DESIGN OF RESILIENT SUPPLY CHAINS NETWORK WITH AN EMERGENCY BACKUP SUPPLY

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ABSTRACT

This paper aims to design a resilient supply chain network under facility disruptions. We consider the concept of an emergency backup supply (EBS) by deciding the second supply facilities (SSFs) when the primary supply facilities (PSFs) cannot satisfy the demand due to disruptions. In addition, we also identify the required extra storage capacity at each facility which provides resilience to the supply chain when any disruption occurs. For this, we propose the framework consisting of the traditional facility location-allocation (TFLA) model plus the scenario-based facility location-allocation (SBFLA) model. Using a case study, we demonstrate the applicability of the framework.

Keywords: resilient supply chain, primal supplying facility, secondary supplying facility, a two-stage stochastic model, scenario-based facility location-allocation.

INTRODUCTION

These days, supply chain performance critically affects the firms' business performance, and firms are relying more on their supply chains. Thus, supply chain resilience has recently become one of the main concerns for major firms to remain competitive [14]. Supply chains are faced with various types of disruptions that could prevent them from their normal operations, negatively affecting the performance by producing undesirable effects such as facility shutdown leading to demand unfulfillment. Particularly, the current trend toward lean inventory management makes the supply chains more vulnerable to any disruptions. Hence, the supply chains must recover from the disruption and function normally as quickly as possible when any disruption occurs. This ability is referred to as supply chain resilience (SCRES) [12][16].

SCRES is different from supply chain risk management (SCRM). SCRM primarily deals with risk identification, evaluation, mitigation, and monitoring to mitigate the likelihood of the risk and its impact on the supply chain [15]. However, it is apparent that not all potential risks can be identified or avoided. Thus, securing a high level of SCRES is desirable in case of disruption. In this sense, Grötsch *et al*. [3] claim that "SCRM's particular objective is to build and maintain resilient supply chains." Developing resilient supply chains means optimizing the location, inventory, distribution channels, capacity, inventory management, and other network parameters to strengthen resilience. One of the better ways to optimize these parameters is to consider them in the supply chain network design phase through diverse mathematical programming models.

Traditionally, the facility location-allocation (FLA) design problem is frequently used in the supply chain network design. The traditional FLA (TFLA) design problem assumes the facility is always available and generates optimized supply chains by minimizing total supply chain cost while satisfying demands by distributing products through the distribution channels to customers. Although deterministic mathematical models are the most common in the past [13], some researchers introduce a two-stage stochastic model to incorporate a number of alternative disruption scenarios into the model because of the significance of uncertainty [11][7].

When there is no risk of disruptions, all facilities in the supply chains are assumed to supply products to customers and satisfy their demands. These facilities are called primary supplying facilities (PSFs). When one or more PSFs are unavailable due to disruptions (e.g., shutdown), customer's demands that the original PSFs should have covered should be satisfied or backed up by other facilities to strengthen the supply chain's resilience. These facilities are referred to as secondary supplying facilities (SSFs), and this process is called an emergency backup supply (EBS). Depending on the design concept, a facility may work as both a PSF and an SSF. Thus, each facility in the resilient supply chain may need to carry more inventories (i.e., higher storage capacity) than the supply chain without any EBS [5].

This paper aims to propose a framework to design a resilient supply chain in the sense of EBS using FLA and two-stage stochastic programming covering diverse facility disruption scenarios. Our framework involves selecting facility locations, establishing their storage capacity and inventory level, roles as PSFs and SSFs for each site. The eventual goal is to obtain resilient supply chains with EBS at the minimum cost.

The remainder of this paper is organized as follows. After the literature review and background, mathematical modeling of the resilient supply chain is provided, followed by a case study and observation. Lastly, conclusions are presented.

LITERATURE REVIEW AND BACKGROUND

Many authors have studied FLA problems since Cooper [2] sets an FLA problem as a mathematical programming model. Manzini and Bennani [9] define FLA problems as the problem to determine the optimal location for each of the new facilities and the optimal allocation of existing requirements to the facilities so that all requirements are satisfied. Askin *et al*. [1] consider the problem of designing a distribution network for a logistics provider that acquires products from multiple facilities and then delivers them to retailers. They show that potential facility locations can decrease total logistics cost (TLC) while maintaining the desired service level. Manatkar *et al*. [8] also consider maintaining the desired service level in addition to reducing the TLC to design FLA problems.

