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A Fuzzy-Based Decision Support System for Supply Chain Disruption Management

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Abstract

Among the supply chain risk types, disruptions that result from natural disasters, sanctions, transportation problems and equipment failure can seriously disrupt or delay the flow of material, information and cash. The aim of this research was to propose a hybrid model for disruption management, which is the process of achieving plans or strategies to reduce the expenses incurred by the disruption. For this purpose; first, we identified disruptions and mitigation strategies by using the nominal group technique. Then, the interaction between disruptions was formulated by the fuzzy DEMATEL technique. Consequently, with regard to the uncertainty of data, fuzzy logic was used for modeling the uncertainty of disruptions. Finally, mitigating strategies were selected and ranked with PROMETHEEII. Considering the existence of 4 types of responses of chain against risks, which include: 1- risk control and endurance 2-risk flexibility 3- risk avoidance 4- risk transfer and assignment; results show that according to the type of disorder, the risk management strategy changes and in general (taking into account the causal relationship between disorders), the risk transfer strategy it was more suitable.

Keywords: *Supply chain disruption; Mitigation; Fuzzy logic; DEMATEL; PROMETHEE*

1. Introduction

With regard to the complex and dynamic environment of supply chains, numerous supply chain risks have been raised. These risks are constantly evolving from sources within and outside of the supply chain [1]. Supply chain risks have been clustered into different groups with classifications differing between papers. The literature categorizes a supply chain risk as either an operational or a disruption risk [2]. Operational risk refers to inherent uncertainties such as uncertain customer demand, supply, and cost. A supply chain faces many types of risks in the daily operation. One of the suppliers might have an emergency shutdown, which due to the late delivery of raw materials to the plants; the transportation might be delayed due to difficulties in the shipment [3]. Disruption risk refers to disruptions resulting from natural disasters, supplier bankruptcy, labor disputes, war, terrorism, sanction and socio-economic political instability. In recent years, disruption risks have been occurring more frequently, which can thus lead to loss in productivity, quality, market share, and reputation of the suppliers and the supply chain [4].

Relative to most of the business practices, the occurrence of a disruptive event is an extraordinary and unusual situation. While a significant amount of researches has been conducted in the area of supply chains, relatively few studies have investigated the impact of supply chain disruptions [5].

This paper integrates DEMATEL, Fuzzy logic and PROMETHEE to disruptions management and ranking of mitigation disruption Strategies in Supply Chain. The paper is organized as follows: Section 2 describes the framework of enablers of supply chain risk mitigation and its associated literature. Section 3 demonstrates the methodology utilized in this paper and briefly reviews DEMATEL, Fuzzy logic and PROMETHEE. The proposed model results are given in Section 4. Finally, our conclusions are offered in Section 5.

2. Research Background

This literature review was carried out by referring to leading journal databases. To date, many articles have been published in regards to supply chain disruption.

According to the study by Khayat Basiri et al [6], the main objective was to determine the enablers of a gas-distribution company to mitigate disruptions. This study developed a new SCD mitigation construct and examined its relationships with the key capabilities in the context of NGSS using SEM, which was founded on the contingency theory. Specifically, the results demonstrated the employment of a supply-chain management lens in which the disruption drivers were not only operational but also physical. On the other hand, social and human related drivers existed that need to be considered.

Mellat Parast [7] investigated the impact of R&D investment on mitigating supply chain disruptions. The results of her study provided several insights for top-level managers who are concerned with improving their organizational resilience to supply chain disruptions. Her first managerial implication pertains to promoting investment in innovation across the organization. Investment in research and development increases organizational resilience to disruptions.

Second, managers should be aware that the impact of R&D investment in mitigating the negative effects of disruptions is not the same for all sources of disruption risks. Managers need to identify the major sources of disruption risks in their supply chain and develop their R&D investment plans. Third, managers investing in disruption mitigation strategies should be aware of the potential trade-off between strategies at the supply chain level vs. the firm level.

