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MODELING AND SIMULATION OF FOOD BANK DISASTER RELIEF OPERATIONS

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ABSTRACT

Food banks obtain in-kind donations (i.e., supplies) from individual donors, and from public and private organizations. The amount of supplies required to support distributing agencies is very dynamic, especially after natural disasters when food banks become major players in the disaster relief efforts. Therefore, planning for the operation of food banks under both, normal and disaster relief conditions, is a challenging problem. In this paper, a discrete-event simulation model is developed to represent the operations of a network of food banks at the supply chain level. The model is used to investigate the impact of multiple disaster relief operational policies (i.e., supply prepositioning, distribution center assignment) in the distribution of supplies and in meeting the demand. The model simulates the flow of donations at three food bank facilities and the demand for supplies of 55 demand locations before and after a natural disaster. The value of the simulation is demonstrated through the analysis of multiple scenarios. The results show that there is a 48% increase in the overall demand fulfillment rate if food banks operate as an integrated network with supply prepositioning and demand splitting between operating facilities.

1 INTRODUCTION

Catastrophic natural hazards have been on the rise over the past few years causing tremendous loss of life and property (Marthak et al. 2021; Kothamasu et al. 2021). Regarding tropical storms and hurricanes, Houston has become one of the most vulnerable urban areas in the world because of its proximity to the Gulf of Mexico. Even before Hurricane Harvey, Tropical Storm Allison (2001), Hurricanes Rita (2005), Katrina (2005), and Ike (2008) all caused widespread flooding. Hurricane Harvey struck Texas on August 25, 2017, and resulted in catastrophic flooding caused by record rainfall that severely affected all counties of Houston (Chakraborty et al. 2019). Most flooding receded within a week, but some areas remained flooded for several weeks (Jonkman et al. 2018). More than 156,000 homes were destroyed and at least 70 people died (Emanuel 2017; Griffin 2017). According to estimates hurricane Harvey caused residential structural damages equal to \$77.2 million and residential contents damages equal to \$36.9 million in Houston (Hicks and Burton 2017). In the immediate aftermath, about 246,000 where in need of emergency relief supplies and community organizations such as food banks where in charge of mobilizing resources to the affected areas.

Food banks are non-profit organizations that collect and distribute supplies to people in need. Food banks obtain donations (i.e., supplies) from the public, and from public and private organizations. Food banks act as food storage and distribution depots for smaller front-line agencies; and usually do not themselves give out food directly to people struggling with hunger. The demand of supplies needed by supporting agencies is very dynamic and difficult to predict. A variety of factors impact how food banks work, from the size of the facility to the number of staff members. But one thing all food banks have in common is that they rely on donors and volunteers to carry out their day-to-day operations. After natural disasters food banks become major disaster relief hubs. Disaster response involve planning, coordination, and distribution among a network supplier and distribution centers. Proper planning can lead to serve more people in need. Planning for disaster relief is challenging due to the uncertainty in terms of donation of supplies, the demand from agencies, and the availability of distribution centers. These challenges create a difficult environment to evaluate best operational practices to better meet the demand for supplies. Thus, a discrete-event simulation model of a network of food banks has been developed to capture some of the most important dynamics and complexities of food bank operations for a region impacted by a natural disaster.

The objectives of this paper are to 1) develop a process flow map of the major activities associated with the food bank operations; 2) design, implement, and validate a discrete-event simulation model for food bank operations at the supply chain level; 3) show the value of discrete-event simulation model when evaluating distribution policies among a network of food banks; and 4) identify and recommend managerial insights for the distribution of supplies after natural disasters. Simulation modeling provides an important method of analysis which is easily verified, communicated, and understood. Across industries and disciplines, simulation modeling provides valuable solutions by giving clear insights into complex systems (Mocarzel et al. 2013; Pérez 2022b; Perez et al. 2020; Pérez et al. 2013; Pérez et al. 2017; Reese et al. 2017; Pérez 2022a). The food bank distribution problem is interesting and challenging due to the stochastic nature of the donation arrivals and the uncertainty in terms of the availability of the distribution centers after natural disasters. In this paper, three food bank facilities are considered: Central Texas Food bank (CTFB), the San Antonio Food bank (SAFB) and the Houston Food bank (HFB). These three facilities serve neighbor areas in central Texas, and all which were affected by Hurricane Harvey.