Pablo *et al*. [11] use a two-stage stochastic model to design resilient supply chains with the risk of facility disruption. They incorporate multiple disruption scenarios of distribution centers (DCs) into the model and minimize TLC and investment costs while satisfying demands. They do not use any concept of PSF and SSF but consider many scenarios to show how the supply chains should be designed against the disruptions in the scenarios. They point out that a supply chain without disruption faces a serious capacity shortage issue when disruptions occur. Hohenstein *et al*. [4] provide a comprehensive review of SCRES in terms of the definition, elements in each phase of SCRES and SCRES assessment and measurement. They conclude that research regarding quantitative analysis to measure SCRES is very limited. They suggest that the overall SCRES level be measured three performance indicators–customer service, market share, and financial performance. Masoud and Mahour [10] use a two-stage stochastic mixed-integer programming model where suppliers with the possibility of disruption are allocated to regions to minimize the expected total network costs. The first stage determines the suppliers and their capacities, while the second stage determines appropriate transportation channels with different costs and times to the customers after potential future disruptions are evaluated.

Hong and Jeong [5] introduce a multi-objective mixed integer programming to design supply chains with distribution centers (DCs) and demand points (DPs) where a DC would feed several DPs. When there is no disruption in DC, it feeds its own DPs in a way to minimize total TLC with a penalty cost for unsatisfied demands and to maximize expected demand simultaneously. Assume that a DC (e.g., DC_1) supplies to DP_1 and DP_2 when there is no disruption (Figure 1(a)). Then, DC_1 is a primary supply facility (PSF) for DP_1 and DP_2. If a PSF (e.g., DC_1) for DP_1 or DP_2 is unavailable due to disruption, the DP_1 and DP_2 should be covered by other DCs (e.g., DC_2 for DP_1 and DC_3 for DP_2) as a part of EBS. In this case, DC_2 and DC_3 serve as a secondary supplying facility (SSF) for DP_1 and DP_2, respectively. The same thing is applied to DC_1. It serves as not only a PSF for DP_1 and DP_2 as but also an SSF for some other DPs whose PSFs become unavailable. In this way, each DP has its own PSF and SSF, and a DC plays a role in both PSF and SSF (Figure 1(b)). Hong and Jeong [5] obtain the optimized supply chain with EBS by solving a multi-objective mixed integer model with Goal Programming. However, they assume that only one PSF disrupts at a time. That is, when multiple PSFs are disrupted simultaneously, there is no EBS available.

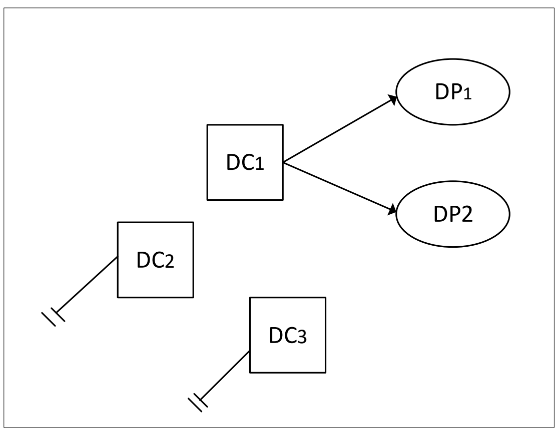


Figure 1(a). Network without EBS

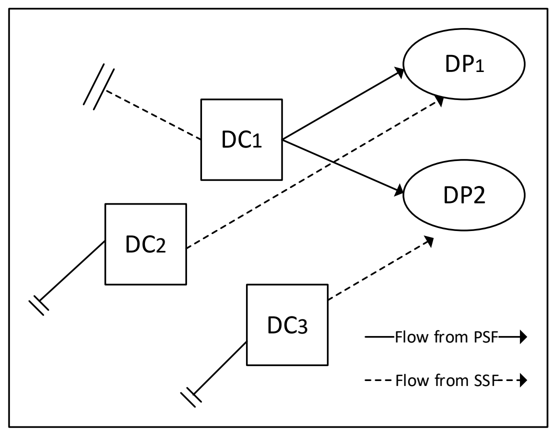


Figure 1(b) Network with EBS

Karatas and Yakici [6] propose the backup *p*-median problem with the objective of minimizing the distances to both primary and backup facilities to locate emergency service systems in congested environments. They employ a combined optimization and simulation approach to determine the level of backup service and demand assignment policy.