Shekarian et al [8], flexibility and agility are two distinct characteristics that effect on improving supply chain responsiveness. In this study, they proposed the multi-objective mixed integer programming (MOMIP) model by using three multi-objective optimization methods. Flexibility and agility can also be created an investment plan to minimize the negative impact of supply chain disruptions by examination of the trade-offs among responsiveness, risk, and cost. Their study showed that the best strategy was investing 60% in flexibility and 40% in agility. Considering this strategy, the best result of our multi-objective problem has 6.41% deviation from the optimum value of responsiveness, 129.11% deviation from the optimum value of risk, and 46.19% deviation from the optimum value of cost. Sanchis et al. [9] studied the preparedness capacity of enterprise resilience, one of its three constituent capacities. To be prepared for the unexpected, it is necessary to identify the most critical disruptive events that companies may face from a supply side and to propose mitigation strategies for providing companies with a set of alternatives to support the enhancement of the preparedness capacity of enterprise resilience. Pariazar and colleagues [10] created a multi-objective stochastic programming model to detect trade-offs between costs and disruption risk. They considered network configuration and operating costs under normal conditions, cost of unsatisfied demand, cost of transporting stained products to the customer, and cost of quality inspection as conflicting objectives that need to be simultaneously reduced. They used a mixed method to identify Pareto-optimal supply chain configurations and to calculate the fitness value. In another study, Qazi et al [11] developed a supply chain risk network management (SCRNM) process. Established techniques from safety and reliability engineering, decision making under uncertainty and multi-criteria decision analysis were adapted and integrated together to operationalize the proposed process. Kumar and colleagues [12] studied how a retailer can use pricing decisions along with sourcing strategies under disruption risk while competing against another retailer with a more reliable supply chain; they found that retailers focus on reliable goods and lower prices when adjusting for cost advantage and higher market potential. Another study [13] formulated a multi-objective MILP model to find the optimal choice of suppliers and their order quantity allocation under disruption risk. Suppliers were evaluated and ranked based on the preference values obtained using a hybrid fuzzy AHP-fuzzy PROMETHEE. Also, Rajesh et al. [14] introduced a new model to enable supply chain risk mitigation; they emphasized on ascertaining the major enablers of supply chain risk mitigation with the emblematic focus on electronic supply chains. A blend of gray theory and DEMATEL approaches had been employed in this research to find out the cause/effect relationships among the enablers of supply chain risk mitigation. Kamalforosh et al. [15] proposed A Dual-Objective Nonlinear Model for Network Design with NSGA Algorithm. aim was to optimize a three-level supply chain so as to decrease objective costs (such as shortage periods) while simultaneously increasing customer service levels. After evaluating the formulated mathematical model, a metaheuristic algorithm was developed capable of determining the number of open distribution centers and allocating retailers to these centers. Final results indicate the superiority of the proposed metaheuristic in comparison to other, competing approaches **.**

Fuzzy expert systems are used in various subjects, Akhoondi and Hosseini [16] had studied the risk of developing heart disease, the results of which showed that accuracy of the proposed Mamdani FES was equal to 79.47% and its accuracy using Sugeno model was equal to 88.43%. This FES was promising for prognosis of the heart disease and conseuently early diagnosis of the disease and improving survival rates. Maghsoudi and Moshiri [17] Applying Adaptive Network-Based Fuzzy Inference System to Predict Travel Time in Highways for Intelligent Transportation Systems. The aim of present research was to offer a strong neuro-fuzzy network and applied it to predict travel time and compared its results with methods like ANN and AIMSUN. Their results indicated that means for neuro-fuzzy prediction remarkably decrease the error criteria of predicted travel time. This research proved the possibility of applying adaptive neuro-fuzzy inference system in predicting travel time, and reveals that it can make very successful analysis on traffic data.