The simulation model presented in this paper is critical for the advancement of the planning and operation of food banks after natural disasters. The validated simulation model is parameterized by values obtained from the analysis if the data provided by the food bank facilities considered in this study. The model will enable future research studies to compare different distribution policies based on different performance measures and scenarios. In addition, it will allow for the planning of the allocation of resources at the different facilities based on the risk of being impacted by a natural phenomenon.

The rest of the paper is organized as follows. Section 2 discusses literature strongly related to this topic. Section 3 describes the food bank operations setting, abstraction of the food bank operations as a simulation model, and model's input parameters, including the verification and validation of the simulation model. Then section 4 defines the experimental design and computational results of the simulation model. Section 5 provides a conclusion from the findings and discusses future research directions.

2 LITERATURE REVIEW

Peng et al. (2014) introduced dynamic environmental factors into the disaster-relief supply chain to characterize the dynamic relations and provide support to further decision-making in relief operations. A system dynamic model was presented to describe the processes of delivering emergency supply. The research in post-seismic rapid damage assessment of road networks and injured were addressed and the impacts of dynamic road condition and delay in information transfer were simulated and analyzed. Simulation results indicated that the road condition influences the system performance significantly; the transport time of relief supplies (i.e., transport delay) is a function of the road capacity and the in-transit volume, so the mechanism of considering the feedbacks of these two factors is important to maintain the stability of the relief system. The simulation models developed in (Peng et al. 2014) are the inventory planning strategies which can help in dealing with the information delay effectively.

Zhang et al. (2014) developed an agent-based discrete-event simulation (AB-DES) modelling framework for transportation evacuation by integrating an event scheduling scheme into an agent-based method. To study an evacuation process and to understand its intrinsic phenomena, the authors modeled the behavior of evacuees including their decision making, cognitive capabilities, and complex interactions among evacuees and emergency agencies. Zhang et al. (2014) integrate agent-based simulation and discrete-event simulation approaches using a hybrid simulation space to capture the traffic behaviors and interactions between traveler agents for evacuation process.

Ribino et al. (2018) performed an agent-based simulation to analyze the behavior of automatic logistic warehouses under the influence of specific factors, thereby obtaining indicators to support decision making during warehouse performance improvement. This study focused mainly on automatic warehouses where goods are moved by automatic guided vehicles (AGV). The authors considered logistic warehouses as critical nodes in supply chain and investigate the behavior of automatic logistic warehouses under the influence of specific factors (i.e., layout configurations, AGV fleet size, and management strategies) to obtain indicators that might support decision making during warehouse performance improvement.

To the best of our knowledge, no discrete event simulation model has been developed to study food bank operations at the supply chain level. In this paper, a discrete event simulation model is presented to study the impact of a natural disaster in the operation of a network of food bank facilities This research study complements the work of Peng et al. (2014), Zhang et al. (2014) and Ribino et al. (2018). Peng et al. (2014) and Zhang et al. (2014) focus on factors affecting disaster relief operations and evacuation processes respectively. Ribino et al. (2018) focused on simulation of warehouse operations to improve performance. Our work combines both planning aspects (i.e., disaster relief and warehouse operations) in a single modeling framework.

3 SIMULATION MODEL

3.1 Description of the Food bank Network and Operations

Food banks receive donations (i.e., supplies) from retailers, individuals, and from public and private organizations. Once donations are received by the food bank, the supplies are sorted, inspected according to quality standards, scanned to update the product in the Enterprise Resource Planning (ERP) system and are then re-packed for storing in the food bank warehouse. Food banks schedule order pick-ups and/or deliveries to distribution centers (i.e., schools, food pantries or individuals). Deliveries are performed using food bank trucks.

