Forecast-Driven Model for Prepositioning Supplies in Preparation for a Foreseen Hurricane

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Abstract

In this paper, we present a forecast-driven dynamic model for prepositioning relief items in preparation for a foreseen hurricane. Our model uses forecast advisories issued by the National Hurricane Center (NHC), which are issued every six hours. Every time a new advisory is issued with updated information, our model determines the amount and location of units to be prepositioned and it also re-prepositions already prepositioned units. The model also determines the best time for starting the prepositioning activities. Our approach uses a combination of Decision Theory and stochastic programming. The outcomes of our model are presented in a way that could be easily understood by humanitarian practitioners who are ultimately the ones who would use and apply our model.

Keywords: prepositioning, dynamic model, decision theory, disaster management

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1 Introduction

Hurricanes are one of the most frequently observed types of natural disasters. According to the National Oceanic and Atmospheric Administration (NOAA), a total of 55 hurricanes struck the USA between 1961 and 2000, among which 20 were major hurricanes (Blake et al., 2005). Hurricanes are not only frequent but potentially devastating. One of the costliest hurricane seasons on record in the USA occurred in 2004, in which four major hurricanes hit US territory. During that year, landfalling hurricanes caused approximately $45 million in economic losses and 168 deaths (Graumann et al., 2005). Given the potential impact and high frequency of hurricanes, it is important to perform activities to reduce the magnitude of their consequences.

Unlike unpredictable disasters such as earthquakes and terrorist attacks, hurricanes can be detected a few days prior to their occurrence. The National Hurricane Center (NHC) issues a forecast advisory approximately five days prior to a hurricane's landfall. Such an advisory contains predictions about the hurricane's location, intensity and time of landfall. Moreover, as the hurricane evolves, subsequent forecast advisory updates are issued every six hours. It is expected that the forecast's accuracy regarding hurricane's landfalling characteristics improves as we get closer to the time of landfall. This information can be used by humanitarian and governmental agencies to strategically deploy resources in the early stages of the hurricane, in order to improve the post-disaster relief effort. Therefore, even though hurricanes are continuously challenging our ability to respond to catastrophic situations, at the same time they provide us with time and forecasted information that we can use for performing preparedness activities that can help to ameliorate their potential impact.

In this paper we present an enhanced version of a previous model given in Galindo and Batta (2012) for prepositioning supplies in preparation for a foreseen hurricane. The setting of our problem is similar to that described in Galindo and Batta (2012). According to such a setting, there is a transportation network where we have a node with a permanent and given source of relief items, namely the Main Distribution Center (MDC). From there, units can be delivered to a set of candidate supply points (SPs) where it is possible to preposition items that are likely to be requested upon the hurricane's landfall. In our model, we represent SPs as nodes, but in practice, SPs can be tents, prefabricated units or existing facilities such as old buildings, schools, churches, etc. (Balcik et al., 2008). Prepositioned units would be later used to serve demand arising as consequence of the hit of the hurricane. It is assumed that demand would be concentrated at some specific nodes denominated as Demand Points (DPs), which represent the locations that are affected by the hurricane (analogous to the Affected Area defined in Bozorgi-Amiri et al. (2013)). In other words, DPs are consequence of where and how hard the hurricane strikes, i.e. they are input data for our model. SPs are considered to be located close to the potential affected area and therefore they would be useful for serving demand in an efficient way. However, by having SPs close to the potential affected area, they are vulnerable to the impact of the hurricane. Consequently, our problem needs to consider the tradeoff between efficiency and risk.

Prepositioning of supplies can be applied by either private, humanitarian or governmental organizations. According to Salmerón and Apte (2010), after hurricane Katrina, the Federal Emergency Management Agency (FEMA) has warehoused supplies, and has planned routes and designations for temporary shelters in hurricane-prone regions. Afshar and Haghani (2012) offers a detailed description about FEMA's logistic network, which is composed of seven main components. These components can be classified into three types of facilities: (1) permanent facilities that store and ship commodities and are considered as "sources"; (2) temporary facilities where items are prepositioned for their later deployment; and (3) demand points where commodities are directly distributed to disaster victims. We could say that our problem setting is analogous to FEMA's approach, since our MDC can be seen as a type-1 facility, whereas our SPs would be of type-2 and our DPs could be classified as type-3. Horner and Downs (2010) also considers a humanitarian logistic network with facilities of similar types to those defined by FEMA, which are used by the Division of Emergency Management of the State of Florida.

The novelty of the model presented in this paper is that it is forecast-driven since it incorporates the use of forecast information updates. An important characteristic of forecast information is that it is not 100% accurate and its uncertainty is greater during the earlier stages of the hurricane. Therefore, if we develop our plan for relief efforts too many days before the hurricane strikes, we will likely face great uncertainty about the actual intensity, location and time of the hurricane's landfall. On the other hand, waiting too long for initiating the prepositioning can also be undesirable and it could even leave us without enough time for applying the prepositioning plan. Moreover, logistic costs are likely to increase as the hurricane approaches due to potential inefficiencies and complications (Lodree and Taskin, 2009). For instance, it is conceivable that we need to make use of overtime hours or more expensive transportation modes in order to promptly locate the supplies where required. The tradeoff between forecast accuracy and logistic costs is one of the issues addressed by the model presented in this paper, by determining an appropriate time to start the prepositioning activities.

Also, unlike the static model discussed in Galindo and Batta (2012) in which the prepositioning decisions were made and executed only once, in our forecast-driven model we use a dynamic approach. Such an approach uses the periodic forecast updates issued by the NHC in order to consider three possible actions: (1) to preposition additional supplies, i.e. to send additional units from the MDC to selected SPs, (2) to re-preposition items, i.e. to relocate those units that had been already prepositioned among the SPs, and (3)to do nothing, i.e. wait and see. In order to clarify these two actions, let us consider a case in which we are at time period t_0 and we decide to send 100 units from the MDC to SP_1. This would be a prepositioning action since the units are delivered from the MDC to a SP. Now, let us assume that in time period t_1, the new forecast indicates that it is better to preposition in SP_2 and SP_3. Then, our model would allow us to re-preposition those 100 units that are currently in SP_1 into either SP_2 or SP_3. Notice that both actions occur prior to the occurrence of the hurricane.

The purpose of our model is to determine the optimal amount of supplies to be located at each SP at every time period of our planning horizon. The outcomes of our model are thought to be presented in a way that could be easily understood by humanitarian practitioners who are ultimately the ones who would use and apply our model.

The remainder of this paper is organized as follows: In Section 2 we offer a literature review. In Section 3 we present our problem description. In Section 4 we discuss our dynamic model and Decision Theory approach for selecting the best prepositioning strategy in any given time period. In Section 4.3 we present our approach for deciding whether or not to start the prepositioning in any given time period. Section 5 shows our computational experience, where we discuss the data input generation for our model, and our results. Section 6 presents some important considerations to improve the performance and evaluation of the forecast-driven model. Finally, Section 8 presents our remarks and conclusions.

2 Literature Review

Galindo and Batta (2012) contains a literature review about prepositioning supplies in preparation for a disaster that also relates to our forecast-driven model. Among the papers discussed in Galindo and Batta (2012), the ones that are most closely related to the model presented in this paper are the ones given by Lodree and Taskin (2009), and Taskin and Lodree (2011). In Lodree and Taskin (2009), the authors consider the problem of prepositioning supplies in preparation for a hurricane from the perspective of a single private sector supplier that experiences demand peaks from a single retailer upon the occurrence of a hurricane. In their problem, the supplier uses a hurricane's forecast in order to design an inventory policy for its products. A hurricane's forecast is composed of sequential advisories issued every six hours that predict the hurricane's wind speed at the time of landfall. It is assumed that earlier advisories have a greater uncertainty, whereas logistic costs are assumed to be lower during the earlier stages of the hurricane. The problem is composed of two decisions: (1) when to stop taking observations and perform the prepositioning activities, and (2) how much to preposition. The authors approach the problem as an optimal stopping problem with Bayesian updates. The paper given by

Taskin and Lodree (2011) extends their prior work by considering a multi-retailer supply chain, and by incorporating official forecasts from the NHC.

A major drawback from the papers given by Lodree and Taskin (2009), and Taskin and Lodree (2011) is that they assume statistical independence of sequential forecast advisories. This assumption seems unrealistic and would need to be verified in order to guarantee the applicability of their study under real-life settings.