Bradley [18] suggested a five step method for SCRM: 1) identify risks, 2) measure risks, 3) Prioritize risks for mitigation, 4) evaluate risk mitigation tactics, and 5) implement risk mitigation tactics. He then explored the first three steps, naming them as the foundation for evaluating and implementing mitigation tactics. With respect to the risk identification step, suppliers and locations are considered two physical aspects of a generic supply chain where disruptions may threaten the normal flow of goods from upstream. Supplier disruptions are due to flaws and problems in suppliers' operations.
In this study, we extend Bradley's study to cover the last two steps, evaluating and Implementing risk mitigation tactics, and to address the call for new analytical research in this area. We consider: 1- external disruption, which makes a number of suppliers in the same location unavailable (same natural disaster and sanction); 2- internal disruption in supply chain (same: transportation, equipment failure and supplier disruption). We then analyze the interaction between risks of using different mitigation tactics to design a supply chain resilient and responsive to supplier and environmental disruptions. We examine the effectiveness of adding four types of mitigation strategy (Control and endurance, Flexibility, Avoidance and Transfer and Assignment) to the supply chain and suggest contingency plans to help implement each of the strategies. Our study is unique in that we examine the effectiveness of four mitigation tactics against five types of disruptions in the upstream of a supply chain; we take into account suppliers' disruption dependence or independence.
In order to determine the most effective method, managers must be able to analyze disruptive events and their possible effects. Despite the importance of this issue, information on supply chain disruptions and their effects is scarce. Due to this lack of information, the current paper investigates a model for determining how disruptions of supply chain components are causally related to each other as well as identifying the ways of disruption propagation.
Cause–effect relationships plotted facilitate managers to ascertain primary causal enablers that need imperative attention in dealing with vulnerability issues of supply chain. Managers can take proactive steps to address and implement primary causal enables of risk mitigation into practice for reducing total risk impacts of the supply chain.

3. Contributions of this study and Proposed model

Our study extends previous research in supply disruption and resource allocation. we first design an algorithm to find the likelihood of all scenarios that may happen as the result of failures in suppliers (supplier disruptions) and regions (environmental disruptions); then, using a decision mixed model, we determined interaction between supply chain disruptions , as well as selection and allocation of disruption mitigation resources.
Our study makes important contributions to supply chain risk management literature. In order to examine the impact of disruptions and incorporating disruption mitigation strategies, we ranked mitigation strategies using a three-stage mixed model. This approach to modeling supply chain disruptions has been used in previous studies in disruption and disaster management in order to evaluate pre- and post-disruption decisions.The model incorporates the risk of disruption by assigning probabilities for each scenario due to internal failure (supplier disruptions) or external failure (environmental disruptions). The model provides insight for the firm's development.

To the best of our knowledge, it is one of the first studies that examine interaction disruptions and the impact of different disruption mitigation strategies in system, particularly identify effective disruptions and mitigation strategies selection.
The model can function as a classification model; it generally consists of four modules. Module 1 identifies disruptions and mitigation strategies by using the nominal group technique. Module 2 applies fuzzy DEMATEL to determine the interaction between disruption and its effects on performance factors; we used fuzzy DEMATEL to calculate the influence score (or impact rate). Module 3 utilizes a fuzzy inference system to compute disruption value. Module 4 applies the ROMETHEE method for ranking the mitigation strategies proposed for each disruption. Figure 1 depicts the diagram of the proposed model.4

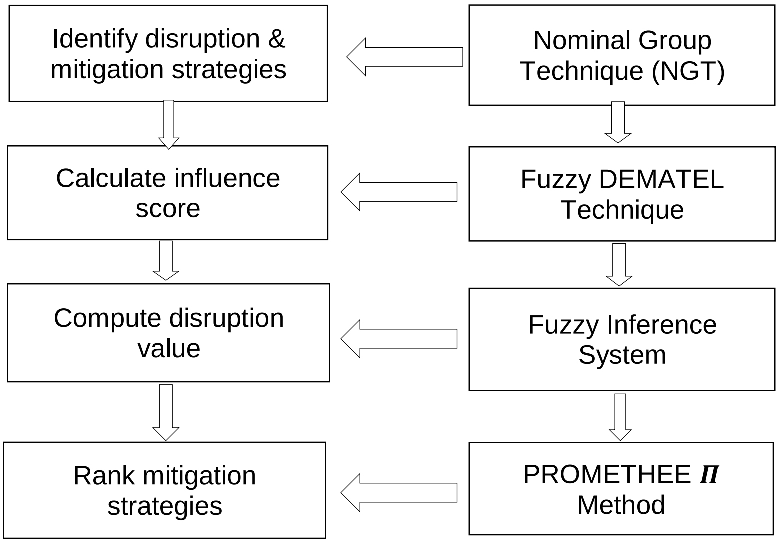

Figure 1. Schematic diagram of the proposed model for evaluating disruptions and ranking mitigation strategies

3.1. The fuzzy DEMATEL method

The Fuzzy DEMATEL method was applied as follows:
Step 1. We can turn ambiguous judgments into triangular fuzzy numbers according to Table 1 [19].

