sum_{j\in B} y_{ibj}^{\omega}) \qquad \forall\, f \in F,\; b \in B, \omega \in \Omega \qquad (15)$$

$$r_{fb}^{\omega} \geq Fl_f * (\sum_{i \in F} \sum_{d \in D} s_{idb}^{\omega} + \sum_{i \in F} \sum_{j \in B} y_{ijb}^{\omega} + \sum_{i \in F} z_{ib} + \sum_{i \in F} z_{ib}'^{\omega} - \sum_{i \in F} \sum_{j \in B} y_{ibj}^{\omega}) \quad \forall f \in F, b \in B, \omega \in \Omega \qquad (16)$$

$$r_{fb}^{\omega} \leq \sum_{d \in D} s_{fdb}^{\omega} + \sum_{j \in B} y_{fjb}^{\omega} + z_{fb} + z_{fb}'^{\omega} - \sum_{j \in B} y_{fbj}^{\omega} \quad \forall f \in F, b \in B, \omega \in \Omega \qquad (17)$$

$$\sum_{f \in F} z_{fb}'^{\omega} \leq Bcap_b * \alpha z_b'^{\omega} \quad \forall\ b \in B, \omega \in \Omega \qquad (18)$$

$$k_b'^{\omega} \geq Tl_b * \alpha z_b'^{\omega} + k_b^{\omega} \quad \forall\ b \in B, \omega \in \Omega \qquad (19)$$

$$\sum_{d \in D} \sum_{f \in F} Tc_{fb} * Td_{db} * x_{fdb} + \sum_{\substack{i \in B \\ (i,b) \in N}} \sum_{f \in F} Tc_{fb} * Tb_{ib} * y_{fib}^{\omega} + \sum_{f \in F} Tc_{fb} * Tk_b * r_{fb}^{\omega} + \sum_{f \in F} Pc_{fb} * z_{fb} + \sum_{f \in F} Pc_{fb} * z_{fb}'^{\omega} \leq Bud_b + eb_b^{\omega} \quad \forall b \in B, \omega \in \Omega \qquad (20)$$

$$\alpha x_{db}, \alpha y_{ij}^{\omega}, \alpha z_b, \alpha z_b'^{\omega} \in \{0,1\} \quad \forall\ (d,b) \in A, (i,j) \in N, b \in B, \omega \in \Omega \qquad (21)$$

$$x_{fdb}^{\omega}, y_{fij}^{\omega}, z_{fb}, k_b, k_b'^{\omega}, r_{fb}^{\omega}, u_c^{\omega}, eb_b^{\omega}, et_b^{\omega} \geq 0 \quad \forall\ f \in F, d \in D, b \in B, (i,j) \in N, \omega \in \Omega \qquad (22)$$

The objective function (1) seeks to minimize the sum of $E_{\Omega}[\Pi(U,\omega)]$, and the costs associated with the allocation of donations and anticipated purchase of food. As stated by equation (1'), $E_{\Omega}[\Pi(U,\omega)]$ computes the expected value over all scenarios $\omega \in \Omega$ of the anticipated mean and maximum unmet demand, and the average extra budget and time required by banks B in each scenario ω. The extra budget eb_b^{ω} required by the network represents emergency funds commonly held by organizations like BAMX. We assume that these funds and the extra response time are limited to give a clearer picture of the proportion of extra budget and time needed for each modeling strategy. These proportions are penalized by factor β that allows the decision-maker to fine-tune the importance granted to these extra resources.

Constraint (2) ensures that the donations shipped in each scenario are not larger than the volume planned to be shipped, whereas constraint (3) limits the flow to the sum of donations supplied. Constraint (4) ensures for each scenario that the volume of food sent from a bank to other banks is not larger than the amount of food they received. Constraints (5) and (6) identify the assignments to transport food within the network, and constraint (7) identifes the banks that place anticipative orders to purchase food from retail suppliers. Notice that the banks' capacities have been used to bound the flow in constraints (5)–(7). Together, constraints (8) – (11) and (19) calculate the expected time required to complete the operational cycle. Constraint (12) tracks the fraction of expected unmet demand at each bank. Meanwhile, constraint (13) ensures that each donor is assigned to at most one bank. Constraint (14) enforces that the food flow received at each bank is not greater than its capacity $Bcap_b$. Further, constraints (15) – (17) set the limit r_{fb}^{ω} of deliverable food by calculating the kilograms of food f that meet the mixture proportions $Fprop_f$

relative to the sum of all food types and by ensuring that volume is not greater than the input of donations to the bank. Constraint (18) identifies banks that place reactive (stage 2) orders to retail suppliers, using the bank's capacity as an upper bound for its incoming flow. Moreover, Constraint (20) tracks the expected expenditure of each bank's budget Bud_b. Constraints (21) and (22) define the variables' domains.

