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Assessing Supply Chain Resilience Under Imprecise Transportation Delays Using Simulation and Fuzzy DEA

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Abstract: *This study investigates the resilience of a three-echelon supply chain (SC) subject to potential disruptions in the transportation system. Four key resilience factors—visibility, velocity, redundancy, and flexibility—are considered. A simulation model is developed to represent the SC, and multiple scenarios are evaluated, each reflecting a unique combination of these resilience policies. Performance metrics such as average time in the system, resource utilization, number of breakdowns, and total operational cost are computed for each scenario. To determine the most effective strategy, fuzzy data envelopment analysis (FDEA) is applied, allowing for decision-making under uncertainty. The findings highlight the critical importance of visibility and redundancy in enhancing supply chain resilience. The proposed framework offers practical guidance for managers in selecting optimal strategies to mitigate the impact of transportation disruptions.*
Keywords: *supply chain; resilience; disruption; transportation delay; simulation; fuzzy data envelopment analysis*

INTRODUCTION

In recent years, supply chains have been increasingly exposed to a broader and more complex array of disruptions. Predicting how a supply chain (SC) will respond to various types of disturbances has become a significant challenge for businesses worldwide. Effective management and organizational strategies are now essential to mitigate these disruptions, emphasizing the need to build resilient supply chains. Resilience has emerged as a critical capability in supply chain management. It is commonly defined as the ability of a system to absorb unforeseen disturbances, adapt to changing conditions, and rapidly recover to its original or an improved state following a disruption. This concept has gained significant attention in academic literature and industry practice as a means to enhance operational continuity and competitive advantage. Given the complexity and stochastic nature of modern supply chains—especially those involving large-scale operations—analytical solutions are often impractical. As a result, simulation has become a powerful and widely accepted tool for modeling supply chain behavior under disruption. Simulation enables the estimation of key performance indicators (KPIs), such as cost, system time, and resource utilization, by replicating the dynamic and uncertain conditions of real-world systems. This study focuses on evaluating the resilience of a three-echelon supply chain facing potential transportation disruptions. It considers four key resilience factors: visibility, velocity, redundancy, and flexibility. Various scenarios, each representing a unique combination of these resilience policies, are developed and simulated. The resulting performance data are analyzed using Fuzzy Data Envelopment Analysis (FDEA), a technique that accommodates uncertainty and imprecision in decision-making. Through this approach, the most effective resilience strategy is identified, offering practical insights for supply chain managers aiming to enhance operational robustness.

METHODOLOGY

Simulation represents one of the tools most frequently used to observe the behavior of SCs in order to highlight its lack of efficiency and evaluate new management solutions in a relatively short time. The simulation is performed for the following outputs: the number of failure, the average time in system, the total cost of the system and the average resource availability. Due to imprecise nature of transportation delay, an optimistic and pessimistic time has also been considered. For ranking the scenarios, the FDEA approach is used. In this study, Visual Simulation Language for Analogue Modelling (SLAM), as a fully object-oriented simulation language, is used for modelling and simulating the predefined problem.

FDEA model

Investigating the efficiency of different scenarios is of interest and the fuzzy data are inputted to the FDEA model to obtain the ranking of scenarios. This is obtained by considering pessimistic, optimistic and most likely values. There are 13 scenarios with fuzzy transportation delays and this means that simulation will be run 39 times for 39 combinations of all states (pessimistic, most likely and optimistic).

The FDEA method seems to be suitable for problems associated with uncertainty pertinent to the existence of the qualitative data set. The reason for using the FDEA approach is the nature of data which are imprecise. Also in the FDEA approach, criteria do not need weighting, while in other approaches such as fuzzy technique for order performance by similarity to ideal solution (TOPSIS) and fuzzy analytical hierarchy process (AHP), criteria need weighting. Hence, the FDEA approach was chosen to rank the scenarios. Saati, Hatami-Marbini, and Makui (2009)[8] presented a new method for ranking the efficient units based on a Charnes, Cooper and

Rhodes (CCR) model. This was obtained by adding the constraint to the CCR model and achieving the results for a Banker, Charnes and Cooper (BCC) model.[9] The fuzzy BCC $\sum_n \tau_j = 1$ model for ranking the layout alternatives is as follows:

In Model (1), indices i, r and j show the inputs, outputs and scenarios, respectively This is because inputs

$$\min \ \theta$$
$$\text{s.t.}$$
$$y_{rp} \leq \sum_{j=1}^{n} \tau_j \tilde{y}_{rj} \quad \forall r = 1, \ldots, 5, \quad (1)$$
$$\theta x_{ip} \geq \sum_{j=1} \tau_j x_{ij} \quad \forall i = 1, \ldots, 4,$$
$$\sum_{j=1}^{n} = 1 \quad \forall j = 1, \ldots, 18.$$

should be reduced, while outputs should be increased in optimisation problems. $\tilde{x}_{ij}$ and $\tilde{y}_{ij}$ are, respectively, the input and output variables of FDEA which are triangular shaped fuzzy numbers, and $\tilde{x}_{ip}$ and $\tilde{y}_{rp}$ are the optimistic value for input variables $\tilde{x}_{ij}$ and pessimistic value for output variables $\tilde{y}_{ij}$, respectively. Substituting fuzzy values $\tilde{x}_{ij}$ and $\tilde{y}_{ij}$ with $\tilde{x}_{ij} = (x^p, x^m, x^o)$ and $y = (y^p, y^m, y^o)$, respectively, and using α-cuts method, Model (1) can be stated as follows:

$$\min \ \theta$$
$$\text{s.t.}$$
$$\theta(\alpha x^m_{ip} + (1-\alpha)x^p_{ip}) \geq \sum_{j=1} \tau(\alpha x^m_{ij} + (1-\alpha)x^p_{rj}) \quad \forall i = 1, \ldots, 5, (2)$$
$$\alpha y^m_{rp} + (1-\alpha)y^0_{rp} \leq \sum_{j=1} \tau_j(\alpha y^m_{rj} + (1-\alpha)y^p_{rj}) \quad \forall r = 1, \ldots, 4,$$
$$\sum_{j=1}^{n} \tau_j = 1 \quad \tau_j \geq 0 \forall j = 1, \ldots, 18.$$

In Model (1), a is a parameter belonging to the interval [0 1]. Model (1) is a parametric linear programming model which can be used for obtaining the optimum solution for each given value of a. Since the objective of this study is to analyse the efficiency of resilience scenarios based on output indicators, the output-oriented BCC model has been utilised, and the efficiency and rank of each layout are determined based on Model (1) for different α value.

INVESTIGATION

This study includes an investigation that has an SC consisting of three stages. At the first stage, it has two factories that produce five types of parts: three types at the first factory and two types at the second one. Let us denote the products of the first as M1, M2 and M3; and of the second as M4 and M5. The supply of the first stage is infinite, meaning that whenever we need these parts, they are available. With three different vehicles, these parts are transported to two other factories: M1, M2 and M3 to the first factory and M4 and M5 to the second one. These two factories assemble the parts into C1 and C2. Again, the vehicles transport two of them to a factory where final assembly is done. The appropriate vehicle takes the final product to the ultimate plant. A schematic view is shown in Figure 1. For assembly at stage 2, one unit of each arrived part is needed; and for assembly at stage 3, 2 units of C1 and 3 units of C2 is needed. The time of processing at stage 2 has the exponential.

Figure 1. The SC network.

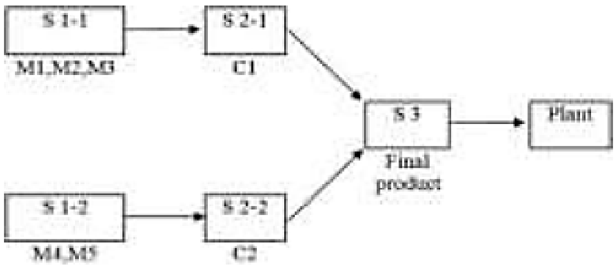

Table 1 . The requisite trucks and corresponding times for transportation between stages.

From		To											
		S 2-1			S 2-2			S 3			Plant		
		10	20	30	10	20	30	10	20	30	10	20	30
S 1-1	No. of trucks assigned		3										
	No. of alternative trucks		1										
	Time of transportation		$0.8^{\sim}$										
S 1-2	No. of trucks assigned						2						
	No. of alternative trucks				1								
	Time of transportation					$0.8^{\sim}$							
S 2-1	No. of trucks assigned								1				
	No. of alternative trucks							1					
	Time of transportation								$0.8^{\sim}$				
S 2-2	No. of trucks assigned									1			
	No. of alternative trucks							1					
	Time of transportation								$0.8^{\sim}$				
S 3	No. of trucks assigned										1		
	No. of alternative trucks										1		
	Time of transportation											$1.8^{\sim}$	

distribution with mean value of 1, and the time at stage 3 has the exponential distribution with mean value of 2. Five trucks with capacity of 20 units per load, three trucks with capacity of 30 and Five with capacity of 10, are available.

