CHARACTERIZING AND PLANNING FOR KEY LOGISTIC OBSTACLES IN FOOD BANKS OPERATIONS AFTER HURRICANE EVENTS

by

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DEDICATION

To my family, friends, and teachers

for their unyielding love, patience, and encouragement.

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ABSTRACT

Food banks are non-profit, charitable organizations that distribute food and products to people in need. Food bank facilities receive donations from public and private agencies and distribute them with the help of city organizations, agencies, and volunteers. Natural disasters, such as hurricane Harvey, have exposed the complexities and challenges associated with those tasks. Food bank facilities become disaster relief centers for affected communities after natural disasters. These facilities typically experience an increase in product demand and an increase in the volume of donations after the impact of a natural disaster. Disaster response involves the planning, coordination, and distribution of supplies in an effective manner to the affected population. The goal of this research is to analyze and forecast the amount of donations received by food bank facilities impacted by natural disasters. A stochastic programming model is also presented which considers prepositioning strategies among food bank facilities located in high risks areas for hurricanes.

The first part of this thesis analyzes the donations received by two food bank facilities affected by hurricane Harvey in 2017. An extensive numerical study is performed that compares the donation behavior at each facility before and after the hurricane event. Multiple forecasting models are evaluated to determine their accuracy in predicting the observed behavior. The results deduced from this part can be used to develop policies that can help in planning for future events. Predictions for total food donations provided least mean absolute percentage error for the analysis. Predictions

using econometric model too provided least error for Houston Food Bank for disaster relief period.

The second part of this thesis proposes a stochastic model that considers the uncertainty associated with the impact of the hurricane at each facility in terms of the number of available supplies, donations received at the facility, and the expected demand for their service region. The first-stage decisions attempt to minimize the number of people not receiving the needed supplies by prepositioning the existing supplies at each facility. Second-stage decisions maximize the system responsiveness by trying to satisfy the observed demand for the scenarios under consideration such that unmet demand is minimized. The experiments consider scenarios in which one or two food bank facilities are shut down after the disaster and study the impact of prepositioning supplies. Analysis revealed unmet demand observed for the experiments conducted. The implementation of this model can have a global outreach by minimizing the damage due to any natural disaster by making key food allocation decisions and having an ideal response strategy.

1. INTRODUCTION

Food insecurity is the result of people having limited access to nutritious food for a healthy life. Food bank facilities strive to counteract the effects of food insecurity by providing food and first necessity products to people in need. Food banks are non-profit organizations that collect and distribute needed supplies to people in need. They solicit and stock donations from community, private, and government sources; store these items in a warehouse; and distribute donations through local organizations. Food banks often support people by providing other products such as cleaning supplies and diapers. Catastrophic natural events have been on the rise over the past few years causing tremendous loss of life and property. To minimize the damage arising after a natural disaster, government, private and non-profit organizations provide assistance to people affected by the event in terms of food and first need products. Food bank facilities also become disaster relief centers for affected communities after natural disaster events. The donation-driven environment of food bank facilities complicates the problem of matching supply with demand. The problem becomes more challenging when the facility needs to serve the additional demand caused by natural disasters. Their role and responsibility increase during disasters as they have more population to support and may experience uncertainty in the amount of donations received at the facility.

The goal of this research is to analyze and forecast the amount of donations received by food bank facilities impacted by natural disasters followed by making decision making models that aid in supply-demand management during calamity. Natural disaster events impact communities in multiple ways, including the loss of life, material possessions, and homes. These events result in long lasting consequences which could take up to several years for the affected region to recover. Thus, the planning for disaster relief plays a pivotal role in minimizing these adversities and in helping people get back on their feet. In this thesis, a comprehensive statistical analysis is performed to quantify the extent of variability in terms of donors, product, and pounds per donor in food banks.

The first objective of this research is to analyze the donation behavior at two separate food bank facilities that were affected by Hurricane Harvey. The two facilities are the Houston Food Bank (HFB) and the Central Texas Food Bank (CTFB) located in Austin, Texas. Several published studies examine the challenges faced by food bank facilities and their unpredictable supply [1]. However, to the best of the authors knowledge, the use of statistical analysis techniques to analyze and compare the donation supply uncertainty in food bank facilities impacted by natural disasters has not been addressed in literature. The resulting models will provide insight and valuable information that will increase the potential of non-profit organizations to meet their objectives. The results will enable food banks to better predict the type, quantity, frequency, and source of donations to expect during natural disasters.

The second goal of this thesis is to develop a decision-making model that considers the uncertainty when coordinating the distribution of supplies for emergency relief. The model considers the uncertainty associated with the impact of the hurricane on a network of food banks in terms of the number of available supplies, donations received per facility, and the expected demand for their service region. In this research, a model is proposed to address the supply and demand coordination problem as it relates to the pre-positioning of needed supplies. Pre-positioning are activities performed prior to the predicted natural disaster event, in which locations are selected to store human or material assets in preparation for disaster relief. The idea is to prepare the supply chain for quick distribution to satisfy the demand post-event. The proposed model will identify the least-cost strategy associated with pre-positioning existing supplies that will satisfy the demand needs after a natural disaster.

The food bank donation-driven environment complicates the classic supply chain dilemma of matching supply with demand. For instance, supply uncertainty exists because the facility does not know in advance the frequency, amount, and quality of donated items. In terms of demand, the uncertainty occurs because estimates of food need are driven by complex factors related to poverty, unemployment, and disaster relief events. Donation-driven environments such as food banks are considerably different from commercial supply chains which typically prize greater speed and/or cost effectiveness to generate increased profits. Even though food bank supply chains wish to rapidly move items to individuals in need in an effective manner, the principal goal is not profit driven. As non-profit organizations, food banks search for maximizing assistance.

Current research addressing food banks operations explains that greater efficacy during emergencies is achieved by establishing partnerships before the arrival of the expected natural disaster event [1]. Early planning contributes to prompt recovery after disasters primary because it addresses some of the events unknows and because it establishes cooperative efforts among multiple agencies early in the process. In addition, early planning facilitates the involvement of local and international agencies to form part of the recovery process of disaster-prone areas [2, 3].

The deliverables mentioned in this thesis are substantial as it will benefit the non-profit organizations, such as food banks, to enhance their operational effectiveness for disaster relief efforts and normal operations. This study has significant merit because it is important for food bank organizations to have access to better models and technology to improve their operational effectiveness during both, normal and disaster relief conditions. Equipping these facilities with better predictive information on supply donation behavior will allow them to make informed downstream distribution decisions. The models are built considering the normal operations and disaster-relief period. The outcomes can be replicated by any food bank or non-profit organization to predict the donations and make key decisions such that damage is minimized, and more population is served.

1.1. Thesis outline

This thesis is structured as follows. Chapter 2 reviews literature closely associated to the goals of this research. It is explained in two sections; the first section explores the previous work done on donation behavior at food banks and forecasting models studied, and the second section studies the uncertainty and related to decision making. Chapter 3 states the followed methodology to analyze estimate the donation behavior at two food bank facilities using times series models. The donation data is analyzed, and forecasting models are built to understand the donation behavior. Chapter 4 discusses the stochastic programming model used to assist on the decision-making process by optimally allocating resources during hurricanes. The chapter mentions the prepositioning model and the response stage decisions to be considered before and after hurricane. Section 6 states the conclusion and discusses the implications of the obtained results in the planning and operation of food bank facilities and also steers the potential future scope.

2. LITERATURE REVIEW

The literature review for this thesis is detailed according to the sections addressed. Section 2.1 reviews the literature reviewed for analyzing the time series models pertaining to forecasting donations for food bank. Since food donations are a major component for a food bank, this section focuses in aspects that are similar to the objectives stated. Section 2.2 discusses the literature on stochastic programming models targeted at resource allocation before and after the occurrence of hurricane. This section encapsulates the challenges faced while making decisions during hurricanes and the different factors involved while determining the right distribution.

2.1. Analyzing donations and time series model

A group of papers in the public policy and health literature examine the challenges associated with the operation of food banks including limited and unpredictable supply [4-6], nutritional initiatives [7, 8], and the impact of donations [9, 10]. However, to the best of the authors knowledge, food banks operational challenges and supply chain uncertainty after natural disasters, such as hurricanes, has not been addressed.

After natural disasters, food banks usually deal with a large influx of small and sometimes random donations. Planning for the appropriate allocation and use of those donations is challenging. Several studies have documented the negative effect of in-kind donations. For instance, Van Wassenhove [11] and Holguín-Veras et al. [12] state that management of these donations require moving volunteers from other important tasks to sort and inspect low priority donations. These challenges are often caused by the lack of advanced knowledge about the type and timing of the in-kind donations. Currently, in-kind donations are mostly treated as known inputs in the literature and then focusing on strategies to effectively use these donations further downstream [13, 14]. However, the management of in-kind donations is critical for the effective operation of food banks after natural disasters.

Only some published studies address the problem of dealing with the uncertain behavior of in-kind food and product donations. Most of these studies utilize well-known probability distributions to estimate donation quantities and then use this information to build simulation models to assess operational decisions. For instance, Mohan et al. [15] recommends the best layout configuration to improve the flow of donated food from receipt to storage. Phillips et al. [16] develop routing schedules to pick-up donations from local supermarkets. Sönmez et al. [17] also studies the problem of scheduling collection during a finite planning horizon.

Current research addressing food banks operations explains that greater efficacy during emergencies is achieved by establishing partnerships before the arrival of the expected natural disaster event [1]. Early planning contributes to prompt recovery after disasters primary because it addresses some of the events unknowns and because it establishes cooperative efforts among multiple agencies early in the process. In addition, early planning facilitates the involvement of local and international agencies to form part of the recovery process of disaster-prone areas [2, 3]. As reported in the natural disaster response literature, these agreements or partnerships should be formed within the first two phases of the disaster management process which are mitigation and preparedness [18]. Planning such partnerships or agreements is a challenging task since supporting agencies have limited resources and because multiple areas associated with the recovery process could require some level of partnership. However, it is important to develop methods to generate at least a functional level of cooperation with the agencies in the response efforts [19]. To achieve sustainable and productive partnerships with agencies, it is necessary to understand the dynamics and outcomes of the natural disaster and their impact in the food bank operations.

2.2. Stochastic Decision-Making model

Stochastic decision-making models have been applied to multiple settings including healthcare [20-22], wind energy [23, 24], manufacturing [25-27], and humanitarian logistics. Resource pre-positioning is not a new concept and has been applied in the military for quite some time [28]. However, lately the concept is becoming more promising as an effective strategy for planning the response to natural disasters. Humanitarian logistics research can be classified based on the nature and timing of the decisions to be made. (preparedness vs. post-event relief). The decisions can address distribution of relief supplies [29, 30], stocking of relief supplies [31, 32], or location of supply centers [33]. For instance, [31] focus on inventory planning for an humanitarian emergency. Authors in [34] consider supplies prepositioning for natural disasters while [32] include in their research information on hurricane intensity such as wind speed data and [35] develop a more comprehensive model incorporating location, inventory and distribution decisions for a multi-product system.

The studies in [29], [30], [33], focus on post disaster relief response. The work in [33] is to develop a model to determine the location of medical services during large scale emergencies. The authors classify large-scale emergencies as those that have a sizeable and sudden volume of demand and low frequency of occurrence. They present two parameters to describe this uncertainty and suggest location models to (1) maximize the demand to be covered by a group of facilities, (2) minimize the demand weighted distance between the new facilities and the demand points, and (3) minimize the maximum service distance. Contribution [35] also integrates location choices in their model. They study a multi-commodity pre-positioning and location problem to fulfill the requests resulting from a hurricane. The goal is to discover the number of new facilities to open, the dimension of the facilities and the acquisition quantities related with the three commodities considered. The problem is framed as a stochastic mixed integer programming model with uncertainty in demand, damage to roads, and damage to facilities determined from hurricane scenarios. [36] considers the damage done to roads and the impact of transportation limitations in the disaster relief response. The author addresses the problem using sample average approximation to help make policies that could help make policies that may be applicable for preparing against potential disasters. [37] states that inventory plays a pivotal role during the disaster times. The author asserts that disaster relief inventory has uncertainties involved and proposes a framework based on responding, locating, and controlling the inventory.

The work presented in this thesis complements the work done in this area and builds on the work of [34] and [35]. The proposed model incorporates the uncertainty associated with the impact of the hurricane at a network of food banks in terms of the number of available supplies, donations received at the facility, and the expected demand for their service region. Donations are categorized as regular donations and disaster-relief donations to understand their impact in the recommended decisions. The proposed model provides further insights to the donation behavior that influences decision-making in disaster relief.

3. ANALYZING DONATION BEHAVIOR AND TIME SERIES MODELS

This chapter is aimed at developing time series models by studying the historical data of food donations provided by food banks. This study involves applying various times series models to the observed data to develop predictions. The predictions are then evaluated using statistical computational methods to evaluate the best model. The forecasting models are created for two scenarios, the former being for a non-disaster period and the latter being for a disaster relief period. The goal of this section is to determine which forecasting model would work best for the defined class.

3.1. Methodology

3.1.1. Problem background

The data for this research was provided by the Houston Food Bank (HFB) and the Central Texas Food Bank (CTFB) located in Austin, Texas. Both facilities provided data for two years, 2016 and 2017. The Houston Food Bank serves about 18 counties in the Southwest Texas area and distributes approximately 104 million nutritious meals through its network of 1500 community partners in Southeast Texas. The facility serves about 800,000 individuals each year [28].

The Central Texas Food Bank located at Austin, Texas is among the fastest growing food banks in the nation [38]. With the help of 21 Partner Agencies in 21 counties across Central Texas, it provides more than 39.2 million pounds of food to families per year, at an average of 200,000 individuals each month. Both the Houston Food Bank and the Central Texas Food Bank are members of Feeding America [30], a non-profit organization with a nationwide base of over 200 Food Banks feeding approximately 46 million people through food pantries, soup kitchens, shelters, and other community-based agencies.

After Hurricane Harvey passed the Houston area on August 27, 2017, food banks just outside the disaster zone worked overtime to support the Houston area refugee shelters. For instance, the Central Texas Food Bank in Austin TX was operating at full capacity and under challenging circumstances to support the recovery efforts in the Houston area. The food bank goal was to support the Houston community while also serving individuals in need in Central Texas. However, since these two food banks have never operated after a major disaster like Hurricane Harvey, the decisions of what, when, how, and where to send the needed assistance were made with limited information. The lack of data to support operational decisions minimized the impact of the disaster relief effort.

This research seeks to develop an understanding of the donations received in food bank facilities before and after natural disasters. The information provided by the food bank facilities includes the name of the donor, the date, type of donor, type of product donated, and quantity of the corresponding donation. Donors are categorized into twelve different types, and product donated is classified in eleven different types (Table 1). In order to understand the in-kind donation behavior, this research addresses these major questions: i) Does food donation behavior vary over time? ii) Does food donation behavior change as a function of donors, donor type, product, and product type? iii) Given information about the donor and product type, which information should be used to construct forecasts? iv) After analyzing the performance and behavior of donation data, which forecasting model provides most accurate results to quantify the incoming donations at the time of disaster?

To answer these questions, two years of data has been analyzed for both food banks. The data is then grouped according to the clusters defined in Table 1. Using these clusters, six forecasting methods are evaluated on these clusters to understand the behavior of times series. The results are then analyzed as a function of forecast accuracy and donation variability. The details of the approach are briefed in the following sections.

3.1.2. Data collection method

HFB and CTFB provided two calendar years of data. Each calendar year starts on January 1st and ends on December 31st. The data contains daily food donations receipts at both location by posting date. The Houston Food Bank database contains approximately 272,979 records whereas Austin's Central Texas Food Bank contains around 92,929 records, for both years combined. Each donation receipt has multiple fields including information about the donor and type of donation. However, in this study, only fields relevant for this research were considered. The relevant fields and clusters considered in this research are listed in Table 1. The quantity in pounds of product received from donors is recorded in amount field. Each donor corresponds to a particular donor type, as mentioned in the clusters and similarly each product type corresponds to a distinct product type accordingly. The data acquired over a span of two years has been analyzed weekly.

3.1.3. Descriptive donation behavior methods

Two food banks were considered in this study, Houston Food Bank and Central Texas Food Bank in Austin. The studied donation behavior was analyzed over two phases, pre-disaster phase and post disaster phase. This timeline separation allows to better understand the impact of natural disasters on food bank normal operations. In this study, the impact of Hurricane Harvey on the operation of food bank facilities located in central Texas is analyzed. The disaster period under consideration is the last week of August 2017. The donation behavior observed showed high variability after the disaster, affecting number of donors and quantity of donations. Variability is analyzed in terms of number of unique donors, total amount of donations and average donation per donor. Variability is assessed using coefficient of variation (CV). The coefficient of variation measures the uncertainty in a sample by expressing its standard deviation relative to its mean value ($\bar{x}$). It is computed as a ratio of standard deviation and sample mean as expressed in Equation (1).

$$CV = \frac{s_x}{\bar{x}} * 100 \qquad (1)$$

Table 1: Summary of key fields for donors

Field	Description	Levels
Donor ID	Unique identifier of the donor	
Donor type	Differentiates donor per industry	**Wholesaler**, **Manufacturer**, **Retailer**, **Corporate**/**Corporation,** **Government**, Foundations, Hotels/Kitchen/Restaurant, Schools/Church, Hospital/Healthcare/Banks/Event, Red Barrel, Individual/Family, Non-Profit/ Food Drives
Product type	Classification level for the donated food (e.g. produce)	**Meat/Fish/Poultry, Prepared and Perishable Food, Fresh Fruits and Vegetables, Packed food, Assorted Non-Food**, Pharmacy, Baby Food/Formula, Snack Food/Cookies, Water, Household Cleaning Product, and Pet Food/Pet Care
Food bank	The receiving location	Central Texas Food Bank, Houston Food Bank.
Posting date	The date the item was received in	

Field	Description	Levels
	the warehouse.	
Amount	The amount received in pounds.	

3.2. Predictive donation behavior methods

3.2.1. Clustering Approach

In this research, seven different class structures are defined to facilitate understanding of the forecasting information and its corresponding accuracy. The classes represent different information about the donations. The classes considered in this study include: (1) the donations for food bank, (2) donor type, (3) product type, (4) donor type and product type, (5) food bank and donor type, (6) food bank and product type, and (7) donor type along with product type for a food bank. Different combinations of product and donor types are analyzed for analysis considering both food banks. Table 2 lists the class structures analyzed in this study. C_i is an information class defined on characteristic i with members $c \in C_i$. Associated with each observation is a function that uniquely maps the observation to a member c in C_i. An information specific time series is built using the historical data according to the classes mentioned. A new time series consisting of donations from one specific class can be constructed. A subset of all combinations is explored in this research. The data is analyzed, at both food banks, with their corresponding donor and product type ranking. Disaggregation of the data according to a desired information class allows for analysis and prediction by donor, location, product type, or a combination thereof (donor and product). Disaggregation of data is essential as both food banks are of different capacity and volume. The selected donor type and product type vary per food bank as each have unique characteristic and different operating conditions. Also, since the donations are analyzed according to phases (before and after disaster), disaster relief operations might affect product demands at different locations, because equitable distribution of donated food is a concern and sharing across branches can ensure food equity among charitable agencies. Three major contributors of donor type and product type have been identified forming the classes for both food banks. The selected major contributors are used to form classes individually for both food banks. Data analysis is then conducted on each class for each food bank to build forecasts.

The splitting of data by different classes and combination of food bank, donor, and product type, enables better understanding and improves prediction models by different classes, as mentioned in this research. Analyzing the data by different component leads up to improved forecasting models and may prove to be an asset for food banks while dealing with natural disasters such as hurricane. As a result, the food banks would be in a better state to determine what kind of donations to expect from what donor type and plan accordingly. Also, the product type predictions can provide food banks with a head start to what food type could be donated and, consequently, allocate the stocks such that the supply matches the demand. It leads to a better planning and optimum utilization of resources during natural disasters; thus, serving majority of the population in need. For example, if the food bank receives more of packed food, then it can correspond with other food bank and/or agencies to manage the surplus quantity. Similarly, if a food bank is falling short of a particular type of product, at the time of disaster, other food banks can contribute to supplement the shortage. Combinations of different donors and product types help food banks to foresee what donations to expect from a particular type of donors.

In this work, the three major contributors in terms of donor type and product type were considered in the analysis for both food banks. The major **donor** contributors for Houston Food Bank before hurricane are *Retail*, *Government*, *Manufacturer*, *Wholesale*, and *Non-Profit*; while major **product types** are *Packed food, Produce food, Meat/fish/poultry food, Dairy/prepared/perishable food*, and *Water*. Major **donor** contributors for Central Texas Food Bank are *Retail*, *Company/Corporation*, *Manufacturer*, *Wholesale*, and *Non-Profit* donors, while **product types** are *Packed food*, *Produce food, Meat/fish/poultry*, *dairy/prepared/perishable food*, and *Assorted non-food products*.