Additional to the papers discussed in Galindo and Batta (2012), two interesting papers that study the prepositioning of supplies in preparation for disasters are those given by Lodree (2011), and Lodree et al. (2012). In both papers, the authors examine the problem of prepositioning supplies from the point of view of a private sector supplier that experiences demand surge as a consequence of a severe storm. In the first paper, the author uses a minimax-decision-criteria approach to explore reactive and proactive inventory strategies. In Lodree et al. (2012), the authors focus on a proactive approach by means of a two-stage stochastic programming model for determining the inventory levels to be prepositioned throughout a set of retailers.

Some additional related work is given by Davis et al. (2013), who propose a stochastic programming model for the prepositioning of commodities within a given network, and for the posterior distribution of supplies. In Davis et al. (2013), the authors use short-term hurricane forecast information related to the storm intensity and location in order to estimate the possible affected area. In their case, they consider that there is available a certain level of supplies throughout the network, instead of using an approach where supplies are purchased. Another related paper is that given by Ozguven and Ozbay (2011), in which the authors study the problem of determining the inventory levels in preparation for a disaster with the objective of preventing disruptions, while minimizing the expected costs. The novelty of this latter paper is that it incorporates Intelligent Transportation Systems (ITS) technologies that allow an online inventory framework for minimizing the impact of unforeseen disruptions during the actual disaster relief stage.

A fundamental contribution of our work is that it uses a dynamic approach in which the prepositioning decisions can be modified before the hurricane makes landfall, as new forecast information updates become available. To our knowledge, this approach has not been considered yet in previous related research. Also, unlike Lodree and Taskin (2009) and Taskin and Lodree (2011) we do not assume statistical independence of successive advisories. Instead, we use an alternative approach based on a working paper given by Czajkowski and Woodward (2010). In their paper, the authors develop a model for establishing the optimal evacuation time for a given household when a hurricane is approaching. As in Lodree and Taskin (2009) and Taskin and Lodree (2011), the objective is to determine when to stop taking observations, and then start the evacuation process. In Czajkowski and Woodward (2010), the authors model the hurricane forecasts as a Markovian process that assumes that the forecast in the next time period depends only on the current forecast and not on the previous. We use the approach from Czajkowski and Woodward (2010) for modeling the forecasting process, as discussed in Section 5.1.

3 Problem Description

Let us assume that a hurricane has been predicted to make landfall within a few days. From the possible locations of the hurricane at landfall, we define an affected potential area (APA) that is at risk of being affected by the hurricane. Within the APA there is a set of DPs that represents the locations from which we can expect requests of relief items upon the occurrence of the hurricane. Our purpose is to preposition relief supplies in order to improve the post-disaster relief efforts.

We consider a distribution network that is identical to that defined in Galindo and Batta (2012). Basically, such a distribution network is composed of the MDC, a set of candidate SPs, and the set of DPs. All units of supply are first gathered at the MDC. From there, they would be delivered to selected SPs before the occurrence of the hurricane. Then, after the hurricane has occurred, supplies would be delivered to the DPs from those selected SPs that have not been affected by the hurricane. Our model also allows for supplies to be directly delivered from the MDC to DPs. The objective of our model is to determine the level of storage at selected SPs and the planned flow of units from surviving SPs to DPs.

We consider the following set of assumptions:

1. The MDC has unlimited capacity, whereas the capacity of SPs is fixed and given.

2. In order to improve the post-disaster relief efficiency, SPs are located close to DPs, within an area that might be hit by the hurricane. This implies that SPs can be affected by the hurricane. On the other hand, the MDC is placed in a safe given location where it cannot get affected by the hurricane. Location of DPs is given depending on the hurricane's characteristics.

3. Any given SP that gets affected by the hurricane becomes inoperative. This means that it cannot serve demand during the relief process.

4. There is a fixed set up cost for each candidate SP, and there is available a given budget for setting up SPs. This budget allows us to handle setup and distribution costs separately. The purpose is to pool resources for uncertain logistic costs, by limiting the budget for setting up SPs (Richardson et al., 2010).

5. The forecast accuracy increases as the hurricane approaches mainland, whereas transportation costs are non-decreasing from one forecast period to the next.

6. There is a lead-time which is defined as the remaining time until the hurricane's landfall.

7. We assume that the set of DPs is given depending on the strength and geographic location of the hurricane's landfall, i.e. we do not make decisions regarding selection of DPs.

8. We only focus on transporting goods to the affected areas. We do not consider the last-mile distribution of relief items, which includes the final delivery of goods to each of the affected individuals. For this type of problems we refer the reader to Balcik et al. (2008).

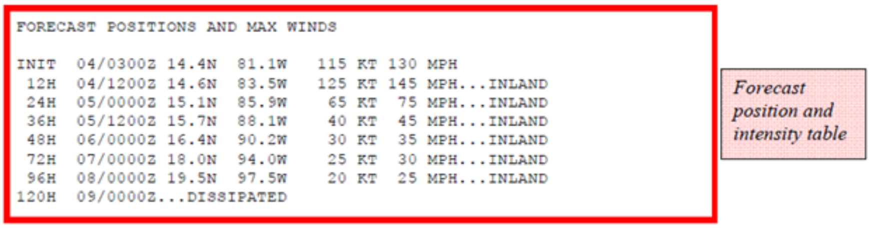
For further details regarding the characteristics of the distribution network considered in our problem, we refer the reader to Galindo and Batta (2012).

We consider a planning horizon which is composed of discrete time periods corresponding to the delivery of updated forecasts. In the first time period, we need to determine if it is desirable to start prepositioning immediately, or if it would be better to wait for the next forecast to arrive in order to reduce the uncertainty about the hurricane's conditions at time of landfall. If we decided to wait, then in the following time period we would face the same dilemma of either starting prepositioning immediately or waiting for the following forecast. Once we have made the decision for starting the prepositioning activities, we need to make a decision about the location and quantities of the units that we want to preposition. Then, at every subsequent time period we have three alternatives: (1) to preposition additional units, (2) to re-preposition already prepositioned units, or (3) to do nothing and to wait for the next forecast advisory. In cases in which we opt for alternative (1) or (2) we also need to define the flows of relief units, i.e. their origin, destination and quantity.

In summary, we can decompose the system into three states:

1. Initial State: This is the original state of the system. When in this state, no prepositioning has been performed yet. For any given time period, there are two possible actions: wait for the next advisory or start prepositioning items. We remain in this state as long as we keep waiting for a next advisory to start the first prepositioning activities.

2. Active State: We enter this state upon the performance of the first prepositioning activity. For every time period within this state, there are three possible actions: to preposition more items, to re-preposition already prepositioned units, or to do nothing and wait for the next advisory. We abandon this state to enter the Final State.



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FORECAST POSITIONS AND MAX WINDS

INIT  04/0300Z 14.4N  81.1W   115 KT 130 MPH
 12H  04/1200Z 14.6N  83.5W   125 KT 145 MPH...INLAND
 24H  05/0000Z 15.1N  85.9W    65 KT  75 MPH...INLAND
 36H  05/1200Z 15.7N  88.1W    40 KT  45 MPH...INLAND
 48H  06/0000Z 16.4N  90.2W    30 KT  35 MPH...INLAND
 72H  07/0000Z 18.0N  94.0W    25 KT  30 MPH...INLAND
 96H  08/0000Z 19.5N  97.5W    20 KT  25 MPH...INLAND
120H  09/0000Z...DISSIPATED
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Figure 1: Tropical Cyclone Discussion Advisory

***Source: NHC Products Description User's Guide. Retrieved from** http://www.nhc.noaa.gov/aboutnhcprod.shtml#TCR*

3. Final State: We enter this state when the estimated time until the occurrence of the hurricane is not enough to perform additional prepositioning or re-prepositioning activities.

As mentioned before, we allow for supplies to be re-prepositioned several times prior to landfall as updated information becomes available. This is especially helpful in cases in which the hurricane changes its direction and, therefore, its APA. In those cases it is possible that supplies that have been already prepositioned become either too far or too close to the updated APA. Then, the model considers the economic viability of re-prepositioning those items taking into consideration updated logistic costs and risks.

3.1 Description of the Forecast Advisories and Definition of Scenarios

As mentioned in Section 1, the NHC delivers a series of forecasts advisories every six hours (at 0300, 0900, 1500, 2100 UTC) and each advisory offers predictions about the hurricane's location and intensity valid 12, 24, 36, 48, 72, 96 and 120 h after the hurricane's nominal initial time (nominal initial time refers to the beginning of the forecast process, c.f. Cangialosi and Franklin 2011). Figure 1 offers a portion of a forecast advisory, from which it is possible also to estimate the period at which a hurricane will make landfall.

Based on the information collected from the forecast advisories, it is possible to define a set of possible scenarios that characterize the hurricane conditions at the time of landfall.