Instruction

$$S_{fb}(1,\xi) = \min\{\sum_{d\in D} x_{fdb} + z_{fb}, \sum_{d\in D} (\Delta Don_{fd}(2,\xi) + Don_{fd}) * \alpha x_{db} + z_{fb}\} \quad (24)$$

$$X_{fdb}(1,\xi) = x_{fdb} \quad (25)$$

$$Z_{fb}(1,\xi) = z_{fb} \quad (26)$$

$$K_b(1,\xi) = \max_{(d,b)\in M}\{\frac{Td_{db}}{Vsp} * \alpha x_{db}\} + \sum_{f\in F} \frac{Tp_b}{1000} * S_{fb}(1,\xi) \quad (27)$$

Reaction

$$\min f(U,\xi) = \frac{1}{|B|}\sum_{b\in B}(u_b(2,\xi) - H_b) + max_b\{u_b(2,\xi) - H_b\} + \frac{\beta}{|B|}\left[\sum_{b\in B}\frac{eb_b(2,\xi)}{Bud_b} + \frac{et_b(2,\xi)}{Tmax}\right] \quad (28)$$

subject to

$$I_{fb} \le S_{fb} \qquad \forall f \in F, b \in B \quad (29)$$

$$\sum_{f\in F}\sum_{j\in B} y_{fjb}(2,\xi) + \sum_{f\in F} z'_{fb}(2,\xi) - \sum_{f\in F}\sum_{j\in B} y_{fbj}(2,\xi) \le Bcap_b - \sum_{f\in F} S_{fb} \qquad \forall b \in B \quad (30)$$

$$r_{fb}(2,\xi) \le Fu_f * (\sum_{i\in F} I_{ib}(2,\xi) + \sum_{i\in F}\sum_{j\in B} y_{ijb}(2,\xi) + \sum_{i\in F} z'_{ib}(2,\xi) - \sum_{i\in F}\sum_{j\in B} y_{ibj}(2,\xi)) \qquad \forall f \in F, b \in B \quad (31)$$

$$r_{fb}(2,\xi) \ge Fl_f * (\sum_{i\in F} I_{ib}(2,\xi) + \sum_{i\in F}\sum_{j\in B} y_{ijb}(2,\xi) + \sum_{j\in F} z'_{ib}(2,\xi) - \sum_{i\in F}\sum_{j\in B} y_{ibj}(2,\xi)) \qquad \forall f \in F, b \in B \quad (32)$$

$$r_{fb}(2,\xi) \le I_{fb}(2,\xi) + \sum_{j\in B} y_{fjb}(2,\xi) + z'_{fb}(2,\xi) - \sum_{j\in B} y_{fbj}(2,\xi) \qquad \forall f \in F, b \in B \quad (33)$$

$$\sum_{j\in B} y_{fbj}(2,\xi) \le S_{fb}(1,\xi) \qquad \forall f \in F, b \in B \quad (34)$$

$$\sum_{f \in F} y_{fij}(2,\xi) \leq Bcap_b * \alpha y_{ij}(2,\xi) \qquad \forall\, (i,j) \in N \qquad (35)$$

$$\sum_{f \in F} z'_{fb}\,(2,\xi) \leq Bcap_b * \alpha z'_b(2,\xi) \qquad \forall\, b \in B \qquad (36)$$

$$k'_b(2,\xi) \geq \frac{Tb_{ib}}{Vsp} * \alpha y_{ib} + K_b(1,\xi) \qquad \forall\, b \in B, (i,b) \in N \qquad (37)$$

$$k'_b(2,\xi) \geq Tl_b * \alpha z'_b + K_b(1,\xi) \qquad \forall\, b \in B \qquad (38)$$

$$k'_b(2,\xi) \leq Tmax + et_b(2,\xi) \qquad \forall\, b \in B \qquad (39)$$

$$\sum_{i \in B} \sum_{f \in F} Tc_{fb} * Tb_{ib} * y_{fib}(2,\xi) + \sum_{f \in F} Tc_{fb} * Tk_b * r_{fb}(2,\xi) + \sum_{f \in F} Pc_{fb} * z'_{fb}(2,\xi) \leq Bud_b - \sum_{d \in D} \sum_{f \in F} Tc_{fb} * Td_{db} * X_{fdb}(2,\xi) - \sum_{f \in F} Pc_{fb} * Z_{fb}(1,\xi) \qquad \forall\, b \in B \qquad (40)$$

$$u_b(2,\xi) \; = \; \frac{1}{Dem_b + \Delta Dem_b}\left(Dem_b + \Delta Dem_b - \sum_{f \in F} r_{fb}(2,\xi)\right) \qquad \forall\, b \in B \qquad (41)$$

$$\alpha y_{ij}(2,\xi), \alpha z'_b(2,\xi) \in \{0,1\} \qquad \forall\, (i,j) \in N, b \in B \qquad (42)$$

$$I_{fb}, y_{fij}(2,\xi), z'_{fb}(2,\xi), r_{fb}(2,\xi), k'_b(2,\xi), u_b(2,\xi) \; \geq 0 \qquad \forall\, f \in F, b \in B, (i,j) \in N \qquad (43)$$

Function (28) minimizes the actual values of equation (1’). Constraint (29) ensures that the value of available inventory I_{fb} for the reactive phase is at most the quantity of food procured in the anticipative phase (stage 1). Meanwhile, constraint (30) ensures that capacity at each bank is respected. Constraints (31) – (33) limit the amount of deliverable food by the mix proportion requirements $Fprop_f$ and the total amount of food available at each bank. Constraint (34) ensures that each bank b sends to other banks at most the quantity of food procured in the anticipative phase. Meanwhile, constraint (35) identifies which assignation is made to transport food within the network, whereas constraint (36) identifies the banks placing reactive orders to retail suppliers. Together, constraints (37) – (39) calculate the time required to complete the operational cycle. Constraint (40) tracks the actual expenditure of each bank’s budget Bud_b, whereas constraint (41) tracks the fraction of actual unmet demand at each bank. Finally, constraints (42) and (43) define the variables’ domains.