The analysis for post disaster donation analysis shows *Government*, *Retail*, *Manufacturer*, *Company/Corporation*, and *Non-Profit* as top **donors** for Houston Food Bank whereas *Packed food*, *Produce*, *Water*, *Meat/Fish/Poultry*, and *Snack food* being top **product types**. *Retail*, *Company/Corporation, Manufacturer*, *Wholesale,* and *Hospital/Healthcare/Banks/Events* constitute top **donors** for CTFB while major **product type** being donated is *Packed food*, *Produce*, *Water*, *Meat/Fish/Poultry*, and *Assorted non-food*.

Table 2: Information class structure for donations

Class (C_i)	**Description**	**Class members { $c \vert c \in C_i$ }**
C_D	*Donor type*	***{Wholesaler***, ***Manufacturer***, ***Retailer***, ***Corporate/Corporation, Government***, *Foundations, Hotels/Kitchen/Restaurant, Schools/Church, Hospital/Healthcare/Banks/Event, Red Barrel, Individual/Family, Non-Profit/ Food Drives}*
C_P	*Product type*	*{**Meat/Fish/Poultry, Prepared and Perishable Food, Fresh Fruits and Vegetables, Packed food, Assorted Non-Food, Water**, Pharmacy, Baby Food/Formula, Snack Food/Cookies, Household Cleaning Product, Pet Food/Pet Care}*
C_F	*Food bank*	*{Austin, Houston}*
C_{DP}	*Donor type/Product type*	C_D *x* C_P

3.2.2. Exponential smoothing models

In general, forecasting models use subjective and/or objective information for the prediction of an outcome of one or more periods in the future. One highly used approach relies on past information as observed through a time ordered series. Numerous quantitative models are used to represent the relationship between past observations and future outcomes. This research employs two models based on exponentially weighted moving average (EWMA), also known as double and triple exponential smoothing, along with an econometric model. Table 3 lists the parameters definition for the models. The methods are elaborated in detail in [39].

Table 3: Parameters in forecasting models

Parameter	Description
$\hat{Y}_t$	denotes the supply forecast in time t
Y_t	denotes the observation of the supply in time t
Y_{tl}	denotes the observation of the supply at time t for previous period l
$\hat{X}_t$	denotes estimates of the level or systematic component
T_t	denotes estimates of the level or systematic trend
I_t	denotes estimates of the level or systematic seasonality
m	denotes the number of periods in the seasonal cycle
τ	denotes the number of periods in the forecast lead time
b	denotes slope or rate of change of Y given X_{nt}
X_{nt}	denotes a predictor of Y
L	denotes same week L used for previous year

Table 4 summarizes the smoothing models investigated in this research, which are defined in recurrence form [40]. In addition to the EWMA models, centered moving average (CMA), naïve model, and the econometric model are considered. Y_t denotes the observation of the supply in month *t*. $\hat{Y}_t$ represents the supply forecast for month *t*. Estimates of the level or systematic component, trend, and seasonality are denoted by $\hat{X}_t$, T_t, and I_t, respectively. The subscript m denotes the number of periods in the seasonal cycle and τ denotes the number of periods in the forecast lead time.

Table 4: Forecast models

Model	Forecast equation	Parameters
Centered Moving average	$\hat{X}_t = n^{-1}(\sum_{i=1}^{n} Y_{t-1})$ $\hat{Y}_t = \hat{X}_t$	n
Holt's double exponential smoothing	$\hat{X}_t = \alpha Y_t + (1-\alpha)(\hat{X}_{t-1} + T_{t-1})$ $T_t = \beta(\hat{X}_t - \hat{X}_{t-1}) + (1-\beta)T_{t-1}$ $\hat{Y}_t = \hat{X}_t + T_t$	α, β
Holt-Winters triple exponential smoothing	$\hat{X}_t = \alpha(Y_t/I_{t-m}) + (1-\alpha)(\hat{X}_{t-1} + T_{t-1})$ $T_t = \beta(\hat{X}_t - \hat{X}_{t-1}) + (1-\beta)T_{t-1}$ $I_t = \gamma\left(\frac{Y_t}{\hat{X}_t}\right) + (1-\gamma)I_{t-m}$ $\hat{Y}_{t(\tau)} = (\hat{X}_t + \tau T_t)I_{t+\tau-m}$	α, β, γ, m
ARIMA forecasting	$\hat{Y}_t = c + \sum_{i=1}^{p} a_i Y_{t-i} - \sum_{i=1}^{q} b_i \epsilon_{t-1} + \epsilon_t$	p, d, q, a_i, b_i
Econometric model	$\hat{Y} = b_0 + b_1\hat{Y}_{t-1} + b_2X_{1t} + b_3X_{1(t-1)} + b_4X_{2t} + b_5X_{1t}X_{2t} + \cdots$	b, X_{nt}
Naïve	$\hat{Y}_t = Y_{tl}$	L

The selection of the appropriate model is based on the existence of a trend and/or seasonality in the plotted time series [39]. Trend-based methods outperform non-trend-based methods when a distinguishable trend is present in the data. There are multiple ways to incorporate trends into forecasting models (e.g., additive, damped additive, multiplicative). In this research, the additive trend approach is investigated, commonly known as the Holt's method. The model with additive trend and multiplicative seasonality, which is commonly referred to as Winter's method [39], is also studied when trend and seasonality are present. The identification of a trend or seasonality is determined by graphing the series over time.

The forecasting parameters are determined using R: a free language and environment for statistical computing [41]. R was used to manipulate, graph and analyze the fed historical data to calculate the smoothing parameters. For the moving average forecasting, a centered moving average approach is adopted by taking a three weeks period into account, as it yielded the least forecasting error than other periods. For the Holt and Holt-Winters forecasting, the smoothing parameters α, β are estimated and the model is fitted accordingly. To determine the parameter values, an iterative search over the possible values for the forecast parameter was conducted to determine the parameter that minimizes the total relative error. The predictions have been generated for 95% prediction interval. The centered moving average correspond to the average calculated over the rolling series of data observed. For each observation, in this research, the average is calculated using three observations from the dataset for all the data points.

3.2.3. ARIMA Model

In addition to the traditional EWMA models, Autoregressive Integrated Moving Average (ARIMA) models are also considered for the analysis of the data. ARIMA models are appropriate if the time series is stationary and the data is correlated with prior observations and/or random shocks [42]. In general, the ARIMA model can be specified by: i) the number of autoregressive terms (p); ii) the number of past forecast errors (q); and, iii) the number of differences needed to make a nonstationary time series stationary (d).

More specifically, a nonstationary time series can be transformed to a stationary time series through differencing. The number of times the series is differenced is represented by d. The forecast equation for a stationary time series (ARIMA(p,d,q)) is defined in Equation (2) where a_i and b_i are the correlation coefficients associated with prior observations and random shocks ϵ_t, respectively. The intercept is represented by the parameter c. ARIMA models are represented as:

$$\hat{Y}_t = c + \sum_{i=1}^{p} a_i Y_{t-i} - \sum_{i=1}^{q} b_i \epsilon_{t-1} + \epsilon_t \tag{2}$$

When fitting an ARIMA model to the data, the data is initially tested for being nonstationary using the Augmented Dickey–Fuller unit root test [10]. Based on the results of this test, the original time series data is differenced until stationarity is achieved. The autocorrelation function (ACF) and partial autocorrelation function (PACF) is examined to determine the number of autoregressive terms (p) and moving average terms (q) to consider. ARIMA models will be identified by matching obtained patterns of ACF and PACF plots with theoretical patterns. If an autocorrelation at some lag is significantly different from zero, the correlation will be included in the ARIMA model. The selected models are validated by ensuring that the residuals are a series of random errors. If all the residuals of the model are a series of random errors, there should be no sizable full or partial autocorrelations remaining in the data.

3.2.4. Econometric Model

In addition to the forecasting methods discussed above, the donations are also analyzed considering the economic factors deemed to be associated with the amount of donations. The economic factors taken into consideration in this research are unemployment rate, average gas prices, productivity index, and Consumer Price Index (CPI). Lags for the econometric model are determined by unemployment, gas prices, CPI, and Productivity using the cross-correlation function. The econometric model is built using the applicable lags for that period on a weekly data. The data is considered for the cities of Austin and Houston. The econometric model is a statistical linear regression model used to establish a relationship between amount of in-kind donations and economic factors as defined above. Unemployment is a reflector of the health of the economy. It means the economy is operating below its potential capacity and is inefficient. Transportation could be affected by the gas prices as it affects the movement of goods from one location to another. For various donors, transporting food from their location to a food bank is essential. Productivity highlights the output in an economy. It shows how efficiently the inputs are converted into outputs. The CPI is a measure of the average change in the prices paid by urban consumers for a market of consumer goods and services over time. The data for the econometric model is obtained from Bureau of Labor Statistics [43]. The econometric model for this research is represented in Equation (3):

$$\hat{Y} = b_0 + b_1\hat{Y}_{t-1} + b_2X_{1t} + \ b_3X_{1(t-1)} + \ b_4X_{2t} + b_5X_{1t}X_{2t} \ + \cdots \tag{3}$$

Where X_{nt} is a predictor of Y and $b_{i>1}$ denotes estimates of the slope of Y given X_{nt}, b_1 is the estimate of the first-order autocorrelation coefficient and b_0 the estimate of the y-intercept. The econometric model tries to establish a relation to determine whether any of the economic factors had any influence on the donations made at both food banks. It tries to corelate each econometric factor with the donation made during that period.

3.2.5. Naïve Forecasting

A naïve forecasting method uses historical values as estimates for future values. This technique does not apply any adjustment to the historical values. It simply uses data from last observed period as a forecast for the next period. Naïve forecasting model is represented in Equation (4).

$$\hat{Y}_t = Y_{t-l} \tag{4}$$

Naïve method of forecasting is commonly used in industry where last period's results are used as current period's reference. Although it not an elaborate method, it has been commonly used in many sectors because it is easy to compute and provide quick results.

3.3. Predictive model selection and evaluation

Six forecasting models are tested over the in-sample time series defined by the classes in Table 4. The forecasting models used in this research are moving average, Holt, Holt-Winters, ARIMA, Econometric, and naïve model. Six forecasting models are then fitted in the in-sample data sets as defined by Table 4.

For each model, one period forecasts $\hat{Y}_{t+1|t}$ will be generated where $Y_1 \ldots Y_t$ are assumed to be known. The model that has the smallest mean absolute percentage error (*MAPE*) will be applied to the out-of sample data to assess model validity for future time periods. In particular, one period ahead forecasts are constructed for the out-of-sample series data and the MAPE is determined according to Equation (5).

$$MAPE = T_0^{-1}\left[\sum_{t=T}^{T+T_0}\left|\frac{\hat{Y}_{t+1|t} - Y_{t+1}}{Y_{t+1}}\right|\right] * 100 \tag{5}$$

Besides using the MAPE to evaluate the forecast accuracy for a specific time series, it is also used to assess the improvement in the forecast across series given different information classes. More specifically, when comparing the value of using donor versus product information, a mean absolute percentage error closer to zero implies greater forecast accuracy.

3.4. Using forecast for decision making

The forecasts models identified in this research can be used to improve the operations of food banks. For example, knowing the expected number of donations can help in prepositioning supplies for disaster relief operations. Food banks in the Feeding America network determine their distribution effectiveness by analyzing the pounds distributed. This aspect is referred to as pounds distributed per person in poverty (PPIP) and it provides a way to analyze food distribution activities done across counties in the service area [10]. The forecasts generated can be used to have in-depth understanding the supply chain and the distribution. Assuming that there are K counties served by a food bank and for each county, $k \in K$, then the number of people in poverty is defined as p_k. Using p_k, a_k known as the fair share percentage is computed using $a_k = \frac{p_k}{\sum_k p_k}$. Consider d_k as prior total distribution quantity (in pounds) for the food bank for a specific time period. Then the amount of supplies that should be numerically allocated to each county k is $a_k \widehat{Y}_t$. The total forecast of $PPIP_k$ for county k is determined as follows.

$$PPIP_k = \frac{a_k(\widehat{Y}_t + d_k)}{p_k}$$

If $PPIP_k$ is below 75, then a county is considered underserved. To construct a forecast value of $PPIP_k$ for each week, the researcher has performed the following steps.

1. Generate a forecast donation using the information from a specific time period.
2. Use the forecasted values to generate the 95% prediction interval for time period t.
3. Compute $PPIP_k$ for each county.

$PPIP_k$ calculated for each county using the prediction interval considers the potential demand and supply to the county by the food bank. The possible unmet demand can be understood from this analysis and policies can be made and implemented to improve the food bank services and distribution. Section 4.6 further discusses the results and managerial decisions that can be taken to optimize the distribution during a hurricane event. A potential shortfall is determined for each county suggesting the surplus quantity of donations that need to be supplied to meet the requirements.

3.4.1. Computational Results

A comprehensive numerical study is performed to quantify the extent of uncertainty in terms of donors, product, and pounds per donor in food banks. In addition, predictive models are developed to estimate the quantity of in-kind donations. The results show the relationship between forecast accuracy, donation behavior, and donations uncertainty. Equipping these facilities with better predictive information on supply-donation behavior will allow them to make informed downstream distribution decisions. The resulting models provides statistical data and valuable information that will increase the potential of the supply chain to meet the organizational objectives.

3.4.2. Results of donation behavior as a function of donation characteristics

The following section illustrates the variability of the associated factors impacting donations at the studied food banks facilities following Hurricane Harvey. The analysis considers the pre-disaster time period (i.e. from January 1, 2016 until July 31, 2017) and the post-disaster time period (i.e. from August 2017 until December 2017). Figure 1 depicts the variation in donation behavior in terms of pounds received, number of donors, and pounds received by donor at the Houston Food Bank before and after Hurricane Harvey. Figure 2 shows the variability in donation behavior in terms of pounds received, number of donors, and pounds received by donor at the Central Texas Food Bank in Austin before and after Hurricane Harvey. The coefficient of variation is an important parameter to determine the accuracy of the data. It measures how spread the data is and how much the data points differ from each other. Variance determine how close the datapoints are to the mean of the data and the square root of variance is called standard deviation. In this research, daily donations involve pounds of food being donated. During disaster, it is important to predict the quantity of donations such that the food banks are able satisfy the demand of the served population.

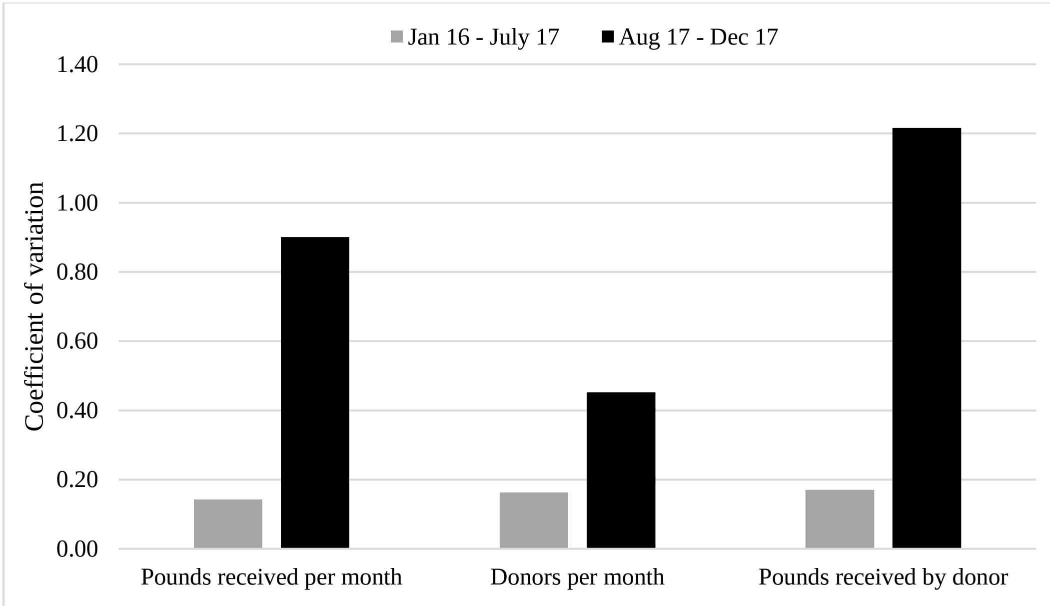

Figure 1: Uncertainty in food donation behavior in terms of pounds received, number of donors, and pounds received by donor at Houston

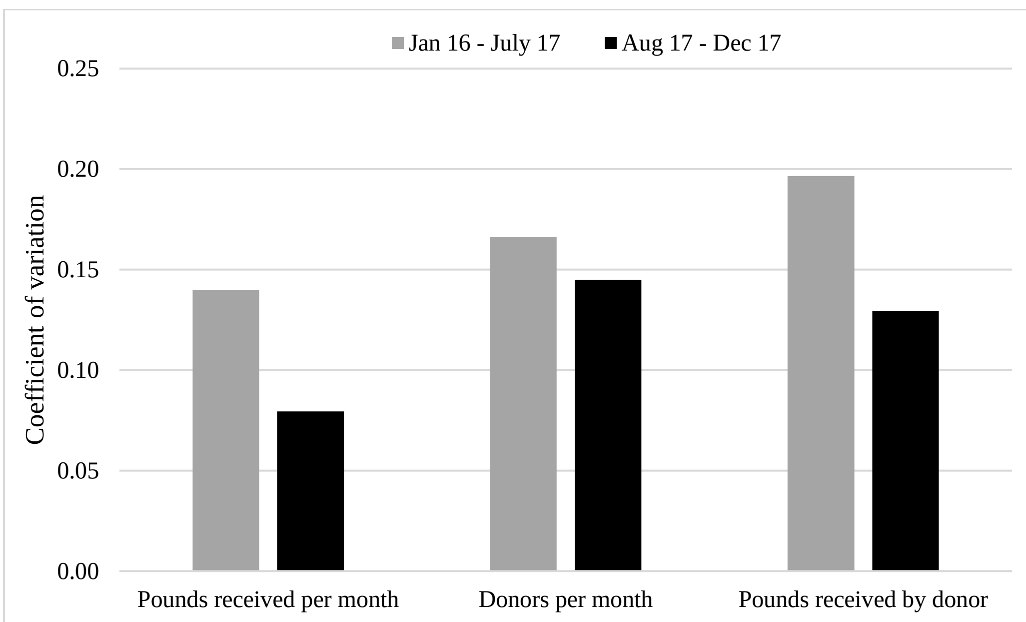

Figure 2: Uncertainty in food donation behavior in terms of pounds received, number of donors, and pounds received by donor at Austin

3.4.3. Pre-Disaster donation behavior

The analysis for this section is done independently for Houston Food Bank and Central Texas Food Bank. Figure 2 suggests there was less variation in terms of number of donors and donations at Houston food bank during pre-disaster phase. It can be noted that Houston Food Bank experienced normal operations prior to disaster and it faced no significant shocks. However, repercussions of hurricane can be understood from Figure 1 where the variation in number of donors, pounds donated per month, and pounds received by donor increased. Also, maximum variation is observed in total pounds donated per month. Referring to Figure 2, it can be observed that Central Texas Food Bank had no major effect of hurricane Harvey on its operations. The results agree with the proximity of the facilities to the area impacted by the hurricane

3.4.4. Disaster and post disaster donation behavior

Referring to Figure 1, it is observed that the variability is consistent with the impact Hurricane Harvey had on regular operations of Houston Food Bank prior to disaster. The unpredictability in terms of donors and donation at Houston Food Bank amount increased almost three times and six times respectively during normal operations and post-disaster phase, A higher increase in variability in total donation amount and pounds donated by donor is observed at Houston Food Bank. Referring Figure 2, Central Texas Food Bank did not experience a significant effect on the donations made. It is in consistent to the fact that it was not directly affected by the hurricane Harvey. Houston Food Bank’s higher variability is consistent with the fact that it is the largest food bank in United States and has more capacity in terms of storage and volunteers than Central

Texas Food Bank.

3.4.5. Relationship between number of donors and donations amount

Figure 3 and Figure 4 outlines donation behavior in terms of number of donors and the quantity donated by them weekly, for 2016 and 2017 for both food banks analyzed is this study. There is a notable linear relationship between number of donors and total pounds received for the Houston Food Bank. However, there are some instances in which a large number of donors contribute to a relatively less amount of donations and at times less donors contribute more quantity.