In order to evaluate resilience strategies in the proposed SC, 13 different scenarios are defined as follows:

Scenario 1 (basic scenario): In this scenario, the main SC is supposed, without disruption and any resilience strategy. For comparing the situations in which disruptions may occur (i.e. the one needing resilience factors), we need this basic scenario.

Scenario 2 (disruption scenario): In this scenario, the disturbance may occur but no resilience strategy has been assumed. The failure occurs with a specific distribution. This scenario is needed to evaluate the effectiveness of resilience strategies in disturbance situations.

Scenario 3 (resilient scenario 1): This scenario is our first scenario in which a resilience factor is considered. The factor is velocity that means the increase in rate of system recovery. Velocity is one of the agility factors, and this makes this scenario agile.
Scenario 4 (resilient scenario 2): In this scenario, we assume the visibility factor which means the quick response of the system to any disruption. In our case, immediately after a truck breaks down, system responds (i.e. there is no delay between failure of a resource and replacing it with another one). As it was mentioned, the visibility is one of the agility factors. So in other words, this scenario also expresses the agility of the SC.
Scenario 5 (resilient scenario 3): In this scenario, we are taking the redundancy factor into account. Redundancy means the augmentation in the number of resources.
Scenario 6 (resilient scenario 4): In this scenario, the system has both factors of visibility and velocity together. That means the system is definitely agile. The system responds to any disruption without delay and repairs with a faster rate.
Scenario 7 (resilient scenario 5): This scenario includes velocity and redundancy together. In addition to availability of more resources, the recovery time is less. The combination of two resilience factors is assumed in this case.
Scenario 8 (resilient scenario 6): In this scenario, the concept of redundancy along with visibility has been considered. It is obvious that having extra resources and a quick response to disruption makes the system more resilient.
Scenario 9 (resilient scenario 7): Extra resources and flexibility of using them in place of each other is supposed in this case. The aforementioned characteristics make our system redundant and flexible.
If a resource breaks down, not only an extra one is available, but also it can be replaced by other resources as needed.
Scenario 10 (resilient scenario 8): Seeking for a resilient system is led to combining redun- dancy, velocity and visibility strategies. When a resource needs recovery, the system reacts immediately by offering more resources and repairing the failed one rapidly.
Scenario 11 (resilient scenario 9): Among the resilience factors, velocity, flexibility and redundancy are assumed in this scenario.
Scenario 12 (resilient scenario 10): Visibility, flexibility and redundancy make this scenario more resilient.
Scenario 13 (resilient scenario 11): Finally, in this scenario, all the aforementioned resilient factors are taken into account.
As we mentioned earlier, in each scenario we considered some resilience factors. The summaries of assumptions are shown in Table 2.

Table 2 . The scenarios details.

	Visibility	Flexibility	Redundancy	Velocity
Scenario 1		Basic		
Scenario 2				
Scenario 3				√
Scenario 4	√			
Scenario 5			√	
Scenario 6	√			√
Scenario 7			√	√
Scenario 8	√		√	
Scenario 9		√	√	
Scenario 10	√		√	√
Scenario 11		√	√	√
Scenario 12	√	√	√	
Scenario 13	√	√	√	√

Simulation network modelling
In the simulation network, the products (i.e. raw materials and assembled parts) are considered as entities; and the trucks are taken up as resources. In this process, the raw materials are sent into the original network by a CREATE node and since the plant orders one unit each day, they double to make enough of C1 and triple to make enough of C2. If the requisite resource (i.e., truck) is available, they will arrive

to the factory where the first assembly gets done. Otherwise, they wait in the AWAIT node. The nodes employed for modelling the process are UNBATCH, ASSIGN, BATCH, QUEUE, FREE, COLCT, ASSEMBLE, RESOURCE, PREEMPT and TERMINATE. The network of the first scenario shows the situation with no resilience policy. Scenario 2 has the factor of disruption. At the third scenario, velocity, as a resilience factor, plays a part. At the fourth scenario, the assumption of visibility is taken into account. Scenario 5 has the factor of redundancy.

RESULTS AND DISCUSSION

After running the simulation, the reports are collected. Table 4 shows the results of simulation for pessimistic, most likely and optimistic situations. The transportation delays of these situations are shown in Table 3. In Table 4, total cost of system consists of the costs of trucks and the costs to repair them.

