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Prepositioning of Relief Goods Under Network Uncertainty for Tropical Cyclones with Information Updates: A Humanitarian Supply Chain

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***Abstract* — Tropical cyclones is a type of natural disaster that is being monitored ever since its development up until its landfall or dissipation. This information paves the way for the possibility of prepositioning relief goods in the areas forecasted to be hit by the tropical cyclone in order to help the post disaster distribution of relief goods in a humanitarian supply chain. However, since these forecasts are not perfect and are constantly updated in relation to the actual development of the tropical cyclone, there is value in waiting for an updated forecast information at the expense of an expedited logistics cost due to a shorter lead time. Furthermore, in order to fully utilize the advantages of prepositioning, response times and cost objectives are studied. The key feature of the models developed is that the prepositioning decisions incorporates the possibility that the flow of goods in the post disaster links may be limited or reduced due to the effects of the tropical cyclone. Finally, linear physical programming was used for the optimization of the multiple objectives as it allows the incorporation of the decision maker's preferences regarding the objectives.**

Keywords* — *prepositioning; forecast information update; network uncertainty; linear physical programming, humanitarian supply chain

I. Background

Natural processes of the earth may often times cause a natural disaster if a catastrophic event affects an inhabited area. These natural disasters often leave some form of loss in terms of human lives, loss of properties, economic losses, and transportation and infrastructure damages. One technique being done to help the victims of the disasters is to preposition relief goods. However, due to the high degree of uncertainty in the inventory problems faced by humanitarian logistics, redundancy such as sending goods through different routes or storing them in different places can be considered and although prepositioning can be done in order to address this, it can be very costly [1]. As such, literatures on prepositioning mainly focus on the minimization of the costs incurred by the prepositioning strategy [2, 3, 4, 5, 6, 7].

However, humanitarian supply chains deal with life and death and as such, the goal is to deliver the right supplies at the right quantities at the right time [8]. The real goal of prepositioning is to help post disaster relief distribution of goods have a faster response time by having the supplies nearer to the demand points (DP). This is extremely important in a humanitarian supply chain as delivering the wrong amount of supplies or delivering the supplies slowly could still result in massive loss of life. Because of this, logistics take up a huge role in providing humanitarian assistance because the way supply chains are operated has huge impact on the speed and quality of the assistance [9]. This led to some researchers focusing on objectives other than cost such as maximizing the probability that a demand point will be served [10], response times [11, 12], or unmet demand [12, 13, 14].

The consideration of the main goal of prepositioning, which is to have fast response in order to accommodate the victims should come as a priority. However, while prepositioning can speed up the delivery of emergency aid, it is also crucial to monitor the time frames and the costs incurred in order for it to be effective and efficient [15]. Thus, there is a need for the consideration of both the cost, and the response in a prepositioning context.

Furthermore, certain complications in humanitarian logistics may arise during a tropical cyclone such as a disruption in the network or uncertainty in demand. According to [16], one of the key challenges in optimization of a humanitarian logistics plan as opposed to a business logistics is the addition of uncertainties such as unstable routes, demand uncertainties, etc. While there were studies that considered response times like [17] who minimized the average weighted response time in a prepositioning context, they did not consider the effects that road disruptions could have on the response time. The consideration of network uncertainty is important when prepositioning, as prepositioning in a nearer but riskier place would make post disaster distribution more difficult.

Previous literatures that tried to incorporate network uncertainty such as the study of [7] fails to address capacities in the links wherein there are only a number of goods that can be delivered due to the potential impact of the storm. The possibility that links are just partially unusable is never considered. This has huge implications in the response times as the goods are still allowed to be transferred to the disrupted route but only with a reduced number of goods.

Furthermore, tropical cyclones bring intense winds and rainfall which contributes to the uncertainty of the safety of the prepositioned goods, and therefore affect the post disaster distribution of goods. In this regard, researches have focused on the prepositioning strategy regarding the potential destruction of a prepositioned supply point [2, 4]. The problem with this approach is that it does not consider the possibility that the road network will be disrupted. If a certain supply point is destroyed, it cannot serve all the demand points connected to it. However, if only a road from a certain supply point to a certain demand point is destroyed, the supply point can still serve other demand points.

Another huge factor contributing to the network uncertainties that is not considered in past studies is the forecast information. Disasters such as the earthquake and tsunami that occurred in Japan back in March 2011 were so sudden that they left little to no time to prepare [4]. Tropical cyclones, on the other hand, is a type of natural disaster that is constantly being monitored with forecast information becoming available through numerical weather prediction. This lead to some researchers utilizing the forecast information to reduce the uncertainty involved in a tropical cyclone setting [17,18, 19].

The utilization of forecast information allows decision makers such as the government or various relief agencies to have a basis for their prepositioning strategy and to make their plans regarding where to preposition their goods and how many to preposition at each location. However, these forecasts are usually updated constantly as the storm nears land which leads to the issue of which forecast should decision makers use. Due to this, researchers had already started incorporating the problem of updating forecast information in a tropical cyclone setting [3, 20, 21, 22].