In this respect, let us define a scenario as the event characterized by three attributes of the hurricane at the moment of landfall: location, intensity and time of landfall. We will have a set of scenarios determined by the possible combinations among these three characteristics. A reasonable assumption is that the values of some parameters such as demand and destruction of SPs would be scenario-dependent. At the moment of performing the prepositioning activities, i.e. before the hurricane makes landfall, we cannot know which scenario will occur. However, we can estimate the set of possible scenarios and their probabilities using the information from the forecast advisories. In Section 5.1, we illustrate a possible methodology for defining scenarios and determining their probabilities as part of our computational example.

In the next sections we present our methodology for solving our problem. We first discuss how to determine the pre- and re-prepositioning flows once the prepositioning activities have already been started, and then in Section 4.3 we offer a discussion on how to define a convenient time for starting the prepositioning.

4 Dynamic Stochastic Model with Decision Theory

Recall that in Section 3 we have described our system by defining three different states: (1) Initial State, (2) Active State, and (3) Final State. As mentioned in that section, the characteristic of the Initial State is that we do not perform any prepositioning or re-prepositioning activities, but we just observe the forecasts, waiting for the right time to start the first prepositioning action. Such right time would arrive when we consider that waiting for a higher accuracy of an additional time period, does not compensate the estimated increment in logistic costs. Then the two main problems that we must address are: (1) establishing the moment to start the first prepositioning activity, and (2) defining subsequent prepositioning and re-prepositioning measures. In this section, we propose a dynamic stochastic model that focuses on giving answer to these two problems. In terms of the states defined in section 3, the problems are to decide when to abandon the Initial State, and what actions to perform while in the Active State. We seek a decision model that can be easily understood by humanitarian practitioners without a strong background in OR.

Our approach uses forecasts information updates regarding hurricane's location, intensity and time of landfall in order to update the whole prepositioning scheme. Naturally, the forecasts are not totally accurate. In order to model the forecast's uncertainty, we consider multiple scenarios (where scenarios are defined as described in Section 3.1) about the actual conditions of the hurricane at landfall, whose probabilities are computed based on the available forecasts. More specifically, once we obtain a forecast at the current time t_c, we identify the possible scenarios and estimate their probabilities.

Regarding the problem of establishing the moment to start prepositioning, let us assume that the system is in its Initial State. We know that the uncertainty about the hurricane's landfall at the next time period t_{c+1} should be lower than that of current time period t_c. In the worst case, they would be equal. If that worst case happened, we would incur an opportunity cost for not having started prepositioning at time t_c, when the logistic costs were lower, since we were waiting unsuccessfully for a lower uncertainty at time t_{c+1}. The key question becomes: how much are we willing to risk in term of opportunity cost for hoping to achieve a lower uncertainty? Then, in order to determine if a given time t_c should be the time for initiating the prepositioning, we evaluate the cost of acting at time t_c and compare it to that obtained from waiting one more period to start prepositioning, i.e. begin activities at time t_{c+1}. If the difference between waiting and acting immediately is lower than the risk that we are willing to make, we decide to wait one more period.

Once we have reached the breaking point at which we have abandoned the Initial State, we need to establish the prepositioning and re-prepositioning activities at every time period. This involves determining the amount of supply to be allocated at each selected SP. To do so, we build a set of possible solutions. A solution is denoted as a 3-dimension matrix that gives the flow of units from each SP (including the MDC) to each SP at each time period. Our objective is to find a set $\mathbb{Q}$ of feasible solutions, evaluate

Solutions	Scenarios			
	1	2	$\cdots$	$\mid \mathbb{S} \mid$
1				
2				
$\vdots$				
$\mid \mathbb{Q} \mid$				

Table 1: Solutions versus Scenarios

them under each possible scenario and then recommend a solution that outperforms the others.

We use a Decision Theory approach for finding the best solution based on a selected criteria. Two types of criteria are considered: minimization of expected cost, and minimization of the maximum regret. Our approach is summarized in Table 1. The columns of Table 1 denote the set of possible scenarios, whereas its rows represent a set of possible solutions.

In the following sections we present our mathematical model for building the set of possible solutions (Section 4.1) and selecting the best solution for any given time period (4.2). These two sections comprises all the procedures needed to define any prepositioning or re-prepositioning action while in the Active State. Also, such procedures are involved in the selection of the starting time for the first prepositioning activity, which is discussed in Section 4.3.

4.1 Mathematical Model for Building the Set of Solutions

Once a forecast advisory is obtained and the possible scenarios are defined, we can build a universe of possible solutions. Our approach consists in finding the best solution for each possible scenario. Therefore, at every time period we will have as many solutions as possible scenarios.

4.1.1 Notation

Sets

- $\mathbb{J}$: Set of potential DPs (indexed with j and with $\mid \mathbb{J} \mid= m$)

- $\mathbb{I}$: Set of potential SPs (indexed with i and with $\mid \mathbb{I} \mid = n$)
- $\mathbb{S}$: Set of possible scenarios (indexed with s)
- $\mathbb{T}_s$: Set of planning horizon periods (indexed with t and k) under scenario s
- $\mathbb{H}_s$: Set of surviving SPs under scenario s
- $\bar{\mathbb{H}}_s$: Complement of set $\mathbb{H}_s$

Parameters

- t_c: Current time period
- t_{f_s}: Lead-time under scenario s in number of periods
- a_{ijs}: Distribution cost per unit supplied from SP $i \in \mathbb{I} \cup \mathrm{MDC}$ to DP j, if SP i is set up and not destroyed, under scenario s
- $b^t_{ii's}$: Distribution cost per unit supplied from SP $i \in \mathbb{I} \cup \mathrm{MDC}$ to a SP $i \in \mathbb{I}$ at time $t \geq t_c$, under scenario s
- $v^{kt}_{ii'}$: Binary value that equals 1 if one unit delivered at time k from SP $i \in \mathbb{I} \cup MDC$ can reach SP $i' \in \mathbb{I}$ before time t; 0 otherwise
- $f^t_{i'i}$: Flow of units that were shipped from SP $i \in \mathbb{I} \cup \mathrm{MDC}$ to a SP $i' \in \mathbb{I}$ at time $t < t_c$
- l_i: Binary value that equals 1 if SP $i \in \mathbb{I}$ was set up as part of an action executed at time $t < t_c$
- sur: Cost of one unit of overstock
- $short$: Cost of one unit of unmet demand
- r: Cost of one unit of supply stored at an SP that becomes inoperative
- cap_i: Capacity of SP i if it is set up

- B: Available budget for setting up SPs
- D_{js}: Demand at point j under scenario s
- g: Cost of one unit that is still in transit at the moment of landfall
- h: Cost of acquiring one unit of supply
- c_i: Set up cost for SP i

Decision Variables

- y_{ijs}: Flow of units delivered from SP $i \in \mathbb{I} \cup \text{MDC}$ to DP j under scenario s
- w_i: Binary variable that equals 1 if $i \in \mathbb{I}$ is set up; 0 otherwise
- $u^t_{ii'}$: Flow of units from $i \in \mathbb{I} \cup \text{MDC}$ to $i' \in \mathbb{I}$ at time $t \geq t_c$
- x^t_i: Level of storage at SP $i \in \mathbb{I} \cup \text{MDC}$ at the end of time $t \geq t_c$
- z_s: Number of in-transit units at time of landfall under scenario s

4.1.2 Binary Mixed Integer Programming Model Formulation

In this section we present the mathematical formulation for our problem $P1(t_c, s)$, which is a deterministic model that must be solved every time we reach a new current time period t_c (the stochastic part of our formulation will be presented in Section 4.2.2). $P1(t_c, s)$ determines how to use the prepositioned units in the best way under a given scenario s.