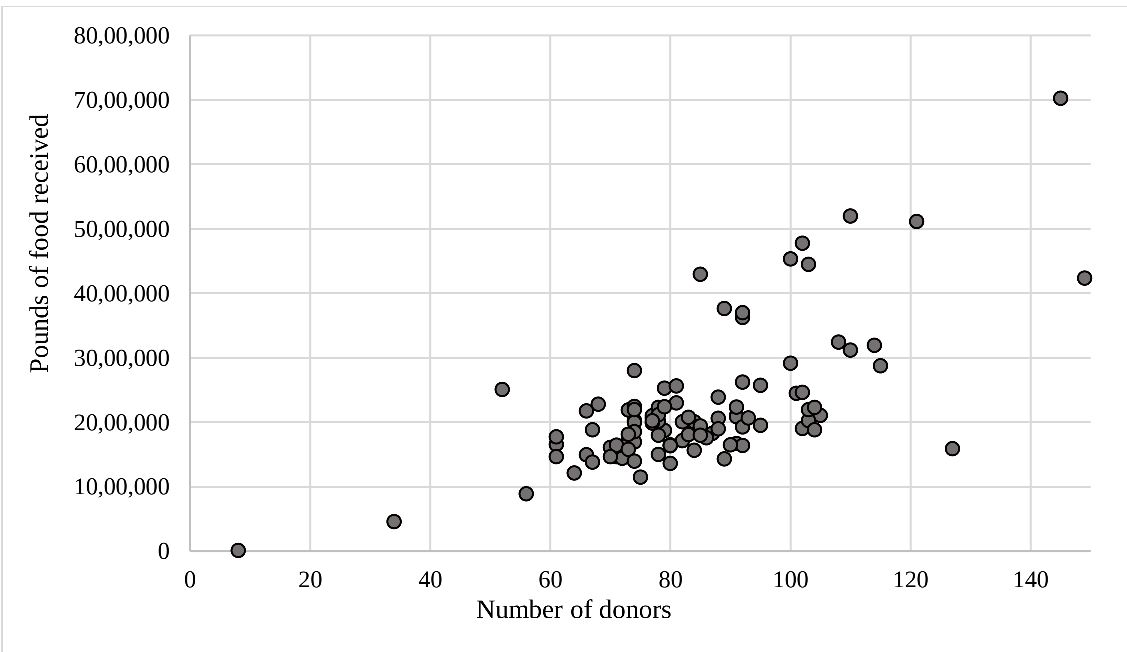

Figure 3: Uncertainty in donor behavior as measured by scatterplot of donors versus pounds received for Houston Food Bank

For the Central Texas Food Bank, the number of donors and the volume of donations are less than those at the Houston Food Bank. Remember the Houston Food Bank is the largest food bank in the nation and its facility is much bigger than the CTFB.

Figure 4 illustrates that, at Central Texas Food Bank, the number of donors is reduced and there is a large variability in the amounts that each donor contributes; whereas, in Houston donors are more similar in their contribution amount indicated by the linear shape.

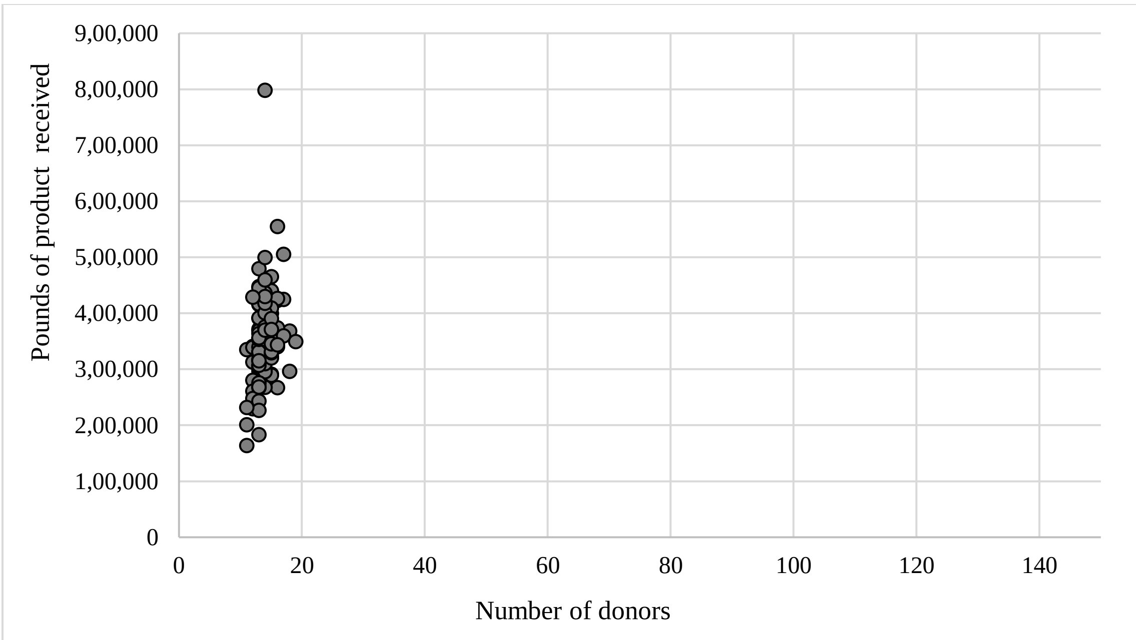

Figure 4: Uncertainty in donor behavior as measured by scatterplot of donors versus pounds received for Central Texas Food Bank

3.5. Descriptive analysis of donation behavior over time

In this subsection the donation behavior for both food bank facilities are discussed. Figure 5 represents the donations plotted over time at the Houston Food Bank and the Central Texas Food Bank at Austin. The graphs presented in this subsection denote the quantity of donations calculated for each month over a specified time period. The analysis also considers donation behavior pre-disaster and post-disaster at both facilities.

Figure 5 illustrates the time series plot for the total pounds of donations received at the Houston Food Bank and the Central Texas Food Bank for 2016 and 2017. The graphs demonstrate the product donation behavior observed overtime for years 2016 and 2017. Figure 5 shows that the quantity of donations received at the Houston Food Bank are significantly higher than the donations received at the Central Texas Food Bank. Houston Food Bank received approximately nine times more donations than the Central Texas Food Bank.

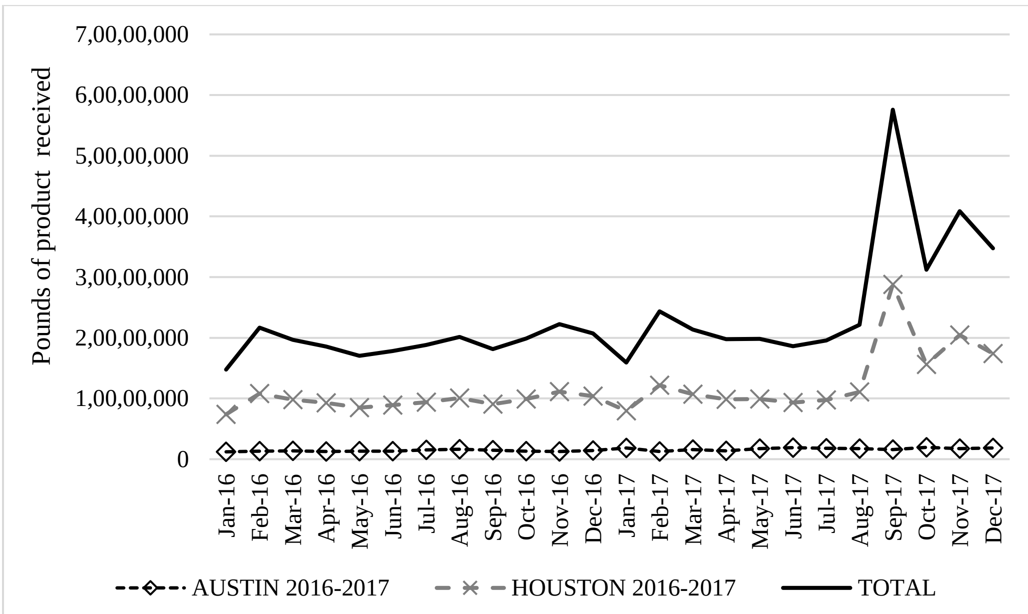

Figure 5: Time series plot of food donations: FB total, Houston, and Austin

Hurricane Harvey impacted Texas at the end of August 2017. The event caused a rise in total pounds donated at both facilities in the following months until the end of the year. The total donations were approximately three times higher at the Houston Food Bank during the post-disaster phase. The donations at the Central Texas Food Bank also increased. The following two subsections discuss the donation behavior observed in both food bank facilities in the pre-disaster and post-disaster period respectively. As stated earlier, the pre-disaster relief period goes from January 2016 until the end of July 2017 and the post-disaster relief period goes from August 2017 until December 2017.

3.5.1. Pre-Disaster donation behavior

The following analysis considers only the top donor types and product types for both food bank facilities as indicated in Section 3.4. The Houston Food Bank top donor types are Retail, Government, Manufacturer, Wholesale, and other Non-Profits as depicted in Figure 6. The plot shows that there is significant variability across time for all the donor types represented in Figure 6. Figure 7 illustrates the donor behavior in term of pounds donated for the Central Texas Food Bank. In this facility, the Retail category dominates the total pounds donated. Retail (i.e. supermarkets) is followed by the Wholesale (i.e. Sam’s Club), Company/corporation (i.e. Electronics), Manufacturer (i.e. Growers), and Non-Profits categories accordingly. Retail donations constitute approximately more than four times the other donations for the Central Texas Food Bank which indicates that this facility depends mostly from business like supermarkets.

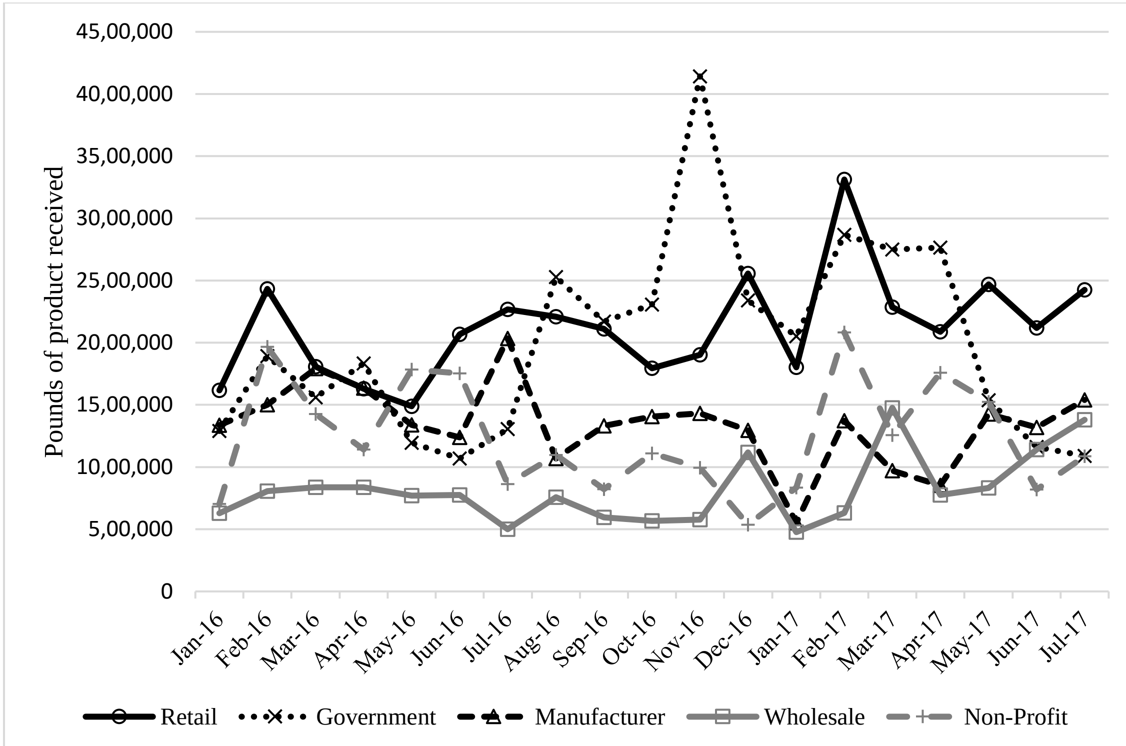

Figure 6: Time series plot of food donations by donor (top 5) for Houston (Jan 2016 to July 2017)

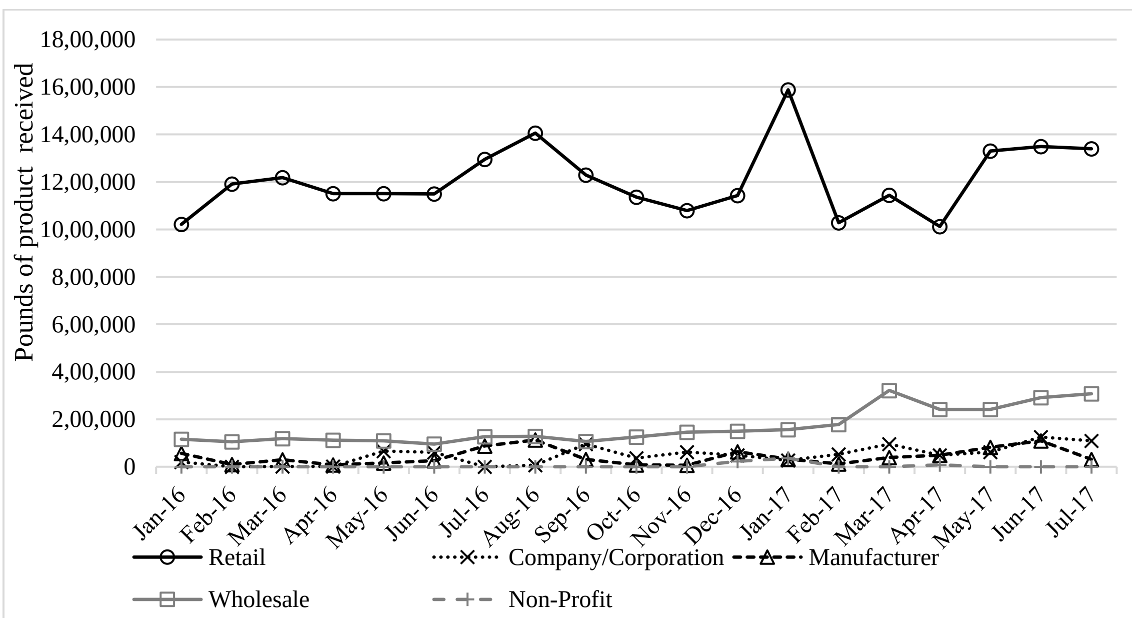

Figure 7: Time series plot of food donations by donor (top 5) for Austin (Jan 2016 to Jul 2017)

Analysis and examination of food donations by the product type shows the following results. The period for analysis is same as donor type. Figure 8 and Figure 9 shows packed food being the maximum product donated for both food banks individually during pre-disaster phase. It is followed closely by Fresh/Produce food, Meat, Dairy and Non-Food products. There is absence of any noticeable trends in this period. Figure 8 shows that there is a minor decline in overall food donations for Houston Food Bank during January 2017 owing to it remaining non-operational for few days. However, donations resume back to normal during February evidenced by the graphical data.

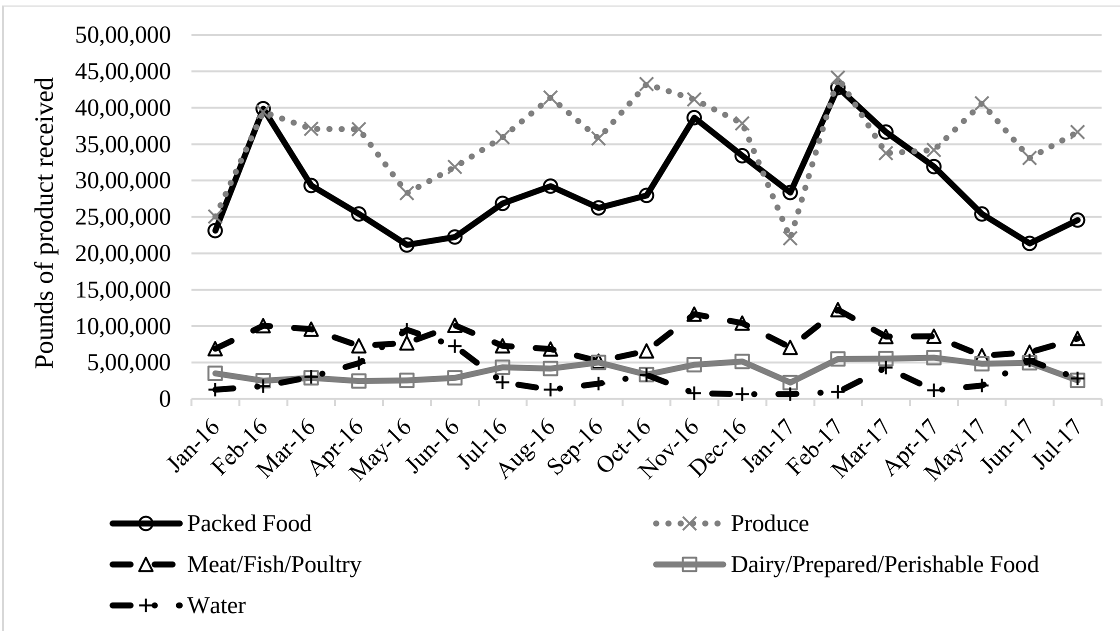

Figure 8: Time series plot of food donations by product type (top 5) for Houston (Jan 2016 to July 2017)

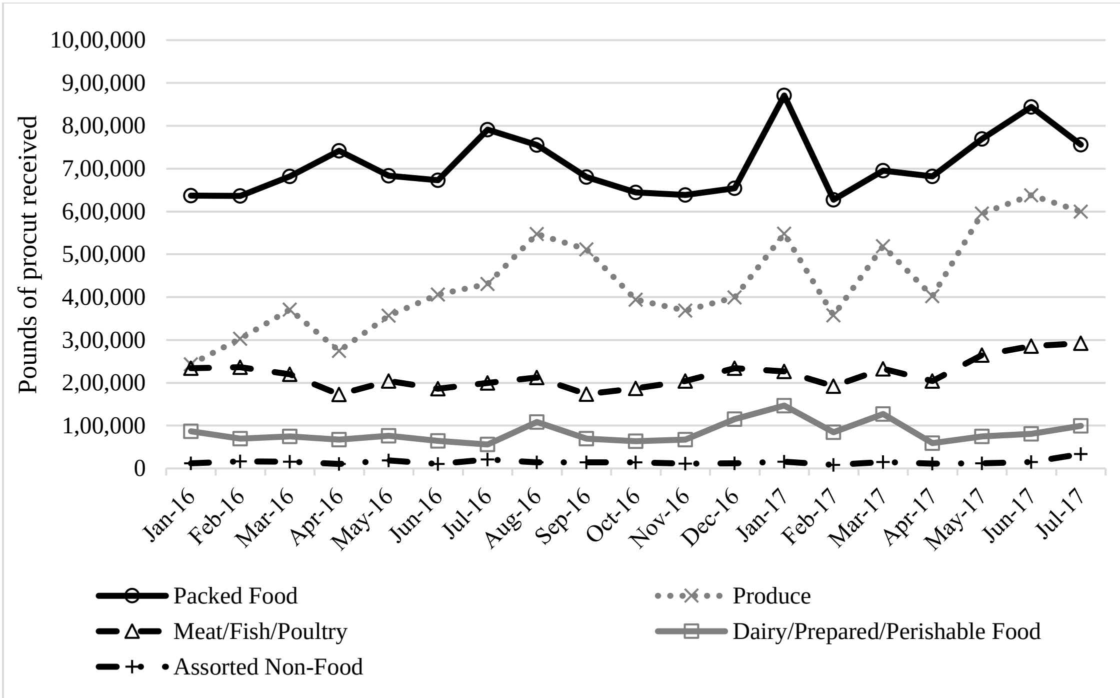

Figure 9: Time series plot of food donations by product type (top 5) for Austin (Jan 2016 to July 2017)

3.5.2. Post Disaster donation behavior

The following analysis considers only the top donor types and product types for both food bank facilities as indicated in Section 3.4. The Houston Food Bank top donor types during the post disaster period are Government, Retail, Manufacturer, Company/corporation, and other Non-Profits as depicted in Figure 10. The plot shows that there is a surge in donations from all major donor categories. The peak thus indicates the influx of donations from different donors, due to hurricane Harvey. After the disaster, the donations subsequently reduce in months following Harvey. A similar behavior is not observed at Central Texas Food Bank as indicated by Figure 11.