One way of reducing the uncertainty involved for humanitarian supply chains is through the use of forecast information. This is because effective information systems in humanitarian logistics are particularly crucial from early warning and preparedness to emergency response and recovery activities [23]. As forecast information may be used to give an idea as to which paths may possibly be disrupted, it is important to also consider the updating of this information. The consideration of information updates reduces the uncertainty and allows updates to the network which in turn affects the prepositioning strategy.

II. Problem Description

The system begins with an initial forecast about the characteristics of the tropical cyclone. This forecast contains information pertaining to the possible intensity and location of the tropical cyclone. The specific probabilities of wind speed per location can be obtained from weather forecast stations. It is based on this information that the decisions must be made regarding the prepositioning activities.

A. Supply Points

A single main distribution center (MDC) acts as the main source of supply. All the relief supplies are assumed to be initially located in the MDC. The supply in the MDC is assumed to be sufficient to satisfy all the demand. This could be true for supplies that are abundant and rarely run out. These could represent a main warehouse in which all the relief supplies are positioned prior to prepositioning. The main distribution center will then supply the potential supply points (SP) with some quantity relief goods with a corresponding transfer cost. This is called the prepositioning activity and it may happen at some time interval after the initial tropical cyclone forecast and before the tropical cyclone landfall.

The potential SP may represent a warehouse or a facility that can be quickly converted for use into a warehouse for relief goods. A facility that can be set up quickly may be a school, gymnasiums, or other public facilities that is able to accommodate relief goods and is a secure location.

At these locations, an amount of relief supplies can be accommodated after the setup activities. This set up activity will incur a setup cost which represents possible equipment, manpower, or other resources required to prepare the location for the safe storage of relief supplies. These relief supplies may then be transferred to other SPs on the next time period, which would incur a transfer cost.

B. Demand Points

Various demand points (DP) are located in the potential area that may be affected. These DPs generally represent facilities such as an evacuation center or some form of relief shelter. It is assumed that the people evacuate to these locations and need some amount of relief goods.

According to [24], demand in a humanitarian context can be estimated by the characteristics of the natural disaster. The quantity and locations of demand for relief goods are assumed to be dependent with the intensity and location of the tropical cyclone. The quantity of demand is expected to increase at higher intensities of the tropical cyclone and at locations closer to the central locations of the tropical cyclone's path.

Logistics take up a huge role in providing humanitarian assistance because the way supply chains are operated has a huge impact on the speed and quality of the assistance [9]. Determining where to preposition and how much to preposition is important because prepositioning at the wrong place or with the wrong amount would be detrimental to the post disaster relief operation.

Furthermore, prepositioning at the wrong place would mean that there would be areas where there is demand but there is no supply. While disaster relief organizations may still opt to meet the demand on time and with the right quantity in the post disaster by doing necessary additional actions such as using alternative modes of transportation (e.g. airlifting), purchasing additional resources, subcontracting, etc., this is external to prepositioning and would entail an additional expedited cost in the post disaster.

C. Network Links

Throughout the network, various links are used to represent the connections between the different locations. These links generally represent main highway roads or path networks which will be used to transport the relief goods from one location or facility to another.

These links have a certain capacity, which represent the amount of goods that can be transferred using these links given a certain amount of time. Some of these links may be damaged in some way due to the effects of the tropical cyclone. Heavy torrential rains and heavy winds of hurricanes can severely affect transportation infrastructure, rendering it difficult to use, if not unusable [25]. It is assumed that the capacity of these links may be reduced due to damage to the network links. Due to this, there would be an expected effective capacity for each road which would be the multiplication between the actual road capacity and the percentage of the road that is still usable.

Since it takes time to transfer goods from one location to another, one challenge presented by these capacities is in ensuring that the purpose of prepositioning in reducing response times can be met, by considering these capacities in relation to the concept of lead times. The links between the demand and supply points can be a measure of the expected response times achieved by prepositioning at the supply points which corresponds to the amount of goods to be transferred divided by the effective road capacity.

In general, transporting goods through the links would incur transportation costs. However, it is important to take note of the possibilities of disruptions when prepositioning because it will greatly affect the performance of the possible solution. For instance, if a link is damaged and cannot accommodate the sufficient transport of supplies, then having wrongly prepositioned supplies for a demand point may actually incur expedited costs instead. This would correspond to cost of necessary actions or resources needed to satisfy the demand such as more expensive modes of transportation for logistics or more manpower and vehicles to facilitate transfer of goods.