Even though most food banks are part of the Feeding America network (Cohn 2014), each facility typically operates as independent supplier which takes care of agencies located within a certain distance radius. In general, collaboration between food banks is very limited. Natural hazards, like hurricane Harvey in 2017, showed that better planning and collaboration are needed between food bank facilities. The demand for relief supplies increases after a natural disaster and a single facility might be unable to cover such demand. In addition, natural hazards could damage roads and buildings which can limit the operation capacity of food banks located close to area impacted by the natural phenomenon.

In this research, the operation of three Texas food bank facilities is studied. The group of facilities includes the Central Texas Food bank (CTFB) in Austin, the San Antonio Food bank (SAFB) and the Houston Food bank (HFB). As shown in Figure 1, these three facilities serve neighbor areas in central Texas and all were impacted at some degree by Hurricane Harvey. HFB, CTFB, and SAFB experienced higher than normal demands after hurricane Harvey. CTFB and SAFB distributed supplies in the Houston area after Hurricane Harvey. However, since no plans were developed for collaboration between facilities, the distribution of supplies was inefficient which impacted the number of people that was served. The simulation model presented in this research is developed with the goal of helping food bank facilities prepare better for disaster relief operations.

3.2 Performance Measures

The primary performance measures considered for each food bank facility in this study were: *unmet demand*, *total demand met, daily number of trips*, *delivery cycle time, demand fulfilment rate, and the order fulfilment rate*. The *unmet demand* is the number of supplies (in pallets) which the food bank is unable to supply to distribution center. The average weekly unmet demand per food bank is calculated at the end of every week. The *total demand met in pallets* is considered as total demand of the distribution center satisfied by the food bank facility at the end of simulation run. The *number of trips* considers one trip as complete only when truck delivers the supplies to the distribution center and return to the food bank post-delivery at distribution center. The daily average number of trips by trucks are calculated at the end of each day of simulation. The *delivery cycle time* is the time taken by the food bank to deliver the supplies to the distribution center once the order is requested. The *demand fulfilment rate* is the percentage of overall demand (in pallets) met by the food bank facilities at the end of simulation run. The *order fulfilment rate* is the percentage of orders completed by the food bank facilities at the end of simulation run. Overall demand fulfillment rate and order fulfilment rates are calculated as below.

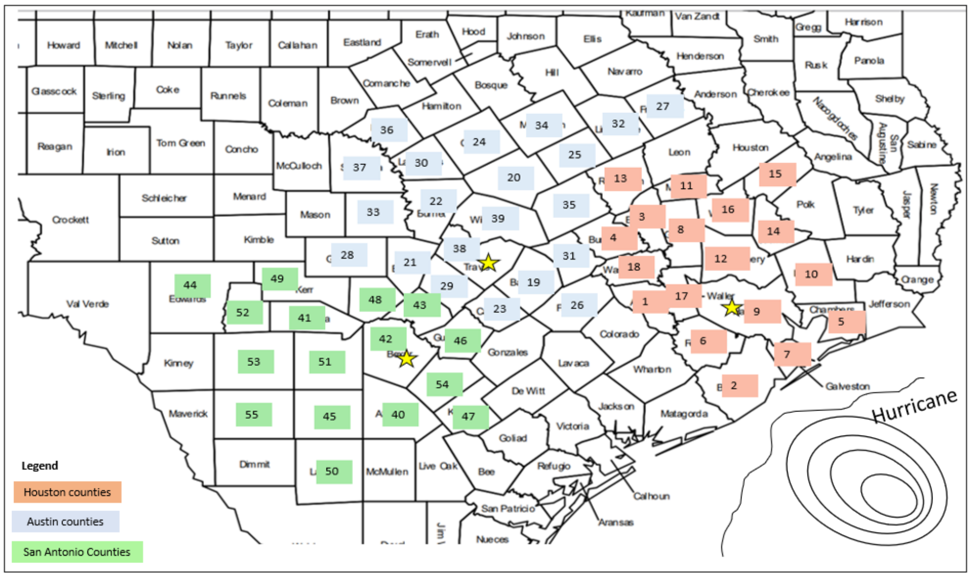

Figure 1: Counties map of Houston, Austin, and San Antonio food banks.