Table 1. The relationship between and fuzzy number

Linguistic judgments	**Corresponding triangular fuzzy number**
No influence	(0, 0.1, 0.3)
Very low influence	(0.1, 0.3, 0.5)
Low influence	(0.3, 0.5, 0.7)
High influence	(0.5, 0.7, 0.9)
Very high influence	(0.7, 0.9, 1)

Step 2. Fuzzy matrix $\tilde{Z}$ (the initial direct-relation fuzzy matrix) is produced, as shown, where $\tilde{z}_{ij} = (l_{ij,}\, m_{ij,}\, u_{ij})$ shows the triangular fuzzy number in this matrix.

$$\tilde{Z} = \begin{bmatrix} 0 & \tilde{z}_{12} & \cdots & \tilde{z}_{1n} \\ \tilde{z}_{21} & 0 & \cdots & \tilde{z}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}_{n1} & \tilde{z}_{n2} & \cdots & 0 \end{bmatrix} \tag{1}$$

Step 3. We acquire normalized direct-relation fuzzy matrix $\tilde{X}$ by normalizing the initial direct-relation fuzzy matrix, which is shown as

$$\tilde{X} = \begin{bmatrix} 0 & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & 0 & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & 0 \end{bmatrix} \quad \text{Where} \quad \tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{\tilde{R}} = \left(\frac{\tilde{z}_{ij,l}}{r_l}, \frac{\tilde{z}_{ij,m}}{r_m}, \frac{\tilde{z}_{ij,u}}{r_u}\right) \quad \text{and}$$

$$r_s = \max_{1\le i\le n}\left(\sum_{j=1}^{n} \tilde{z}_{ij,s}\right), (s = l, m, u) \tag{2}$$

Step 4. In this step, the total-relation fuzzy matrix $\tilde{T}$ is computed, which is defined as

$$\tilde{T} = \left(\tilde{X} + \tilde{X}^2 + \cdots + \tilde{X}^w\right) = \tilde{X}(1 - \tilde{X})^{-1} \tag{3}$$

Therefore, matrix $\tilde{T}$ could be demonstrated as follows:

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \cdots & \tilde{t}_{1n} \\ \tilde{t}_{21} & \tilde{t}_{12} & \cdots & \tilde{t}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{t}_{n1} & \tilde{t}_{n2} & \cdots & \tilde{t}_{nn} \end{bmatrix} \quad \text{Where } \tilde{t}_{ij} = \left(t_{ij,l,}\, t_{ij,m,}\, t_{ij,u}\right) \tag{4}$$

The overall influence rate of the decision maker for each criterion i against criterion j
Step 5. The sum of rows and sum of columns of the sub matrices t_l , t_m, t_u denoted by the fuzzy numbers D˜_i and R˜_i can be obtained through $\widetilde{D}_i = \sum_{i=1}^{n} \tilde{t}_{ij}$ and $\widetilde{R}_i = \sum_{j=1}^{n} \tilde{t}_{ij}$ (5)

Step 6. To finalize the procedure, $\widetilde{D}_i \, and \, \widetilde{R}_i$ are defuzzified through suitable defuzzification methods. Then, there would be two numbers: $\widetilde{D}_i^{def} + \widetilde{R}_i^{def}$, which shows how important the strategic objectives are, and $\widetilde{D}_i^{def} - \widetilde{R}_i^{def}$ that shows which strategic objective is the cause and which one is the effect [20].