This study extends Hong and Jeong [5] and Pablo *et al*. [11] to allow for the multiple DC disruption scenarios using the scenario-based mathematical modeling and design the resilient supply chains with EBS. Further, instead of using any direct penalty cost as in Hong and Jeong [5], this study calculates all TLC triggered by a fictitious DC when actual DC's capacity is not enough for DPs, and the TLC cost is considered a penalty cost. Pablo *et al*. [11] have no concept of PSF and SSF for DC, but this study identifies the roles of DC into PSF and SSF or both. It further calculates how many extra inventories are required to conduct the twofold roles, providing resilience. Using a scenario-based approach in the two-stage stochastic model, all DC disruption scenarios can be incorporated into the model, which would improve resilience to the supply chain by customizing capacity at each facility. In this study, a site (e.g., DP) may have multiple SSFs depending on different facility disruption scenarios since multiple sourcing is allowed, while Hong and Jeong [5] allows only one SSF for each DP due to single sourcing only.

It is apparent that a supply chain may not satisfy all demands at DPs when there are not enough inventories at DCs. Thus, a resilient supply chain may need to carry more inventories (or capacities) at higher inventory cost. Even in that situation, some DPs may still not be supplied in some cases (e.g., all facilities are disrupted). Thus, it is useful to track the fill rate–the percentage of customer orders the supply chain is able to meet without running out of stock at any given time–at each scenario as the performance measure. To achieve this objective, our framework starts with a traditional FLA model to identify PSFs for all DPs and compute the required inventories to satisfy all demands. After this, we apply a two-stage stochastic program (i.e., scenario-based FLA model) to obtain a resilient supply chain with EBS with extra inventories

MATHEMATICAL MODELING OF THE RESILIENT SUPPLY CHAINS

The following nomenclature is used:

Sets:

$j \in C$: index set of potential sites for DCs, $j = 1, 2, \ldots, M$

$C = C_R \cup C_F$, where C_R is a set of a regular DCs and C_F is a set of a fictitious DC

$m \in P$: index set for DPs, $m = 1, 2, \ldots, N$

$s \in S$: index set for DC disruption scenarios, $s = 1, 2, \ldots, K$

Note that $C \subseteq P$, since DC is located at site j, site j should feed itself, and otherwise, it is used as DP.

Parameters:

b_j: minimum number of DPs that DC j can cover

B_j: maximum number of DPs that DC j can cover

c_{jm}: cost of shipping one unit of demand per mile from DC j to DP m

CAP_j^{max}: design capacity of DC j

d_{jm}: distance between DC j and DP m

D_m: demand for the DP m, in units/period

f_j: amortized fixed cost for constructing and operating DC j

v_j: cost per capacity at DC j

F^{max}: maximum number of DCs can be built

h_j: holding cost per unit per period at DC j

p_j: risk probability of DC's being disrupted, located at site j

π_s: disruption probability of scenario s

T_{sj}: indicator for DC j's availability in scenario s.1 if DC j is available (no disruption); 0 otherwise in scenario s

N: number of periods

Decision Variables:

F_j: binary variable deciding whether a DC located is located at site j

cap_j: storage capacity at DC j

y_{jm}: percentage of DP m's demand satisfied by the storage capacity distributed from DC j. It is a real number between zero and one

y_{sjm}: percentage of DP m's demand satisfied by the storage capacity distributed from DC j. It is a real number between zero and one in scenario s. It is a real number between zero and one

Assumptions:

(i) A DC can be located at any potential facility site. If a facility is located at the facility site j, the distance, d_{jm}, is assumed to equal to zero if j = m. Also, the site where a facility is located is assumed to be covered by the facility, that is, $y_{jm} = 1$ if j = m.

(ii) Each DC will have a designed capacity, represented by CAP_j^{max}, and actual storage capacity (cap_j) is determined by demands in the supply chain. Thus, the storage capacity cannot exceed the designed capacity.

(iii) Each DC follows a periodic review base-stock inventory policy with zero lead time for simplicity. DCs place a replenishment order at the beginning of every period and starts with the base-stock level at the beginning of the period.