3.3 Model Abstraction

In this section, the abstraction of the discrete-event simulation model is presented. There are three major processes considered as part of the simulation: arrival of donations, warehouse operations, and distribution of supplies. The following subsections explain the abstraction for these three major processes.

3.3.1 Arrival of Donations

Figure 2 explains the arrival process of donations. When the food banks receive these donations from trucks, the volunteers will check if the entry doors and forklifts are available for unloading the supplies. Entry doors is the place in loading and unloading area of the food bank where the donations arrive to the food bank. Forklifts are used for unloading or loading the supplies in the food bank. If the entry door is available, the supplies will be unloaded from the truck and transferred to food bank warehouse using a forklift. If the entry door is not available, then the volunteers must wait for the availability of the entry door by performing other tasks in the food bank.

3.3.2 Warehouse Operations

Figure 3 shows the steps involved once the donations reach warehouse of the food bank. Once the supplies arrive the warehouse, they will be unloaded from the forklift, sorted, will be provided with a barcode, and then will be placed in the shelves of the warehouse. The barcoding helps to monitor the inventory level of the supplies in the warehouse. Once the food bank receives order request from distribution center, food bank operations manager will check the current inventory level of the food bank. The inventory levels are computed based on the items placed on the shelves and does not include items waiting to be unloaded from the trucks. If the demand can be met by the food bank, then the order will be processed, and supplies will be seized for delivery to the distribution center. If food bank is unable to meet the demand, then the order request is considered as cancelled.

3.3.3 Distribution of Supplies

Figure 4 explains the process of supply distribution to the distribution center (i.e., agencies). Once the supplies are ready for the delivery, the volunteers will check for the availability of exit doors, forklifts, and trucks for loading the supplies into the truck to deliver at distribution center as per order request. Trucks are used for delivering the supplies to the distribution center from the food bank. If the exit doors, forklifts, and/or trucks are not available, then the volunteers must wait for the availability of these resources by performing other tasks in the food bank. Once all three resources (exit doors, forklifts, and trucks) are available the volunteers will load the supplies in the truck and will be shipped to the distribution center. Each truck visits a single county agency per trip and travel times are estimated based on the distance traveled. This completes the order request process of the food bank. The availability of trucks in the food bank for shipping depends on the transportation time for delivering the supplies of previous orders.

3.4 Data

This section describes model input and parameter values. The parameters used in this research are obtained from 2-year historical data provided by all three food bank facilities for years 2016 and 2017. Food banks provided the data for donations, initial inventory of each food bank and demand requirement of distribution centers for both disaster relief and regular operations. There are total number of 55 counties in the scope of current research study of which counties labelled from 1 to 18 belong to HFB, counties from 19 to 39 belong to CTFB and from 40 to 55 belongs to SAFB.

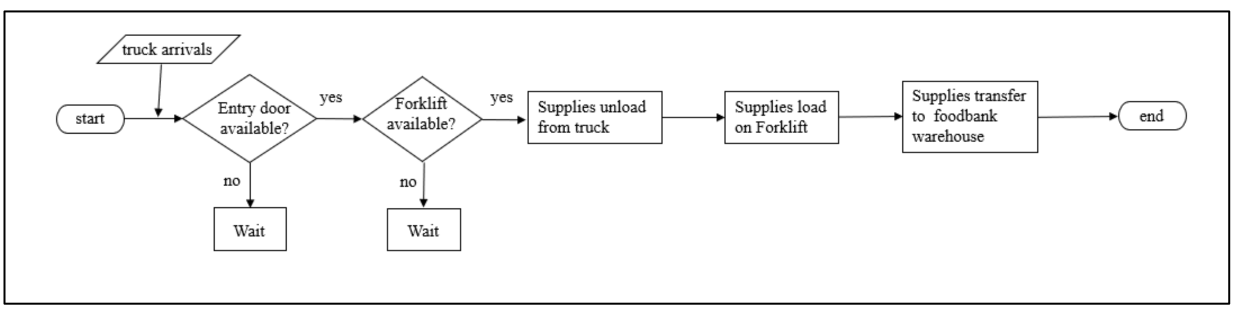

Figure 2: Flowchart of donation arrivals.