$P1(t_c, s)$:

$$
\begin{aligned}
\min Z_1(t_c, s) = & \sum_{(t_c \leq t \leq t_{f_s})} \sum_{(i \in \mathbb{I} \cup \text{MDC})} \sum_{(i' \in \mathbb{I})} u^t_{ii'} b^t_{ii's} + \sum_{(i \in \mathbb{H}_s)} \sum_j a_{ijs} y_{ijs} + \sum_{(i \in \bar{\mathbb{H}}_s)} r x_i^{t_{f_s}} \\
& + \sum_{(i \in \mathbb{H}_s)} sur \left(x_i^{t_{f_s}} - \sum_j y_{ijs} \right) + \sum_j short \left(D_{js} - \sum_{(i \in \mathbb{H}_s)} y_{ijs} \right) + g z_s \\
& + h \left[\sum_{i \in \mathbb{I}} \sum_{t \geq t_c} u^t_{\{MDC\}i} - \sum_{i \in \mathbb{I}} \sum_{t \leq t_c} f^t_{i\{MDC\}} v^{t,tc}_{i\{MDC\}} \right]
\end{aligned} \tag{1}
$$

subject to:

$$x_i^t \leq cap_i w_i \quad \forall i, t \geq t_c \tag{2}$$

$$\begin{aligned} x_i^t = &\sum_{(k<t_c)} \sum_{(i' \in \mathbb{I} \cup \mathrm{MDC})} f_{i'i}^k v_{i'i}^{kt} + \sum_{(t_c \leq k<t)} \sum_{(i' \in \mathbb{I} \cup \mathrm{MDC})} u_{i'i}^k v_{i'i}^{kt} - \sum_{(k<t_c)} \sum_{(i' \in \mathbb{I} \cup \mathrm{MDC})} f_{ii'}^k \\ &- \sum_{(t_c \leq k<t)} \sum_{(i' \in \mathbb{I} \cup \mathrm{MDC})} u_{ii'}^k \quad \forall i, t \geq t_c \end{aligned} \tag{3}$$

$$u_{ii'}^t \leq x_i^{t-1} v_{ii'}^{t,t_{fs}} \quad \forall i, i', t \geq t_c \tag{4}$$

$$\sum_{i'} u_{ii'}^t \leq x_i^{t-1}, \quad \forall i, t \geq t_c \tag{5}$$

$$c_i w_i \leq B \tag{6}$$

$$w_i \geq l_i, \quad \forall i \tag{7}$$

$$\sum_j y_{ijs} \leq x_i^{t_{fs}} \quad \forall i \in \mathbb{H}_s \tag{8}$$

$$\sum_j y_{ijs} \leq 0, \quad \forall i \in \bar{\mathbb{H}}_s \tag{9}$$

$$z_s = \sum_t \sum_i \sum_{i'} f_{ii'}^t (1 - v_{ii'}^{t,t_{fs}}) \tag{10}$$

$$x_i^t \in \mathbb{Z}^+ \quad \forall i, t \geq t_c \tag{11}$$

$$y_{ijs} \in \mathbb{Z}^+ \quad \forall i, j \tag{12}$$

$$u_{ii'}^t \in \mathbb{Z}^+ \quad \forall i, j \tag{13}$$

$$w_i \quad binary \quad \forall i \tag{14}$$

$P1(t_c, s)$ gathers information about the actions that have been already applied from time periods prior to t_c. The problem computes actions to be carried at current time t_c and also in future time periods $t \geq t_c$. However, we only actually execute actions corresponding to the current time period t_c. The reason for considering actions for future time periods is that we might have units that have been already shipped but that are still in transit in time t_c. So, we plan what to do with them once they have arrived at their destination. However, future actions might change when we reach the next time period t_{c+1} and solve $P1(t_{c+1}, s)$.

The first term in the objective function given by (1) corresponds to the cost for delivering units from the MDC to SPs and among SPs during time periods t_c to t_{f_s}; the second term refers to the cost of serving DPs from surviving SPs; the third, relates to the penalization cost for affected units at destroyed SPs; the fourth term describes the cost for surplus units at surviving SPs; the fifth term gives the cost for unsatisfied demand; the sixth term gives the cost of in-transit units at landfall; and the seventh term gives the acquisition costs. Acquisition costs apply for the total number of units that would be delivered from the MDC to SPs from time t_c and beyond, minus the units that have been sent back from SPs to the MDC in previous periods.

Among the costs that are specified in (1), the shortage costs are the most difficult to estimate. From the perspective of a private company, shortage costs can be defined in terms of lost sales, loss of goodwill or cost of backorder. In the case of a humanitarian organization, shortage costs can be computed as the cost to obtain and promptly distribute relief goods to attend the unmet demand. For instance, they can be defined as the estimated cost of an emergency order to be supplied by means of fast transportation modes, such as airplanes or helicopters (Consuelos Salas et al., 2012). In the literature, shortage costs are generally considered to be much greater than purchase costs before the disaster. For example, in the computational experiment given by Rawls and Turnquist (2010), the authors use a shortage cost equal to 10 times the acquisition cost. Consuelos Salas et al. (2012) also uses a shortage cost that significantly exceeds the purchase cost. Shortage costs will also depend on the type of commodity being provided. As stated by Consuelos Salas et al. (2012), additionally to the cost of emergency orders, experts need to carefully quantify potential disturbance and related issues for every specific case.

Constraints (2) are the capacity constraints. Constraints (3) define the amount of stored units at SP i at the end of period t. Constraints (4) ensures that if a supply i' cannot be reached from SP i before landfall, then SP i does not deliver units to SP i'. Constraints (5) limit the number of units that can be delivered from SP i at period t to the final inventory at i at period $t-1$. Constraints (6) state that the financial resources for setting up SPs at time t_c cannot exceed the available budget. Constraints (7) enforce SPs that were opened before time t_c to remain open. Constraints (8) limits the number of units that can be delivered to surviving SPs to their inventory at time t_{f_s}. Constraints (9) state that destroyed SPs cannot serve demand. Constraint (10) gives the number of in-transit units at landfall. Constraints (11) through (14) describe the nature of the decision variables.

Once we have solved $P1(t_c, s)$ for every s, we will have $\mid \mathbb{S} \mid$ solutions, where each solution q_{t_c} is characterized by a matrix with the values $u^t_{(q_{t_c})ii'}$ which gives the flow of units to SPs under solution q_{t_c}.

4.2 Decision Theory Approach for Selecting the Best Solution for a Given Time Period

In the previous section we describe how to build a set of solutions for our problem. In this section we present our approach for selecting which, among the solutions generated by solving problem $P1$, should be applied in any given time period. In Subsection 4.2.1 we discuss a mathematical model for evaluating the performance of each solution in our set $\mathbb{Q}$ under every possible scenario. Then in Subsection 4.2.2 we use the results of the overall performance of each solution across all of the scenarios in order to finally select the solution that would be applied.

4.2.1 Mathematical Model for Evaluating the Performance of each Solution under each Scenario

Once we have found the set $\mathbb{Q}_{t_c}$ of possible solutions by solving the problem $P1(t_c, s)$ for all possible scenarios, we need to evaluate the performance of each solution q_{t_c} under each scenario s. To do so, we solve the problem $P2(t_c, s, q_{t_c})$ for every q_{t_c} and every s:
$P2(t_c, s, q_{t_c})$:

$$\begin{aligned}\min Z_2(t_c, s, q_{t_c}) = \sum_{(i\in\mathbb{H}_s)}\sum_{j} a_{ijs}y_{ijs} + \sum_{(i\in\bar{\mathbb{H}}_s)} rx^{t_{f_s}}_{(q_{t_c})i} + \sum_{(i\in\mathbb{H}_s)} sur\left(x^{t_{f_s}}_{(q_{t_c})i} - \sum_j y_{ijs}\right)\\ + \sum_j short\left(D_{js} - \sum_{i\in\mathbb{H}_s}\sum_j y_{ijs}\right)\end{aligned} \tag{15}$$

subject to:

$$y_{ijs} \le x^{t_{f_s}}_{(q_{t_c})i}, \quad \forall i \in \mathbb{H}_s \tag{16}$$

$$x^{t_{f_s}}_{(q_{t_c})i} = \sum_{t\le t_c}\sum_{i'\in\mathbb{I}\cup MDC} f^t_{i'i}v^{t,t_{f_s}}_{i'i} + \sum_{t_c\le t\le t_{f_s}}\sum_{i'\in\mathbb{I}\cup MDC} u^t_{q_{t_c}i'i}v^{t,t_{f_s}}_{i'i}, \quad \forall i \tag{17}$$

$$y_{ijs} \le 0, \quad \forall i \in \bar{\mathbb{H}}_s \tag{18}$$

$$z_s = \sum_t\sum_i\sum_{i'}\left[f^t_{ii'}(1 - v^{t,t_{f_s}}_{ii'}) + u^t_{(q_{t_c})ii'}(1 - v^{t,t_{f_s}}_{ii'})\right] \tag{19}$$

$$y_{ijs} \in \mathbb{Z}^+, \quad \forall i, j \tag{20}$$

Recall that each solution q_{t_c} is characterized by the values of the flows from the MDC to SPs and among SPs in each time period. Therefore, in this case $u^t_{(q_{t_c})ii'}$ are not decision variables, but parameters corresponding to solution q_{t_c}. The problem above is in fact simply a transportation problem.

In P2 we assume that we will deliver the flows as defined by solution q_{t_c}, but under scenario s. Note that the lead-time for scenario s might be shorter than the lead-time under which q_{t_c} was computed as the optimal solution. Then, when trying to implement q_{t_c} under scenario s, there might be flows that we will not actually schedule, because they fall beyond the lead-time t_{f_s}. Also, there will be units that will not reach their destination before such a lead-time. Therefore, the planned flow of units from a SP to all

DPs is limited to the amount of units that we will actually be able to position at such a SP under scenario s, following actions given by solution q_{t_c}, as stated in constraints (16) and (17).