Table 3 . The transportation delay between stages in pessimistic (P.), most likely (M. L.) and optimistic (O.) situations.

	To											
	S 2-1			S 2-2			S 3			Plant		
From	P.	M. L.	O.	P.	M. L.	O.	P.	M. L.	O.	P.	M. L.	O.
S 1-1	1	0.8	0.5									
S 1-2				1	0.8	0.5						
S 2-1							1	0.8	0.5			
S 2-2							1	0.8	0.5			
S3										2	1.8	1.6

Table 4. Results of simulation in pessimistic (P.), most likely (M. L.) and optimistic (O.) situations.

	The average time in system			The average utility of resources			The average number of breakdowns			Total cost of system		
	P.	M.L.	O.	P.	M. L.	O.	P.	M. L.	O.	P.	M. L.	O.
Scenario 1	21.156	17.191	12.991	2.642	2.188	1.495	0	0	0	632.119	571.832	509.001
Scenario 2	26.105	26.105	20.534	2.295	2.295	1.616	3.191	3.191	2.898	915.343	915.343	810.22
Scenario 3	24.413	20.076	15.476	2.647	2.22	1.527	3.538	2.988	2.655	1002.539	891.548	790.509
Scenario 4	30.928	26.105	20.534	2.65	2.295	1.616	3.752	3.191	2.898	1000.105	915.343	810.22
Scenario 5	6.593	3.792	2.848	2.986	2.602	1.847	1.632	1.344	1.317	488.278	420.507	414.629
Scenario 6	24.099	19.876	15.305	2.638	2.195	1.503	3.491	2.973	2.781	989.338	887.199	798.743
Scenario 7	4.901	3.733	2.839	2.96	2.477	1.738	1.532	1.39	1.389	491.444	465.374	466.546
Scenario 8	5.538	3.748	2.815	3.013	2.576	1.821	1.457	1.342	1.317	449.212	420.29	414.415
Scenario 9	19.101	12.682	2.858	3.97	3.402	2.297	3.129	2.61	1.317	872.923	750.594	414.612
Scenario 10	4.55	3.679	2.799	2.943	2.452	1.707	1.547	1.389	1.444	488.915	465.158	465.351
Scenario 11	4.902	4.654	2.837	3.593	3.091	2.187	1.532	1.784	1.389	491.443	574.06	460.557
Scenario 12	13.793	12.667	2.826	3.875	3.38	2.271	2.735	2.625	1.317	772.759	749.46	414.408
Scenario 13	4.541	3.654	2.8	3.522	2.905	2.155	1.546	1.389	1.442	488.894	465.301	465.232

In this study, the FDEA approach is used as an effective method to rank the scenarios and analyze the data. [10] All the performance indicators are imported to the FDEA model in order to determine the efficiency score and rank of scenarios. Table 5 shows the results of using the FDEA approach. In a real-word setting, determining the α-cut value depends on the extent of the system under study. These values are related to the measure of certainty in a real-world case. When the certainty increases and the fuzzy system goes to the certain situation, α goes to one; so depending on the limit of certainty, the most appropriate α is selected. This study covers a wide range, so the different values of α-cuts between 0 and 1 are considered. As seen in Table 5, for α-cut-1, scenario 1 reaches the first place and this was predictable since this scenario is the basic scenario where no disruption happens and no work stoppage occurs. For α-cut-0.01, 0.1 and 0.2, scenario 4 reaches the first place and this shows the importance of visibility in the system. It is certain that a system should be visible to withstand the situations in which disruption may occur, because having a clear view of the system becomes more critical in case of a disturbance. Scenario

8 for α-cut-0.3, 0.4, 0.5, 0.6, 0.7 and 0.8 is the best which shows the significant role of visibility and redundancy. Redundancy plays a significant role especially when the disruption occurs in a transportation system which is our case. Finally, for α-cut-0.9, 0.95 and 0.99, scenario 5 achieves the first place. The factor that was considered in scenario 5 was redundancy. So, the results of the FDEA approach show the importance of considering visibility and redundancy among the factors of resilience.

Table 5. The results of FDEA approach: technical efficiency (T. E.) and ranking (R.) of scenarios for each α-cut.