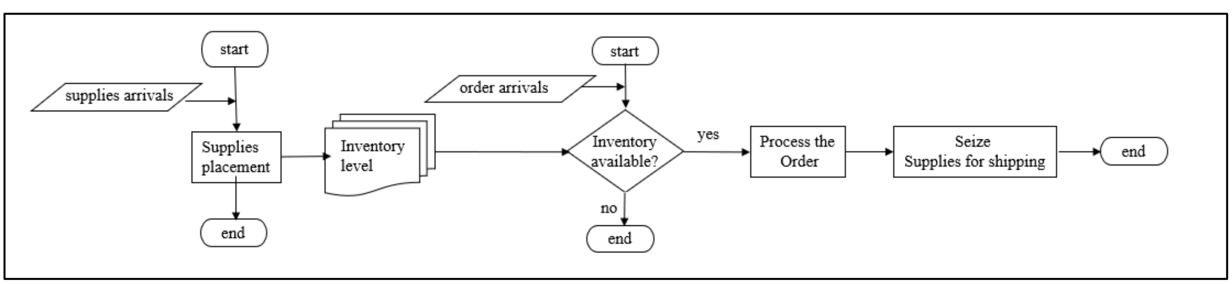

Figure 3: Flowchart of warehouse operations.

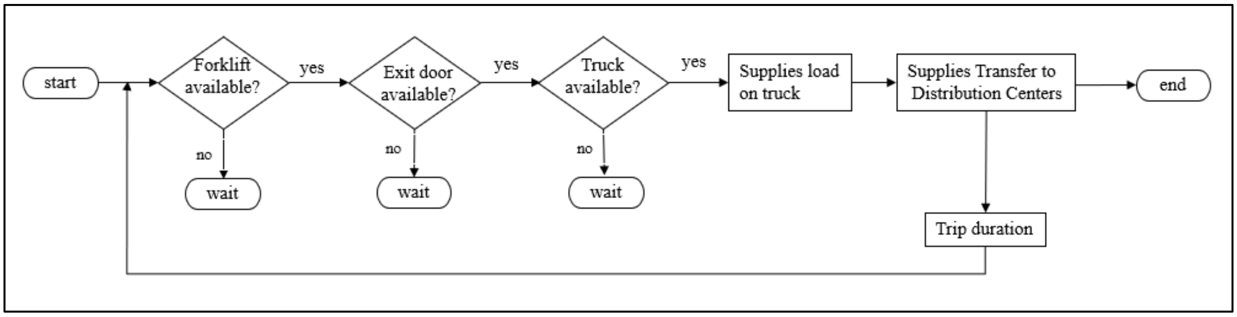

Figure 4: Flowchart of supplies distribution.

3.4.1 Model Parameters

The simulation model requires several input parameters that define the food bank capacities, including resource capacities and the regular food bank operating hours. Resource capacities of each food bank is labeled as M entry doors, N exit doors, O forklifts and T trucks. It is assumed that the maximum load the truck can carry is 3 pallets and each pallet weights about $4600\ lbs$. Trucks are used to ship the supplies from food bank to the distribution center. Table 1 depicts the resources for HFB, CTFB and SAFB food bank facilities. For model validation in Section 3.6, the assumptions of resources are $M = 4$ entry doors $N = 3$ exit doors, $O = 3$ forklifts and $T = 8$ trucks operating for 8 hours in a day.

3.4.2 Model Probability Models

The *interarrival rate of donations* were estimated based on the number of trucks arriving to each facility every day. The *quantity of donated supplies* per truck was estimated in pallets. Each truck delivered on average from 2 to 3 pallets per arrival. Processing times for *unloading trucks*, *placing supplies on the warehouse shelves*, and for *retrieving the supplies from the warehouse's shelves* were also considered random. Finally, the *demand for supplies* from each agency was also considered random. Two different operational scenarios were considered in this work: pre-disaster (i.e., normal conditions) and post-disaster (i.e., after a natural disaster).