D. Dynamic Nature of the Problem

Forecasts usually increase in accuracy through time as they near landfall, and utilize knowledge on the current state of the weather. While forecast information improves as it nears landfall, there are tradeoffs. Prepositioning using the knowledge from the early development stages of the tropical cyclone could be risky because the characteristics of the tropical cyclone such as wind speed and path are still highly uncertain or unreliable due to the storm being far from landfall. On the contrary, waiting for the storm to near landfall, resulting in a more accurate forecast can also be detrimental as there would be less time to preposition which may incur higher costs due to pre-disaster expedited logistic costs. This is due to the cost of necessary actions or resources needed to satisfy the demand such as more expensive modes of transportation for logistics or more manpower and vehicles to facilitate transfer of goods during the planning stage.

After receiving an initial forecast, a decision must already be made about whether or not it would be beneficial to implement prepositioning activities or to wait until more information becomes available. Either way, updates are continuously received at certain time intervals about the characteristics of the tropical cyclone. Due to this, it is reasonable to assume that the scenarios lessen through time due to the increase in the accuracy of the forecasts as the storm nears landfall. This would mean that given no cost considerations, the better the accuracy of the forecast, the better the response time would be. The tradeoff now evolves between that of the cost and of the response time. While prepositioning in the later stages would account for a faster response due to more accurate information, the cost would be higher due to the need to rush the goods. Inversely, the cost would be lower in the early stages, but the response might suffer due to the use of inaccurate information.

At each period, decisions can be made regarding the prepositioning activities, to allow for possibilities of allocation/reallocation, or to postpone the prepositioning activities. Since the updating of forecast information also affects the uncertainties in quantity of the demand, as well as the reliability of the network link capacities, it is possible that a better allocation of relief goods exist.

In order to consider the dynamic nature of network uncertainty and demand, after every forecast update, the decision of allocation of the relief goods may be reconsidered due to the availability of more reliable information. Therefore, the decision must be taken to consider possible reallocation of supplies between the supply points. To summarize, the dynamic nature of the problem is caused by the updates of forecast information and affects the network link uncertainty, the demand, and in turn the optimal prepositioning strategy.

III. MODEL FORMULATON

A. Modelling Overview

The approach to model the decision of whether to wait for more information or to preposition at the current time period is through a decision theory approach. Due to this, there is a need to develop several mathematical models as various objectives are estimated under different scenarios and different possible decisions. It is important to note that the two main models are models B and C. Even though models A and B_0 are just a variation of B, they are still called models for easier referencing.

The first model, "Model A" gives an idea of what the minimum cost and response time would be in the optimal prepositioning strategy if a certain scenario is known to happen. In other words, "Model A" is a perfect information model. The second model, "Model B" is an extension and solves for an optimal prepositioning strategy under all the scenarios. Simply put, "Model B" would be the model under uncertainty. "Model B_0" is a variation of the second model, and solves for a prepositioning strategy under some projected cost parameters. Model B_0, is in a way, a representation of the cost of getting more information. The final model, "Model C" uses the insights gained from the previous models to decide whether it is beneficial to implement prepositioning or to wait for further information. In other words, model C is the decision model on whether to preposition or to wait for more information.

Following a decision theory approach, model C decides whether it would be better to preposition now, or to wait for more information. In order to do this, there would need to be a comparison between the cost of the prepositioning strategy under the perfect information (model A) vs the cost of the prepositioning strategy under uncertainty (model B). This comparison would give the cost of wrongly prepositioning. The cost of wrongly prepositioning is then compared to the cost of waiting for more information which is derived from the comparison of the model under uncertainty (model B) and the model under projected cost parameters (model B_0). Furthermore, before recommending a decision, the model C also takes into account the response time outputs of the perfect information (model A) and the model under uncertainty (model B). After taking into consideration the comparisons between the three models (A, B, and B_0), the model C recommends the decision to either wait or preposition using the current forecast information. The formulation and a more extensive discussion of each model would follow in the next sections.

1) Notation (Model A, B, and B_0)

a) Indices

s	supply nodes
d	demand nodes
p	scenarios
o	objective

b) Parameters

PS_p	probability of scenario *p*
XNI_s	initial level of storage at supply node *s*
$TCsd_{sd}$	unit transfer cost from supply node *s* to demand node *d*
$TCss_{ss'}$	unit transfer cost from supply node *s* to *s'*
$TCms_s$	unit transfer cost from MDC to supply node *s*
PC_d	unit post disaster expedited cost for demand node *d*
SC_s	setup cost of supply node *s*
$SNCAP_s$	capacity of supply node *s*
DN_{dp}	quantity of demand in node *d* at scenario *p*
PR_d	post disaster expedited response time for demand node *d*
$LCAP_{sdp}$	effective link capacity from supply node *s* to demand node *d* at scenario *p*
ADN_d	quantity of demand in node *d* under assumption of a known scenario
$ALCAP_{sd}$	effective link capacity from supply node *s* to demand node *d* under assumption of a known scenario