5.2. Anticipative–reactive decision-making

ARDM anticipative model is given by (1) – (17) and (20) – (22), with two modifications: all variables drop the index ω, and z'^{ω}_{fb} is removed from all equations. The instruction and reaction remain the same as AADM, given by (24) – (27) and (28) – (43), respectively.

5.3. Detached decision-making

The DDM anticipation model is formulated by (1) – (22) in addition to:

$$y_{fij}^{\omega}, \alpha y_{ij}^{\omega}, z_{fb}^{\prime\omega}, \alpha z_{b}^{\prime\omega} = 0 \qquad \forall\ f \in F, b \in B, (i,j) \in N \tag{44}$$

The instruction and reaction in AADM remain the same, given by (24) – (27) and (28) – (43), respectively.

5.4. Anticipative decision-making

The ADM anticipation model is the same as the ARDM anticipation model, with a unique solution U. Therefore, ADM drops the instruction and reaction.

5.5. Reactive decision-making

The reactive approach does not consider anticipative decisions; thus, the logistic operations of the upper level of the supply chain are imported from the network's day-to-day operation. The instruction represents these decisions:

$$X_{fdb}(1,\xi) = \begin{cases} Don_{fd} + \Delta Don_{fd}, (d,b) \in A \\ 0, (d,b) \in A' \end{cases} \tag{45}$$

$$S_{fb}(1,\xi) = Don_{fd} + \Delta Don_{fd}(2,\xi)\ \forall (d,b) \in A \tag{46}$$

$$K_b(1,\xi) = \max_{(d,b)\in A}\{\frac{Td_{db}}{Vsp}\} + \sum_{f\in F}\sum_{d\in D} Tp_b * S_{fdb}(1,\xi) \tag{47}$$

The reactive model is described by the objective function (28) and constraints (29)–(43).

6. Solution method

Set Ω might include an infinite number of scenarios, thus making the proposed stochastic models intractable. The Monte Carlo simulation-based sample average approximation (SAA) method has been demonstrated to be very efficient in dealing with stochastic programming models, producing high-quality solutions and tight statistical bounds [49]. Basically, SSA's idea is that the expected objective value of the stochastic problem can be approximated by the corresponding value of a sampling problem. The sampling procedure is repeated several times to obtain enough potentially appealing solutions. Hence, at each SAA replication I, a random sample of size N is selected from the population Ω. $|I|$ independent random samples $\Omega_i = \{\omega_i^1, \omega_i^2, \ldots, \omega_i^N\}, \forall\ i \in I$, of size N are thus generated, and for each sample i, the expected value function $E_{\Omega}[\Pi(U,\omega)]$ in (1) is replaced with the following SAA program:

$$\Pi(U,\omega_i) = \frac{1}{N}\sum_{\omega_i\in\Omega_\text{i}}\left[\frac{1}{|B|}\sum_{b\in B}\left(u_b^{\omega_i} - H_b\right) + max_b\{u_b^{\omega_i} - H_b\} + \frac{\beta}{|B|}\sum_{b\in B}\left[\frac{eb_b^{\omega_i}}{Bud_b} + \frac{et_b^{\omega_i}}{Tmax}\right]\right] \tag{48}$$

The SAA program is solved for every sample $i \in I$, and the "best" solution found is selected. Even the large mixed-integer program can be solved with commercial solvers, such as Gurobi, given a moderate sample size N. As the sample size N increases, the quality of the decisions improves, and the solution of the SAA program converges with a probability of 1 to the optimal solution of the "true" problem [49].

An important issue of the SAA's approach is selecting the best solution among the I solutions. Thus, the quality of a candidate solution is evaluated by estimating a statistical optimality gap and confidence intervals. We measure how close the candidate solutions are to the optimal solution to the true problem by evaluating them using the independent set of scenarios Ξ, which have the same distribution as Ω and sample size $N' \gg N$. Appendix B describes the algorithm to solve the SAA problem.

7. Numerical experiments

This section aims to demonstrate the possibility of the reactive, predictive, and mixed models to lead to very different performance levels, depending on the amount of monetary and time resources available for the disaster response. We believe that understanding and quantifying these differences are important because the adoption of one or any of the proposed models has consequences from a managerial standpoint. Furthermore, we explore how these differences change under different scenarios of supply uncertainty.

We first present the instances. Then, we present the scenarios included in the experimental design proposed for the analysis. Finally, we reported and discussed the numerical results.

7.1. The generation of test instances

In order to generate a comprehensive testbed, we were inspired by the BAMX's disaster operations in response to Hurricane Willa in México during October 2018. An instance consists of the bank of each region ($B = |9|$) and three donors assigned to each bank ($D = |27|$). Donors are randomly located within the space of each region as a spatial generalization of the total offer location.