The pre-disaster *interarrival rate of donations* was estimated based on the number of trucks that arrived at each facility from January 1st, 2016 until July 31st, 2017. The post-disaster *interarrival rate of donations* was estimated based on the number of trucks that arrived at each facility August 1st, 2017 until December 31st, 2017. It was assumed that the number of arrivals per unit time is Poisson distributed. Therefore, the *interarrival rate of donations*, of both pre-disaster and post-disaster scenarios, follow the exponential distribution. This exponential distribution has a single parameter that specifies the mean, $expo(\lambda)$. Table 2 shows the interarrival rate of donations for each food bank facility when considering the pre-disaster and post-disaster scenarios. The data provided by SAFB was very limited. However, since CTFB and SAFB are about the same size and serve similar populations, they were modeled using the same probability distributions.

Table 1: Food bank input parameters (HFB- Houston food bank, CTFB-Central Texas food bank, SAFB-San Antonio food bank).

Food bank	**Entry Doors ($\boldsymbol{M}$)**	**Exit Doors ($\boldsymbol{N}$)**	**Forklifts ($\boldsymbol{O}$)**	**Trucks ($\boldsymbol{T}$)**
HFB	4	5	3	10
CTFB	4	3	3	8
SAFB	3	3	3	8

The quantity of donated supplies were modeled using the Normal distribution (i.e., $N(\mu, \sigma)$), the Weibull distribution (i.e., $Weib(\alpha, \beta)$) and Gamma distribution (i.e., $\Gamma(\alpha, \beta)$). Table 3 indicates the distribution of the number of donations received at each food bank for pre-disaster and post-disaster scenarios.

Table 2: Interarrival rate of donations to the Food bank (HFB- Houston food bank, CTFB-Central Texas food bank, SAFB-San Antonio food bank).

Food bank	Distribution of Inter-Arrival Rate of Donations (In minutes)	
	Pre-disaster	Post-disaster
HFB	$expo(30.87)$	$expo(24.49)$
CTFB	$expo(73.188)$	$expo(75.92)$
SAFB	$expo(73.188)$	$expo(75.92)$

Table 3: Amount of donations received by food bank (HFB- Houston food bank, CTFB-Central Texas food bank, SAFB-San Antonio food bank).

Food bank	Distribution for Amount of Donations at Food bank	
	Pre-disaster (In Pallets)	Post-disaster (In Pallets)
HFB	$N(2.26,1.28)$	$N(3.64,2.36)$
CTFB	$\Gamma(3.52,0.435)$	$Weib(1.63,1.83)$
SAFB	$\Gamma(3.52,0.435)$	$Weib(1.63,1.83)$

3.4.3 Demand for Supplies

The *demand for supplies* was modeled for each of the 55 county agencies considered in this work. Table 4 list the probability models used to represent the demand in pallets for each county agency. A uniform distribution with parameters 0 and 1 was assumed for those counties where the demand was very low. A rounding function is used to specify the integer quantities required to model the demand. The Beta distribution is represented using two shape parameters α and β; Beta (α, β). The lognormal distribution using parameters normal mean and normal standard deviation as $LOGN(\mu, \sigma)$. According to the food banks' historical data of order requests, HFB receives order requests every 1 to 2 days from the distribution centers, whereas CTFB and SAFB receive order requests every week. Hence, the interarrival rate of demand order requests for HFB is $U(1,2)$ days, and for CTFB, SAFB is $U(5,7)$ days. Only the probability distribution for HFB are presented in this manuscript due space limitations. The probability distributions used in the simulation model obtained p-values higher than 0.05 for both the Chi Square Test and the K-S Test.

3.5 Model Verification and Validation

The simulation model was implemented in SIMIO. The simulation results are verified and validated with the real-time experiment data at the food bank site. The approach examines the outputs by comparing direct model outputs between the simulated food bank operations and the real-time food bank operations to ensure the systems were stable. Unmet demand, delivery cycle time, and the daily average number of trips are the performance measures used for the simulation model's verification and validation.