(iv) When a DC is disrupted, it becomes inoperable/unavailable. As a result, a disrupted DC can't cover any DPs.

(v) Each DC has enough delivery capacities so that it can deliver the items to each DP directly.

(vi) A disruption event of each DC is independent.

Mathematical Model without EBS

We first present a traditional FLA (TFLA) mathematical model without any EBS. We assume that the supply chain consists of DCs and DPs without any facility disruption. Thus, all DCs located by the FLA model work as PSFs. Note that this is a capacitated FLA model, and the model will identify locations and allocations when all capacity constraints are met. Later, we will also use the TFLA model to see what would happen to the supply chain if a disruption occurs through what-if analysis. Due to the nature of the capacitated constraints, we introduce a fictitious DC with *zero* probability of disruption, *infinite capacity*, *infinite fixed cost*, and *infinite distance* from any site to this fictitious DC. In this way, this fictitious DC supplies products to DPs only when all remaining capacity from the regular DCs is fully used and this cost is considered as a penalty cost.

The objective function is to minimize the total logistics cost for N periods when there is no EBS, $TLC_{\overline{EBS}}$, which consists of the amortized fixed cost of locating and operating facilities and cost for storage capacity (terms in the first parenthesis), the transportation/shipping cost from PSFs to DPs (2nd term), and inventory cost (last term) as shown (1)

$$TLC_{\overline{EBS}} = \left(\sum_{j\in C} f_j F_j + \sum_{j\in c} v_j cap_j\right) + N\sum_{j\in C}\sum_{m\in P} y_{jm} D_m d_{jm} c_{jm} +$$

$$N\sum_{j\in C}\left(cap_j - 0.5\sum_{m\in P} y_{jm} D_m d_{jm}\right) h_j, \tag{1}$$

Thus, the TFLA model without EBS is formulated as follows:

$$minimize \qquad TLC_{\overline{EBS}}$$

$$\sum_{j\in C} y_{jm} = 1, \qquad \forall m \in P \tag{2}$$

$$\sum_{j\in C} F_j \le F^{max}, \tag{3}$$

$$cap_j \le F_j\, CAP_j^{max}, \qquad \forall j \in C \tag{4}$$

$$\sum_{m \in P} D_m y_{jm} \leq cap_j, \qquad \forall j \in C \tag{5}$$

$$y_{jm} \leq F_j, \qquad \forall j \text{ and } \forall m \in M \tag{6}$$

Constraints (2) make certain that each site is covered by one or more DCs, allowing multiple sourcing. Constraints (3) define the maximum number of DCs to be built. Constraints (4) ensure that storage capacity at each DC should be less than or equal to the design capacity when it is built. Constraints (5) ensure that each DP can only be covered by DC within DC's storage capacity. Constraints (6) indicate that each DP is covered by DC *j* only when DC is available/built at site *j*.

The TFLA model without EBS provides the least expensive supply chain network and storage capacity at each DC without any disruptions. Each DC, in this case of no disruptions, plays the role of PSF since it supplies to its designated DPs.

Mathematical Model with EBS

Now, a two-stage stochastic model is considered to incorporate disruption scenarios of DCs into the supply chain for resilience. We first consider a number of discrete scenarios which explain disruption risks for DCs, and the two-stage stochastic model uses this information as input data. For this reason, the stochastic model is called the scenario-based FLA model (SBFLA). We can calculate the probability where each random scenario occurs using p_j, risk probability of DC's being disrupted at site *j*. The set of scenarios denoted by *S* represents all unique combinations of disruptions of DCs. Thus, the total number of scenarios is equal to $K = |2^{F^{max}}|$. Each scenario $s \in S$ consists of a unique combination of DCs disrupted. If *E* represents a set of disruption events, the disruption probability of each scenario is calculated as in Equation (7), and it determines the potential availability of DCs:

$$\pi_s = \prod_{j \in E} p_j \prod_{j \notin E} (1 - p_j) \tag{7}$$

The objective function is to minimize the TLC under all scenarios, TLC_{EBS}, for *N* periods, given by equation (8). Again, it consists of the amortized fixed cost of locating and operating facilities and cost for storage capacity (terms in the first parenthesis), the transportation/shipping cost from DCs to DPs (2nd term), and inventory cost (last term). The structure of the two-stage in the SBFLA model is explained as follows: The first stage decisions are involved with the selection of DCs, F_j, and their capacity, cap_j, from the set of candidates set, *C*. The second-stage decision involves allocating capacity to DP *m*, y_{sjm}, according to the availability of DCs determined by the scenarios, $s \in S$.