2) Variables

a) Decision Variables

XN_s	level of storage at supply node *s*
$XTsd_{sdp}$	amount of goods to transfer from supply node *s* to demand node *d* at scenario *p*
$XTss_{ss'}$	amount of goods to transfer from supply node *s* to *s'*
$XTms_s$	amount of goods to transfer from MDC to supply node *s*
$AXTsd_{sd}$	amount of goods to transfer from supply node *s* to demand node *d* under assumption of a known scenario

b) System Variables

Z_o	objective function value for objective *o*
• Z_1	total cost
• Z_2	maximum response time
• Z_3	weighted response time
PD_{dp}	level of penalized demand at demand node *d* at scenario *p*
LRT_{sdp}	link response time from supply node *s* to demand node *d* at scenario *p*
PRT_{dp}	post disaster expedited response time for demand node *d* at scenario *p*
DRT_{dp}	demand node response time for demand node *d* at scenario *p*
APD_d	level of penalized demand at demand node *d* under assumption of a known scenario
$ALRT_{sd}$	link response time from supply node *s* to demand node *d* under assumption of a known scenario
$APRT_d$	post disaster expedited response time for demand node *d* under assumption of a known scenario
$ADRT_d$	demand node response time for demand node *d* under assumption of a known scenario

c) Binary Variables

SNO_s	1 if supply node *s* is opened, 0 otherwise
YP_{dp}	1 if the level of penalized demand is greater than zero in scenario *p*, 0 otherwise
AYP_d	1 if the level of penalized demand is greater than zero under assumption of a known scenario, 0 otherwise

B. Model A

Model A attempts to jointly optimize the costs and response times when the scenario is known. The purpose of this model is to give the best possible solution since there is no uncertainty involved (perfect information). At the beginning of every time period, Model A is solved for all the remaining possible scenarios.

The input for this model would correspond to the initial position of the goods, parameters which correspond to various costs, and parameters which define each scenario, such as the effective capacity of the links and the quantity of demand. The output of the model would be the optimal level of storage at each supply node, as well as the quantities of goods to transfer from each node in order to achieve its objectives given a particular scenario.

1) Objective Functions

Equation (1) represents the objective function which minimizes the total costs. The first three terms represent the various transfer costs. The first term represents the transfer costs from the main distribution center to the supply points, the second term represents the transfer costs between supply nodes, and the third represents the transfer costs from the supply node to the demand nodes. The fourth term represents the post disaster expedited cost for the demand not met by prepositioning activities. The post disaster expedited cost corresponds to the cost of necessary actions or resources needed to satisfy the demand such as more expensive modes of transportation for logistics or more manpower and vehicles to facilitate transfer of goods in the post disaster if the prepositioned goods wasn't enough. This ensures that the demand would always be satisfied. The last term represents the setup costs of setting up a new supply point.

$$Minimize\ Z_1 = \sum_{s}(TCms_s)(XTms_s) + \sum_{ss'}(TCss_{ss'})(XTss_{ss'}) + \sum_{sd}(TCsd_{sd})(AXTsd_{sd}) + \sum_{d}(PC_d)(APD_d) + \sum_{s}(SC_s)(SNO_s) \quad (1)$$

Equation (2) represents the objective function which minimizes the maximum response time for any demand node. This is linearized by the form of (3).

$$Minimize\ Z_2 = \max_{d}\{ADRT_d\} \quad (2)$$

$$Z_2 \geq ADRT_d \quad \forall d \quad (3)$$

Equation (4) represents the objective function which minimizes the response time by using the quantity of demand as weights. Both (2) and (4) will be used in considering the response time, however they differ in assumptions. Equation (2) assumes that all demand nodes are equal in weight and the maximum response time for all demand nodes should be minimized despite possibly delaying nodes with larger quantities of demand. Equation (4) on the other hand assumes that the response time should be weighed according to the demand quantity despite possibly accumulating large delays in the nodes with smaller

demand quantity. The consideration of minimizing both (2) and (4) avoids the situation wherein the average response time is low, but there is a single response time that is high and the opposite wherein the maximum response is low, but the average of the response time of all the demand is high.

$$Minimize\ Z_3 = \frac{\sum_d [(ADN_d)(ADRT_d)]}{\sum_d ADN_d} \tag{4}$$

2) Constraints

Equation (5) defines the level of storage for each supply node as the initial level of storage (1st term) in addition to the amount of goods being transferred from the main distribution center to the supply points (2nd term) and the net of the amount of goods being transferred to and from other supply nodes (3rd and 4th term).

$$XN_s = XNI_s + XTms_s + \sum_{s'} XTss_{s's} - \sum_{s'} XTss_{ss'} \quad \forall s \tag{5}$$

Equation (6) ensures that the amount of goods transferred from each supply node to the demand nodes does not exceed the level of storage at that supply node.

$$XN_s \geq \sum_d AXTsd_{sd} \quad \forall_S \tag{6}$$

Equation (7) ensures that the supply node must be opened in order to preposition goods in that supply node. It also ensures that the level of storage does not exceed the capacity of the supply node.