Concerning BAMX's day-to-day parameters, banks' demand (Dem_b), supply ($\sum_f Don_{fd}$), the amount of bought food (Z_{fb}), and the expected unmet demand (I_b) values are based on the 2018 BAMX operations records (see Appendix A).

Three types of food are considered: f_1, f_2, and f_3. f_1 represents food with a low nutritional value, which is undesirable for aid content, f_2 represents nutritious food with very limited shelf life left, and f_3 represents long-lasting food with high nutritious value. The food offered by each donor is randomly divided according to the allowed mixture proportions of the aid sent by each bank, defined by $Fu_f = (10\%, 30\%, 90\%)$ for the upper limit and $Fl_f = (0\%, 5\%, 60\%)$ for the lower limit. The transportation cost of a kilogram of food per kilometer is set to facilitate the evaluation of expenses, and the purchasing costs are set to $Pc_f = (300, 200, 400)$. Based on BAMX's reports, we assumed that 5% of the food delivered by each bank is bought, which consists entirely of food f_3, given its better features.

Assuming that the banks are designed to operate under demand levels close to the day-to-day requirements, their capacity $Bcap_b$ was set to 120% of their demand Dem_b. Budget Bud_b was set to cover 100% of the transportation costs of the total volume of donations Don_{fdb} plus the expense of purchasing food. Vehicles' speed was set to the maximum-allowed speed for cargo vehicles in Mexican roads ($Vsp = 70\ km/h$) [50]. We assume that infrastructure and labor force at each bank allow it to process their incoming flow in a single workday so that $Tp_b = 8hr/Dem_b$. Operation cycle's length $Tmax$ is calculated based on the maximum delivery time required among all banks, which can be defined by:

$$\max_{b}\{\max(\frac{Td_{db}}{Vsp}) + standar\ processig\ time + Tl_b + Tk_b\}$$

Finally, due to the impact of Hurricane Willa, the demand of the affected region is increased by ΔDem_b.

7.2. The scenarios and experimental design

Several instances were generated to assess the performance and the behavior of the proposed models facing different scenarios of donations' variability. Adopting the *design of experiments* terminology, we refer to these scenarios as *treatments*, to their distinctive features as *factors*, and the available choices of those factors as *levels*. We apply a full factorial 2^k design composed of four factors with two levels, resulting in 16 different treatments.

The first factor is the direction of the variability (Dir). It indicates whether the actual donations are greater or lower than the "promised" ones. Setting Dir to level 0 denotes an "optimistic" variability so that actual donations will be at least what donors promised. Contrarily, setting Dir to 1 represents a "pessimistic" scenario, where the actual donations can reach at most the promised quantities.

The second factor is $Dvar$, the maximum proportional amount of promised goods a donor could fail to deliver. We refer to this proportion as a variability range V and classify donors as high-reliability donors or unknown reliability donors (URDs). The factor is defined by the URD variability range value, where $V_d = 0.3\ \forall\ d \in HDR \mid Dvar = 0$ and $V_d = 0.6\ \forall\ d \in HDR \mid Dvar = 1$, whereas $V_d = 0.1\ \forall d \in URD$. Therefore,

$$\widetilde{\Delta Don}_{fd}^{\omega}(1,\omega) \sim \begin{cases} U\left[\Delta Don_{fd}(1 - V_d), \Delta Don_{fd}\ \right], Dir = 0 \\ U\left[\Delta Don_{fd}, \Delta Don_{fd}\ (1 + V_d)\right], Dir = 1 \end{cases} \tag{49}$$

The third factor is the variability of the food types among donations (MP). When $MP = 0$, the amount of each food type delivered by each donor varies independently like in (49). Meanwhile, $MP = 0$ assumes that all food types delivered by the same donor vary proportionally according to a donor variability value:

$$\delta_d^{\omega} \sim \begin{cases} U[(1 - V_d), 1] \; \forall d \in URD \mid Dir = 0 \\ U[1, (1 + V_d)] \; \forall d \in URD \mid Dir = 1 \end{cases}$$

Consequently, when $MP = 1$, the volume of actual donations delivered is defined by:

$$\widetilde{\Delta Don}_{fd}^{\omega}(1, \omega) = \delta_d^{\omega} \Delta Don_{fd}$$

Lastly, to test the suitability of the models on different scenarios of extra budget, time availability, or priority levels, we included two levels of β as an experimental factor. A low-level penalty is represented by $\beta = 2$, and the high-level is set to $\beta = 20$.

7.3. Computational results

This subsection intends to assess the models' performance in terms of effectiveness and efficiency, so managers can choose the most suitable for their priorities. Before tackling the analysis, we briefly discuss the setting of the parameters in the SAA method which is used to solve the instances. Then, we present the results and analyze how the network's performance metrics were impacted by the factors characterizing the different scenarios.