Step 7. The model used in this research was a combination of the fuzzy DEMATEL, fuzzy logic and PROMETHEE method. To calculate disruption value with fuzzy logic, we required weights (impact rate or importance of the disruption) that were obtained from the fuzzy DEMATEL method. The importance of the disruption was calculated by using the following equation:

$$w_i = \{(\widetilde{D}_i^{def} + \widetilde{R}_i^{def})^2 + (\widetilde{D}_i^{def} - \widetilde{R}_i^{def})^2\}^{1/2} \tag{6}$$

The importance of any disruption can be normalized as follows: [16]

$$w_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{7}$$

4. Case study

In this section, we propose a numerical example to illustrate the application of the proposed method described in the previous section. This case study illustrates the stages including determination of the interaction between disruptions, disruption values and selection of mitigation strategies for the supply chain in the gasoline industry of Iran. Management aims to decrease and control the disruption risks in the supply chain. After several meetings, we identified five possible disruptions and four strategies. Table 2 presents these disruptions.

Table 2. Possible disruptions in the gasoline industry supply chain

Symbol	**Disruption**
C1	Transportation
C2	Supplier
C3	Equipment failure
C4	Sanction
C5	Natural disasters

These disruptions are not independent of each other. In fact, one event can be the cause of another event and these disruptions are closely interrelated with each other; therefore, we used the fuzzy DEMATEL technique to examine the relationship between these disruptions. Tables 3-8 present the outputs of the DEMATEL model and figure 2 shows the relation between the disruptions.

Table 3 -The linguistic scale direct-relation matrix by expert 1.

expert 1	C1			C2			C3			C4			C5		
	L	M	U	l	m	u	L	M	U	L	M	u	L	M	U
C1	0	0.1	0.3	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.1	0.3	0.5
C2	0.5	0.7	0.9	0	0.1	0.3	0.7	0.9	1	0.3	0.5	0.7	0.1	0.3	0.5
C3	0.5	0.7	0.9	0.7	0.9	1	0	0.1	0.3	0.1	0.3	0.5	0.1	0.3	0.5
C4	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0	0.1	0.3	0.3	0.5	0.7
C5	0.7	0.9	1	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7	0	0.1	0.3

Table 4 -The average linguistic scale direct-relation matrix by all experts.

AVERAGE	C1			C2			C3			C4			C5			
	L	M	U	l	m	u	L	m	u	L	m	u	l	M	U	uj
C1	0	0.1	0.3	0.5	0.7	0.9	0.56	0.76	0.93	0.23	0.43	0.63	0.1	0.3	0.5	3.3
C2	0.56	0.76	0.93	0	0.1	0.3	0.7	0.9	1	0.3	0.5	0.7	0.1	0.3	0.5	3.4
C3	0.56	0.76	0.93	0.63	0.82	0.96	0	0.1	0.3	0.23	0.36	0.56	0.1	0.3	0.5	3.3
C4	0.63	0.82	0.96	0.63	0.82	0.96	0.63	0.82	0.96	0	0.1	0.3	0.23	0.43	0.63	3.8
C5	0.63	0.82	0.96	0.36	0.56	0.76	0.56	0.76	0.93	0.3	0.5	0.7	0	0.1	0.3	3.7

Table 5 – Normalized Matrix (according to equation 2).

Normalized Matrix	C1			C2			C3			C4			C5		
	L	M	U	l	m	U	L	m	U	L	M	U	L	m	U
C1	0	0.03	0.08	0.13	0.18	0.24	0.15	0.2	0.24	0.06	0.11	0.17	0.03	0.08	0.13
C2	0.15	0.2	0.24	0	0.03	0.08	0.18	0.24	0.26	0.03	0.13	0.18	0.03	0.08	0.13
C3	0.15	0.2	0.24	0.17	0.22	0.25	0	0.03	0.08	0.06	0.09	0.15	0.03	0.08	0.13
C4	0.17	0.22	0.25	0.17	0.22	0.25	0.17	0.22	0.25	0	0.03	0.08	0.06	0.11	0.17
C5	0.17	0.22	0.25	0.09	0.15	0.2	0.15	0.2	0.24	0.08	0.13	0.18	0	0.03	0.08

Table 6 –The generalized direct-relation matrix (according to equation 4).