$$XN_s \leq (SNCAP_s)(SNO_s) \quad \forall s \tag{7}$$

Equation (8) ensures that the demand node is satisfied through either the transfer of goods from the supply nodes, or through other means (post disaster expedite).

$$ADN_d \leq APD_d + \sum_s AXTsd_{sd} \quad \forall d \tag{8}$$

Equation (9) ensures that response time for each node takes into consideration the response time of the post disaster expedited units.

$$APRT_d = (PR_d)(AYP_d) \quad \forall d \tag{9}$$

Equation (10) provides the relationship that forces the binary variable AYP_d to be 1 if there is demand for post disaster expedited units. In this case, the summation of all the demand is used as a sufficiently large number to enforce this.

$$APD_d \leq (AYP_d)\left(\sum_d ADN_d\right) \quad \forall d \tag{10}$$

Equation (11) defines the link response time as the amount of goods transferred through the link divided by the effective capacity of the link each period.

$$ALRT_{sd} = \frac{AXTsd_{sd}}{ALCAP_{sd}} \quad \forall s, d \tag{11}$$

Equation (12) defines the response time for each demand node as the maximum response time it takes to satisfy the demand, through either the links or post disaster expedited activities. This is linearized by (13) and (14).

$$ADRT_d = \max_s\{ALRT_{sd}, APRT_d\} \quad \forall d \tag{12}$$

$$ADRT_d \geq ALRT_{sd} \quad \forall s, d \tag{13}$$

$$ADRT_d \geq APRT_d \quad \forall d \tag{14}$$

The remaining constraints (15) and (16) define the variables according to their respective types. These are binary variables for (15) and, nonnegative variables for (16). For the binary variable definition $SNO_{s'}$, this is fixed to have a value of 1 if it is opened already in the previous periods. This relationship is seen in (17) and is implemented in between runs of each period.

$$SNO_s,\ AYP_d \in \{1,0\} \quad \forall s,d \tag{15}$$

$$XTms_s;\ APD_d;\ APRT_d;\ ADRT_d;\ ALRT_{sd};\ AXTsd_{sd};\ XTss_{ss'} \geq 0 \quad \forall s,s',d \tag{16}$$

$$SNO_{st} \geq SNO_{s(t-1)} \quad \forall s,t \tag{17}$$

C. Model B and B_0

Model B attempts to jointly optimize the costs and response times under uncertainties which are modelled through scenarios. The purpose of this model is to give the solution under uncertainty. Model B is solved at every time period and considers all the remaining possible scenarios.

The input for this model would correspond to the initial position of the goods, parameters which correspond to various costs, the parameters which define each scenario such as the effective capacity of the links and the quantity of demand, and the probabilities for each scenario. The output of the model would be the optimal level of storage at each supply node, as well as the quantities of goods to transfer to supply points from the MDC and the other supply points, and also the best way to use the stored goods at each particular scenario which refers to the quantity of goods to transfer from the supply points to the demand points.

Model B has a variation called model B_0 wherein Model B is solved with an additional input. The only difference of model B_0 with model B is the inputs. The additional input for model B_0 would be the cost information projected for the following time period, t+1. The purpose of model B_0 is to determine the cost of gaining more information. The difference between Model B and B_0 would be the input of using pre-disaster expedited transportation costs.

Model B and B_0 are derived from the previously formulated Model A. The inclusion of the scenarios, indexed *p*, is the major relevant difference, as it forces the model to solve while giving consideration to the different possible scenarios, each with a probability, PS_p.

1) Model Summary for B and B_0

$$Minimize\ Z_1 = \sum_s (TCms_s)(XTms_s) + \sum_{ss'} (TCss_{ss'})(XTss_{ss'}) + \sum_{sdp} (PS_p)(TCsd_{sd})(XTsd_{sd}) + \sum_{dp} (PS_p)(PC_d)(PD_{dp}) + \sum_s (SC_s)(SNO_s) \tag{18}$$

$$Minimize\ Z_2 = \max_{dp}\{DRT_{dp}\} \tag{19}$$

$$Minimize\ Z_3 = \frac{\sum_{dp}(PS_p)(DN_d)(DRT_{dp})}{\sum_{dp}(PS_p)(DN_d)} \tag{20}$$

Subject to:

$$Z_2 \geq DRT_{dp} \quad \forall d,p \tag{21}$$

$$XN_s = XNI_s + XTms_s + \sum_{s'} XTss_{s's} - \sum_{s'} XTss_{ss'} \quad \forall s \tag{22}$$