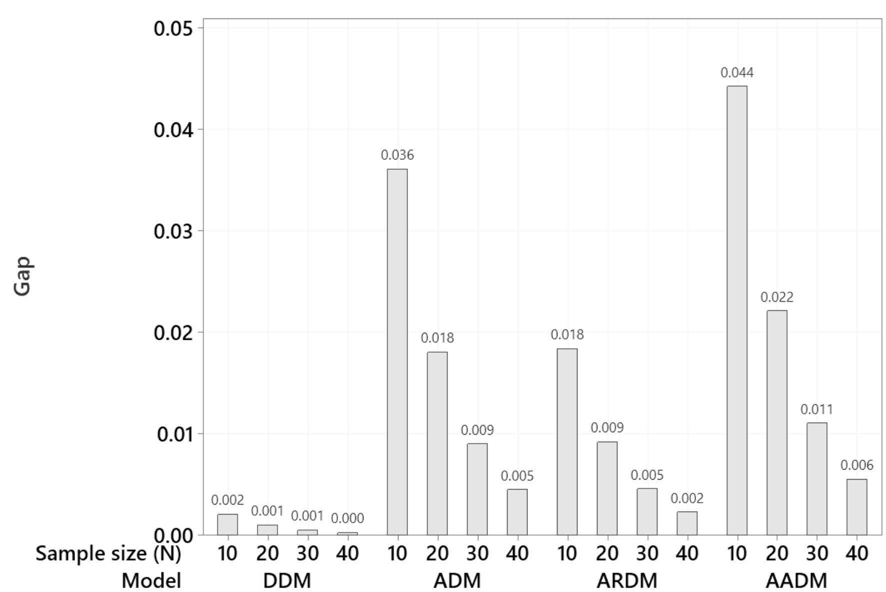

Figure 3 Average optimality gaps produced using the SAA method for each model for samples of size $N \in \{10, 20, 30, 40\}$

The statistical validation of the solutions obtained using the SAA method is performed by evaluating the objective function of the candidate solutions with samples of size $N \in \{10, 20, 30, 40\}$ with respect to their results under certainty. Figure 3 reports the optimality gaps produced by each stochastic model (DDM, ADM, ARDM and AADM) for different values of sampling size N (see Appendix B). Gaps are reasonably low (around 4.4% in the worst case) and, as expected, they become tighter as sample size N increases. These results indicate the capability of stochastic modeling method to produce robust solutions in various uncertain environments.

In the following, we set $I = 10$ samples of size $N = 40$, and each sample was evaluated over $N' = 400$ scenarios. This setting was repeated for each of the 16 experimental treatments, and thus, 6 400 instances were solved during the experiments.

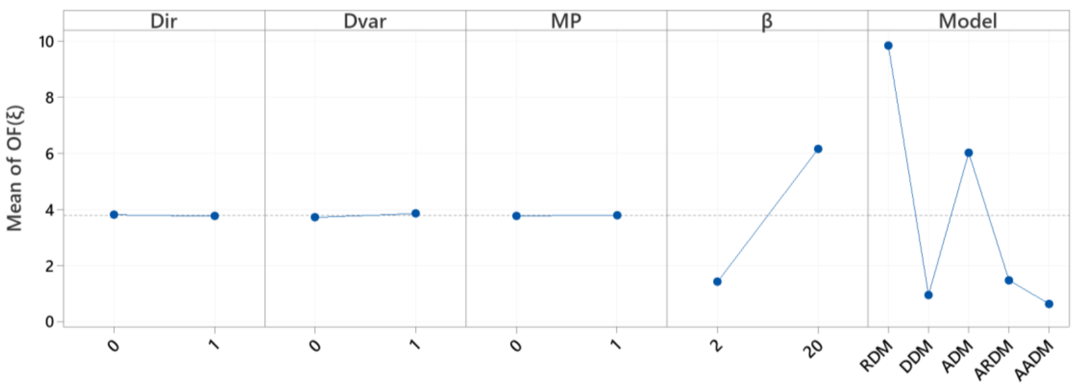

Figure 4 Fitted means of the objective function value (OF) among scenarios ξ for each level of the experimental factors (Dir, Dvar, MP, β, Model)

Let us first discuss the statistical relevance of each factor. Figure 4 illustrates the main effects of the levels of each factor on the objective function value by displaying their fitted means, which use least squares to predict the mean response values. Figure 4 shows that the supply variability factors *Dir*, *Dvar*, and *MP* do not impact or impact the results weakly. In contrast, the model selection and the value of the penalty β strongly affect the objective function values. Given these outcomes, we focused on each model performance without considering the scenario-related factors in the following analysis.

7.3.1. Performance of the models

To illustrate the differences between the results produced by the proposed models, we present the breakdown of metrics evaluated in the objective function**.** Table 1 displays, for each value of parameter β, the average and half-width of the 95% confidence intervals (after the symbol "±") for the objective function value (OF), and the key performance metrics (e.g., the average unmet demand ($\bar{u}$), maximum unmet demand ($\max(u)$), extra proportion of budget spent (eb), and proportion of extra response time (et)). The metrics in Table 1, except for OF, are expressed as percentages (they are originally represented as proportions in the models).