$$TLC_{EBS} = \left(\sum_{j \in C} f_j F_j + \sum_{j \in c} v_j cap_j\right) + N \sum_{s \in S} \pi_s \sum_{j \in C} \sum_{m \in P} y_{sjm} D_m d_{jm} c_{jm} + N \sum_{s \in S} \pi_s \sum_{j \in C} h_j \left(cap_j - 0.5 \sum_{m \in P} y_{sjm} D_m d_{jm}\right), \tag{8}$$

Thus, the SBFLA model is formulated as follows:

minimize $\quad TLC_{EBS}$

$$\sum_{j \in C} y_{sjm} = 1, \qquad \forall m \in P, \forall s \in S \tag{9}$$

$$\sum_{j \in C} F_j \leq F^{max}, \tag{10}$$

$$cap_j \leq F_j \, CAP_j^{max}, \qquad \forall j \in C \tag{11}$$

$$\sum_{m \in P} D_m y_{sjm} \leq \; T_{sj} cap_j, \qquad \forall j \in C, \forall s \in S \tag{12}$$

Constraints (9) make certain that each site is covered by one or more DCs at scenario *s*, explaining the multiple sourcing again. Constraints (10) and (11) are the same as before in the TFLA model without EBS. Constraints (12) ensure that assigning products from DC *j* to DP *m* at each scenario *s* can be done only when the DC with enough storage capacity for the demand at DP *m* is available.

Note that the TFLA model without EBS identifies PSFs for all DPs. As being assumed, if a disruption occurs at any DC *j*, the demands of DPs covered by the DC *j* cannot be satisfied since there is no EBS. The TFLA model without EBS focuses on a more efficient supply chain since it attempts to satisfy all demands with the minimum cost. In contrast, the SBFLA model with EBS focuses on a more resilient supply chain with extra storage capacity at each DC through SSF for DP *m* when its PSF is disrupted.

After obtaining solutions from two mathematical models, we can get the following information: For both models, *TLC* consists of two components, *TLC* from regular DCs and *TLC* from a fictitious DC. That is,

$$TLC = TLC_{j \in C_R} + TLC_{j \in C_F} \tag{13}$$

In the same reasoning, Fill Rate (*FR*) for both problems are calculated at the regular DCs only, which is given by

$$FR = \frac{\sum_{j \in C_R} cap_j}{\sum_m D_m} \tag{14}$$

CASE STUDY AND OBSERVATIONS

To demonstrate the applicability of the frameworks presented, we conduct a case study using major disaster declaration records in South Carolina (SC) that Hong and Jeong [5] use. When historic flooding damaged SC in October 2015, the Federal Emergency Management Agency (FEMA) opened disaster recovery centers (DRCs) in several SC counties to help SC flood survivors. We use the problem of locating DRCs in SC as our case study. Forty-six (46) counties are clustered based on proximity and populations into twenty counties. Then, one city from each clustered county based on a centroid approach was chosen. We assume that all population within the clustered county exists in that city. The distance between these cities is considered to be the distance between counties. We assume that when a major disaster is declared, the DRC in that county is not available due to the damaged facility. Based on the historical record from the FEMA database and the assumption, the risk probability for each site is calculated in Table 1. The four sites–Charleston, Columbia, Florence, and Greenville–are the candidates for DRC, and the fixed investment costs are given in Table 1. For the case study, the hypothetically pre-determined input parameters are in Table 2. As shown in Table 6, we consider 16 DRC disruption scenarios with their probabilities, calculated from Table 1.