The total cost of solution q_{t_c} under scenario s would be given by the objective value in (15) plus the costs due to in-transit units at landfall; units that must be purchased to deliver flows before landfall; and delivery costs from the MDC to SPs and among SPs under the given scenario s. Note that these amounts do not affect the optimization process of P2, since they are fixed from q_{t_c}. These costs are given in equation (21).

$$\begin{aligned} & gz_s + h\left[\sum_{i\in\mathbb{I}}\sum_{t_c\leq t\leq t_{f_s}} u^t_{(q_{t_c})\{MDC\}i} - \sum_{i\in\mathbb{I}}\sum_{t\leq t_c} f^t_{q_{t_c}i\{MDC\}} v^{t,tc}_{i\{MDC\}}\right] \\ & + \sum_{(t_c\leq t\leq t_{f_s})}\sum_{(i\in\mathbb{I}\cup MDC)}\sum_{(i'\in\mathbb{I})} u^t_{(q_{t_c})ii'} b^t_{ii's} \end{aligned} \tag{21}$$

4.2.2 Selecting the Best Solution

Based on the performance of each possible solution under every possible scenario, we can apply different criteria to select the most convenient solution in a given time period. We use two criteria for this purpose: (1) minimum expected cost, and (2) minimum of the maximum regret.

- Strategy 1: Select the solution, $q^*_{t_c}$, with the minimum expected cost over all the possible scenarios. Let us denote $c(P2(t_c, s, q_{t_c}))$ as the optimal cost for problem $P2(t_c, s, q_{t_c})$. Then the expected cost for each solution q_{t_c} would be given by $C(q_{t_c}) = \sum_s [c(P2(t_c, s, q_{t_c}))]p_s$, where p_s is the probability of scenario s. The selected solution would be $q^*_{t_c} \mid C(q^*_{t_c}) \leq C(q_{t_c}), \forall q_{t_c}$.

- Strategy 2: Apply a min-max regret approach, where the selected solution, $q^*_{t_c}$, is the one that has the minimum-maximum regret value. The regret, $R(s, q_{t_c})$ from applying solution q_{t_c} under scenario s can be defined as $c(P2(t_c, s, q_{t_c})) - \min_{q_{t_c}} c(P2(t_c, s, q_{t_c}))$. The maximum regret $R_{max}(q_{t_c}, s)$ would be equal to $\max_s R(s, q_{t_c})$. Then the selected solution $q^*_{t_c}$ would be given by $q^*_{t_c} \mid R_{max}(q^*_{t_c}, s) \leq R_{max}(q_{t_c}, s), \forall q_{t_c}$.

Since we are using a rolling horizon approach, once we have selected $q^*_{t_c}$, we will actually deliver only those units corresponding to the flow $u^{t_c}_{(q^*_{t_c})ii'}$, i.e. the units that are scheduled to be delivered immediately. Also, when we reach the next time period, namely t'_c (where $t'_c = t_c + 1$) this flow would become $f^{(t'_c-1)}_{ii'}$ when we apply our methodology for finding $q^*_{t'_c}$

4.3 When to Start the First Prepositioning Activity

As mentioned in previous sections, there is a trade-off between forecast accuracy and logistic costs. In the early stages of the hurricane, while the system is in its Initial State, once a forecast advisory has been issued, we face two alternatives: (1) start the prepositioning activities immediately to avoid higher logistic costs, or (2) do nothing and wait until the next advisory in order to reduce the uncertainty of the hurricane predictions. In this section we propose a strategy for aiding the user to make a decision in this situation.

We can decide whether to start prepositioning immediately or wait an additional period by applying the algorithm described below. The function of such an algorithm is to compare the costs from both alternatives (waiting or acting immediately) and suggest a course of action based on the difference of such costs.

- Step 1: If current time $t_c = t_{f_s-1}$, solve the problems $P1(t_c, s)$ and $P2(t_c, s, q_{t_c})$, and apply solution $q^*_{t_c}$, since there is no further opportunity for taking more observations. Otherwise, solve the problem $P1(t_c, s)$ for current time t_c.

- Step 2: Solve the problems $P1(t_{c+1}, s)$ and $P2(t_{c+1}, s, q_{t_c})$, assuming that no action is carried at time t_c.

- Step 3: In Section 4.2 we discuss two ways for selecting q^*_t. Independently of which alternative we use, let us denote $c(t)$ as the cost from the solution q^*_t obtained for time t. Then we would start prepositioning at time t_c if $c(t_{c+1}) - c(t_c) \geq \pi, \pi > 0$. Otherwise, we wait until reaching time t_{c+1} and go to Step 1.

This approach is based on the assumption that the worst case that we can expect is that the probabilities for the scenarios computed in time period t_{c+1} are exactly the same as those computed at time period t_c, i.e. the prediction in t_{c+1} is not more accurate than that of period t_c. In this case, π would represent the maximum opportunity that we are willing to risk for taking one more observation.

5 Computational Experience

In this section we present the results that we have obtained from applying our model to a set of computational instances. First, we discuss our methodology for generating the set possible scenarios and their corresponding probabilities. Later, we discuss our data inputs and results.

5.1 Set of Possible Scenarios and Computation of their Probabilities

One of the fundamental inputs of our model is the definition of the possible scenarios along with their probability of occurrence. One possible approach is that given by Czajkowski and Woodward (2010). The methodology proposed by Czajkowski and Woodward (2010) contains some limitations, but we found it to be reasonable enough to illustrate the application of our study.

In the paper written by Czajkowski and Woodward (2010), the authors use a Markovian approach that assumes that the forecast in the next time period depends only on the current forecast, and not on the forecast of previous periods. The state of the Markov process is defined by three attributes of the hurricane: intensity and location at landfall, as well as time of landfall. Regarding hurricane's intensity, there are five possible categories, which correspond to the ones established by the Saffir-Simpson scale [1]. The location of the hurricane at time of landfall is measured in terms of the distance from a

[1]The Saffir-Simpson scale uses information about hurricanes' wind speed to classify them into five categories. Major hurricanes are those that reach Category 3 or higher. This classification can be used to estimate the potential property damage for a given hurricane. For further information we refer the reader to http://www.nhc.noaa.gov/aboutsshws.php

point of reference. The possible states for the location are: within 25 miles, 25 - 75 miles, 75 -125 miles, 125 - 175 miles, 175 - 225 miles, 225 - 275 miles, and more than 275 miles. Finally, the authors define the lead-time as the hours remaining until the strike of the hurricane. The possible values for lead-time are 96 h, 72 h, 48 h, 36 h, 24 h, and 12 h. A lead-time of 72 means that the hurricane is expected to make landfall in less than 72 h but in more than 48 h.

The three attributes that define the Markovian state in the approach used by Czajkowski and Woodward (2010) can be determined from the hurricane's forecast advisory issued by the NHC (Figure 1). The hurricane's category and location can be read directly from the advisory. Regarding the time of landfall, we have that the advisory from the NHC labels as "INLAND" the time periods in which the hurricane is expected to have touched mainland. Then, Czajkowski and Woodward (2010) uses this information to estimate the lead-time. For instance, in the advisory given in Figure 1, the first period that has the label "INLAND" is the one that corresponds to 12 h which is interpreted as a lead-time of 12 h. Note that this actually implies that the hurricane is expected to occur *within* 12 h.

Tables 2, and 3, give the one-step transition probability matrices offered in Czajkowski and Woodward (2010) for hurricane's intensity and location, respectively. Table 4 is a partial example of the whole transition matrix for lead-time built by Czajkowski and Woodward (2010). In Table 2, we have that, for instance, there is a probability of 0.83 that the forecast in time $t + 1$ says that the hurricane will be of category C2, given that the current forecast at time t says that the hurricane is of category C1. A similar analysis applies for the transition matrix given in Table 3. In relation to the lead-time, notice that each possible state is defined as XX.YY, where XX is the lead-time in hours, whereas YY keeps track of the number of times that we have had a forecasted lead-time equal to XX. For example, the first time that we have a forecast of 96 hours, we will be in state 96.01; the second time we get the same forecasted lead-time, we will be in state 96.02 and so on.