Table 1 Average effectiveness results produced for each model and value of parameter β

β	Model	OF	$\bar{u}$ (%)	$\max(u)$ (%)	eb (%)	et (%)
2	RDM	1.75 ± 0.05	1.0 ± 1.6	37.9 ± 4.2	12.3 ± 0.9	17.3 ± 18.5
	DDM	1.25 ± 0.59	3.4 ± 2.1	38.5 ± 1.2	7.3 ± 5.3	0.0 ± 0.0
	ADM	2.04 ± 1.06	1.3 ± 2.0	37.0 ± 0.6	17.4 ± 11.5	0.0 ± 0.0
	ARDM	1.34 ± 0.40	16.9 ± 12.2	47.9 ± 17.8	7.0 ± 3.1	0.1 ± 1.7
	AADM	0.67 ± 0.41	15.4 ± 17.7	48.9 ± 27.3	0.4 ± 1.0	0.0 ± 1.0
20	RDM	17.92 ± 0.66	2.7 ± 1.8	56.1 ± 7.1	19.7 ± 1.0	1.1 ± 6.4
	DDM	0.65 ± 0.21	20.6 ± 6.5	38.2 ± 1.8	0.1 ± 0.2	0.0 ± 0.0
	ADM	9.99 ± 1.59	8.0 ± 4.5	37.3 ± 0.5	10.0 ± 2.0	0.0 ± 0.0
	ARDM	1.61 ± 0.25	37.5 ± 15.5	93.8 ± 19.3	0.3 ± 0.4	0.0 ± 0.0
	AADM	0.58 ± 0.25	13.2 ± 14.3	44.6 ± 14.6	0.0 ± 0.0	0.0 ± 0.0

Concerning the objective function values, Table 1 shows that AADM produced the best (i.e., the lowest) average values. However, these values are not statistically different from the values produced by DDM and ARDM. Also, noteworthily, RDM and ADM results deteriorate when the penalty β increases from its low to high value, which is linked to their inability to reduce the expenditure of extra resources.

Although AADM, DDM, and ARDM models produced the best results regarding the objective function value, their performance concerning the other metrics varied. Indeed, if we look at $\bar{u}$, AADM, DDM, and ARDM were outperformed by RDM and ADM. These results can be explained by the tendency of models anticipating the decisions of the second-stage in the first-stage to be more conservative in the use of the budget under uncertainty, collecting fewer donations and therefore decreasing the total volume of food delivered. The values produced for $\bar{u}$ by RDM and ADM are comparable when β = 2. However, model RDM is the most appropriate when β = 20. On a more negative note, model ARDM produced the worst results when β = 20.

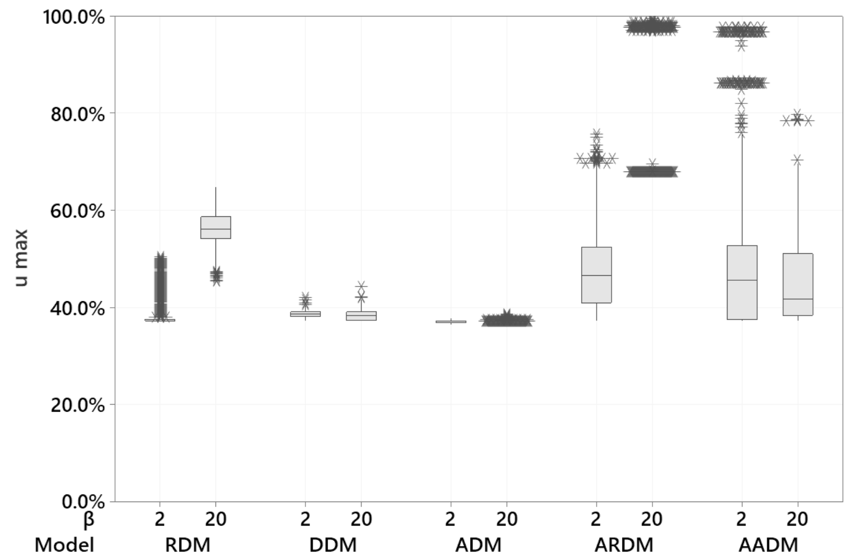

Figure 5 Boxplot of maximum unmet demand

Two-stage anticipative models seem also to be outperformed when looking at the maximum unmet demand, $max(u)$. Figure 5 displays the results of $max(u)$ produced by each model and the value of β. The graph shows that the RDM, ARDM, and AADM models offer relatively poor performance in terms of the maximum unmet demand in the network. It also confirms that ARDM and AADM reach extreme levels of unmet demand, close to 100%, in certain scenarios. These results are critical because they demonstrate that although the models seek to minimize the same goals, their results differ significantly concerning specific metrics that could make one or other model unsuitable for humanitarian organizations.

Table 2 Average efficiency and commitment results produced for each model and value of parameter β

β	Model	CE	$\sigma(u)$ (%)	$\sigma(TC)$ (%)
2	RDM	107276 ± 539	13.5 ± 0	105.3 ± 0
	DDM	140176 ± 536	15.2 ± 0.1	84 ± 0.5
	ADM	104527 ± 601	6.5 ± 1.4	120.9 ± 1
	ARDM	64223 ± 870	6.7 ± 1.1	73.5 ± 0.2
	AADM	25667 ± 639	6.4 ± 1.4	37.6 ± 0.2
20	RDM	94881 ± 357	19.1 ± 0	124.5 ± 0.1
	DDM	80855 ± 2117	17.1 ± 0.1	38 ± 0.1
	ADM	110424 ± 200	6.6 ± 1.5	89 ± 0.5
	ARDM	44766 ± 1465	6.5 ± 1.4	39.1 ± 0.1
	AADM	26293 ± 471	6.4 ± 1.4	36.2 ± 0.1

We now discuss the proportion of additional budget and time spent by each model as presented in Table 1. The results vary significantly depending on the level of β that, as the reader recall, expresses the relative importance accorded by the user to excess in the use of budget/time. As expected, eb was lower when β = 2, except for the RDM strategy. Unlike previous metrics, the best results were obtained using the two-stage anticipative models ARDM and AADM. Concerning the extra proportion of time required by the network to complete the distribution of aid, Table 1 shows that, in the considered instances, all the models could satisfy the time limit adequately. The RDM strategy with β = 2 was the only one to show a consistent requirement of extra time for the operation with a mean value of 17.3%, whereas ARDM and AADM strategies required it only for specific occasions.