Table 1. Data for DRC location-allocation

No	City	County	POP, D_m (K)	p_i	F_i ($K)	DRC No
1	Anderson	Anderson/Oconee/Pickens	373	0.1250		
2	Beaufort	Beaufort/Jasper	187	0.0630		
3	Bennettsville	Marlboro/Darlington/Chesterfield	96	0.3750		
4	Conway	Horry	269	0.3750		
5	Georgetown	Georgetown/Williamsburg	93	0.4380		
6	Greenwood	Greenwood/Abbeville	92	0.1250		
7	Hampton	Hampton/Allendale	33	0.1880		
8	Lexington	Lexington/Newberry/Saluda	318	0.3130		
9	McCormick	McCormick/Edgefield	35	0.2500		
10	Moncks Corner	Berkeley	178	0.3130		
11	Orangeburg	Orangeburg/Bamberg/Calhoun	123	0.3750		
12	Rock Hill	York/Chester/Lancaster	321	0.3130		
13	Spartanburg	Spartanburg/Cherokee/Union	367	0.3130		
14	Sumter	Sumter/Clarendon/Lee	157	0.3750		
15	Walterboro	Colleton/Dorchester	135	0.2500		
16	Aiken	Aiken/Barnwell	184	0.3130		
17	Charleston	Charleston	350	0.2500	5,000	1
18	Columbia	Richland/Fairfield/Kershaw	461	0.3750	5,000	2
19	Florence	Florence/Dillon/Marion	203	0.4380	5,000	3
20	Greenville	Greenville/Laurens	521	0.1250	5,000	4
21	Fictitious DC		0	0	100,000	5

Table 2. Input data used for the case study

Symbol	Meaning	Value
c_{jm}	Cost of shipping one unit of demand per mile from DRC j to site m	\$0.10, $\forall j$ *and* m
CAP_j^{max}	Designed capacity for DRC j	2,500, $\forall j$
h_j	Holding cost per item per unit time at DRC j	\$5.00, $\forall j$
F^{max}	Maximum number of DRCs to be built	5
v_j	Cost per capacity	\$50, $\forall j$

Table 3. Scenarios with their occurrence probability

No (s)	Charleston (1)	Columbia (2)	Florence (3)	Greenville (4)	Fictitious (5)	Probability (π_s)
1	1	1	1	1	1	0.230507813
2	1	1	1	0	1	0.032929688
3	1	1	0	1	1	0.179648438
4	1	1	0	0	1	0.025664063
5	1	0	1	1	1	0.138304688
6	1	0	1	0	1	0.019757813
7	1	0	0	1	1	0.107789063
8	1	0	0	0	1	0.015398438
9	0	1	1	1	1	0.076835938
10	0	1	1	0	1	0.010976563
11	0	1	0	1	1	0.059882813
12	0	1	0	0	1	0.008554688
13	0	0	1	1	1	0.046101563
14	0	0	1	0	1	0.006585938
15	0	0	0	1	1	0.035929688
16	0	0	0	0	1	0.005132813

By solving the TFLA model without EBS given in (1)-(6), we obtain the PSF for DP and the storage capacity at PSF. Then, we solve the SBFLA model with EBS in (8)-(12) and list the results in Table 4. The PSF-SSFs obtained from the two models are listed in Appendix A. Note that PSFs obtained from the scenario *s1* are identical to the result from TFLA model without EBS since *s1* assumes that there is no disruption. In Appendix A, the four scenarios–*s8, s14, s15, and s16*–where three DCs experience disruption trigger the fictitious DC due to the lack of capacity in the regular DCs, generating the penalty costs. Further, some DPs such as Rock Hill in s1 and Aiken in *s4* have multiple SSFs due to the nature of multiple sourcing.

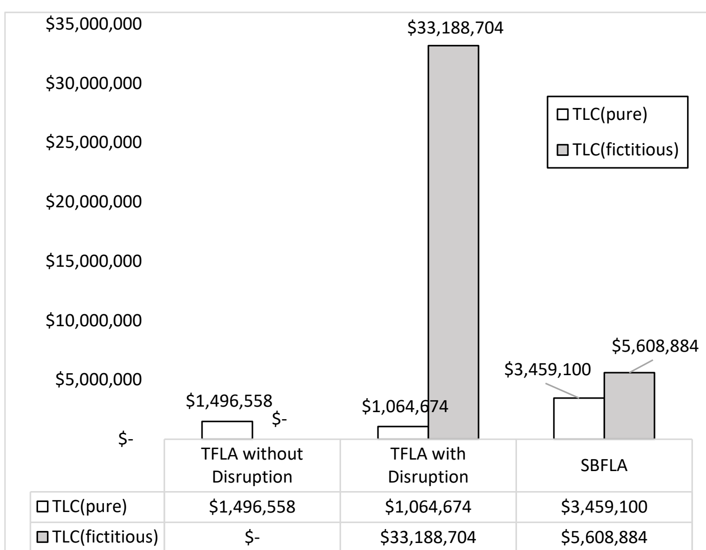
Table 4. Results from TFLA and SBFLA models