	0.01		0.05		0.1		0.2		0.3		0.4		0.5	
α-Cut	T. E.	R.	T. E.	R.	T. E.	R.	T. E.	R.	T. E.	R.	T. E.	R.	T. E.	R.
Scenario 1	0.68554	5	0.69989	6	0.71763	7	0.75243	7	0.7867	8	0.82012	8	0.85256	8
Scenario 2	0.9075	2	0.90482	2	0.90151	2	0.89507	3	0.88885	5	0.88282	5	0.877	7
Scenario 3	0.83333	4	0.83849	4	0.84485	5	0.85723	5	0.8692	6	0.88078	6	0.89198	5
Scenario 4	0.90926	1	0.91353	1	0.91879	1	0.92904	1	0.93895	2	0.94853	2	0.9578	2
Scenario 5	0.54535	10	0.67936	9	0.7814	6	0.85377	6	0.88911	4	0.91395	3	0.93428	3
Scenario 6	0.87221	3	0.87495	3	0.87832	3	0.8849	4	0.89126	3	0.89741	4	0.90336	4
Scenario 7	0.52434	13	0.52755	13	0.53782	13	0.60579	13	0.71071	13	0.77842	13	0.82592	13
Scenario 8	0.53788	11	0.73946	5	0.8515	4	0.92242	2	0.94982	1	0.96494	1	0.97487	1
Scenario 9	0.67898	6	0.69399	7	0.71247	8	0.74855	8	0.78348	9	0.81732	9	0.85011	10
Scenario 10	0.53625	12	0.54029	12	0.54404	12	0.62949	12	0.73644	11	0.8043	10	0.85094	9
Scenario 11	0.64591	8	0.65803	10	0.67295	10	0.70207	11	0.73111	12	0.78074	12	0.83051	12
Scenario 12	0.67114	7	0.6854	8	0.70296	9	0.73723	10	0.77041	10	0.80255	11	0.8337	11
Scenario 13	0.63641	9	0.64813	11	0.66257	11	0.74114	9	0.80029	7	0.84358	7	0.87873	6
	0.6		0.7		0.8		0.9		0.95		0.99		1	
Scenario 1	0.88401	8	0.91447	6	0.94394	5	0.97244	5	0.98634	5	0.99729	5	1	1
Scenario 2	0.87702	10	0.88609	13	0.90778	13	0.93099	12	0.94459	11	0.95548	10	0.9582	9
Scenario 3	0.90282	6	0.91333	7	0.92758	9	0.94251	10	0.94979	9	0.95552	9	0.95694	10
Scenario 4	0.96678	2	0.97547	2	0.9839	3	0.99207	3	0.99607	3	0.99922	4	1	5
Scenario 5	0.95219	3	0.96862	3	0.98404	2	0.99672	1	0.99841	1	0.99968	1	1	6
Scenario 6	0.90912	4	0.9147	5	0.92386	11	0.93549	11	0.94115	12	0.94559	12	0.9467	12
Scenario 7	0.86121	13	0.88855	12	0.91043	12	0.92785	13	0.9356	13	0.94257	13	0.94433	13
Scenario 8	0.98213	1	0.98781	1	0.99249	1	0.99646	2	0.99823	2	0.99965	2	1	7
Scenario 9	0.88191	9	0.91275	8	0.94269	6	0.97176	6	0.98598	6	0.99721	6	1	8
Scenario 10	0.88477	7	0.91029	9	0.93011	8	0.9443	9	0.94887	10	0.95375	11	0.9551	11
Scenario 11	0.87131	11	0.90729	10	0.94021	7	0.97095	7	0.98566	7	0.99716	7	1	2
Scenario 12	0.8639	12	0.8932	11	0.9248	10	0.96281	8	0.9815	8	0.99631	8	1	3
Scenario 13	0.90804	5	0.93391	4	0.95813	4	0.98171	4	0.99343	4	0.99964	3	1	4

CONCLUSION

Supply chains are increasingly exposed to unpredictable disruptions, particularly in transportation systems, which can significantly impair performance. Therefore, resilience has become essential for supply chain sustainability. This study presents a comprehensive framework that integrates simulation and fuzzy data envelopment analysis (FDEA) to assess the impact of various resilience strategies in a three-echelon supply chain.We modelled 13 distinct scenarios, each representing a different policy combination of four key resilience factors: visibility, velocity, redundancy, and flexibility. The simulation results, evaluated through FDEA, demonstrate that implementing resilience-enhancing factors leads to improved system performance. Among these, visibility and redundancy emerged as the most influential in mitigating transportation-related disruptions. The proposed framework offers practical insights for supply chain managers, helping them identify and implement optimal resilience strategies under uncertainty. Future research can expand on this work by exploring additional resilience dimensions and incorporating real-time data analytics to further enhance decision-making in dynamic supply chain environments.

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