$$XN_s \geq \sum_{dp} XTsd_{sdp} \quad \forall_{s,p} \tag{23}$$

$$XN_s \leq (SNCAP_s)(SNO_s) \quad \forall s \tag{24}$$

$$DN_{dp} \leq PD_{dp} + \sum_s XTsd_{sdp} \quad \forall d,p \tag{25}$$

$$PRT_{dp} = (PR_d)(YP_{dp}) \quad \forall d,p \tag{26}$$

$$PD_{dp} \leq (YP_{dp})\left(\sum_d DN_{dp}\right) \quad \forall d,p \tag{27}$$

$$LRT_{sdp} = \frac{XTsd_{sdp}}{LCAP_{sdp}} \quad \forall s, d, p \tag{28}$$

$$DRT_{dp} = \max_{s}\{LRT_{sdp}, PRT_{dp}\} \quad \forall d, p \tag{29}$$

$$DRT_{dp} \geq LRT_{sdp} \quad \forall s, d, p \tag{30}$$

$$DRT_{dp} \geq PRT_{dp} \quad \forall d, p \tag{31}$$

$$SNO_s;\ YP_{dp} \in \{1,0\} \quad \forall s, d, p \tag{32}$$

$$DRT_{dp};\ PRT_{dp};\ LRT_{sdp};\ PD_{dp};\ XTms_s;\ XTsd_{sdp};\ XTss_{ss'} \geq 0 \quad \forall s, s', d \tag{33}$$

$$SNO_{st} \geq SNO_{s(t-1)} \quad \forall s, t \tag{34}$$

D. Model C

Model C attempts to minimize the cost of wrongly prepositioning and the cost of waiting for more information. It also takes into account the minimization of the maximum and the average response time. Model C is solved at every time period and decides whether to implement the prepositioning activities described by Model B or to wait for further information without implementing any prepositioning activities at all.

The input for model C would correspond to the costs and response times of prepositioning activities as described by Model A, Model B, and Model B_0. The output of the model would simply be the decision as to implement prepositioning activities or to wait and postpone decisions.

1) Notation

a) Parameters

PS_p	probability of scenario *p*
$CostA_p$	minimum cost value of "Model A" at scenario *p*
$CostB$	minimum cost value of "Model B" under implementation of prepositioning
$CostB_0$	projected minimum cost value of "Model B" using estimated expediting costs
$MaxRTB$	minimum maximum response time of "Model B" under implementation of prepositioning
$MaxRTA$	average of the minimized maximum response time of "Model A"
$AveRTB$	minimum average response time of "Model B" under implementation of prepositioning
$AveRTA$	average of the minimized average response time of "Model A"

b) Binary Variable

YW	1 if prepositioning activities will be postponed, 0 otherwise

2) Objective Function

Equation (35) defines the objective function of minimizing the costs of wrongly prepositioning and the cost of waiting for further information. The first term defines the cost of wrongly prepositioning as the cost output of Model B compared to the ideal cost described in Model A at each scenario. The average of this is weighed by the probabilities of each scenario. The second term represents the cost of waiting, in which the prepositioning activities described in Model B is compared to the expedited costs of similar activities at a later time period.

$$Minimize\ Z_1 = (1 - YW)\sum_{s}[(CostB - CostA_p)(PS_p)] + (YW)(CostB_0 - CostB) \tag{35}$$

These are based on the assumptions that the worst case is that the information is complete for the next period and thus waiting was a missed opportunity (for the first term of the cost), or that it remains the same at the next time period, and the optimal prepositioning activities will remain relatively similar and therefore incurring expediting costs without much benefit.

Equations (36) and (37) represent the maximum and average response times respectively of doing the prepositioning activities or waiting. Similar to the cost objectives, the worst case for prepositioning now is when the next update gives perfect information such as in model A. The same is thus assumed in the formulation. The definition of these response times are given in (39) and (40). On the other hand, prepositioning now gives the response times taken from model B.

$$Minimize\ Z_2 = (1 - YW)(MaxRTB) + (YW)(MaxRTA) \tag{36}$$

$$Minimize\ Z_3 = (1 - YW)(AveRTB) + (YW)(AveRTA) \tag{37}$$

3) Constraints

$$MaxRTA = \sum_p (PS_p)(Z_{A2p}) \tag{38}$$

$$AveRTA = \sum_p (PS_p)Z_{A2p}) \tag{39}$$

Constraint (40) simply defines the nature of the decision variable as binary. In the objective function, if it takes on a value of 1, then the cost of waiting is lower or the response time does not improve very much from prepositioning activities, and therefore prepositioning activities should be postponed, while if it takes on a value of 0, then the cost of wrongly prepositioning is smaller, it is better to implement prepositioning activities earlier.

$$W \in \{1,0\} \tag{40}$$

E. Multi Objective Optimization

Linear physical programming (LPP), developed by [26], is the method that was used in solving the multiple objective optimization problem. Physical programming provides a way to capture a decision maker's preferences without the need for specifying weights. This is done by specifying physical values for the preferences then separating the normalization and preference formulation with the use of criterion functions. Physical programming defines ideal, desirable, tolerable, undesirable, and unacceptable ranges for individual objectives. This allows decision makers to not have to go through the trouble of specifying weights that may be hard to quantify (weighted sum approach). Furthermore, while goal programming can also specify a physical value, physical programming can capture more comprehensively the preferences of the decision maker as opposed to that of goal programming [27].