For creating our scenarios we first determine the corresponding lead-time. For practical purposes, we rename the lead-time given in Czajkowski and Woodward (2010) as the *forecasted* lead-time, and we redefine the lead-time of a scenario as the amount of hours remaining to obtain a forecasted lead-time of 12.01. To compute the lead-time we use the fact that the advisories are issued every six hours. Let us assume that there is a probability equal to 1.0 that the next advisory gives a forecasted lead-time of 12.01 given that the current advisory has predicted a forecasted lead-time of 24.02. In this case, our lead-time would be six hours, which is equal to the time between the two advisories. The reason to consider the occurrence of a forecasted lead-time of 12.01 for computing our lead-time is that in Czajkowski and Woodward (2010) a forecasted lead-time of 12.01 means that the hurricane will occur in less than 12 h, which could imply that it might even occur within 1 h. Then, at that point we would not have any time left to perform prepositioning activities.

To clarify even further how we relate the scenarios in our model with the corresponding lead-time, consider that the current forecast is 48.01 and that the forecasted lead-time matrix given in Table 5 applies. In this case, the possibilities for lead-time would be as follows: with probability 0.18, we could pass from 48.01 to 48.02, then to 24.01 and then to 12.01, which gives a total of three more advisories for a lead-time of 18 h; with probability 0.12, we could pass from 48.01 to 24.01 and then to 12.01 for a lead-time of 12 h; with probability 0.28, we could pass from 48.01 to 24.01, then to 24.02 and then to 12.01 for a lead-time of 18 h; and with probability 0.42 we could pass from 48.01 to 48.02, then to 24.01 and then to 12.01 for a lead-time of 24 h. Then, if the current forecasted

	0	**1**	**2**	**3**	**4**	**5**
0	100%	0%	0%	0%	0%	0%
1	11%	83%	6%	0%	0%	0%
2	0%	15%	60%	25%	0%	0%
3	0%	0%	4%	68%	28%	0%
4	0%	0%	0%	18%	79%	4%
4	0%	0%	0%	18%	79%	4%
5	0%	0%	0%	0%	50%	50%

Table 2: Intensity Markov Transition Probability Matrix

	0	**25**	**75**	**125**	**175**	**225**	**225**
0	0.4%	30.0%	39.5%	19.8%	4.9%	3.7%	1.6%
25	15.0%	20.2%	24.9%	22.2%	11.7%	3.3%	2.7%
75	19.8%	24.9%	2.9%	16.9%	20.6%	9.9%	5.1%
125	9.9%	22.2%	16.9%	1.2%	15%	19.8%	15.0%
175	2.5%	11.7%	20.6%	15.0%	0.4%	15.0%	34.8%
225	1.9%	3.3%	9.9%	19.8%	15%	0.4%	49.8%
275	0.8%	1.9%	2.5%	9.9%	19.8%	15.0%	50.2%

Table 3: Location Markov Transition Probability Matrix

	96.01	**96.02**	**96.03**	**96.04**	**96.05**	**96.06**	**72.01**	**72.02**	**72.03**	**72.04**	**72.05**	**72.06**	**72.07**	**72.08**	**72.09**	**72.10**	**72.11**	**72.12**	**48.01**
96.01		83%					17%												
96.02			67%				33%												
96.03				50%			50%												
96.04					40%		60%												
96.05						30%	70%												
96.06							100%												
72.01								81%											19%
72.02									72%										19%
72.03										81%									19%
72.04											78%								22%
72.05												75%							25%
72.06													71%						29%
72.07														67%					33%
72.08															61%				39%
72.09																56%			44%
72.10																	50%		50%
72.11																		25%	75%
72.12																			100%

Table 4: Lead-Time Markov Transition Probability Matrix

lead-time is 48.02, we have three possible lead-times: 18 h with probability of 0.46, 12 h with probability 0.12, and 24 h with probability 0.42. We perform similar computations for defining the possible lead-time values and their probabilities for every possible value of forecasted lead-time.

By knowing the lead-time for any given forecasted lead-time, we can know the corresponding number of additional advisories. For instance, a lead-time of 18 h gives 3 more advisories. With that information, we can establish the possible intensities and locations for hurricane's landfall. To do so, we compute the n-steps probability matrices for intensity and location from the one-step transition probability matrices given in Tables 2 and 3, where n would be the number of additional advisories until landfall. For

	Forecasted Lead-Time in $t+1$			
Forecasted Lead-Time in t	**48.02**	**24.01**	**24.02**	**12.01**
48.01	0.6	0.4		
48.02		1.0		
24.01			0.7	0.3
24.02				1

Table 5: Example of Lead-Times to Create Scenarios

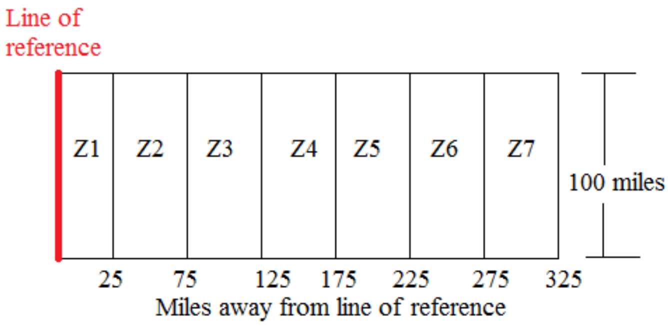

Figure 2: Zones for Computational Instances

the computations of our model, we assume that the intensity and location of hurricane's landfall are independent for any given lead-time. Therefore, the probability of a scenario with lead-time equal to T, category equal to C and location equal to L would be given by $P(Category = C \mid Lead - Time = T) * P(Location = L \mid Lead - Time = T) * P(Lead - Time = T)$.

The number of scenarios can be quite large in theory. For instance if every combination (location, intensity and lead-time) is considered, from the data in Tables 3 to 5, we would have a total of 798 scenarios. However, suppose that the current forecast is Category 1, Distance = 25, and lead-time of 24.04, and that we have only one more time period ahead. Then the total possible scenarios are only 14.

Recall that the data about the location of hurricane's landfall delivered by Czajkowski and Woodward (2010) uses a point of reference, and that the hurricane's possible location is measured in relation to such a point. Based on the possible locations for hurricane's landfall given by Czajkowski and Woodward (2010), we have defined the possible affected area as the one shown in Figure 2. Instead of using a point of reference, we have set a line of reference which corresponds to the left border of our area. Each zone depicted in Figure 2 corresponds to one of the categories for hurricane's location at landfall defined in Czajkowski and Woodward (2010). Locations for the SPs and DPs are randomly generated, taking care that the SPs and DPs are similarly distributed through out all the zones. The location of the MDC is selected to be safe, away from the possible affected area.

5.2 Data Input

For our computational experience, we have generated a fixed APA that contains given sets of SPs and DPs. Parameters that are not scenario-dependent and that are part of the basic model discussed in Galindo and Batta (2012) (such as budget (B), setup costs (c_i), capacities of SPs (cap_i), among others), are generated in a similar way as described in Galindo and Batta (2012). Specifically, for each instance, we randomly generated the locations of SPs and DPs by uniformly assigning their x and y coordinates respectively along the width and height of the APA. Also, we randomly generate the population for each DP using a Uniform distribution. To compute set up costs and capacities for SPs, we have used the approach given by Cornuejols et al. (1991). According to such an approach, the set up cost for a given SP is computed as $a + b\sqrt{cap_i}$, where a and b are random numbers uniformly generated between 0 and 90, and between 100 and 110, respectively. The capacity of each SP was randomly generated in such a way that the total capacity approximates 70% of the global population. The available budget is uniformly generated between 10% and 80% of the sum of set up costs. The values for costs, populations, capacities and all the remaining parameters in our model should be regarded as illustrative only, even though they are designed to be realistic. For further information regarding the generation of the data described above, we refer the reader to Galindo and Batta (2012) and Cornuejols et al. (1991).

Additionally, for each instance in our computational tests, we have randomly generated an initial forecast for each of the hurricane's characteristics: location, intensity, and lead time. In the generation of such an initial forecast, we have assigned equal probability to all of the possible values that each of these characteristics can take. Then, based on the initial forecast, we used a Monte Carlo simulation, where the probability of each possible scenario was computed using the reasoning discussed in the previous section, in conjunction with the information given in the Markovian transition probability matrix from Czajkowski and Woodward (2010). Also, parameters corresponding to demand values (D_{js}), set of surviving SPs ($\mathbb{H}_s$), and delivery costs from SPs and from the MDC to DPs (a_{ijs}) are scenario-dependent and relate to the situation that we might find once the hurricane has made landfall. These parameters take values depending on the hurricane's category and location. For instance, the SPs that would be destroyed in a given scenario are those that are within a certain distance from the hurricane's location at landfall, where such a distance depend on the hurricane's category; a similar reasoning applies for computing the demand of each DP. In our simulation, as well as in real-life, it is possible that the hurricane dissipates before it makes landfall. In such a situation, there is no demand at DPs and no destruction at SPs. Another parameter that is scenario-dependent is the delivery cost from the MDC and from SPs to other SPs (b^t_{ijs}). This cost applies before the hurricane's landfall and we assume it to be a decreasing function of the lead-time, and dependent on the forecasted category.