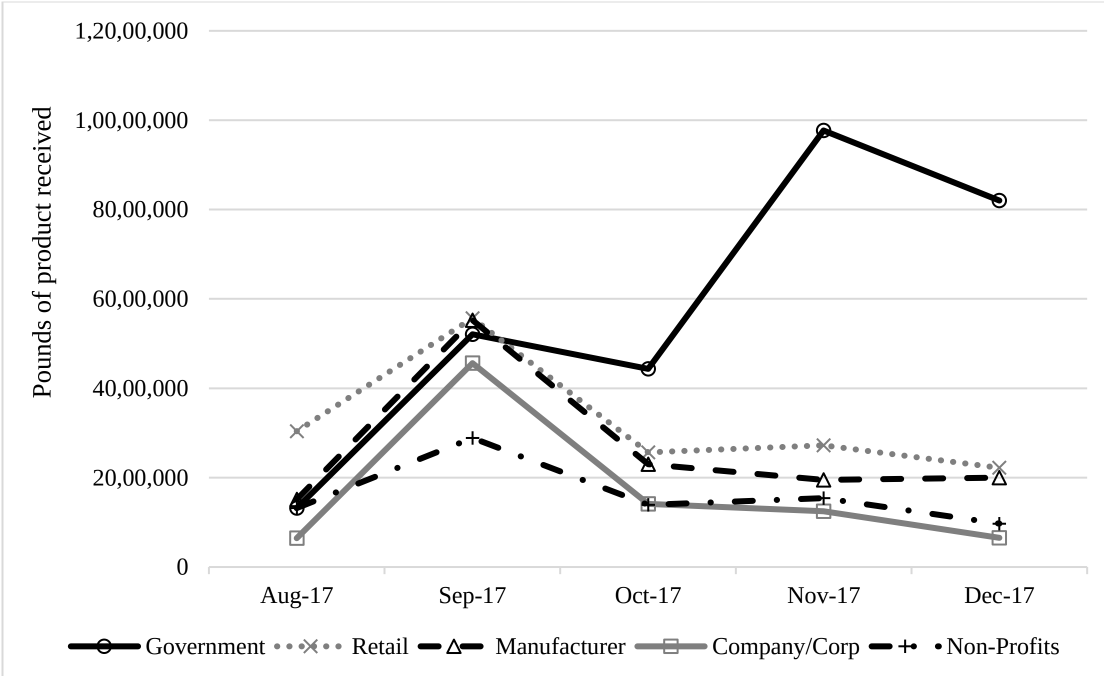

Figure 10: Time series plot of food donations by donor (top 5) for Houston (Aug 2017 to Dec 2017)

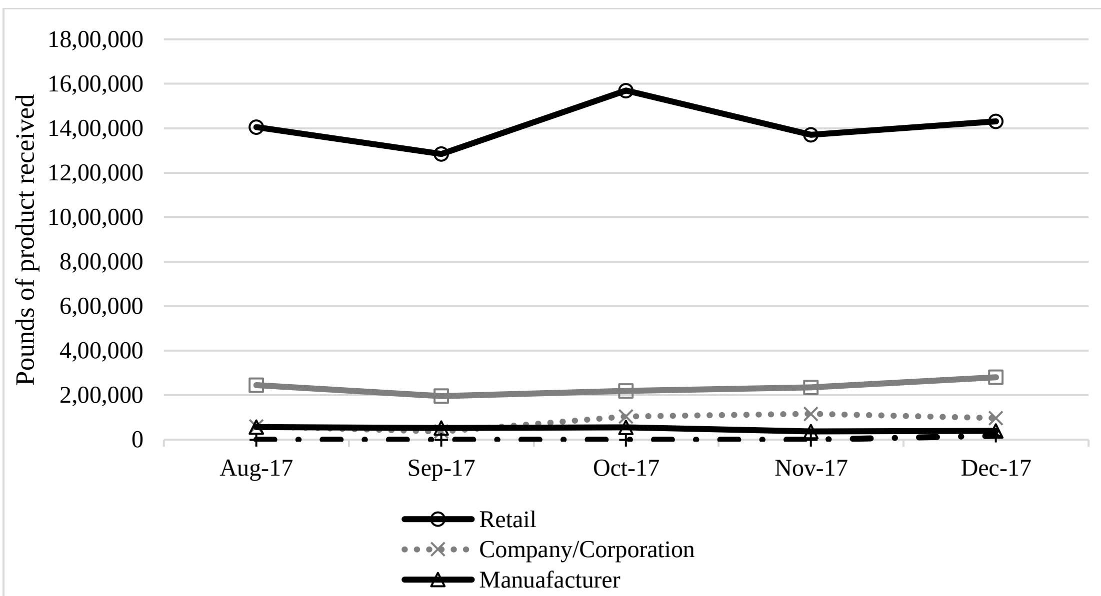

Figure 11: Time series plot of food donations by donor (top 5) for Austin (Aug 2017 to Dec 2017)

During the post disaster period, as noted in Figure 12 for the Houston Food Bank, the packed food product type is the major contributor to total food donations. It is followed by produce, meat, dairy, and snack food products. Snack food became one of the major contributions, replacing water during the post disaster period, as illustrated in Figure 12. There is an increase in packed food donations during September denoting influx of donations as an aftermath of the disaster.

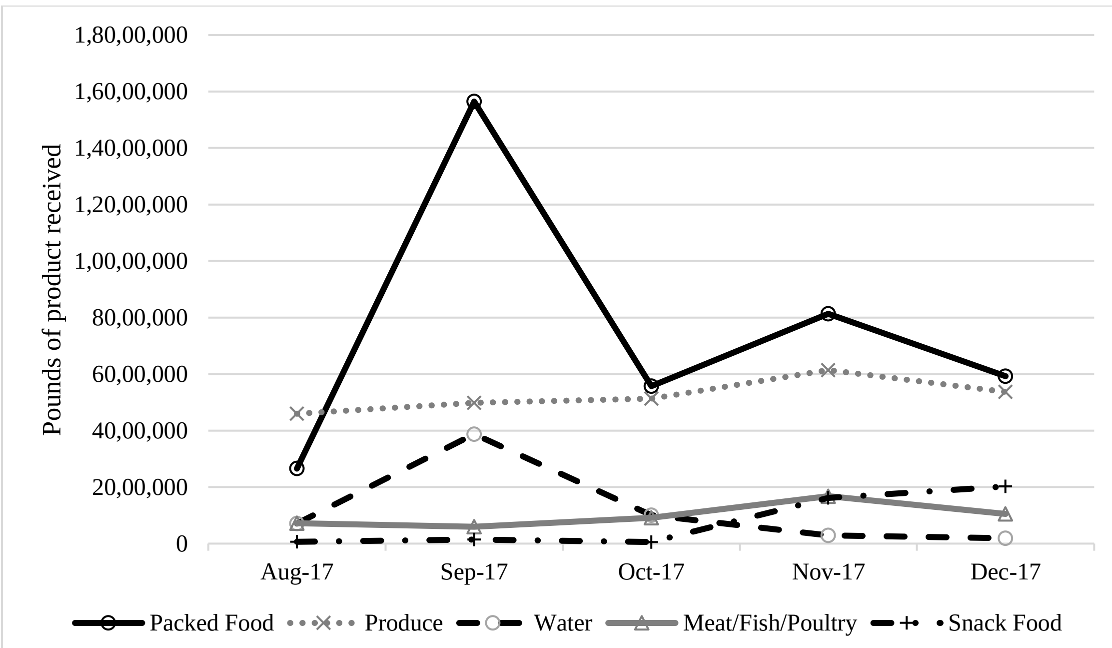

Figure 12: Time series plot of food donations by product type (top 5) for Houston (Aug 2017 to Dec 2017)

Figure 13 depicts the behavior for the Central Texas Food Bank. The plot shows that packed food donations is the major contributor during the disaster phase. There is a minor decrease in packed food donations and a corresponding rise in produce-food donations during November 2017. Other major contributors include meat, produce, and non-assorted food products. Though, no significant trends appear on the donation patterns for both food banks and for both phases suggesting the random nature of donations.

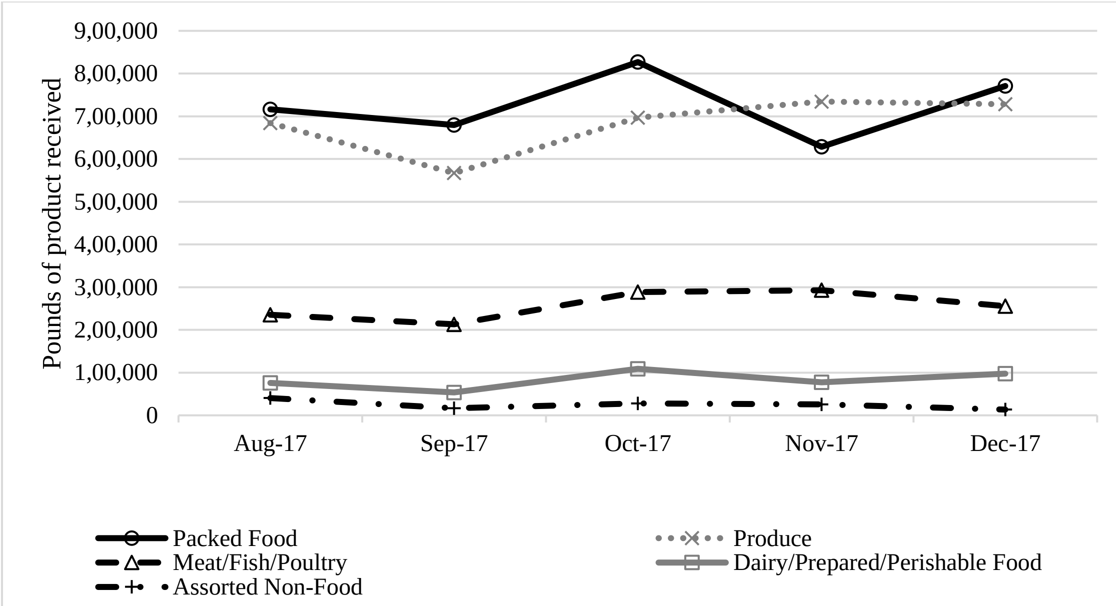

Figure 13: Time series plot of food donations by product type (top 5) for Austin (Aug 2017 to Dec 2017)

3.5.3. Insights from donation behavior analysis

The food donation behavior certainly varies over time. As seen in Figure 5, there was an increase in food donations at Houston Food Bank after Hurricane Harvey. There is variation in total quantity of donations and also for donations categorized by donor and product type. The food donations vary significantly by donor types at both the food banks. The amount of donations varies amongst the different donor types but overall contribution by each remains unaffected. This is evidenced by consistent donations received from retailers and company/corporations at Austin, and Retail and Government at Houston. Consistent donations of a particular type are not just limited to donors but also to type of product donated. The packed food is the highest donation through both years at both locations. Also, produce and meat are other product type whose contribution remains consistent at both food banks.

The analysis also proved there was lack of noteworthy donations of pharmaceutical products, baby food, and pet food. The was no substantial contribution during the disaster and post-disaster period as well. There's an increase in donations at Houston Food Bank following the disaster period. It is, however, not observed at Central Texas Food Bank. It may be attributed to the area of impact of the disaster as Houston was directly affected by the hurricane and hence has attracted most of the donations. The disaster hardly had any impact on donations at Austin. Retail and Government donations being the most amongst other food items donated at that period. There is absence of donations by Government at Central Texas Food Bank. Packed food is at the top of the food donations at Austin and Houston food bank. Packed food is closely followed by produce/fresh food during both the phases at Austin. Produced/fresh food donations formed the majority of donations at Houston before the disaster period.

3.6. Statistical analysis of donation behavior

Paired *t*-tests are often used to compare two population means for paired random samples whose differences are approximately normally distributed. The test statistic t has $n-1$ degrees of freedom and is computed by $t = \frac{\bar{d}}{s\sqrt{n}}$, $\bar{d}$ is the mean difference between two paired samples, s is the standard deviation of the differences, and *n* is the sample size. The results are considered to be significant if *p-values* < 0.05. The results for the test statistic t are presented in Table 5.

The data for this study was partitioned into two sets: *in*-sample dataset and an *out*-of-sample dataset. There are two *in*-sample data sets in this study, 1) a "normal" operation data set (January 2016 – August 2016), and 2) a "disaster relief" operation data set (September 2017 – December 2017). This research identifies the activities from

September 2017 to December 2017 as the "disaster relief" period where relief actions were in full effect after Hurricane Harvey. The *in*-sample data sets are used to fit the forecasting model parameters.

The *out*-sample dataset identified for this study goes from January 2017 to August 2017. The *out*-of-sample dataset is used to validate the forecasting models by measuring their accuracy against real observed data. Cross validation was only performed for the forecasting models developed with the *in*-sample dataset corresponding for the "normal" operations data set (i.e. January 2016 – August 2016). The forecasting models for the disaster relief operation *in*-sample dataset (i.e. i.e. September 2017 – December 2017) were assessed using the MAPE since *out*-of-sample data for a similar hurricane event was not available at the time of this research work. Table 5 summarizes the results of p-values obtained from the *t*-test to determine the *in*-sample dataset and an *out*-of-sample dataset.

Table 5: Results of paired *t*-test

Houston	Jan.-Apr. 2016	May-Aug. 2016	Sep.-Dec. 2016	Jan.-Apr. 2017	May-Aug. 2017	Sep.-Dec. 2017
Jan.-Apr. 2016	-	**0.512**	**0.712**	**0.472**	**0.640**	4.012E-06
May-Aug. 2016	-	-	**0.076**	**0.170**	**0.652**	2.288E-06
Sep.-Dec. 2016	-	-	-	**0.592**	**0.165**	5.963E-06
Jan.-Apr. 2017	-	-	-	-	**0.222**	2.608E-05
May-Aug. 2017	-	-	-	-	-	2.582E-06
Sep.-Dec. 2017	-	-	-	-	-	-

3.7. Forecast model results

3.7.1. Forecast model accuracy

Table 6, Table 7, Table 8, and Table 9 presents the results of the model fitting for each class for both food banks. In the table, C_i refers to the class and $|C_i|$ represents to the number of time series evaluated for each class (see Table 2). Only the three major contributors of donor type and product type for each food bank were considered in the analysis. Different combinations are then analyzed to determine the best fitting model. Several statistics are considered when evaluating the forecast model accuracy for each class. The average coefficient of variation ($\overline{CV}$) is calculated for each class by computing the mean of all *CV*'s calculated over different combinations evaluated for that class. Analyzing the results for the Houston Food Bank and the Central Texas Food Bank, it is evident that the most accurate forecasts are achieved for the total food donations in both food banks. The mean absolute percentage error ($\overline{MAPE}$) for both food banks for total donations is approximately 13%.

Referring to Table 6, analysis of Houston Food Bank for different classes shows better donation forecasts are observed with predictions involving product type than donor type. It implies a more consistent nature of product type donated. The average *MAPE* observed for product type donations is 21.49% with minimum error of 17%. The forecasts considering donor type have an average error of 30% with higher coefficient of variation. The minimum error observed for donor type forecasts is 20%. Also, the coefficient of variation is lower when forecasts are constructed predicting the type of product donated. It can be understood that as the combinations of food increases the higher is the variability and it produces a large average *MAPE*'s. It can be suggested that predicting the donor type and product type together, leads to higher variability (CV) and large MAPEs as the values are 1.6% and 90.56%, respectively.

Referring to Table 7, analysis for Central Texas Food Bank during pre-disaster period shows similar forecasting results as that of Houston Food Bank. Forecast results for donations related to product types shows an average *MAPE* of 11.86%. Error percentage for total donations at Central Texas Food Bank is 12%. While higher average *MAPE* is observed for donations involving donor type with a minimum value *MAPE* value of 12%.

Table 6: Model testing results for Houston under "normal" operations (Jan. 2016 – Aug. 2016)

C_i	$\|C_i\|$	$\overline{CV}$	$\overline{MAPE}$	Minimum	Std. Dev.
C_F	1	-	14.584	-	-
C_D	3	0.276	30.063	20.265(CMA)	8.164
C_P	3	0.214	21.492	17.243(Econometric)	4.605
C_{DP}	9	1.609	90.564	16.38 (Econometric)	145.737

Table 7: Model testing results for Austin under "normal" operations (Jan. 2016 – Aug. 2016)

C_i	$\|C_i\|$	$\overline{CV}$	$\overline{MAPE}$	Minimum	Std. Dev.
C_F	1	-	12.332	-	-
C_D	3	0.704	131.622	12.726 (CMA)	92.656
C_P	3	0.129	11.866	9.722 (Econometric)	1.533
C_{DP}	9	1.194	157.978	9.503 (Econometric)	188.569

Analyzing the post-disaster forecasting results for Houston Food Bank using Table 8, it can be seen that forecasting error percentage for total donations increased vs the one gotten for pre-disaster forecasts. The best forecast can be observed for predictions involving donor type, with average *MAPE* of 10.43% and 0.498 coefficient of variation. Product type donation yield an average *MAPE* of 19.40% with a minimum error percentage of 6.572%.

Table 8: Model testing result for Houston under "disaster relief" operations (Sep.17 – Dec.17)

C_i	$\|C_i\|$	$\overline{CV}$	$\overline{MAPE}$	Minimum	Std. Dev.
C_F	1	-	23.649	-	-
C_D	3	0.498	10.430	5.495 (Econometric)	5.191
C_P	3	0.473	19.404	6.572 (Econometric)	9.176
C_{DP}	9	2.403	346.732	8.927(Econometric)	833.171

Examination of post-disaster forecasts for CTFB in Table 9, reveals more unpredictability in donations. Forecast for total food donations has an average *MAPE* of 47%. Also, the minimum *MAPE* for product type forecasts and donor type forecasts is 35% and 51% respectively. There is an increase in coefficient of variation across all classes analyzed. The change is also reflected in an increase in standard deviation observed through all classes analyzed before and after hurricane.

Table 9: Model testing result for Austin under "disaster relief" operations (Sep.17 – Dec.17)

C_i	$\|C_i\|$	$\overline{CV}$	$\overline{MAPE}$	Minimum	Std. Dev.
C_F	1	-	47.087	-	-
C_D	3	0.602	191.636	51.370 (CMA)	115.435
C_P	3	0.270	53.045	35.019 (CMA)	14.315
C_{DP}	9	1.521	462.163	39.478 (CMA)	702.927

It can be conjectured that better and accurate forecasts can be constructed for certain types of donors and products. Coefficient of variation and *MAPE* increases as more classes are clustered and fragmented. It should be observed that donations involving product types had lesser variation, specifically packed food which was donated more frequently. The results are important as it helps improve the forecast. Also, the forecasts involving only total donation for the food bank gave the best results (i.e., least coefficient of variation). Through data analysis, the researcher observed that the variability and *MAPE* for the forecasts was observed to be high for classes which involved a combination donor type and product type.

3.7.2. Forecast model comparison

Table 10 and Table 11 summarize the forecast model selection per class for the Houston Food Bank and the Central Texas Food Bank, respectively, under "normal" conditions (i.e. pre-disaster). The data used to build the forecasting models include January 2016 until August 2016 which is the in-sample dataset. Of all the forecasting methods analyzed for Houston, the naïve method proves to be the most accurate as it provided predictions with least error. The naïve method performs well in this scenario as the donations amount were similar to the observed values for previous period. Holt, ARIMA, Econometric, and Holt-Winters gave the best forecasting results for some of the instances of each class C_i.

Table 10: Model selection summary for Houston under "normal" operations (Jan. 2016 – Aug. 2016)

C_i	CMA	Holt	Holt-Winters	ARIMA	Econometric	Naïve
C_F	-	-	-	-	-	1
C_D	-	-	-	2	-	1
C_P	-	-	-	-	1	2
C_{DP}	-	2	1	2	2	2
Total	0	2	1	4	3	6

Table 11 summarizes the model selection for the Central Texas Food Bank in Austin TX. The centered moving average (CMA) proves to be the most useful method to build forecasts for this facility under "normal" conditions (i.e. pre-disaster). CMA provided the best results in six instances. ARIMA proved to be second best method giving best results in four instances.

Table 11: Model selection summary for Austin under “normal” operations (Jan.16 – Aug.16)

C_i	CMA	Holt	Holt-Winters	ARIMA	Econometric	Naïve
C_F	-	-	-	-	1	-
C_D	2	1	-	-	-	-
C_P	1	-	-	2	-	-
C_{DP}	3	1	2	2	1	0
Total	6	2	2	4	2	0

Table 12 and Table 13 summarize the forecast model selection per class for the Houston Food Bank and the Central Texas Food Bank, respectively, under “disaster relief” conditions (i.e. post-disaster). The data used to build the forecasting models include September 2017 until December 2017 which is the second in-sample dataset. Table 14 shows that for the Houston Food Bank, the Econometric method proves to be the most accurate forecasting model since it computed predictions with least percentage error. Econometric model accounts for various economic factors which can potentially influence the donation behavior at the food bank location. The economic factors considered in this research can possibly have an impact on donation behavior at Houston during disaster-relief period. CMA provides the best forecasting results for the rest of the instances of each class C_i.

Table 12: Model selection summary for Houston under "disaster relief" operations (Sep.17 – Dec.17)

C_i	CMA	Holt	Holt-Winters	ARIMA	Econometric
C_F	-	-	-	-	1
C_D	-	-	-	-	3
C_P	1	-	-	-	2
C_{DP}	6	-	-	-	3
Total	7	-	-	-	9

Table 13 summarizes the model selection for the Central Texas Food Bank in Austin TX. The centered moving average (CMA) proves again to be the most useful method to build forecasts for this facility under "disaster relief" conditions (i.e. post-disaster). CMA provided the best results in nine out of the fifteen instances.