The three objectives (cost, maximum response time, and average response time) formulated in the models are used to form an aggregate objective with the application of LPP. The class functions of all three objectives belong to class 1S (smaller the better). By applying the LPP weights algorithm, the three objective functions will be normalized. This allows a weighted deviation to be minimized in the aggregate objective function.

The formulation of [26] for the LPP is presented wherein the objective function (41) minimizes the sum of the incremental weighted deviations from the target values provided by the decision maker. These are subject to the constraints (42) to (45), which define the relationship of the deviation, the objective function, and the target values.

$$Minimize\ AOF = \sum_{oc} (\overline{w}_{oc})(dev_{oc}) \tag{41}$$

Subject to:

$$Z_o - dev_{oc} \leq trgt_{o(c-1)} \quad \forall (o > 1), (c < 5) \tag{42}$$

$$Z_o \leq trgt_{o(c-1)} \quad \forall (o > 1), (c = 5) \tag{43}$$

$$Z_o - dev_{oc} \leq trgt_{o(c-1)} - Cost_{prev} \quad \forall (o = 1), (c < 5) \tag{44}$$

$$Z_o \leq trgt_{o(c-1)} - Cost_{prev} \quad \forall (o = 1), (c = 5) \tag{45}$$

A change in the first objective function, which reflects the cost must be made in order to account for historical costs incurred from the previous time periods. While these are sunk costs, these must be appropriately reflected into the preference given by the decision maker and thus subtracted from the target values. The constraints and objective functions from models "Model A", "Model B", "Model B_0", or "Model C" are plugged in as additional constraints to the LPP formulation to obtain an LPP formulation of the respective models.

In addition, a change has to be made to Model C, where the objective function (35) must be scaled in order to be comparable with the target values set by the decision maker as shown in (46). This is done by using the cost obtained from "Model B" for the case where prepositioning is recommended and the cost from "Model B_0" for the case where it is not. This allows the incremental costs being compared to become also compatible with the LPP formulation.

$$Z_1 = (1 - YW)\left[CostB + \sum_s \left(CostB - CostA_p\right)\left(PS_p\right)\right] + (YW)\left[CostB_0 + (CostB_{0)} - CostB)\right] \tag{46}$$

F. Model Operationalization

Forecasts are updated with some time interval. Due to this, the models developed need to be run every time there is a new forecast. First, the preferences of the decision maker must be input to all models and then the LPP weight algorithm would have to be solved. Model A would then be solved for all scenarios. Model B would also be solved with the solution and costs potentially incurred by model B being stored. The projected cost parameters are input in order to solve B_0. The solution of the model B_0 is then stored.

Finally, all the stored values of models A, B, and B_0 would be input to model C for solving. Model C is then solved. After model C is solved, the model would give a decision regarding whether it is beneficial to preposition or to wait for more information. If the model's decision is to preposition, the initial level of storage (XNI_s), the historical cost ($Cost_{prev}$), and the cost parameters are updated for the next period. If the models' decision is to wait for more information, only the cost parameters are updated. After solving, the next time period will update the scenario probabilities and the models would need to be solved again. If it is the last time period, the process ends.

IV. RESULTS

The value of waiting for a more accurate forecast comes at the expense of higher logistic costs due to a shorter lead time. Moreover, the more accurate the information, the better the prepositioning strategy will be in terms of response time. Furthermore, the models developed allow the decision maker to provide their preferences regarding the objectives. The conflicting nature of the objectives and the inclusion of preferences calls for the analysis of the effect of the preferences regarding objectives.

Figure 1, show the cost vs the response time with respect to the different preferences. The orange and blue point represent the point wherein this is the optimal value that the system can achieve given that it is a single objective problem. The two leftmost points in the graph consist of the type of preference that placed an emphasis on the cost. The two points in the middle consist of the type of preference that is balanced, while the two rightmost points consist of the preference that placed an emphasis on the response time. Here, it is seen that the preferences of the decision maker is important in determining the optimal solution. If the decision maker's preferences for the cost is generous, then the response would benefit. If the decision maker's preferences for the cost is restrictive, then the response would suffer.

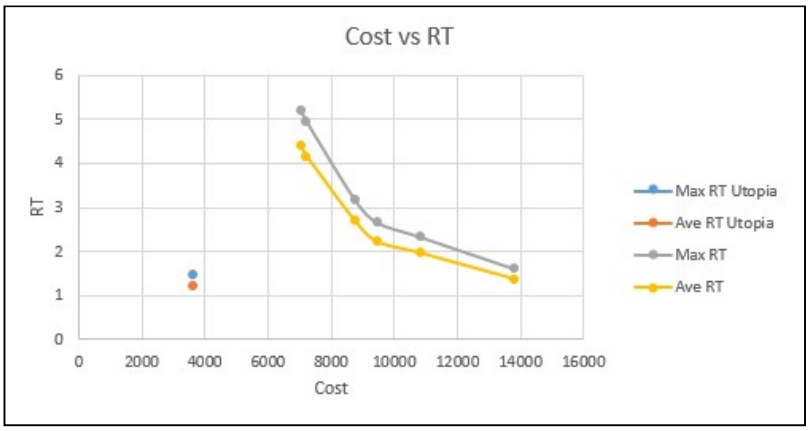

Fig. 1. Cost vs Response Time

If the decision maker ignores the response time and focuses on the cost, then the decision maker would not make an effort to improve the response time due to extra costs. The decision maker would be content with just ensuring that the demand points get the goods, and not on how fast they get the goods. This is because ensuring that the demand points get the goods fast would entail additional costs incurred by opening additional supply points, and the additional transferring of supplies.