In summary, there is a set of data that varies for each instance in our simulation, which includes location of SPs and DPs, DPs' population, set-up costs, SPs' capacities, available budget and the initial forecast regarding hurricane's location, intensity and lead time. Once this data has been specified for a given instance of our problem, we use a Monte-Carlo simulation to simulate the subsequent forecast advisories, including the final status of the hurricane. Then we use that information to generate demand values, destruction of SPs and delivery costs among locations. We have two extreme cases: (1) the hurricane dissipates without making landfall; and (2) the hurricane makes landfall with Category 4 or 5. Our simulation stochastically considers both extremes as well as the possibilities in between.

5.3 Results

We have that the following four approaches are possible for resource deployment:

- Solution No. 1: obtained by applying the forecast-driven model discussed in Section 4, where the solution for each time period was found using the minimum expected cost.

- Solution No. 2: obtained by applying the forecast-driven model, but this time we used the min-max regret approach to select the most appropriate solution in each time period.

- Solution No. 3: obtained by applying the static model discussed in Galindo and Batta (2012). In this case, we assume that the model is applied once we obtain a forecasted lead-time of 48 h.

- Solution No. 4: obtained by applying a wait-and-see approach in which no actions are carried out before the occurrence of the hurricane, i.e. all arising demand is served from the MDC.

Taking into consideration the four approaches stated above, we have performed a series of computational tests in order to answer the following questions:

1. In the forecast-driven model, is the minimum expected cost strategy better than the min-max regret strategy?

2. Are the strategies used in the forecast-driven model better than the static model given in Galindo and Batta (2012)?

3. Are the strategies used in the forecast-driven model better than a wait-and-see approach?

In order to give answers to the questions above within a short period of time, we used small instances of our problem. Our findings are discussed in the following section. Then, we present our results for larger instances, where we offer some insights about computational solution times.

5.3.1 Results for Small Instances

Our computational tests were performed on instances of the problem with 7 SPs and 14 DPs. In Figure 3 we present our results. For obtaining the results shown in Figure 3, we have simulated the evolution of a hurricane since it is first forecasted, until we obtain a forecasted lead-time equal to 12.01. At that time, we assume that the hurricane occurs with the conditions given by the last forecast. The initial forecast regarding the characteristics of the hurricane (category, location and lead time) are randomly generated and thereafter, the subsequent forecasts are randomly created using the Markovian transition probabilities from Czajkowski and Woodward (2010). The cost of each solution is computed taking into consideration the cost of the units that were actually delivered before the hurricane; the cost of destroyed units; surplus and shortage costs; and the cost to deliver units after the hurricane from the surviving points and from the MDC.

Among the 15 instances in our simulations, the maximum number of scenarios for any time period was 230. One way in which the number of scenarios can be reduced is by grouping some of the categories for each of the hurricane's attributes. For instance, instead of considering a hurricane of Category 0, 1, 2, 3, 4 and 5 as different states, we can define three states as: "no hurricane" (category 0), "minor hurricane" (categories 1 and 2), and "major hurricane" (categories 3, 4 and 5). However, this aggregation is left as part of future research since it cannot be performed solely with the information contained in the one-step probability matrices given in Czajkowski and Woodward (2010).

We have used the cost from Solution No. 1 as a value of reference for computing the values in the y-axis in Figure 3, where each value is given as the cost of the corresponding solution over the cost obtained for solution No. 1. This is why we obtain a horizontal line in $y = 1$ for solution No. 1. The reason for using solution No. 1 as our reference is that this approach was the one that generally gave the best results.

From Figure 3, we note that the wait-and-see approach is generally the one that gives the worst results. It usually outperforms the other strategies for the cases in which hurricane's category at landfall is very low, i.e. 0 or 1. Solutions from the forecast-driven model are always at least as good as the other two approaches. Figure 4 shows our results when considering only the two solutions obtained from the forecast-driven model. As we can see, the approach that considers the minimum expected cost is usually better than the one based on the minimization of the maximum regret. The reason for this is that, generally, the min-max regret approach uses a scenario that is very unlikely to occur,

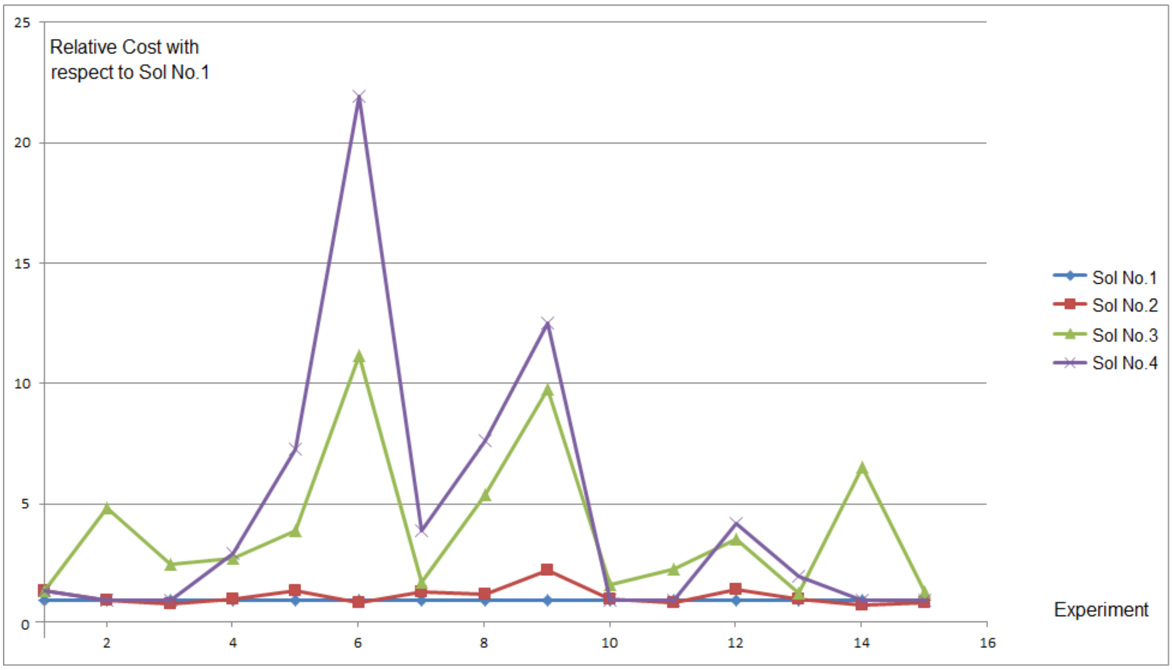

Figure 3: Relative Costs for Solutions No. 1 to No. 4

and what actually happens, is very different from that worst-case scenario. The following section presents some insights regarding the circumstances under which Solutions No.1 and No.2 outperforms each other.

5.3.2 Insights Regarding Solutions No.1 an No.2

In order to obtain insights regarding the results presented in Figure 4, we have created several types of instances for our problem, according to the following design based on the initial forecast for hurricane's category and lead time:

1. Hurricane's intensity: strong hurricanes, i.e. initial forecasted category equal to 5, and weak hurricanes, i.e. initial forecasted category of 1.

2. Hurricane's lead time: long lead times, i.e. initial forecasted lead time of 96 h, and short lead times, i.e. initial forecasted lead time of 48 h.

Hence, we have 2^2 types of instances of our problem. We tested 20 runs that were randomly generated for each type of instances. Our findings are summarized in Table 6.

From Table 6, we can see that when the initial forecast indicated that the hurricane would be strong and the lead-time long, Solution No.1 tended to be the best alternative.