To evaluate the cost efficiency of each model, Table 2 reports the kilograms of food delivered by the percentage of budget spent (CE). Counterintuitively, the value of β used to penalize the use of extraordinary budget has a relatively low impact on this metric. The lowest CE values were obtained from the ADDM strategy, whereas the models that include only one stage (RDM and ADM) and the one that solves both stages independently (DDM) can offer the best efficiency.

7.3.2. Measuring the commitment of the banks in the network

A common problem in operations carried out collaboratively by independent organizations is that the efforts and fulfillment of individual objectives may not be balanced across the network. In other words, some banks may wonder why they should use their resources to help other banks when they are unable to fulfill the needs of their own regions. We present two metrics that aim at measure how well the different models enforce commitment across the network: the standard deviation of unmet demand among banks $\sigma(u)$, and the standard deviation of the proportion of budget required among banks $\sigma(TC)$.

Table 2, which displays the values of $\sigma(u)$ produced by the proposed models, confirms that the non-anticipative models RDM and DDM lead to significant variability in the mean unmet demand among banks. This is because models that involve the reactive decisions in the uncertainty phase (ADM, ARDM, and AADM) anticipate which banks will have fewer resources for the reaction or adjustment phase, assigning more donations to them and ensuring an equal distribution among the communities. However, Table 2 also displays that the RDM and ADM models had the highest total cost variability $\sigma(TC)$ among banks. The most equitable model in terms of monetary expenses incurred by the banks was AADM, with an average $\sigma(TC)$ among all instances of 37%.

7.4. Managerial insights

Altogether, the numerical results demonstrate that the tested anticipative stochastic models can be used to obtain robust solutions when facing various supply availability scenarios. The results show that the selection of the decision-making timing strategy has a high impact on the expected network performance, and this behavior can vary depending on the grade of penalization of the usage of extraordinary budget and response time. Although the AADM model offered the best objective function values, the different metrics that compose it vary significantly across the five models. Generally, two-stage anticipative models offer higher unmet demand levels but require less extraordinary resources. In contrast, the RDM, DDM, and ADM models offer lower levels of unmet demand, but at higher costs. These results can be greatly worsened if no emergency budget is available.

The RDM strategy requires high amounts of extra budget or extra response time, and the ARDM strategy performs as a similar—but inferior version—of the AADM strategy. The resource allocation among banks may vary significantly depending on the selected strategy. Although the RDM and DDM models have low unmet demand values, this performance is achieved unequally along the banks in the network.

In a practical context, other managerial factors must be considered to determine whether a strategy is worth implementing. Two-stage anticipative strategies involve higher number of decisions and adjustments, whereas reactive strategies showed more variability in the performance of the banks within the network. This increases the complexity of negotiations and communication within a cooperative network. Organizations should evaluate which strategy is easier to implement in their management and operational context, and whether the potential improvement in any performance metric justifies the increased complexity of planning and negotiation.

8 Conclusions

This study focuses on analyzing the effect of decision-making timeframes for a humanitarian network that must adapt to an emergency response while maintaining its routinary operation. Inspired by the BAMX organization, a Mexican network of food banks, we present five different decision-making models representing alternatives between anticipatory and reactive decisions to face food supply uncertainty. Moreover, a two-stage mathematical formulation is proposed to formalize each model. Using a case study based on the disaster response operation of BAMX from October 2018 Hurricane Willa in México, we examine the effectiveness and efficiency of each decision-making model under different supply availability scenarios. Moreover, we suggest some managerial insights into the adaptation of humanitarian organizations’ logistic operations for emergency response.

The SAA method was applied to solve the stochastic formulations with Gurobi. The experimental design showed that the factors of donation distribution and quantity, used to build the test scenarios, have a lesser impact than the selection of the decision-making timeframe represented by each model. It also showed that the weight of the penalties, which is attributed to the excess budget and time required by the network, changes the expected behavior of the models' performance. However, the magnitude of change in each metric depends on the model.

Counterintuitively, anticipative approaches—the most common among the literature related to emergency response—were the worst performers in terms of average and maximum unmet demand. Nevertheless, they required the lowest amount of additional resources by the network. Measuring solely costs or the overall objective function values yields a conclusion that these modeling strategies outperform the rest. However, a more detailed analysis shows that the behavior of the metrics composing the OF varies according to the applied strategy. This is because two-stage models tend to be more conservative in the usage of resources in the anticipative phase. Results show that conservative decisions in donation procurement lower the total quantity of food delivered by limiting the donation recollection volume, even if a phase of readjustment is performed later. On the positive side, anticipative strategies offer equal demand fulfillment levels among the communities.