Similarly, if the decision maker isn't concerned with cost, and is only concerned with response time, then the decision maker could just wait for the last and most accurate forecast before landfall and rush the prepositioning of goods. This would give the prepositioning strategy the best possible expected response time since the most accurate forecast was used, but it would also be the most costly since all the goods were rushed.

An important decision taken into account in the study is the decision to wait or to implement prepositioning activities immediately. The main factors identified for this decision were the uncertainty inherent in the forecasts and the expediting

costs. The probability of certain scenarios may be relatively smaller or larger compared to the probability of other scenarios, and the extent of this can be estimated by the standard deviation of the probabilities of all the scenarios.

As seen in fig. 2, the results of the runs based on the decision to preposition or to wait can be plotted for the different expediting costs and the generated probability sets. The results indicate that there is a balance that is struck between the two, with the recommendation favoring the decision to preposition when expediting costs are higher and there are less evenly distributed probabilities; and favoring the decision to wait when the expediting costs are lower and there are more evenly spread probabilities between the scenarios.

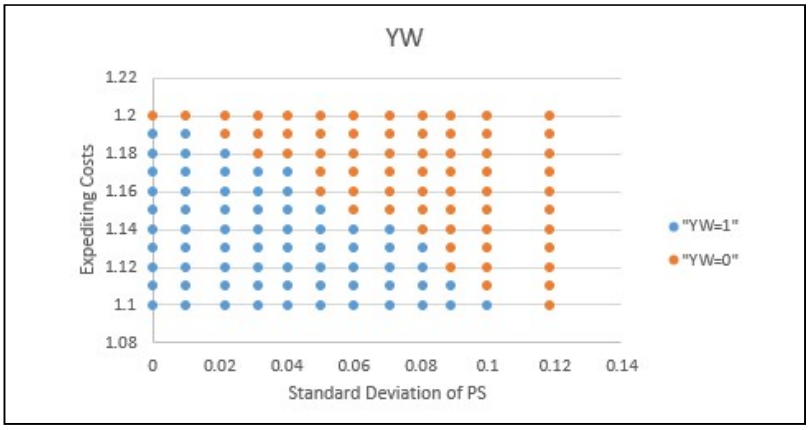

Fig. 2. Waiting vs Prepositioning

V. Conclusions and Recommendations

Relative to other disasters such as earthquakes, tornadoes, or terrorist attacks, tropical cyclones benefit from numerous forecasts before its landfall. These forecasts increase in accuracy as the storm evolves from its initial development. Furthermore, the length of the planning horizon can also be identified. These characteristics make planning, particularly prepositioning for an incoming storm, ideal.

The models developed provide a framework for prepositioning under information updates with the consideration of network uncertainty. The updates in the information not only give the potential demand and location of it, but also the potential effect of the tropical cyclone to the links in the affected area. This paves the way for preparation for disruptions in the links which would affect the post disaster distribution of goods. The consideration of network uncertainty provides a conflicting tradeoff with the usually minimized objective in prepositioning that is cost. While the minimization of costs is a necessary consideration as prepositioning is very costly, it is also important to consider the response time of the prepositioning strategy. The models developed, particularly "Model C", considers this tradeoff wherein the cost worsens through time, but the response improves.

The models developed allow the articulation of preferences by a decision maker through linear physical programming. This is particularly useful as decision makers have the power to control the decision of the model with their physical ranges of preferences. Moreover, decision makers could easily adjust their preferences to a cost heavy preference, response heavy preference, or a balanced preference depending on their situation.

The models presented provide an initial research regarding the consideration of both response times and costs in a prepositioning strategy that considers information updates. Listed below are the possible extensions that could be done in future studies.

- Consideration of multiple commodities

The models developed cater only to a single commodity. Incorporating multiple commodities would be more realistic and could provide interesting situations regarding the preferences and response times. This is particularly the case when the multiple goods being considered consists of food vs. clothes. Clothing could be needed by the affected area, but it might not as urgent as food. Thus, the decision maker could opt to delay the response times of clothing in exchange for faster response on food.

- Limited supply from the MDC

In the system developed, it is assumed that the main distribution center would never run out of stock. In other words, the supply is unlimited. Consideration of a limited supply from the MDC would be a more realistic approach.

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