Table 13: Model selection summary for Austin under "disaster relief" operations (Sep.17 – Dec.17)

C_i	CMA	Holt	Holt-Winters	ARIMA	Econometric
C_F	-	-	-	1	-
C_D	2	1	-	-	-
C_P	3	-	-	-	-
C_{DP}	4	2	-	1	1
Total	9	3	-	2	1

3.7.3. Forecast model validation

Table 14 and Table 15 report the values for the best forecasting models when compared to the *out*-of-sample datasets for the Houston Food Bank and the Central Texas

Food Bank respectively. The tables represent the different parameters evaluated for each series in the class C_i, the minimum forecast error, and the standard deviation of the forecast error. The forecast error and coefficient of variation is also reported in relation to the average *CV* and *MAPE* from *in*-sample dataset. Ratios that are less than 1 are in consistent with reduction in variability (R_V) or forecast error (R_C), respectively. C_i represents the classes analyzed and $|C_i|$ represents the number of classes evaluated for building forecast. Minimum indicates the least *MAPE* observed over the particular instance. Std Dev denotes the standard deviation for class C_i. $\overline{CV}$ represents the average co-efficient of variation observed over different classes. $\overline{MAPE}$ represents the average mean absolute percentage error observed over a specified class.

Table 14: Model validation results for the Houston Food Bank

C_i	$\|C_i\|$	$\overline{MAPE}$	Minimum	Std Dev	$\overline{CV}$	R_V (Jan.-Dec.)	R_V (Sep.-Dec.)	R_C (Jan.-Dec.)	R_C (Sep.-Dec.)
C_F	1	18.730	-	-	-	-	-	0.623	0.798
C_D	3	48.777	28.001	16.132	0.331	1.218	0.664	1.623	4.676
C_P	3	29.032	21.642	5.232	0.180	0.841	0.381	1.351	1.496
C_{DP}	9	79.543	33.131	36.626	0.460	0.286	0.192	0.878	0.229

Table 15: Model validation results for the Central Texas Food Bank in Austin

C_i	$\|C_i\|$	$\overline{MAPE}$	Minimum	Std Dev	$\overline{CV}$	R_V (Jan.-Dec.)	R_V (Sep.-Dec.)	R_C (Jan.-Dec.)	R_C (Sep.-Dec.)
C_F	1	10.621	-	-	-	-	-	0.861	0.226
C_D	3	180.761	15.490	121.789	0.674	0.957	1.119	1.373	0.943
C_P	3	19.991	13.482	7.1407	0.357	2.765	1.323	1.685	0.377
C_{DP}	9	178.734	11.951	150.724	0.843	0.706	0.554	1.131	0.387

Several observations are deduced from these results. First, forecasts generated for overall donations for both food banks are the most accurate and for both considered sample groups. For Houston Food Bank and Central Texas Food Bank, an increase in variability is usually accompanied by an increase in average forecast error. Also, classes with less average *MAPE* and variability tend to have lower standard deviation which signifies a consistency in donations. Forecasts generated for classes which involves a combination of donor type and product type prove to have larger average *MAPE* and coefficient of variation for all the instances considered. Forecasts generated for product type prove to give better results as compared to other classes. The analysis indicates an increase in variation and on the average *MAPE*'s for all classes during the post-disaster phase. There's also a corresponding increase in absolute percentage error for this phase.

3.8. Using forecast for decision making

This section aims to provide a guide on how to use the results reported in this research. Consider the donation requirements for a number of counties surrounding a food bank. For the purpose of this work, eight counties associated to the Houston Food Bank are considered. For each county $k \in K$, the number of people in poverty p_k is known, as well as pre-defined allocation of branch supply a_k known to be fair-share percentage. The pounds distributed per person in poverty, $PPIP_k$, is computed as discussed in Section 3.6. The term d_k represents the 11^{th} -time period distribution quantity, in pounds, for county k. The amount of supply that should be theoretically allocated to each county k is $a_k(\widehat{Y}_t + d_k)$. A 95% prediction interval is constructed for total supply and it is [2,055,434.91, 7,287,576.64] pounds.

Table 16 denotes the corresponding interval forecast of *PPIP* for each county served by the food bank. The statistics, as indicated in Table 16, shows the counties served by the Houston Food Bank that may potentially be under-served as their *PPIP* values are less than 75. Shortfall of supplies is then determined to denote the additional pounds of food to be supplied to these counties to reach a threshold *PPIP* of 75. Thus, management can improve their existing policies or bring new ones to match the supply with demand.

Table 16: Forecast summary PPIP

County Name	**PPIP**	**Population in poverty**	**Shortfall (Pounds)**
Harris	[1.61, 2.10]	747,080.42	[346,854,467 - 349,151,301]
Galveston	[22.37, 29.17]	40,546.80	[19,799,792 - 22,096,626]
Montgomery	[12.79, 16.68]	52,592.33	[38,777,417 - 41,074,251]
Chambers	[178.04, 232.15]	4,033.13	-
Brazoria	[20.42, 26.62]	33,318.00	[22,223,042 - 24,519,876]
Liberty	[87.56, 114.17]	13,380.07	-
Waller	[142.28, 185.51]	8,234.53	-
San Jacinto	[263.19, 343.17]	5,226.86	-

4. DECISION-MAKING STOCHASTIC MODEL

4.1. Methodology and Assumptions

4.1.1 Problem Definition

This research involves the logistics associated with the disaster relief operations for a network of food bank facilities at risk of getting impacted by a natural disaster (i.e. hurricane). The goal is to plan the prepositioning of supplies that will minimize unmet demand for the counites served by all food bank facilities in the network. The problem is formulated as a two-stage stochastic programming model that considers the uncertainty in terms of available supplies, donations received at the facility, and the expected demand for their service region. The first phase of the model will determine if the system requires pre-positioning of the expected inventory considering the expected donations. The second phase of the model will determine the activities to be undertaken during the response phase.

In this research, the supply nodes are the food bank facilities which are large storage facilities similar to a distribution center or a warehouse. The demand nodes are accessible fixed locations in the service radius of the food bank facility. In this research, demand nodes are represented by the counties served by the respective food banks. The distance between supply and demand nodes are associated to the roadway distances in the network. Supplies are allowed be moved between these supply nodes and demand nodes before and after hurricane. The following section discusses the assumptions considered for this problem.

4.1.2. Assumptions

The researcher, for this study, has considered hurricane Harvey which affected the state of Texas and Louisiana in 2017. The counties served by Houston Food Bank (HFB), Central Texas Food Bank (CTFB), and San Antonio Food Bank (SAFB) have been analyzed for determining the supply and demand nodes. The historical data provided by the food banks gave information about the inventory and capacity for each food bank facility. It is observed that after a natural disaster, such as a hurricane, there is a surge in the demand that needs to be satisfied with the available inventory. The natural disaster can also disrupt normal operations for the food banks by damaging structures, flooding, among other circumstances. In this research, a hurricane event is considered which is based on the data collected from Hurricane Harvey in 2017. The following assumptions are considered by the authors when defining the problem.

- Consider a supply and demand network with N supply nodes, and H demand nodes.
- Each supply node $n \in N$, corresponds to a food bank facility which can store and distribute supplies.
- Each supply node $n \in N$ is associated with maximum a quantity of supplies it can hold. This upper limit is known as capacity. It is the maximum physical volume of goods that can be stored. This research assumes the maximum capacity as pounds of food that can be stored at a facility.
- The set of demand nodes, $h \in H,$ represents locations that show the requirement of the population in a given geographical area. In this research, the counties are considered the demand nodes. These counties serve their respective population, and demand varies considering the population in poverty.

- A demand forecast for each county is known thereby reflecting the population that needs to be served. The demand nodes are satisfied by the supply nodes.
- The actual demand quantity of different counties may increase, decrease, or remain same after the event. The change is estimated by considering the distance of nodes from the impact of disaster. See Figure 14.
- The disaster donations, in addition to regular donations, is determined using the historical data obtained from food bank facilities.
- The interconnections between supply and demand nodes are the transportation routes as illustrated in Figure 14. It is assumed that movement of food takes place using the roadways.
- The size and volume of Central Texas Food Bank, and San Antonio Food Bank is identical. Hence, the values for inventory and donations are considered to be same.

It is believed that the decision-maker has been informed of the incoming disaster and intends to take active approach to planning distribution of supplies before the event. Pre-positioning could take place between the supply nodes before the event takes place using the existing inventory subject to maximum capacity.

4.2. Supply and Demand Nodes

4.2.1. Supply network

The supply nodes in this research are the food banks facilities which are illustrated by circles in Figure 14. The names of the supply nodes considered in this study are (1) Houston Food Bank (H), (2) Central Texas Food Bank at Austin (A), and (3) San

Antonio Food Bank (S). The selection of these three facilities was based on the observed operations during Hurricane Harvey in central Texas. Each supply node has a pre-defined capacity and an associated inventory calculated for each day. In this research a supply node is represented by an index $n \in N$. However, to identify inbound and outbound flows at each supply node n, two additional indices i and j are defined and $i, j, n \in N$.

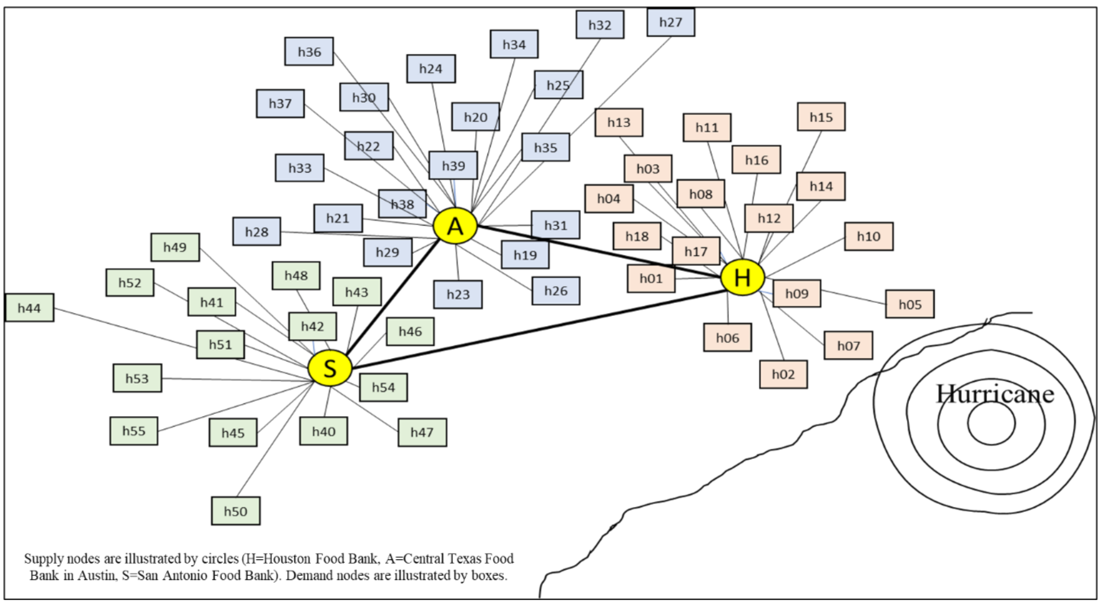

Figure 14: Supply and demand network.

Table 17 shows the distances between food bank facilities (i.e. the supply nodes). Donated supplies are managed by the supply nodes. Typically, after a natural disaster (i.e. disaster relief period), a surge of donations is observed at the supply nodes. Historical data from the studied food bank facilities was used to develop donation forecasts and to model the associated uncertainty. The expected number of donations varies according to the severity of the expected hurricane event. For instance, the expected number of donations will be lower for category 1 hurricane than for a category 4 or category 5. In this research a donation changing factor $\delta_{n,\omega}$, where ω represent hurricane impact scenario, is used to model the fluctuation in donations.

Table 17: Distance matrix in miles between supply nodes $\boldsymbol{n} \in \boldsymbol{N}$

Food bank facility	Houston Food Bank, Houston TX	Central Texas Food Bank, Austin TX	San Antonio Food Bank, San Antonio TX
Houston Food Bank, Houston TX	-	165	208
Central Texas Food Bank, Austin TX	165	-	86
San Antonio Food Bank, San Antonio TX	208	86	-

4.2.2. Demand Nodes and Forecasted demand

Demand nodes are the counties in the service region of each food bank. During the disaster relief period, demand nodes are typically distribution points where the delivery trucks from the food banks can reach out to a large group of people in need (i.e. food pantries). The data obtained by the food banks provided information on the amount of supplies distributed by the food banks after Hurricane Harvey. The information provided a way to estimate the demand after natural disasters in the area.

The demand of supplies for the food banks under normal operation was estimated considering the counties and their corresponding population in poverty [44]. This research estimates the demand for a county using Equation (1) which consider the poverty population (p_c) for each county and the product need factor (H_f) which considers the people that are not classified as in poverty level but that will need help from the food bank for other reasons such as unemployment. Table 18 represents the estimated demand at supply nodes calculated using the equation stated above. County numbers from h01 to h18 represent the counties served by Houston Food Bank, counties h19 to h39 are counties served by the Central Texas Food Bank, and h40 to h55 are counties served by San Antonio Food Bank. The locations for the counties are displayed in Figure 14.

$$Projected\ monthly\ demand\ = \frac{P_C \times H_f \times\ 75}{12} \qquad (1)$$

Table 18: Estimated monthly demand per county

County Number	County Name	Poverty %	Poverty Population	Demand
h01	Austin	10.20%	3,058.88	31,427.00
h02	Brazoria	10.10%	37,390.20	384,146.00
h03	Brazos	23.20%	52,607.86	540,491.50
h04	Burleson	14.80%	2,721.57	27,961.50
h05	Chambers	8.50%	3,608.59	37,074.50
h06	Fort Bend	7.90%	62,240.78	639,460.00
h07	Galveston	12.10%	40,884.69	420,048.00
h08	Grimes	17.50%	4,963.00	50,989.50
h09	Harris	16.50%	775,272.14	7,965,124.50
h10	Liberty	15.10%	13,034.77	133,919.00
h11	Madison	17.90%	2,581.54	26,522.50
h12	Montgomery	9.30%	54,956.03	564,616.50
h13	Robertson	15.80%	2,730.87	28,057.00
h14	San Jacinto	17.50%	5,025.83	51,635.00
h15	Trinity	26.10%	3,847.14	39,525.50
h16	Walker	15.90%	11,524.32	118,400.50
h17	Waller	13.80%	7,331.39	75,322.50
h18	Washington	13.80%	4,844.90	49,776.50
h19	Bastrop	12.60%	10,958.98	112,592.00
h20	Bell	13.00%	46,233.46	475,001.50
h21	Blanco	10.10%	1,181.90	12,143.00
h22	Burnet	11%	5,229.62	53,729.00
h23	Caldwell	14.10%	6,097.83	62,649.00
h24	Coryell	15%	11,221.20	115,286.50
h25	Falls	21.70%	3,761.70	38,647.50
h26	Fayette	13.30%	3,371.42	34,638.00
h27	Freestone	13.70%	2,713.70	27,880.50
h28	Gillespie	9.60%	2,573.18	26,437.00
h29	Hays	13.20%	29,387.29	301,924.00
h30	Lampasas	12.90%	2,738.54	28,135.50
h31	Lee	12.30%	2,108.71	21,665.00
h32	Limestone	22.20%	5,221.22	53,642.50
h33	Llano	12.30%	2,662.46	27,354.00
h34	McLennan	18.90%	48,120.72	494,391.00
h35	Milam	15.60%	3,920.44	40,278.50
h36	Mills	14.60%	718.47	7,381.50
h37	San Saba	16.80%	1,017.07	10,449.50
h38	Travis	12.00%	149,849.16	1,539,546.00

County Number	County Name	Poverty %	Poverty Population	Demand
h39	Williamson	6.40%	36,270.02	372,637.00
h40	Atascosa	15.70%	7,898.67	81,150.50
h41	Bandera	13.40%	3,058.42	31,422.00
h42	Bexar	17.20%	341,600.43	3,509,593.50
h43	Comal	7.10%	10,534.48	108,231.00
h44	Edwards	22.10%	426.09	4,377.50
h45	Frio	27.50%	5,449.40	55,987.00
h46	Guadalupe	8.50%	13,913.99	142,952.00
h47	Karnes	21.80%	3,411.70	35,051.50
h48	Kendall	7.50%	3,423.08	35,168.50
h49	Kerr	13.90%	7,284.30	74,838.50
h50	La Salle	29.60%	2,229.18	22,902.50
h51	Medina	12.30%	6,263.28	64,349.00
h52	Real	18.10%	629.52	6,467.50
h53	Uvalde	22.90%	6,147.73	63,161.50
h54	Wilson	10.90%	5,474.42	56,244.00
h55	Zavala	32.00%	3,834.56	39,396.00

The projected daily demand can thus be calculated from projected monthly demand. This gives us an estimate of the total pounds demanded by each county served by food banks under consideration in this research. The projected demand helps us to get an estimate of how much food is to be distributed, thereby acting as demand nodes. The demand changes according to the severity of hurricane as explained earlier.

4.3. Arcs and other variables

The arcs between supply nodes and demand nodes represent the access between the food banks and supply nodes. The cost associated to using those arcs is represented by the distance between them. These values have been estimated considering the minimum distance between them which includes the state and interstate highways routes. The approximate distance between supply-supply nodes, and supply-demand nodes were calculated using Google Maps [45]. The distances are calculated for each combination of demand node and supply node since during the disaster relief period the model allows food banks to serve any demand node in the network. Table 19 states the distances calculated between the supply and demand nodes.

Table 19: Distance of demand nodes from supply nodes

Food Bank	Demand Node number	Counties	County Name	HFB	CTFB	SAFB
Houston Food Bank	h1	1	Austin	68.9	102	152
	h2	2	Brazoria County	48.2	175	217
	h3	3	Brazos	103	105	186
	h4	4	Burleson	106	85	160
	h5	5	Chambers	45.5	208	251
	h6	6	Fort Bend	41.6	138	181
	h7	7	Galveston	44.7	203	246
	h8	8	Grimes	76.2	122	190
	h9	9	Harris	2.4	162	205
	h10	10	Liberty	47	208	253
	h11	11	Madison	108	140	220
	h12	12	Montgomery	45.9	169	232
	h13	13	Robertson	137	105	187
	h14	14	San Jacinto	60	180	246
	h15	15	Trinity	111	192	262
	h16	16	Walker	80	151	220
	h17	17	Waller	58.3	119	175
	h18	18	Washington	82.4	93.3	161
Central Texas Food Bank	h19	1	Bastrop	145	29.6	108
	h20	2	Bell	185	84.1	155
	h21	3	Blanco	218	54.6	78.1
	h22	4	Burnet	213	62.5	107
	h23	5	Caldwell	165	24.6	74.7
	h24	6	Coryell	221	109	178
	h25	7	Falls	165	110	183
	h26	8	Fayette	110	62.6	124
	h27	9	Freestone	160	168	253
	h28	10	Gillespie	247	83.9	77.7
	h29	11	Hays	193	29.3	75.9
	h30	12	Lampasas	242	92.3	147
	h31	13	Lee	121	54.4	134
	h32	14	Limestone	173	135	215
	h33	15	Llano	245	81.9	111
	h34	16	McLennan	193	107	186
	h35	17	Milam	143	74.6	157
	h36	18	Mills	275	126	179
	h37	19	San Saba	262	117	148
	h38	20	Travis	164	1.7	87.7
	h39	21	Williamson	189	46.1	126
	h40	1	Atascosa	244	120	45.7
	h41	2	Bandera	273	125	65.2
	h42	3	Bexar	211	85.6	1.3

Food Bank	Demand Node number	Counties	County Name	HFB	CTFB	SAFB
San Antonio Food Bank	h43	4	Comal	197	58.6	49.4
	h44	5	Edwards	364	198	164
	h45	6	Frio	264	138	59
	h46	7	Guadalupe	167	50.2	50.9
	h47	8	Karnes	201	94.7	61.4
	h48	9	Kendall	235	82	53.8
	h49	10	Kerr	291	129	94.8
	h50	11	La Salle	293	185	105
	h51	12	Medina	240	114	28.8
	h52	13	Real	327	166	107
	h53	14	Uvalde	301	176	90.5
	h54	15	Wilson	197	83.1	37.7
	h55	16	Zavala	335	172	92.1

4.4. Problem formulation

The decision-making model has been formulated as a two-stage stochastic programming model [46]. The first-stage models the pre-positioning of supplies between food banks while the second-stage provides recourse actions for supplies prepositioning and also considers supplies distribution to the demand nodes under different scenarios. A specific scenario is denoted as ω with the associated probability parameter p_{ω}. First stage decision variables, second stage decision variables and associated parameters are defined in Table 20.Using the notation described in Table 20, the two-stage stochastic linear programing model is formulated using Equations (2) to (4).

Table 20:Decision variable and parameters for Stochastic programming model.