	TFLA		SBFLA	Difference (SBFLA-TFLA)	Percentage (%) (TFLA/SBFLA)
TLC	1,496,557	ND	9,067,984	7,571,426	17
$TLC_{j\in C_R}$	1,496,557	ND	3,459,100	1,962,542	43
$TLC_{j\in C_F}$	0	ND	5,608,884	5,608,884	0
Storage Capacity	4,496 [976, 1,407, 725, 1,388]		9,496 [2,500, 2,500, 1,996, 2,500]	500 [1,524, 1,093, 1,271, 1,112]	47
FR **(%)**	100/72	ND[*1]/DR[*2]	96.5		
Demand Satisfied	3,233±991[*3]	DR	4,337±598		
TLC	34,253,378	DR	9,067,984	-25,185,393	378
$TLC_{j\in C_R}$	1,064,674	DR	3,459,100	2,394,425	31
$TLC_{j\in C_F}$	33,188,703	DR	5,608,884	-27,579,819	591

[*1]ND: no disruption assumed; [*2]DR: disruption considered; mean ± standard deviation

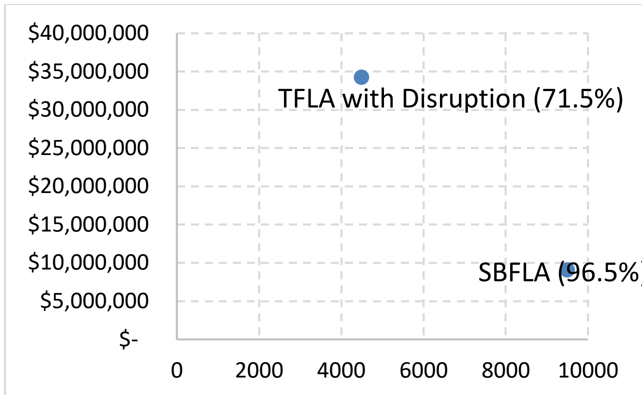
In Table 4, the TFLA model without EBS is executed two times–without disruptions and with disruptions for what-if analysis. Without disruption, TLC is the minimum ($1,496,557) with a 100% fill rate with 4,496 total storage capacity. With disruption as a part of what-if analysis, the model is executed 16 times according to the disruption scenarios in Table 3. We observe that the resulting expected TLC and the fill rate turn out to be $34,253,378 and 72%, respectively. Whenever a DC is unavailable, that DC is replaced by the fictitious DC, generating penalty cost. With the disruption, the expected TLC is much higher than any other case due to the high penalty cost. In Figure 2, we differentiate TLC from regular DCs, TLC(pure), from TLC the fictitious DC, TLC(fictitious) and see that TFLA is really vulnerable to disruption while the SBFLA is resilient.

Figure 2. Comparison of Cost for Models



The resulting TLC is 378% of that in SBLFA. Further, the fill rate reduces to 72% from 100% even with higher capacity variation (3233±991). The SBFLA model with EBS requires $9,067,984 with high storage capacity (9,496) and yields a high fill rate of 96.5%. It also generates some penalty costs due to the scenarios–*s8*, *s14*, *s15*, and *s16*. Note that the difference in capacity between the two models is the extra capacity (500) required to improve supply chain resilience. In Figure 3, we compare TFLA to SBFLA in terms of TLC and capacity, demonstrating the robust performance of SBFLA with EBS over TFLA without EBS. We can see that SBFLA's resilience is much higher than the original TFLA without EBS.

Figure 3. Storage Capacity (X) vs. TLC (Y)



The number in the () represents the fill rate

CONCLUSIONS

Using the traditional facility location-allocation (TFLA) model and the scenario-based facility location-allocation (SBFLA) model, this paper presents a framework to design the resilient supply chain with the emergency backup supply (EBS) under the risk of facility disruptions. In this study, EBS consists of the primal supplying facilities (PSFs) and the designated secondary supplying facilities (SSFs) for each demand point (DP). The extra capacity enhances the resilience, which allows an SSF to cover its designated DPs whose PSF can't function to satisfy the demands due to disruptions.