Table 5 indicates the percentage difference in the average of real-time food bank operations data and the simulation model output for ten replications. If the simulation output is x, and the real-time data report is y, then the percentage difference is computed as $((x - y)/y) * 100$ (Burns et al. 2020). As the percentage difference is less than 15% for all performance measures, the model operates as intended. There is a percentage difference because the detailing of few processes inside the food bank is not modeled. The simulation model may require more data, which leads to increasing the complexity of the model in all aspects of inside operations like sorting, unpacking, quality check, again repacking.

Table 4: Demand probability models for county agencies.

Food bank	County #	Pre-disaster Demand order distribution (In pallets)	Post-disaster Demand order distribution (In pallets)
HFB	1	$U(0,1)$	2.03+.16*$Beta(0.95,0.976)$
HFB	2	1.4+1.21*$Beta(1.1,0.92)$	$U(25,26.7)$
HFB	3	2.02+1.13*$Beta(1.28,1.04)$	35+2.55*$Beta(0.755,0.758)$
HFB	4	$U(0,1)$	1.81+.14* $Beta(0.937,0.892)$
HFB	5	$U(0,1)$	2.4+.18*$Beta(0.827,0.835)$
HFB	6	2.02+ $Weib(1.43,0.816)$	41+3.01* $Beta(0.751,0.751)$
HFB	7	1.53+1.32∗ $Beta(1.09,0.921)$	27.2+1.98* $Beta(0.757,0.751)$
HFB	8	$U(0,1)$	3.3+0.25* $Beta(0.856,0.858)$
HFB	9	$U(31,49)$	$U(519,551)$
HFB	10	$U(0,1)$	8.68+0.64* $Beta(0.799,0.779)$
HFB	11	$U(0,1)$	$U(1.71,1.85)$
HFB	12	2.11+1.18*$Beta(1.28,1.04)$	36.6+2.66* $Beta(0.754,0.751)$
HFB	13	$U(0,1)$	$U(1.81,1.96)$
HFB	14	$U(0,1)$	3.34+0.25* $Beta(0.799,0.845)$
HFB	15	$U(0,1)$	2.56+0.19* $Beta(0.804,0.805)$
HFB	16	$U(0,1)$	7.67+0.57* $Beta(0.813,0.804)$
HFB	17	$U(0,1)$	4.88+0.36* $Beta(0.791,0.788)$
HFB	18	$U(0,1)$	3.22+0.2536* $Beta(0.933,0.914)$

Table 5: Model verification and validation results for the food bank network under normal conditions.

Performance Measure	Real time Data	Simulation Output	Percentage Difference (%)
Unmet Demand	0	0	0
Delivery cycle time	1.75 days	1.68 days	4
Daily number of trips	5.3	4.6	13

4 EXPERIMENTATION

4.1 Design of Experiments

The experimental design considers two scenarios that represent the different ways a hurricane can affect the operation of a network of food banks in central Texas. *Experiment 1* assumes that all food banks can operate after the hurricane and that they work independently during the disaster relief period. *Experiment 2* assumes that all food banks can operate after the hurricane, but they can collaborate (i.e., distribute supplies for agencies outside their region) during the disaster relief period. The simulation considers operations for 8 weeks, of which the first 4 weeks simulate the disaster relief operations for hurricane Harvey and then transition to 4 weeks of normal operations.

4.2 Assignment of County Agencies

As stated earlier, in experiment 1 all food banks are working independently and they only serve their county agencies. However, in experiments 2 collaboration is allowed and food banks can serve county agencies outside their region during the disaster relief period. A two-stage stochastic programming model was used to decide the assignment of county agencies within the network of operating food banks per experiments

(Higle 2005). The stochastic programming model is discussed in (Kothamasu et al. 2021). The first-stage of the model decides if pre-positioning of supplies is needed between food banks. The second-stage provides recursive actions for supplies pre-positioning and decides the distribution of supplies within the network of operating food banks for the disaster relief period. The objective function of the stochastic programming model minimizes the cost associated with the pre-positioning of supplies and the expected unmet demand. Table 6 shows the assignment of county agencies for each food bank per experiment according to the results listed in (Kothamasu et al. 2021).