First-Stage Decision Variables	
S_n	Stored (pre-positioned) quantity of supplies at supply node n
x_{nj}	Quantity of supply units shipped from supply node n to supply node j, $n, j \in N$.
Second-Stage Decision Variables	
$u_{h,\omega}$	Unmet demand quantity at node h, per scenario ω.
$w_{nj,\omega}$	Quantity of supplies shipped from supplier n to supplier j, per scenario ω.
$y_{nh,\omega}$	Quantity of supplies shipped from supplier node n to demand node h, per scenario ω.
Supply Node Parameters	
I_n	Initial inventory stored at supply node n.
C_n	Storage capacity at supply node n.
D_n	Regular (Normal) donations at supplier node n prior to the event.
R_n	Disaster relief donations at supplier node n after the event.
d_{nj}	Unit transportation cost from supply node n to supply node j.
Demand Node Parameters	
F_h	Forecasted demand at demand node h prior to the event.
v_h	Unit cost for unmet demand at demand node h.
d_{nj}	Unit transportation cost from supply node n to demand node h.
t_{nh}	Unit transportation cost from supply node n to demand node h.
Supply and Demand Changing Factors	
$\gamma_{h,\omega}$	Demand changing factor at demand node h per scenario ω.
$\delta_{n,\omega}$	Donation changing factor at supply node n per scenario ω.
$\propto_{n,\omega}$	Inventory changing factor at supply node n per scenario ω.

The first stage pre-positioning model involves the movement of food between supply nodes only. The flow is represented by decision variable x_{ij} to indicate the flow between supply node i to supply node j. The transportation cost between suppliers is represented as d_{nj}. The response phase uses a similar decision variable $w_{nj,\omega}$ which correspond to flow between supplier to supplier under scenario ω. Additionally, the flow from a supplier to a demand node needs to be specified using variable $y_{nh,\omega}$ from supply node n to demand node h with a transportation cost t_{nh}.

The donation changing factor represents the change in donations per scenario ω. It is understood that donation quantity varies according to the severity of event. The inventory changing factor represents the functionality of food bank. In event of a severe hurricane, the food bank facility could find it difficult to operate and may also cease operations till conditions improve. At those times, the inventory stored in facility cannot be used for distribution till situations become better. Similarly, the after-event demand changing factor ($F_h * \gamma_{n,\omega}$) involves the adjustments in demand following the hurricane. Sometimes, the severity of hurricane could be weaker or stronger than what was forecasted, then the predicted demand may vary accordingly. It may happen that people, where the event took place, may have not moved out after being served evacuation notice. Hence the demand may have increased for food. Also, people overestimating the severity of hurricane may have moved out without being issued an evacuation notice may result in decrease in demand. Also, migration of people to safer locations for shelter may influence the forecasted demand. The unmet demand $u_{h,\omega}$ represents the potential loss of life and property due to insufficient supplies. In practicality, it illustrates the cost required to acquire goods from another source at a higher cost.

$$Min \sum_{n}\sum_{j} x_{nj} * d_{nj} + \sum_{\omega\in\Omega} p_{\omega} * \left\{\sum_{n}\sum_{h} y_{nh,\omega} * t_{nh} + \sum_{n}\sum_{j} w_{nj,\omega} * d_{nj} + \sum_{h} u_{h,\omega} * v_{h}\right\} \qquad (2)$$

Subject to

Pre-Positioning Constraints
Modified Flow Balance

$$S_n = \sum_j x_{jn} + I_n - \sum_j x_{nj} + D_n, \qquad \forall n \in N \qquad (3a)$$

Pre-Positioned Storage Capacity

$$S_n \leq C_n, \qquad \forall n \in N \qquad (3b)$$

Response Stage Constraints

Flow Constraint

$$S_n * \propto_{n,\omega} + R_n * \delta_{n,\omega} + \sum_i w_{in,\omega} \geq \sum_j w_{nj,\bar{\omega}} + \sum_h y_{nh,\omega} \quad \forall n \in N, \omega \in \Omega \qquad (4a)$$

Demand Requirement

$$\sum_n y_{nh,\omega} + u_{h,\omega} = F_h * \gamma_{h,\omega} \qquad \forall h \in H, \omega \in \Omega \qquad (4b)$$

Non-Negativity Constraints

$$x_{nj}, w_{in,\omega}, y_{nh,\omega}, u_{h,\omega}, S_n, D_n, R_n \geq 0 \qquad \forall n, j \in N, \forall h \in H, \omega \in \Omega \qquad (4c)$$

The objective function minimizes the cost associated to the prepositioning of supplies and the expected unmet demand. The initial term of objective function illustrates the pre-positioning costs while remainder of it represents the response-phase of after the natural disaster. Constraint $(3a)$ ensures the total of outbound flows and pre-positioned supply quantity equals the total of inflows and initial inventory. Constraint $(3b)$ ensures the stored quantity is always less than or at the most equal to the capacity of warehouse. Constraint $(4a)$ deals with the movement of supplies after the hurricane, ensuring flow balance between supplier to supplier and supplier to demands. Constraint $(4b)$ confirms the supply and demand requirement. Constraint $(4c)$ binds all decision variables to be non-negative.

4.5. Experimental Design

The aim of the experimental design is to gather insights for the prepositioning and distribution of supplies when considering the impact of a natural disaster. In this research, hurricane Harvey served as the case study and the parameters used in the model were estimated using data collected by the food banks before and after the natural disaster. The four experimental situations considered in this study are summarized in Table 21. The experiments consider four *potential situations* that might affect the operation of a network of food banks in charge of providing disaster relief.

Table 21: List of experiments (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

Experiment No.	**Description**	**HFB**	**CTFB**	**SAFB**
1	All food banks open	Operational	Operational	Operational
2	HFB is closed due to hurricane category 4 or 5	Non-operational	Operational	Operational
3	HFB and CTFB are closed due to hurricane category 4 or 5	Non-operational	Non-operational	Operational
4	HFB and SAFB are closed due to hurricane category 4 or 5	Non-operational	Operational	Non-operational

Natural disasters, such as hurricane Harvey, disrupt the normal operations of food bank facilities by damaging structures, flooding, among other circumstances. *The four experiments discussed in Table 21 seek to understand the robustness of the food bank network in terms of operational capacity when one or two facilities in the network become nonoperational after the impact of a hurricane category 4 or 5*. Operational facilities will need to pick up the extra workload if one or two facilities shut down after a natural disaster. The situations defined in the experiments try to determine the applicability of pre-positioning and explore the system capability of meeting the demands for supplies.

4.5.1. Model Data and Scenario Generation

The data used in this research is obtained from the historical data provided by Houston Food Bank, Central Texas Food Bank, and San Antonio Food Bank. The food banks provided the data for donations, inventory, distribution, disaster relief donations, and disaster relief distribution. Table 22 illustrates the data subsequently used to calculate the capacity for the food bank facility.

Table 22: Supply node parameter values

Parameters		Houston Food Bank	Central Texas Food Bank	San Antonio Food Bank
I_n	Initial inventory stored at supply node *n* (daily)	7,995,435.16	5,484,931.36	5,484,931.36
C_n	Storage capacity at supply node *n*	17,500,000.00	9,000,000.00	9,000,000.00
D_n	Forecasted donations at supplier node *n* prior to the event (daily)	261,445.20	44,989.85	44,989.85
R_n	Forecasted disaster relief donations at supplier node *n* after the event (daily)	610,363.92	57,367.28	57,367.28

A total of 21 scenarios are considered in the two-stage stochastic programming model. The probabilities for each scenario are computed using the product of two factors (1) probability of the strength of the natural disaster (i.e. how likely is to be impacted either by a tropical storm or a hurricane level 1, 2, 3, 4, or 5) and (2) probability of citizens reaction to a forecasted event as presented in Table 23 [47].

Table 23: Supply and demand change based on citizen reaction to a natural disaster

Reaction Case	Supply Change	Demand Change	Assumption
1	Decrease	No Change	Structural integrity is compromised and thus supply decreases. The level of decrease depends on the event severity.
2	Decrease	Increase	Demand increases because warnings may have been ignored and the number of actual victims is larger than expected. Structural integrity of supply centers is compromised.
3	Decrease	Decrease	Demand forecast decreases due to a false alarm (for category 1 or 2 event) or because the number of victims is less than expected. Structural integrity of supply centers is compromised.
4	No Change	Increase	Event causes little structural damage and thus supply is not affected. Demand increases due to overreaction by the affected population.
5	No Change	No Change	Event has no effect on the supply or demand, which is only true if the event does not occur.

Data from [48] and [49] was used to compute the probability of the strength of the natural disaster (i.e. how likely is to be impacted either by a tropical storm or a hurricane level 1, 2, 3, 4, or 5) in Texas. Historical data that containing data from tropical storms and hurricanes that occurred since 1970 were considered for the data analysis. The probability of each hurricane is calculated considering the number of times they occurred. The probabilities are based on the number of landfall hurricanes per year and the categorization of the Saffir/Simpson Hurricane Scale [50]. Hurricanes are categorized from least damaging hurricane to most damaging on a scale of 1 to 5. Category 1 is the least damaging and is considered not to affect the supply and demand to a large extent. Category 5 hurricanes are the most damaging hurricanes affecting a larger population. Table 24 summarizes the data used to compute the probabilities per scenario. The probability of each scenario is presented in the sixth column of the table.

Table 24: Experimental scenario and corresponding probabilities

Event	**P(Event)**	**Reaction Case**	**P (Reaction Case | Event)**	**Ω**	**P (ω)**
No Hurricane	0.49	5	1	ω1	0.493671
Category 1	0.13	1 (no change)	0.32	ω2	0.040506
		2 (increase)	0.32	ω3	0.040506
		3 (decrease)	0.04	ω4	0.005063
		4 (increase)	0.32	ω5	0.040506
Category 2	0.10	1 (no change)	0.1	ω6	0.010127
		2 (increase)	0.6	ω7	0.060759
		3 (decrease)	0.1	ω8	0.010127
		4 (increase)	0.2	ω9	0.020253
Category 3	0.06	1 (no change)	0.3	ω10	0.018987
		2 (increase)	0.4	ω11	0.025316
		3 (decrease)	0.1	ω12	0.006329
		4 (increase)	0.2	ω13	0.012658
Category 4	0.13	1 (no change)	0.05	ω14	0.006329
		2 (increase)	0.75	ω15	0.094937
		3 (decrease)	0.15	ω16	0.018987
		4 (increase)	0.05	ω17	0.006329
Category 5	0.09	1 (no change)	0.1	ω18	0.008861
		2 (increase)	0.74	ω19	0.06557
		3 (decrease)	0.15	ω20	0.013291
		4 (increase)	0.01	ω21	0.000886

The level of impact of the hurricane and the behavior of the people before and after the event, as indicated in Table 23, triggers changes in the demand. In this work, the demand changing factor ($\gamma_{n,\omega}$) at demand node h is defined to represent the changes in demand per scenario **Ω**. The values for demand changing factors are available in Appendix.

4.6. Results and Discussion

The four experimental situations considered in this study are summarized in Table 21. The experiments consider four *potential situations* that might affect the operation of a network of food banks in charge of providing disaster relief. The experiments seek to study the impact of shutting down one or two supply nodes due to the direct impact of a hurricane category 4 or 5. The donation changing factor ($\delta_{n,\omega}$) and the inventory changing factor ($\propto_{n,\omega}$) are used to make the donations and inventory unavailable on those facilities closed due to the impact of a hurricane category 4 or 5 in order to represent the four *potential situations*. Table 25 and Table 26 summarizes the inventory changing factors and donation changing factors respectively for each experiment. These values are computed based on the inventory and donation behavior observed at the food banks in years 2016 and 2017. These values are computed based on the inventory and donation behavior observed at the food banks in years 2016 and 2017.

Table 25: Inventory changing factors for experiments 1 to 4 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

Scenario	**Experiment 1**			**Experiment 2**			**Experiment 3**			**Experiment 4**		
Ω	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**
ω1	1	1	1	1	1	1	1	1	1	1	1	1
ω2	1	1	1	1	1	1	1	1	1	1	1	1
ω3	1	1	1	1	1	1	1	1	1	1	1	1
ω4	1	1	1	1	1	1	1	1	1	1	1	1
ω5	1	1	1	1	1	1	1	1	1	1	1	1
ω6	1	1	1	1	1	1	1	1	1	1	1	1
ω7	1	1	1	1	1	1	1	1	1	1	1	1

Scenario	Experiment 1			Experiment 2			Experiment 3			Experiment 4		
Ω	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**
ω8	1	1	1	1	1	1	1	1	1	1	1	1
ω9	1	1	1	1	1	1	1	1	1	1	1	1
ω10	1	1	1	1	1	1	1	1	1	1	1	1
ω11	1	1	1	1	1	1	1	1	1	1	1	1
ω12	1	1	1	1	1	1	1	1	1	1	1	1
ω13	1	1	1	1	1	1	1	1	1	1	1	1
ω14	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω15	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω16	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω17	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω18	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω19	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω20	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω21	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**

Table 26: Donation changing factors for experiments 1 to 4 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

Scenario	Experiment 1			Experiment 2			Experiment 3			Experiment 4		
Ω	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**
ω1	1	1	1	1	1	1	1	1	1	1	1	1
ω2	1	1	1	1	1	1	1	1	1	1	1	1
ω3	1	1	1	1	1	1	1	1	1	1	1	1
ω4	1	1	1	1	1	1	1	1	1	1	1	1
ω5	1	1	1	1	1	1	1	1	1	1	1	1
ω6	1	1	1	1	1	1	1	1	1	1	1	1
ω7	1	1	1	1	1	1	1	1	1	1	1	1
ω8	1	1	1	1	1	1	1	1	1	1	1	1
ω9	1	1	1	1	1	1	1	1	1	1	1	1
ω10	1	1	1	1	1	1	1	1	1	1	1	1
ω11	2	1	1	2	1	1	2	1	1	2	1	1
ω12	2	1	1	2	1	1	2	1	1	2	1	1
ω13	2	1	1	2	1	1	2	1	1	2	1	1
ω14	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω15	2.3	1.3	1.3	**0**	1.3	1.3	**0**	**0**	1.3	**0**	1.3	**0**
ω16	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω17	2.3	1.3	1.3	**0**	1.3	1.3	**0**	**0**	1.3	**0**	1.3	**0**
ω18	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**

Scenario	Experiment 1			Experiment 2			Experiment 3			Experiment 4		
Ω	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**	**HFB**	**CTFB**	**SAFB**
ω19	2.7	1.5	1.5	**0**	1.5	1.5	**0**	**0**	1.5	**0**	1.5	**0**
ω20	1	1	1	**0**	1	1	**0**	**0**	1	**0**	1	**0**
ω21	2.7	1.5	1.5	**0**	1.5	1.5	**0**	**0**	1.5	**0**	1.5	**0**

Figure 15 depicts the prepositioning cost, distribution cost, and combined cost incurred under each experiment. Experiment 1 has the smallest cost and not prepositioning cost associated to it. Under this experiments the network of food banks is capable of supplying to all counties. Figure 16 represents the distribution of food banks to different counties by the three food banks. The Venn diagram illustrate the demand nodes served by each food bank facility. The movement of supplies between the three food banks delivering to common counties varies according to scenarios. The scenarios are associated with the reaction case and hence, quantity shipped varies accordingly. There is no unmet demand in Experiment 1. Thus, the number supplies are expected to be sufficient to maintain a balance of supplies between food banks and the demand nodes. Figure 16 indicates the counties served by the active food banks. Demand nodes depicted in the intersection of the Venn diagram depicts areas that are supplied by more than one food bank facility. The figure shows that the Houston Food Bank is serving a limited number of counties. Since Houston is closer to the Gulf Coast, their expected demand is higher than that for the other two food banks. The computational results indicate that counties in Houston after a natural disaster are served by the other two food banks in the supply network.

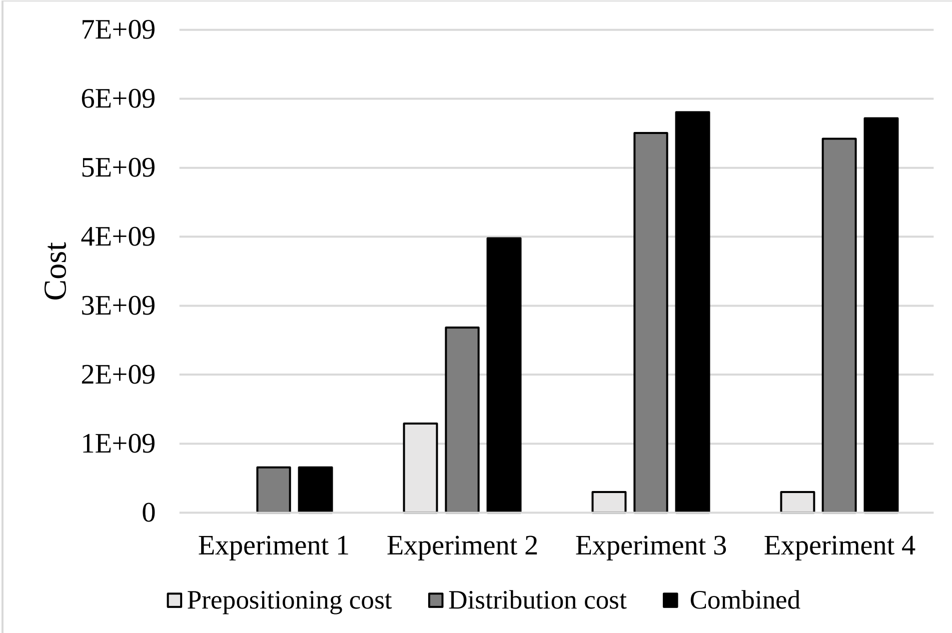

Figure 15: Cost associate to each experiment

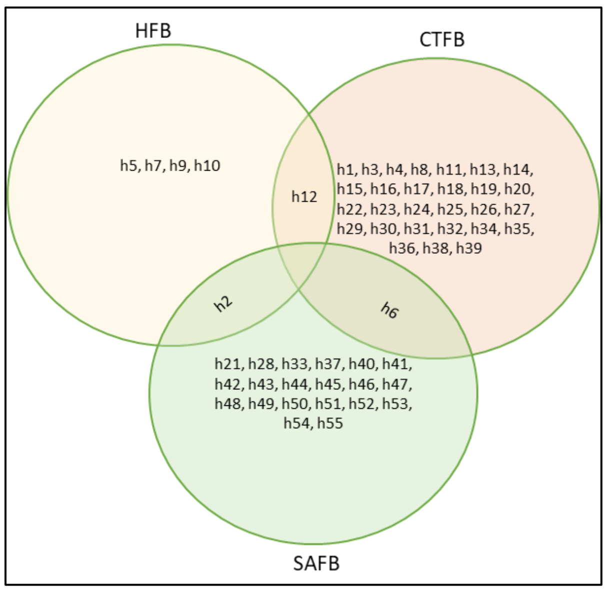

Figure 16: Counties served per food bank in Experiment 1 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

Experiment 2 studies the situation in which the Houston Food Bank becomes non-operational or inaccessible during category 4 and category 5 hurricane. This model intends to investigate the kind of activities that needs to be performed before and after the hurricane. The donation changing factor ($\delta_{n,\omega}$) and the inventory changing factor ($\propto_{n,\omega}$) for Experiment 2 are listed in Table 25 and Table 26 respectively. It can be observed that from scenario 14 to scenario 21, the Houston Food Bank inventory changing factor and donation changing factor are zero. This implies that the Houston Food Bank got adversely affected and became non-operational during category 4 and category 5 hurricane. Thus, the resultant pre-positioned supplies and donations at the Houston Food Bank became unavailable for distribution.

Figure 17 indicates the counties served by the active food banks for the scenarios were hurricane categories 1 to 3 are considered. Demand nodes depicted in the intersection of the Venn diagram depicts areas that are supplied by more than one food bank facility. The figure shows that the Houston Food Bank is serving a limited number of counties. Since Houston is closer to the Gulf Coast, their expected demand is higher than for the other two food banks. The computational results indicate that counties in Houston, after a natural disaster, are served by the other two food banks in the supply network.

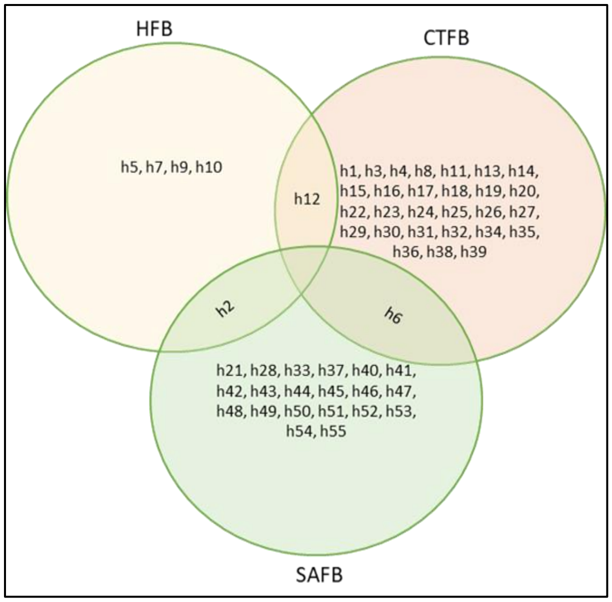

Figure 17: Counties served per food bank in Experiment 2 for hurricane categories 1 – 3 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

Figure 18 shows that the Central Texas Food Bank does majority of distribution when the Houston Food Bank goes down under scenarios considering a hurricane category 4 or 5. The San Antonio Food Bank aids by distributing to counties in Houston and in the Austin area. The three food banks work together to satisfy the demand. The initial inventory and prepositioning actions play an important role in satisfying the demand of the counties. Figure 19 illustrates the counties with unmet demand in Experiment 2.