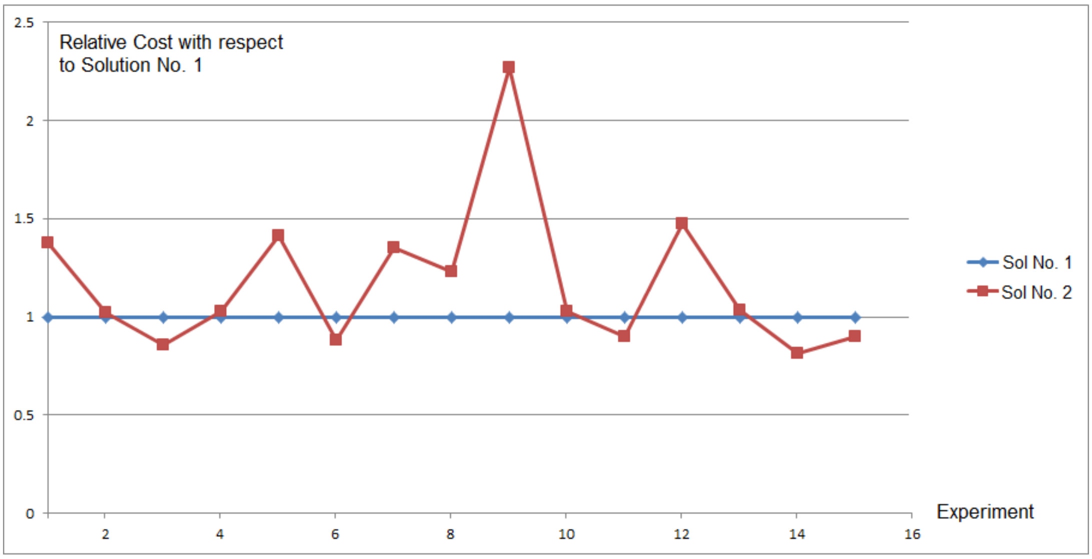

Figure 4: Relative Costs for Solutions No. 1 and No. 2

	Weak Hurricane	**Strong Hurricane**
Short Lead-Time	15	55
Long Lead-Time	50	95

Table 6: Percentage of Times in which Solution No.1 ouperformed Solution No.2

The opposite occurred when we had an initial forecast of a weak hurricane with short lead-time. In the other cases, we did not see any dominance of one solution strategy over the other. However, we did notice that when the hurricane at landfall was strong (independently of the initial forecast) Solution No.1 tended to be the better; whereas Solution No.2 tended to be more convenient for hurricanes that turned out to be weak (again, independently from the initial forecast). In our search for an intuitive reason for these results we realized that Solution No. 1 minimizes the total expected cost. Such an expected cost can be dominated by scenarios with the largest costs, which are likely to be those with stronger hurricanes. In other words, we could expect Solution No. 1 to be better fitted for scenarios with stronger hurricanes and therefore, it should not surprise that its performance is better under these circumstances. On the other hand, when the hurricane turns out to be weak, it is possible that Solution No. 1 has over-prepositioned items that can result in a better performance of Solution No. 2.

Additionally to the analysis above, we have registered the times at which the prepositioning activities started under each type of the instances of our problem. For the cases in which we had a short lead-time in the initial forecast, the model started prepositioning very soon: in all cases prepositioning activities started while the forecasted lead-time was still of 48 h, except for two cases in which the min-max regret strategy did not perform any prepositioning at all. For the instances with long lead-times, for Solution No. 1 90% of the runs started while the forecasted lead-time was equal to 72 h and 10% while it was equal to 48 h. In the case of Solution No. 2, in 10% of the runs, it did not perform prepositioning activities, whereas in 80% the prepositioning started while the forecasted lead time was of 72 h. In the other 10% of the runs, prepositioning activities started while the forecasted lead-time was of 24 h.

To explore the potential applicability of our approach to a realistic situation we solved a large instance with 154 SPs and 301 DPs. The following section relates to the solution of this large problem instance.

5.3.3 Results for Larger Instances

In Table 7 we show the solution times for the two strategies considered in the forecast-driven model, when using a larger instance of the problem. These solution times represent the time that it takes to find a solution for a given time period based on a given forecast. Such solution times include: generating the possible scenarios based on the current forecast, finding the best solution for each scenario, evaluating each solutions under each scenario, and determining the best actions to be performed at each time period (including establishing if current period is a good time to start prepositioning). As it may be seen, the solution times for the forecast-driven model are reasonable. Moreover, solution times given in Table 7 are a good sign that humanitarian practitioners can obtain a solution for any given time period in much less than 6 hours, which is the time between successive advisories. Also, it seems that the solution times for the min-expected cost tend to be slightly larger than for the min-max regret approach.

The simulation times to generate all of the time periods with their corresponding forecast and scenarios are a limitation for testing additional large instances of our problem. Further research for evaluating the computational solution times for the forecast-driven

	154 SPs and 301 DPs	
Period	**Minimum Expected Cost**	**Min-Max Regret**
1	395.0	388.0
2	912.0	917.0
3	575.0	574.0
4	556.0	556.0
5	539.0	339.0
6	579.0	370.0
7	336.0	185.0
8	341.0	204.0
9	283.0	166.0
10	338.0	352.0

Table 7: Solution Times in Seconds for the Forecast-Driven Model

Solution Number	**Cost**
Solution No. 1	7.50E7
Solution No. 2	7.63E7
Solution No. 3	1.19E8
Solution No.4	2.49E8

Table 8: Solutions for 154 SPs and 301 DPs

model when using larger instances of the problem is left as part of future research. In this respect, a variation of the Proposition 2 in Galindo and Batta (2012) would apply for the forecast-driven model to improve solution times by reducing the number of variables of the problems.

Table 8 shows the corresponding costs for all of the four types of solutions that were considered in Figure 3. In this case, the approaches for the forecast-driven model are the ones that give the best solution. On the other hand, the solution from the static model outperforms slightly that from the wait-and-see approach. Also, between the two strategies for the forecast-driven model, the one that uses the minimum expected cost, outperforms the other. These results are consistent to those observed in Figure 3. In other words, from the solution of the large problem, we reach similar conclusions to those obtained by solving the 15 random instances of the smaller problem.

6 Discussion and Future Research Directions

In this section we discuss some of the limitations and future research directions regarding the forecast-driven model.

- Even though the approach given by Czajkowski and Woodward (2010) to generate the input data for our model is very interesting, and it does not rely on the statistical independence of successive advisories, it has some inherent limitations that we suggest be overcome in future computational exercises. It would be more realistic to incorporate part of the history of the latest advisories to generate the transition probabilities in the one-step probability transition matrices. For instance, we could define the probability of the next forecast reporting a hurricane of Category 5, given that the last three advisories have predicted that the hurricane will be of Category 1. Also, we can include a fourth dimension that gives the direction of the trajectory of the hurricane in order to improve the prediction about the hurricane's location at landfall.

- We have assumed that the travel times do not change throughout the planning horizon. Moreover, one of the reasons to have greater logistic costs as the hurricane approaches, is because we would likely need to use transportation modes that are more expensive in order to maintain the same transportation times. A more realistic approach would be to consider travel times that depend on the forecasted lead-time. In this case, we would relate the travel times to the congestion of roads due to evacuation procedures. In the literature, we did not find any research that can provide us with an estimation of travel times based on the forecasted lead-time of a disaster. We believe this would be a valuable future research direction for evacuation and prepositioning models.

- We have used Euclidean distances to compute the travel times between any pair of points. In practice, it would be more realistic to use road-distances that also accounts for possible disruptions on the transportation network.

- The criteria for selecting the starting time for the prepositioning activities can be improved by incorporating the expected accuracy of the future forecast. In this case, we would need to make an estimation of the possible forecasts that might arise in the following periods. Moreover, it is possible to develop a dynamic programming model that takes into consideration all of the possible future forecast advisories throughout all the future time periods. The complications of such an approach would rise from the number of scenarios that would need to be considered.

- As future work, it would be of value to select not only SPs from a set of candidates, but also DPs. In this respect, we would need to consider setup costs for DPs and allocation of demand to selected DPs. We could adjust previous related research that has addressed similar problems before, such as that given by Jia et al. (2007).

7 Conclusions

In this paper we have discussed a forecast-driven model for prepositioning supplies in preparation for a foreseen hurricane. This model enhances the one discussed in Galindo and Batta (2012). The model is based on Decision Theory approach where the user must take an action based on a set of possible states of nature. Such states are defined as the possible scenarios that might occur when the hurricane makes landfall, where each scenario is define in terms of the hurricane's location, category, and lead-time.

Our model determines the time to start prepositioning, and the units to be prepositioned at each selected SP. It also accounts for the possible re-positioning of already prepositioned supplies. We have developed two approaches for selecting the best solution in each time period: minimum expected cost, and min-max regret. These two approaches were tested through a set of computational examples from which we observed that the first approach usually delivers better results than the second, especially for hurricanes that turn out to be of categories 4 or 5. However, neither approach dominates the other. Nevertheless, both approaches are significantly better than the wait-and-see approach and than the static model given in Galindo and Batta (2012).

We have pinpointed some limitations regarding our forecast-driven model, which can be improved through future research, such as the use of road-distances and dynamic travel times. We also found some limitations in relation to the input data used for our computational experience. In this respect, we recommend the use of an improved version of the approach given by Czajkowski and Woodward (2010), that incorporates more than one past advisory to create the transition probability matrices.

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