Table 6: Assignment of county agencies for each food bank per experiment (HFB- Houston food bank, CTFB-Central Texas food bank, SAFB-San Antonio food bank)

Exp #	**Counties fulfilled by HFB**	**Counties fulfilled by CTFB**	**Counties fulfilled by SAFB**
E2: All food banks in operation and collaborating	5,9,10	1,3,4,7,8,9,11,12,13,14,15,16,17,18,19,20,22,23,24,25,26,27,29,30,31,32,34,35,36,38,39	2,6,7,9,21,28,33,37,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55

4.3 Simulation Results

The simulation model results are presented in Table 7. The table show the results for the performance measurements discussed in Section 3.2 per experiment. The only difference between these two experiments is that in experiment 2 collaboration is allowed between the food banks. It is observed that the total demand met (in pallets) for the HFB is less than the total demand unmet (in pallets) on experiment 1 (E1). The reasoning behind this result is that the demand for supplies is very high during the disaster relief period and the inventory available is not enough to cover the demand for all Houston agencies. Specifically, county numbers 2, 3, 6, 9, and 12 of HFB experience high demand for disaster relief operations, of which county 9 demand is very high as it is prone to disaster affected regions. However, the results for experiment 2 demonstrate that the collaboration among the food banks is effective since it produces an increase in the demand fulfillment rate. This increase is demand fulfillment rate is possible because the CTFB is distributing supplies to multiple HFB agencies during the disaster relief period. Table 7 shows that the average number of trips per day increases from 5.1 to 17.36 for the HFB when collaboration is allowed within the food bank network (i.e., experiment 2). Experiment 2 also shows that the number of trips per day for the HFB decreases from 13.54 in experiment 1 to 5.2 is experiment 2. The reasoning behind this result is that HFB is supplying only to those agencies that are located close to the facility which are the ones with the highest demand in the Houston area. In terms of orders' fulfillment rates, the results show that in experiment 2 (i.e., collaboration between food banks) all food bank facilities have a rate higher than 90%.

Table 7: Simulation model experimental results for experiments 1 and 2 (HFB-Houston food bank, CTFB- Central Texas food bank, SAFB-San Antonio food bank).

Experiment number (E#)	Food bank	Total demand met (in pallets)	Total demand unmet (in pallets)	Demand fulfillment rate (%)	Orders' fulfillment rate (%)	Avg. number of trips per day	Delivery cycle time (in days)
E1: All food banks in operation and no collaboration	HFB	3,995	7,775	36.58	86.4	13.54	1.69
	CTFB	239	0		100	5.1	1.72
	SAFB	250	0		100	3.43	1.67
E2: All food banks in operation and collaborating	HFB	6,422	4,653	59.62	93.5	5.2	1.63
	CTFB	239	2		99.7	17.36	1.80
	SAFB	236	10		98.9	5.25	1.71

5 CONCLUSIONS

The research developed a theoretical framework for a discrete-event simulation (Burns et al. 2020) of food bank operations for disaster relief. The food bank simulation model is new and will move the research frontier to consider the dynamic behavior of food bank systems when planning disaster relief operations. The more efficient these facilities can operate; the more people can be served after a natural disaster. In addition, the results of this research are expected to provide insights that can be useful to develop policies for collaboration between food bank facilities which typically function as independent facilities. These results will provide valuable information to increase the supply chain resilience for the food banks facilities.

The simulation model was implemented in SIMIO. The model was verified and validated using data from three food banks located in Central Texas (i.e., Houston Food Bank, San Antonio Food Bank, and Central Texas Food bank in Austin). Multiple simulation runs of the food bank operations were conducted. The results conclude that the generated discrete-event simulation model is an effective tool for studying food bank operations' behavior and comparing different scenarios if there is a disruption in any food banks during hurricanes. The assignments of distribution centers according to the simulation model serves more counties when compared to the assignments according to the stochastic model. Hence, by using the discrete-event simulation models, food banks can schedule the distribution center assignments, reducing the counties' unmet demand. Research in this domain helps bring value to disaster relief operations and helping more people in need during disasters.

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