In summary, our findings reveal that the decision-making timing strategy for the emergency response of a network that must adapt its daily operation should be selected accordingly to the necessities of the population, the priorities of the humanitarian network, and the emergency resources available. In this case, selecting a strategy focused on minimizing operational costs puts a monetary value on human suffering. Additional research is required to confirm the behavior of the models proposed in this paper. Our conclusions are based on the results produced for a given set of instances and must therefore be compared on larger testbeds, and even more important, different contexts to generalize our observations. On a more practical note, the development of new models aiming to capture explicitly the engagement of independent banks to support banks in need constitutes a very appealing line of research on food bank networks. Indeed, whereas most of the past research seeks to achieve a fair distribution of aid from the perspective of the communities, none or very little studied fairness from a network perspective with the aim to assess the extent to which each individual bank is doing its best to help the bank affected by the disaster. This research question is relevant in the case of food bank networks, but also in other contexts where organizations cooperate with a common objective.

Appendix A. Demand and supply amounts in kg

Bank	Demand amount (Dem_b)	Total Supply amount	Amount of food bought (z_{3b})	Expected unmet demand (I_b)	Demand incrase caused by the disaster (ΔDem_b)
B_1	132 420	127 358	6 621	4.2%	0
B_2	84 995	83 183	4 250	2.3%	0
B_3	307 941	293 727	15 397	5.1%	0
B_4	15 577	14 452	779	8.2%	0
B_5	124 557	111 130	6 228	12.7%	0
B_6	17 645	17 146	882	3.1%	0
B_7	32 693	31 980	1 635	2.3%	73 000
B_8	14 227	13 798	711	3.3%	0
B_9	37 559	35,472	1,878	6.2%	0
Total	767 615	728,245	38,381	5.1%	73 000

Appendix B. SAA algorithm

Step 1. Determine the sample sizes, N and N', and the number of SAA replications I. The trade-off for these parameters is between approximation accuracy and computational difficulty.

Step 2. Generate $|I|$ independent samples of N scenarios $\Omega_i^N, \forall\, i \in I$. For each sample, solve the SAA anticipation model. Let o_i^N be the optimal objective value and U_i^N the corresponding optimal solution for each sample, which is represented by the corresponding instruction.

Step 3. Compute the lower bound estimator:

$$\bar{o}_{N,I} = \frac{1}{|I|}\sum_{i\in I} o_i^N$$

It is known that $\bar{o}_{N,I} \geq o^*$, where o^* represents the optimal value of the true problem and therefore provides a lower statistical bound [51]. The variance of $\bar{o}_{N,I}$ is given by:

$$\sigma^2_{\bar{o}_{N,I}} = \frac{1}{|I|(|I|-1)}\sum_{i\in I}\left(o_i^N - \bar{o}_{N,I}\right)^2$$

Step 4. Compute the statistical upper bound and variance estimators.

For each candidate solution U_i^N obtained in Step 2, estimate the true objective function value $f(U_i^N)$ as follows:

$$f_{N'}(U_i^N) = \frac{1}{N'}\sum_{\xi_i \in \Xi_i} \Pi(U_i^N, \xi_i)$$

Note that $f_{N'}(U_i^N)$ is an unbiased estimator of $f(U_i^N)$. Thus, $f_{N'}(U_i^N)$ provides a lower statistical bound on o^*. Compute the variance of the estimator $U_i^{N'}$ as:

$$\sigma^2_{f_{N'}(U_i^N)} = \frac{1}{N'(N'-1)} \sum_{\xi_i \in \Xi_i} \left(\Pi\left(U_i^N, \xi_i\right) - f_{N'}(U_i^N)\right)^2$$

Step 5. Calculate the optimality gap and the confidence interval.

Once computed the statistical upper and lower bounds from Step 3 and 4, the optimality gap of solution U_i^N can be estimated by:

$$Gap_{N,I,N'}\left(U_i^N\right) = \max\{0, \bar{o}_{N,I} - f_{N'}\left(U_i^N\right)\}$$

The variance of the gap is estimated by:

$$\sigma^2_{Gap} = \sigma^2_{\bar{o}_{N,I}} + \sigma^2_{f_{N'}(U_i^N)}$$

An approximate 100(1-α) percent confidence interval for the optimality gap at U_i^N is given by:

$$\left[0, Gap_{N,I,N'}\left(U_i^N\right) + \frac{t_{\frac{\alpha}{2},|I|-1}\sigma^2_{\bar{o}_{N,I}}}{\sqrt{|I|}} + \frac{t_{\frac{\alpha}{2},N'-1}\sigma^2_{f_{N'}(U_i^N)}}{\sqrt{N'}}\right]$$

If the optimality gap or the variance of the gap estimator is larger than the desired, one could consider increasing the sample size N or N' to reduce it.

Step 6. Select the solution $U_i^N, \forall\, i \in I$, with the highest estimated true objective function value $f_{N'}(U_i^N)$.

Author Contributions

Conceptualization, Esteban Ogazón, Neale Smith, and Angel Ruiz; methodology, Esteban Ogazón, Neale Smith, and Angel Ruiz; software, Esteban Ogazón; validation, Neale Smith and Angel Ruiz; writing—original draft, Esteban Ogazón; writing—review and editing, Neale Smith and Angel Ruiz.

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