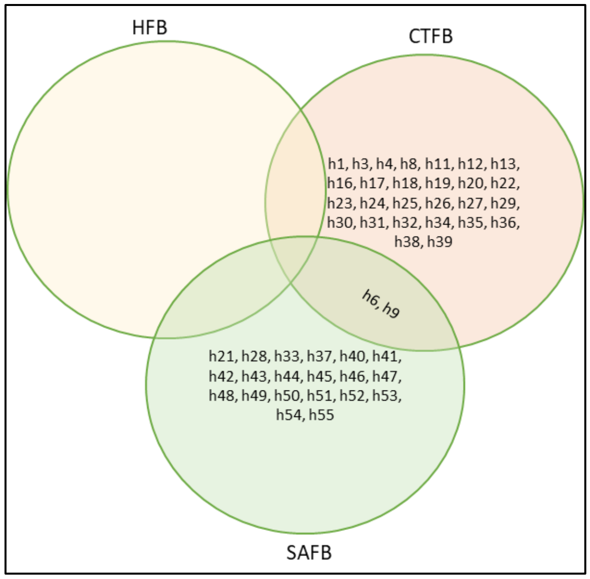

Figure 18: Counties served per food bank in Experiment 2 for hurricane categories 4 – 5 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

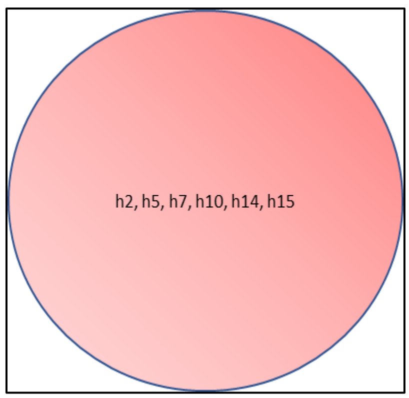

Figure 19: Unmet demand under Experiment 2

Experiment 3 studies the situation in which the Houston Food Bank and the Central Texas Food Bank become non-operational or inaccessible during category 4 and category 5 hurricane. This model intends to investigate the kind of activities that needs to be performed before and after the hurricane. The donation changing factor ($\delta_{n,\omega}$) and the inventory changing factor ($\propto_{n,\omega}$) for Experiment 3 are listed in Table 25 and Table 26 respectively. It can be observed that from scenario 14 to scenario 21, the Houston Food Bank and Central Texas Food Bank inventory changing factor and donation changing factor are zero. This implies that the Houston Food Bank and Central Texas Food Bank got adversely affected and became non-operational during category 4 and category 5 hurricane. Thus, the resultant pre-positioned supplies and donations at the Houston Food Bank and Central Texas Food Bank became unavailable for distribution.

Figure 20 indicates that the counties served by the operational food banks for hurricane categories 1 to 3. Demand nodes depicted in the intersection of the Venn diagram depicts areas that are supplied by more than one food bank facility. The figure shows that the Houston Food Bank is serving a limited number of counties. Since Houston is closer to the Gulf Coast, their expected demand is higher than for the other two food banks. The computational results indicate that counties in Houston, after a natural disaster, are served by the other two food banks in the supply network.

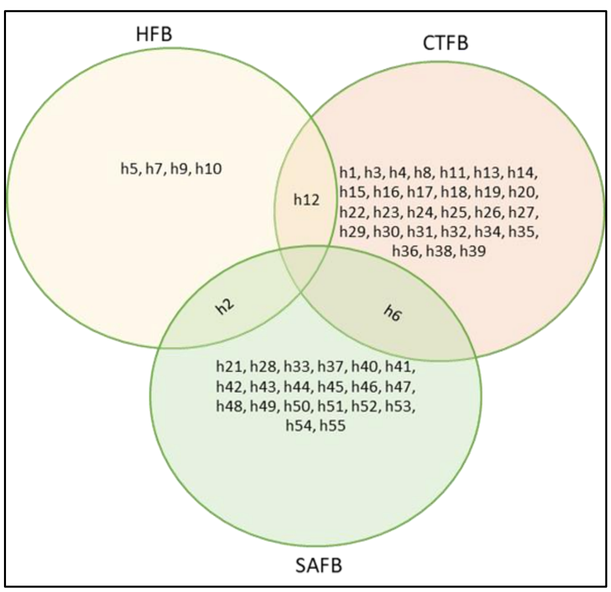

Figure 20: Counties served per food bank in Experiment 3 for hurricane categories 1 – 3 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank).

Figure 21 shows that the San Antonio Food Bank does majority of distribution when the Houston Food Bank and the Central Texas Food Bank go down under scenarios considering a hurricane category 4 or 5. The San Antonio Food Bank aids by distributing to counties in Houston and in the Austin area. The three food banks work together to satisfy the demand. The San Antonio Food Bank tries to meet the demand requirement of each demand node keeping the transportation cost minimum. The initial inventory and prepositioning actions play an important role in satisfying the demand of the counties. Figure 22 illustrates the counties with unmet demand in Experiment 3 and indicates there are sixteen counties which could potentially be undersupplied during category 4 and category 5 hurricane.

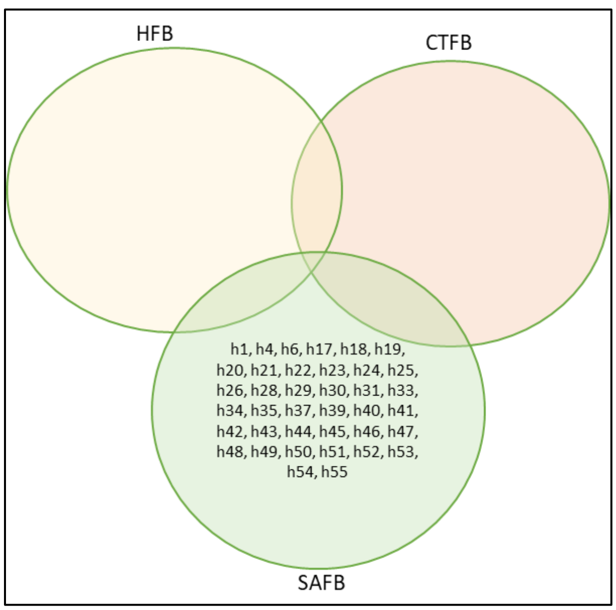

Figure 21: Counties served per food bank in Experiment 3 for hurricane categories 4 – 5 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

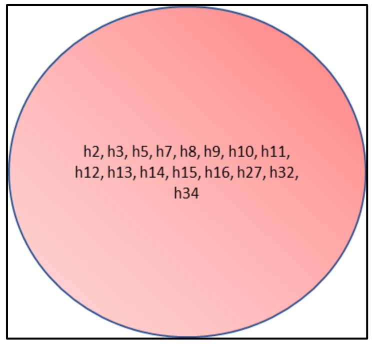

Figure 22: Unmet demand under Experiment 3

Experiment 4 studies the situation in which the Houston Food Bank and the San Antonio Food Bank become non-operational or inaccessible during category 4 and category 5 hurricane. This model intends to investigate the kind of activities that needs to be performed before and after the hurricane. The donation changing factor ($\delta_{n,\omega}$) and the inventory changing factor ($\propto_{n,\omega}$) for Experiment 4 are listed in Table 25 and Table 26 respectively. It can be observed that from scenario 14 to scenario 21, the Houston Food Bank and San Antonio Food Bank inventory changing factor and donation changing factor are zero. This implies that the Houston Food Bank and San Antonio Food Bank got adversely affected and became non-operational during category 4 and category 5 hurricane. Thus, the resultant pre-positioned supplies and donations at the Houston Food Bank and San Antonio Food Bank became unavailable for distribution.

Figure 23 indicates the counties served by the active food banks for the scenarios were hurricane categories 1 to 3 are considered. Demand nodes depicted in the intersection of the Venn diagram depicts areas that are supplied by more than one food bank facility. The figure shows that the Houston Food Bank is serving a limited number of counties. Since Houston is closer to the Gulf Coast, their expected demand is higher than for the other two food banks. The computational results indicate that counties in

Houston, after a natural disaster, are served by the other two food banks in the supply network.

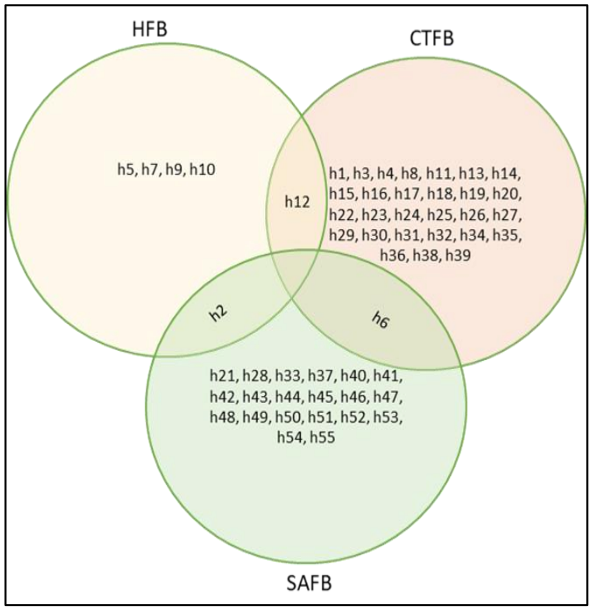

Figure 23: Counties served per food bank in Experiment 4 for hurricane categories 1 – 3 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

Figure 24 shows that the Central Texas Food Bank does majority of distribution when the Houston Food Bank and the San Antonio Food Bank go down under scenarios considering a hurricane category 4 or 5. The Central Texas Food Bank aids by distributing to counties in Houston and in the San Antonio area. The three food banks work together to satisfy the demand. The Central Texas Food Bank tries to meet the demand requirement of each demand node keeping the transportation cost minimum. The initial inventory and prepositioning actions play an important role in satisfying the demand of the counties. Figure 25 illustrates the counties with unmet demand in Experiment 4 and indicates there are fifteen counties which could potentially be undersupplied during category 4 and category 5 hurricane.

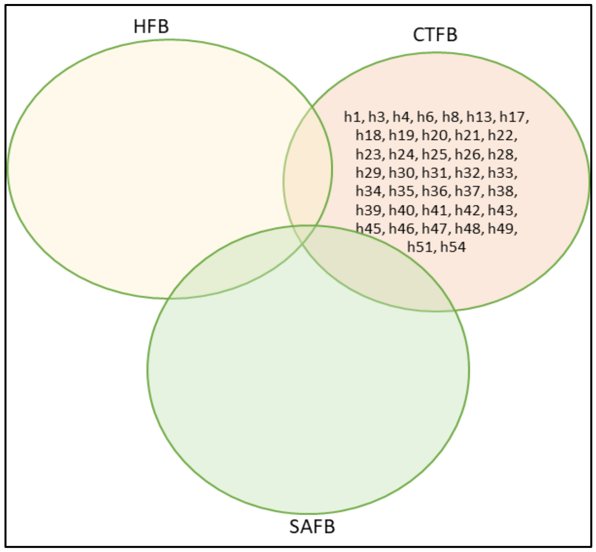

Figure 24: Counties served per food bank in Experiment 4 for hurricane categories 4 – 5 (*HFB*=Houston Food Bank, *CTFB*=Central Texas Food Bank, *SAFB*= San Antonio Food Bank)

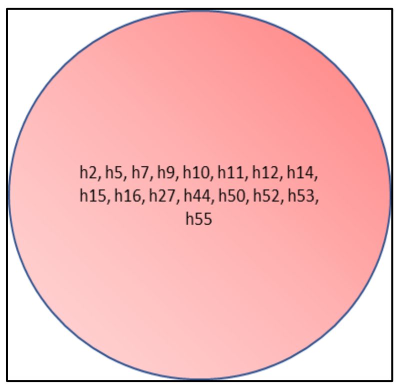

Figure 25: Unmet demand under Experiment 4

5. CONCLUSION

The goal of this research is to analyze and forecast the amount of donations received by food bank facilities impacted by natural disasters and implement the decision-making model. This research is based on data compiled by Central Texas Food Bank in Austin TX and the Houston Food Bank in Houston TX, before and after the impact of a natural disaster. Forecast models were studied to gather insights on the uncertain behavior of product donations faced by food banks during "normal" and "disaster relief" operational periods. The donation behavior is analyzed using two years of data and considering various classes such as donor type, donated product type and/or combination of both, at each food bank.

The results showed that forecast models performed better when all donations were considered together as a group for each food bank when compared to the ones generated for particular donors or product types. However, investigating different clusters and combination of donor type and/or product type provided better insights about measures food banks can take to be better prepared on what to anticipate during hurricanes. The information will help food banks prepare better in future similar scenarios. The forecast models can help food banks to predict what type of product will be donated and avoid accumulation of it by collaborating with subsidiaries or their affiliates in need.

The latter part of this research used a two-stage stochastic programming model to develop a response policy for food banks that would help in assigning the food and food products to the correct demand locations based on probability of an event. The model suggested a pre-positioning policy that would enable food banks to align their resources prior to the occurrence of disaster. The decisions were based on minimizing the transport cost, since food banks are a non-profit organization. It is assumed that pre-positioning would prioritize movement of goods considering the event path. Nodes that were closer to disaster impact were assigned higher priority as they suffered most damage.

This study highlights the impact initial inventory has on food banks' execution of decisions. In the scenarios analyzed, pre-positioning was required as food banks lacked enough reserves for distribution to meet the increasing demand and additional population to be served. Pre-position was also done considering hurricane category 4 and category 5 which could potentially render food banks non-functional and unable to transport food to the demand locations. The donations, both regular and disaster-relief, added to the strong inventory such that only required quantity of pre-positioning was done. Response phase involved a reduced amount of movement of food during the post-disaster period. Increase in initial inventory and capacity had a direct impact on movement of food and the unmet demand for category 4 and category 5 hurricane.

The model was also tested considering different food banks being non-operational due to hurricane under different scenarios. Different costs pertaining to the two stages was analyzed. It can be observed that Houston Food Bank and Central Texas Food Bank becoming non-functional is potentially the costliest situation. Further research could be done in terms of transportation cost variation before and after disaster. Often, after disaster, the transportation cost from one place to another may change depending on severity of hurricane. Also, the roads condition may be damaged after hurricane, such that transport may have to take a longer route. This research is modeled around Hurricane Harvey as natural disaster; future research could undertake other natural disaster such as earthquake and perform the analysis. This model used 3 supply nodes, and 55 demand nodes. It could be made a more complex numerical problem involving other food banks of different volumes. Moreover, the time needed for transportation is not considered in this research which could play a vital role in future study.

This research covered three food banks in state of Texas. Future research could include more food banks that are at greater distance to emphasize more on pre-positioning. Also, the input parameters for different food banks could be different and it could lead to different decisions. Increasing number of natural disasters such as hurricane, earthquakes, typhoons, etc. require better decision-making models and a well-structured supply chain to work for aiding humanity in times of trouble. Future work could consider an ensemble of different activities such that loss of life and property due to natural disasters can be minimized, if not eliminated.

APPENDIX SECTION

APPENDIX A

ALL PRODUCT TYPE

1	Household cleaning product
2	**Meat/fish/poultry**
3	Pet food/pet care
4	**Dairy/prepared/perishable food**
5	**Produce**
6	**Packed food**
7	Assorted nonfood
8	Pharmacy
9	Baby food / formula
10	Snack food / cookies
11	**Water**

APPENDIX B

ALL DONOR TYPES

1	Individual/family
2	**Wholesale**
3	**Manufacturer**
4	**Retail**
5	**Company/corporation**
6	**Government**
7	Foundation
8	Schools/Church
9	Red Barrels (Houston)
10	Hotel/kitchen/restaurants
11	**Nonprofit community/ food drives**
12	Hospital /Healthcare/ Banks /Events

APPENDIX C

DEMAND CHANGING FACTOR FOR HOUSTON FOOD BANK

Scenario	HOUSTON FOOD BANK																	
Ω	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18
ω1	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω2	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω3	51.1	51.3	51.1	51.1	51.3	51.2	51.3	51.1	51.2	51.2	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
ω4	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9
ω5	51.1	51.3	51.1	51.1	51.3	51.2	51.3	51.1	51.2	51.2	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
ω6	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω7	51.2	51.4	51.2	51.2	51.4	51.3	51.4	51.2	51.3	51.3	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2
ω8	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9
ω9	51.2	51.4	51.2	51.2	51.4	51.3	51.4	51.2	51.3	51.3	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2
ω10	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω11	51.3	51.5	51.3	51.3	51.5	51.4	51.5	51.3	51.4	51.4	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3
ω12	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9
ω13	51.3	51.5	51.3	51.3	51.5	51.4	51.5	51.3	51.4	51.4	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3
ω14	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω15	51.4	51.6	51.4	51.4	51.6	51.5	51.6	51.4	51.5	51.5	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4
ω16	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9
ω17	51.4	51.6	51.4	51.4	51.6	51.5	51.6	51.4	51.5	51.5	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4
ω18	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω19	51.5	51.7	51.5	51.5	51.7	51.6	51.7	51.5	51.6	51.6	51.5	51.5	51.5	51.5	51.5	51.5	51.5	51.5
ω20	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9	50.9
ω21	51.5	51.7	51.5	51.5	51.7	51.6	51.7	51.5	51.6	51.6	51.5	51.5	51.5	51.5	51.5	51.5	51.5	51.5
	Austin	Brazoria County	Brazos	Burleson	Chambers	Fort Bend	Galveston	Grimes	Harris	Liberty	Madison	Montgomery	Robertson	San Jacinto	Trinity	Walker	Waller	Washington

APPENDIX D

DEMAND CHANGING FACTOR FOR CENTRAL TEXAS FOOD BANK

Scenario	CENTRAL TEXAS FOOD BANK																				
Ω	h19	h20	h21	h22	h23	h24	h25	h26	h27	h28	h29	h30	h31	h32	h33	h34	h35	h36	h37	h38	h39
ω1	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω2	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω3	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω4	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω5	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω6	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω7	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
ω8	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω9	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
ω10	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω11	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2
ω12	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω13	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2
ω14	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω15	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3
ω16	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω17	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3
ω18	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω19	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4
ω20	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω21	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4
County Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
County Name	Bastrop	Bell	Blanco	Burnet	Caldwell	Coryell	Falls	Fayette	Freestone	Gillespie	Hays	Lampasas	Lee	Limestone	Llano	McLennan	Milam	Mills	San Saba	Travis	Williamson

APPENDIX E

DEMAND CHANGING FACTOR FOR SAN ANTONIO FOOD BANK

Scenario	SAN ANTONIO FOOD BANK															
Ω	h40	h41	h42	h43	h44	h45	h46	h47	h48	h49	h50	h51	h52	h53	h54	h55
ω1	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω2	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω3	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω4	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω5	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω6	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω7	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
ω8	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω9	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1	51.1
ω10	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω11	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2
ω12	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω13	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2	51.2
ω14	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω15	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3
ω16	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω17	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3	51.3
ω18	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω19	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4
ω20	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0
ω21	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4	51.4
County Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
County Name	Atascosa	Bandera	Bexar	Comal	Edwards	Frio	Guadalupe	Karnes	Kendall	Kerr	La Salle	Medina	Real	Uvalde	Wilson	Zavala

APPENDIX F

LIST OF LIBRARIES USED IN R

library(lubridate)

library(tidyverse)

library(readxl)

library(xts)

library(zoo)

library(xlsx)

library(ie2misc)

library(githubinstall)

library(remotes)

library(tidyquant)

library(MLmetrics)

library(forecast)

APPENDIX G

R- program illustrating ARIMA code.

```
data1 <- read_excel("Unaltered_Has_Peak_and_Missing_Dates_File.xlsx")


data.forecast <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`<="2016-12-31") %>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.v <- group_by(.data = data1, DATE) %>% # verification vector
  filter(`FOOD BANK`=="Houston", `DATE`>="2017-01-01",`DATE`<="2017-08-31")
%>%
  summarise(Total_Amount = sum(AMOUNT))



data.forecast.w <- tq_transmute(data.forecast, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)


data.forecast.w <- data.forecast.w[2:53, ]


data.forecast.wv <- tq_transmute(data.forecast.v, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)
```

```
df1 <- adf.test(data.forecast.w$Total_Amount, alternative = c("explosive"))

acf(data.forecast.w$Total_Amount)

pacf(data.forecast.w$Total_Amount)

arima.w <- arima(data.forecast.w$Total_Amount, order = c(1,0,0))

pred1 <- predict(arima.w, n.ahead = 35)

MAPE(y_pred = pred1$pred, y_true = data.forecast.wv$Total_Amount)
```