Through the case study using actual major disaster records in South Carolina, we demonstrate the applicability of our proposed framework. We compare the performance of the TFLA model without EBS to that of the SBFLA model with EBS. From the numerical results, the TFLA model without EBS generates the lowest TLC and the highest fill rate if there is no disruption. In contrast, under facility disruption, its expected TLC in TFLA without EBS is much higher than the TLC in SBFLA with EBS due to high penalty costs for the uncovered sites (378%). We also identify that the robust performance of SBFLA is achieved by adding extra storage capacity (500), covering all scenarios, generating a higher fill rate (96.5%). The study provides a significant managerial insight from the risk management perspective, showing that they should consider the disruption risk in the design phase to save potential costs and build resilience.

The limitations of this study come from the assumption of delivery from the supplying facilities to the affected sites. If the number of vehicles for delivery is limited, the constraints for vehicle routing cases should be addressed in formulating the mathematical programming model for future research.

APPENDIX PSF-SSF for each DP from SBFLA model

No	City	s1 PSF	s2 SSF	s3 SSF	s4 SSF	s5 SSF	s6 SSF	s7 SSF	s8* SSF	s9 SSF	s10 SSF	s11 SSF	s12 SSF	s13 SSF	s14* SSF	s15* SSF	s16* SSF
1	Anderson	Greenville	Columbia		Columbia		Charleston		Fictitious		Columbia		Fictitious		Fictitious		Fictitious
2	Beaufort	Charleston								Columbia	Florence	Columbia	Fictitious	Florence	Fictitious	Fictitious	Fictitious
3	Bennettsville	Florence		Columbia	Charleston			Charleston	Fictitious			Columbia	Fictitious			Fictitious	Fictitious
4	Conway	Florence		Charleston	Charleston			Charleston	Charleston			Columbia	Fictitious			Fictitious	Fictitious
5	Georgetown	Charleston								Florence	Florence	Columbia	Fictitious	Florence	Florence	Fictitious	Fictitious
6	Greenwood	Greenville					Charleston										
7	Hampton	Charleston								Columbia	Columbia, Florence	Columbia	Columbia	Florence	Fictitious	Fictitious	Fictitious
8	Lexington	Columbia				Florence	Charleston	Greenville	Charleston			Columbia, Greenville		Greenville	Florence	Greenville	Fictitious
9	McCormick	Greenville	Columbia		Columbia		Charleston		Fictitious		Columbia		Columbia		Fictitious		Fictitious
10	Moncks Corner	Charleston								Florence	Florence	Columbia	Columbia	Florence	Florence	Fictitious	Fictitious
11	Orangeburg	Columbia			Charleston	Charleston	Charleston	Charleston	Charleston					Florence	Florence	Fictitious	Fictitious
12	Rock Hill	Columbia	Columbia, Florence			Greenville	Florence	Greenville	Fictitious		Florence	Greenville		Greenville	Florence, fictitious	Greenville	Fictitious
13	Spartanburg	Greenville	Columbia		Columbia		Florence		Fictitious		Columbia		Columbia, Fictitious		Fictitious		Fictitious
14	Sumter	Florence		Columbia	Charleston			Charleston	Charleston			Columbia	Columbia			Fictitious	Fictitious
15	Walterboro	Charleston								Columbia	Florence	Columbia	Columbia	Florence	Fictitious	Fictitious	Fictitious
16	Aiken	Columbia			Charleston, Columbia	Greenville	Charleston	Greenville	Fictitious			Greenville		Greenville	Fictitious	Greenville, fictitious	Fictitious
17	Charleston	Charleston								Columbia	Florence	Columbia	Fictitious	Florence	Fictitious	Fictitious	Fictitious
18	Columbia	Columbia				Florence	Florence	Charleston, Greenville	Charleston					Florence, Greenville	Florence	Greenville	Fictitious
19	Florence	Florence		Columbia	Charleston			Charleston	Charleston, Fictitious			Columbia	Columbia			Fictitious	Fictitious
20	Greenville	Greenville	Columbia		Columbia		Charleston, Florence		Fictitious		Columbia		Fictitious		Fictitious		Fictitious
21	Fictitious	Charleston											Columbia		Florence	Greenville	Fictitious

* scenarios where penalty cost occurs due to lack of capacity

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