APPENDIX H

R- program illustrating HOLT code.

```
data1 <- read_excel("Unaltered_Has_Peak_and_Missing_Dates_File.xlsx")


data.forecast <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`<="2016-12-31") %>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.w <- tq_transmute(data.forecast, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)


data.forecast.w <- data.forecast.w[2:53, ]


data.forecast.xts <- as.xts(x = data.forecast.w$Total_Amount, order.by =
data.forecast.w$DATE)


data.forecast.v <- group_by(.data = data1, DATE) %>% # verification vector
  filter(`FOOD BANK`=="Houston", `DATE`>="2017-01-01",`DATE`<="2017-08-31")
%>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.wv <- tq_transmute(data.forecast.v, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)
```

```
#data.forecast.xtsv <- as.xts(x = data.forecast.wv$Total_Amount, order.by =
data.forecast.wv$DATE)

holt1 <- holt(y = data.forecast.xts, h = 10, damped = FALSE, level = 0.9, alpha = NULL,
beta = NULL, gamma = FALSE) %>%
	forecast(n.ahead = 35)

MAPE(y_pred = holt1$fitted, y_true = data.forecast.wv$Total_Amount)
```

APPENDIX I

R- program illustrating HOLT-WINTERS code.

```
data1 <- read_excel("Unaltered_Has_Peak_and_Missing_Dates_File.xlsx")

data.forecast <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`<="2016-12-31") %>%
  summarise(Total_Amount = sum(AMOUNT))

data.forecast.w <- tq_transmute(data.forecast, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)

data.forecast.w <- data.forecast.w[2:53, ]

data.forecast.xts <- as.xts(x = data.forecast.w$Total_Amount, order.by =
data.forecast.w$DATE)

data.forecast.v <- group_by(.data = data1, DATE) %>% # verification vector
  filter(`FOOD BANK`=="Houston", `DATE`>="2017-01-01",`DATE`<="2017-08-31")
%>%
  summarise(Total_Amount = sum(AMOUNT))

data.forecast.wv <- tq_transmute(data.forecast.v, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)
```

```
data.forecast.xtsv <- as.xts(x = data.forecast.wv$Total_Amount, order.by =
data.forecast.wv$DATE)

m1 <- HoltWinters(x = na.omit(data.forecast.xts),gamma = FALSE) %>%
   forecast(h = 35)

pred1 <- predict(object = m1)
pred1 <- as.numeric(pred1[[4]])

MAPE(y_pred = pred1, y_true = data.forecast.wv$Total_Amount)
```

APPENDIX J

R- program illustrating NAÏVE code.

```
data1 <- read_excel("Unaltered_Has_Peak_and_Missing_Dates_File.xlsx")


data.forecast <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`<="2016-08-31") %>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.w <- tq_transmute(data.forecast, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)


data.forecast.w <- data.forecast.w[2:36, ]


data.forecast.v <- group_by(.data = data1, DATE) %>% # verification vector
  filter(`FOOD BANK`=="Houston", `DATE`>="2017-01-01",`DATE`<="2017-08-31")
%>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.wv <- tq_transmute(data.forecast.v, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)


MAPE(y_pred = data.forecast.w$Total_Amount, y_true =
data.forecast.wv$Total_Amount)
```

APPENDIX K

R- program illustrating Centered Moving Average code.

```
data1 <- read_excel("Unaltered_Has_Peak_and_Missing_Dates_File.xlsx")


data.forecast <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`<="2016-12-31") %>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.v <- group_by(.data = data1, DATE) %>% # verification vector
  filter(`FOOD BANK`=="Houston", `DATE`>="2017-01-01",`DATE`<="2017-08-31")
%>%
  summarise(Total_Amount = sum(AMOUNT))


data.forecast.w <- tq_transmute(data.forecast, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)


data.forecast.wv <- tq_transmute(data.forecast.v, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)
data.forecast.w$CMA_3 <- rollmean(x = data.forecast.w$Total_Amount, k = 3, fill =
"extend", n.ahead = 35)


MAPE(y_pred = data.forecast.w$CMA_3, y_true = data.forecast.wv$Total_Amount)
```

APPENDIX L

R- program illustrating ECONOMETRIC code.

```
data1 <- read_excel("Unaltered_Has_Peak_and_Missing_Dates_File.xlsx")
data1$Unemployment <- as.numeric(data1$Unemployment)
data1$GP <- data1$`Gas Prices`
data1$`Gas Prices` <- NULL

data.forecast <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`<="2016-12-31") %>%
  summarise(Total_Amount = sum(AMOUNT), Unemployment1 =
mean(Unemployment, na.rm = TRUE), GP = mean(GP, na.rm = TRUE),
          Productivity =  mean(Productivity, na.rm = TRUE),
          CPI = mean(CPI, na.rm = TRUE))


data.forecast.w1 <- tq_transmute(data.forecast, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)

data.forecast.w2 <- tq_transmute(data.forecast, select = Unemployment1, mutate_fun =
apply.weekly, FUN = mean)
```

```
data.forecast.w3 <- tq_transmute(data.forecast, select = GP, mutate_fun = apply.weekly,
FUN = mean)

data.forecast.w4 <- tq_transmute(data.forecast, select = Productivity, mutate_fun =
apply.weekly, FUN = mean)

data.forecast.w5 <- tq_transmute(data.forecast, select = CPI, mutate_fun = apply.weekly,
FUN = mean)

data.forecast.w <- data.frame(data.forecast.w1, data.forecast.w2, data.forecast.w3,
data.forecast.w4, data.forecast.w5)

econo_1 <- data.forecast.w

econo_1$period <- 1:53
# Unemployment
ccf(x = econo_1$Unemployment1, y =  econo_1$Total_Amount, lag.max = NULL, type
= c("correlation","covariance"),
   plot = TRUE, na.action = na.fail)
#Gas Prices

ccf(x = econo_1$GP, y = econo_1$Total_Amount, lag.max = NULL, type =
c("correlation","covariance"),
```

```
plot = TRUE, na.action = na.fail)

#Productivity

ccf(x = econo_1$Productivity, y = econo_1$Total_Amount, lag.max = NULL, type =
c("correlation","covariance"),
    plot = TRUE, na.action = na.fail)

#CPI

ccf(x = econo_1$CPI, y = econo_1$Total_Amount, lag.max = NULL, type =
c("correlation","covariance"),
    plot = TRUE, na.action = na.fail)

#CPI Lags

econo_1$CPIL1 <- lag(econo_1$CPI, n = 1)

econo_1$CPIL2 <- lag(econo_1$CPI, n = 2)

econo_1$CPIL3 <- lag(econo_1$CPI, n = 3)

econo_1$CPIL4 <- lag(econo_1$CPI, n = 4)
```

```
econo_1$CPIL5 <- lag(econo_1$CPI, n = 5)

econo_1$CPIL6 <- lag(econo_1$CPI, n = 6)

econo_1$CPIL7 <- lag(econo_1$CPI, n = 7)

econo_1$CPIL8 <- lag(econo_1$CPI, n = 8)

econo_1$CPIL9 <- lag(econo_1$CPI, n = 9)

econo_1$CPIL10 <- lag(econo_1$CPI, n = 10)

econo_1$CPIL11 <- lag(econo_1$CPI, n = 11)

econo_1$CPIL12 <- lag(econo_1$CPI, n = 12)

econo_1$CPIL13 <- lag(econo_1$CPI, n = 13)

obj2 <- lm(Total_Amount ~ CPIL1 + CPIL2 + CPIL3 + CPIL4 + CPIL5 +
           CPIL6 + CPIL7 + CPIL8 + CPIL9 + CPIL10 +
           CPIL11 + CPIL12 + CPIL13, data = econo_1)

summary(obj2)
```

```
#2017

data.forecast_f <- group_by(.data = data1, DATE) %>% # groups observations by DATE
  filter(`FOOD BANK`=="Houston", `DATE`>="2016-12-31") %>%
  summarise(Total_Amount = sum(AMOUNT), Unemployment1 =
mean(Unemployment, na.rm = TRUE), GP = mean(GP, na.rm = TRUE),
            Productivity =  mean(Productivity, na.rm = TRUE),
            CPI = mean(CPI, na.rm = TRUE))

data.forecast.w1_f <- tq_transmute(data.forecast_f, select = Total_Amount, mutate_fun =
apply.weekly, FUN = sum)

data.forecast.w2_f <- tq_transmute(data.forecast_f, select = Unemployment1, mutate_fun
= apply.weekly, FUN = mean)

data.forecast.w3_f <- tq_transmute(data.forecast_f, select = GP, mutate_fun =
apply.weekly, FUN = mean)

data.forecast.w4_f <- tq_transmute(data.forecast_f, select = Productivity, mutate_fun =
apply.weekly, FUN = mean)

data.forecast.w5_f <- tq_transmute(data.forecast_f, select = CPI, mutate_fun =
apply.weekly, FUN = mean)
```

```
data.forecast.w_f <- data.frame(data.forecast.w1_f, data.forecast.w2_f,
data.forecast.w3_f, data.forecast.w4_f, data.forecast.w5_f)
econo_2 <- data.forecast.w_f
econo_2$period <- 1:53

# Unemployment
ccf(x = econo_2$Unemployment1, y =  econo_2$Total_Amount, lag.max = NULL, type
= c("correlation","covariance"),
    plot = TRUE, na.action = na.fail)

#Gas Prices


ccf(x = econo_2$GP, y = econo_2$Total_Amount, lag.max = NULL, type =
c("correlation","covariance"),
    plot = TRUE, na.action = na.fail)

#Productivity
ccf(x = econo_2$Productivity, y = econo_2$Total_Amount, lag.max = NULL, type =
c("correlation","covariance"),
    plot = TRUE, na.action = na.fail)

#CPI
```

```
ccf(x = econo_2$CPI, y = econo_2$Total_Amount, lag.max = NULL, type =
c("correlation","covariance"),
    plot = TRUE, na.action = na.fail)


#LAGS
econo_2$Unemployment1L <- lag(econo_2$Unemployment1, n = 1)
econo_2$Productivity1 <- lag(econo_2$Productivity, n = 1)
econo_2$Productivity2 <- lag(econo_2$Productivity, n = 2)
econo_2$Productivity3 <- lag(econo_2$Productivity, n = 3)
econo_2$Productivity4 <- lag(econo_2$Productivity, n = 4)
econo_2$CPIL1 <- lag(econo_2$CPI, n = 1)
econo_2$CPIL2 <- lag(econo_2$CPI, n = 2)
econo_2$CPIL3 <- lag(econo_2$CPI, n = 3)
econo_2$CPIL4 <- lag(econo_2$CPI, n = 4)


obj3 <- lm(Total_Amount ~ Unemployment1L +
             CPIL1 + CPIL2 + CPIL3 + CPIL4 +
             Productivity1 + Productivity2 + Productivity3 + Productivity4, data = econo_2)
summary(obj3)
# MAPE
MAPE(y_pred = obj2$fitted.values, y_true = obj3$model$Total_Amount)
```

APPENDIX M

GAMS CODE FOR STOCHASTIC PROGRAMMING MODEL

```
$ontext

Experiment 1- Policy in use

$offtext


set

n supplier /n1*n3/

h Demand node /h1*h55/

omega scenario /o1*o21/


alias( n, j, i);


parameters


In(n) InitialInventory /

n1  7995435.16

n2  5484931.36

n3  5484931.36

/


C(n) SCapacity/

n1  17500000.00
```

n2 9000000.00

n3 9000000.00

/

E(n) RegDonations/

n1 261445.20

n2 44989.85

n3 44989.85

/

F(n) DisDonations/

n1 610363.92

n2 57367.28

n3 57367.28

/

ForcD(h) Forecasted Demand /

h1   628.54

h2   7682.92

h3   10809.83

h4   559.23

h5   741.49

h6   12789.20

h7 8400.96

h8 1019.79

h9 159302.49

h10 2678.38

h11 530.45

h12 11292.33

h13 561.14

h14 1032.70

h15 790.51

h16 2368.01

h17 1506.45

h18 995.53

h19 2251.84

h20 9500.03

h21 242.86

h22 1074.58

h23 1252.98

h24 2305.73

h25 772.95

h26 692.76

h27 557.61

h28 528.74

h29 6038.48

h30 562.71

h31 433.30

h32 1072.85

h33 547.08

h34 9887.82

h35 805.57

h36 147.63

h37 208.99

h38 30790.92

h39 7452.74

h40 1623.01

h41 628.44

h42 70191.87

h43 2164.62

h44 87.55

h45 1119.74

h46 2859.04

h47 701.03

h48 703.37

h49 1496.77

h50 458.05

h51 1286.98

h52 129.35

```
h53  1263.23

h54  1124.88

h55  787.92

/;

table dss(n,j) SSDist

    n1    n2    n3

n1  1000  165   208

n2  165   1000  86

n3  208   86    1000

;

table dsd(h,n) Supplier to Demand Dist

     n1    n2     n3

h1   68.9  102   152

h2   48.2  175   217

h3   103   105   186

h4   106   85    160

h5   45.5  208   251

h6   41.6  138   181

h7   44.7  203   246

h8   76.2  122   190

h9   2.4   162   205

h10  47    208   253

h11  108   140   220
```

h12	45.9	169	232
h13	137	105	187
h14	60	180	246
h15	111	192	262
h16	80	151	220
h17	58.3	119	175
h18	82.4	93.3	161
h19	1000	29.6	108
h20	1000	84.1	155
h21	1000	54.6	78.1
h22	1000	62.5	107
h23	1000	24.6	74.7
h24	1000	109	178
h25	1000	110	183
h26	1000	62.6	124
h27	1000	168	253
h28	1000	83.9	77.7
h29	1000	29.3	75.9
h30	1000	92.3	147
h31	1000	54.4	134
h32	1000	135	215
h33	1000	81.9	111
h34	1000	107	186

```
h35  1000  74.6  157

h36  1000  126   179

h37  1000  117   148

h38  1000  1.7   87.7

h39  1000  46.1  126

h40  1000  120   45.7

h41  1000  125   65.2

h42  1000  85.6  1.3

h43  1000  58.6  49.4

h44  1000  198   164

h45  1000  138   59

h46  1000  50.2  50.9

h47  1000  94.7  61.4

h48  1000  82    53.8

h49  1000  129   94.8

h50  1000  185   105

h51  1000  114   28.8

h52  1000  166   107

h53  1000  176   90.5

h54  1000  83.1  37.7

h55  1000  172   92.1

;

table scenario(omega,*) scenario probabilities
```

	P
o1	0.494
o2	0.041
o3	0.041
o4	0.005
o5	0.041
o6	0.010
o7	0.061
o8	0.010
o9	0.020
o10	0.019
o11	0.025
o12	0.006
o13	0.013
o14	0.006
o15	0.095
o16	0.019
o17	0.006
o18	0.009
o19	0.066
o20	0.013
o21	0.001

;

table Rd(h,omega) PreP Demand change per Scenario

	o1	o2	o3	o4	o5	o6	o7	o8	o9	o10	o11	o12	o13	o14	o15	o16	o17	o18	o19	o20	o21
h1	51.0	51.0	51.1	50.9	51.1	51.0	51.2	50.9	51.2	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4	51.0	51.5	50.9	51.5
h2	51.0	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4	51.0	51.5	50.9	51.5	51.0	51.6	50.9	51.6	51.0	51.7	50.9	51.7
h3	51.0	51.0	51.1	50.9	51.1	51.0	51.2	50.9	51.2	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4	51.0	51.5	50.9	51.5
h4	51.0	51.0	51.1	50.9	51.1	51.0	51.2	50.9	51.2	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4	51.0	51.5	50.9	51.5
h5	51.0	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4	51.0	51.5	50.9	51.5	51.0	51.6	50.9	51.6	51.0	51.7	50.9	51.7
h6	51.0	51.0	51.2	50.9	51.2	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4	51.0	51.5	50.9	51.5	51.0	51.6	50.9	51.6
h7	51.0	51.0	51.3	50.9	51.3	51.0	51.4	50.9	51.4												

51.0 51.5 50.9 51.5 51.0 51.6 50.9 51.6 51.0 51.7

50.9 51.7

h8 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h9 51.0 51.0 51.2 50.9 51.2 51.0 51.3 50.9 51.3

51.0 51.4 50.9 51.4 51.0 51.5 50.9 51.5 51.0 51.6

50.9 51.6

h10 51.0 51.0 51.2 50.9 51.2 51.0 51.3 50.9 51.3

51.0 51.4 50.9 51.4 51.0 51.5 50.9 51.5 51.0 51.6

50.9 51.6

h11 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h12 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h13 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h14 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h15 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h16 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h17 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h18 51.0 51.0 51.1 50.9 51.1 51.0 51.2 50.9 51.2

51.0 51.3 50.9 51.3 51.0 51.4 50.9 51.4 51.0 51.5

50.9 51.5

h19 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h20 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h21 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h22 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h23 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h24 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h25 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h26 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h27 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h28 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h29 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h30 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h31 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h32 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h33 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h34 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h35 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h36 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h37 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h38 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h39 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h40 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h41 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h42 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h43 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h44 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h45 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0	51.4								
h46	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h47	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h48	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h49	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h50	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h51	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h52	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1
51.0	51.2	51.0	51.2	51.0	51.3	51.0	51.3	51.0	51.4
51.0	51.4								
h53	51.0	51.0	51.0	51.0	51.0	51.0	51.1	51.0	51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h54 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

h55 51.0 51.0 51.0 51.0 51.0 51.0 51.1 51.0 51.1

51.0 51.2 51.0 51.2 51.0 51.3 51.0 51.3 51.0 51.4

51.0 51.4

;

table del(n,omega) DonationRateChangePerScenario

o1 o2 o3 o4 o5 o6 o7 o8 o9 o10 o11 o12 o13 o14 o15 o16 o17 o18

o19 o20 o21

n1 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 2.0 2.0 2.0 1.0 2.3 1.0 2.3 1.0 2.7 1.0

2.7

n2 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.3 1.0 1.3 1.0 1.5 1.0

1.5

n3 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.3 1.0 1.3 1.0 1.5 1.0

1.5

;

table inv1(n,omega) InventoryRateChangePerScenario

o1 o2 o3 o4 o5 o6 o7 o8 o9 o10 o11 o12 o13 o14 o15 o16 o17 o18

```
o19  o20  o21
n1  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
1.0
n2  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
1.0
n3  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
1.0
;
scalar v penalty cost for unmet /2000/;
positive variables
S(n) PrePSupplies
x(i,n) inbound PPFlow
x(n,j) outbound PPFlow
Sr(n,omega) Resultant supply
w(n,j,omega) SS Response Flow
y(n,h,omega) SD Response flow
u(h,omega) unmet demand at h;

Free variables
first first stage cost
second second stage cost
combined obj fctn combined val;
```

Equations

*Descretized SLP

zfirst stage decision

zsecond stage decision

zcombined summation of SLP

*1st stage

FloBal(n) cns: Stored = inbound + InitialInventory + RegDonations - outbound

StorCap(n) cns: Stored < Capacity

*Damage

StoDon(n,omega) PreP Storage Addition

*2nd stage

RDemReq(h,omega) cns: inbound > demand

RFloBal(n,omega) cns: Sr(n) * InventoryRateChangePerScenario + In(s-s) +

(DisDonations * Donation Rate change per scenario) > Out(s-s) + (S-D);

*Descretized SLP--

zfirst .. first =e=

sum((n,j), x(n,j) * dss(n,j));

zsecond .. second =e=

```
sum(omega, scenario(omega,'P')*(sum((n,j), w(n,j,omega)*dss(n,j)) + sum((n,h),
y(n,h,omega)*dsd(h,n))
+ sum(h, u(h,omega)*v)
));
zcombined .. combined =e= first + second;


*--subject to------------------------------------------------------------
*1st stage constraints
FloBal(n) .. S(n) =e= sum(i, x(i,n)) - sum(j, x(n,j)) + In(n) + E(n);
StorCap(n) .. S(n) =l= C(n);


*Prepos Addition
StoDon(n,omega) .. Sr(n,omega) =e= S(n) + (F(n)*del(n,omega)) ;


*2nd stage Constraints
RFloBal(n,omega) .. sum(j, w(n,j,omega)) + sum(h, y(n,h,omega)) =l= (Sr(n, omega) *
inv1(n, omega)) + sum(i, w(i,n,omega));
RDemReq(h,omega) .. sum(n, y(n,h,omega)) + u(h,omega) =e= (Rd(h,omega)) *
ForcD(h);
*--Solve statements-----------------------------------------------------
model PPos /zfirst, zsecond, zcombined, FloBal, StorCap, StoDon, RFloBal, RDemReq/ ;
Solve PPos using lp minimizing combined ;
```

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