Relation Matrix	C1	C2	C3	C4	C5
C1	(0.08,0.34,1.99)	(0.19,0.46,2.07)	(0.22,0.5,2.16)	(0.08,0.29,1.55)	(0.05,0.22,1.31)
C2	(0.08,0.52,2.17)	(0.2,0.35,1.97)	(0.24,0.56,2.22)	(0.06,0.33,1.6)	(0.05,0.23,1.34)
C3	(0.22,0.49,2.12)	(0.23,0.49,2.07)	(0.1,0.35,2.1)	(0.09,0.28.1.53)	(0.08,0.22,1.3)
C4	(0.27,0.58,2.43)	(0.27,0.57,2.36)	(0.28,0.6,2.46)	(0.05,0.27,1.69)	(0.09,0.29,1.52)
C5	(0.26,0.55,2.35)	(0.19,0.48,2.24)	(0.25,0.55,2.37)	(0.12,0.34,1.72)	(0.03,0.19,1.39)

Table 7- Fuzzy result (according to equation 5).

	D+R	D-R
C1	(1.53,4.29,20.14)	(-0.29,-0.67,-2.52)
C2	(2.43,4.34,20.37)	(-0.45,-0.36,-1.4)
C3	(1.81,4.39,20.43)	(-0.37,-0.73,-2.19)
C4	(1.36,3.82,18.55)	(0.56,0.8,2.37)
C5	(1.16,3.26,16.93)	(0.55,0.96,3.21)

Table 8-Difuzzy result (according to 6 &7).

	D+R	D-R	w_i	W_I
C1	7.56	-1.03	7.629843	0.208325
C2	7.87	-0.64	7.89598	0.215592
C3	7.75	-1.005	7.814891	0.213378
C4	6.88	1.13	6.97218	0.190368
C5	6.15	1.42	6.311806	0.172337

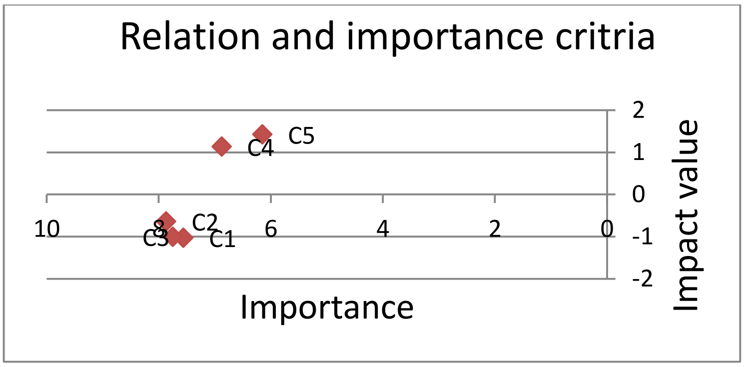

Figure 2. Diagram of the relation and importance of the disruptions

To calculate the probability of the occurrence of each of these disruptions, a questionnaire was prepared to calculate the frequency of occurrence and the severity of the event. In this model, we used the fuzzy logic model to calculate the probability of disruptions. This model consists of three inputs including, severity- whose value is the level of damage effects that occur in the system, occurrence- the value which represents the frequency of failure, and impact rate- the ability of effecting in system and one output include disruption been extracted and they represent the numerical values of the linguistic terms. Other than the impact rate that is a numerical variable derived from the DEMATEL model, the other values are of the linguistic term,

$$D = S(severity) \times O(occurrence) \times I\ (impact\ rate) \qquad (12)$$

In defining this model, disruption, Mamdani inference method, method of aggregation, maximum function and method defuzzification, and the center of gravity were determined. Subsequent membership functions for a term of five variables and fuzzy rule-based were implemented. The structure of the linguistic variables for each of the five terms, including very high (VH), high (H), moderate (MO), low (L) and very low (VL) was formed. A Gaussian function with overlapping membership was 50 percent. Accordingly, Figure 3 was created by using the Matlab software. The values for severity, occurrence and impact rate are presented in Tables 9-11.

Table 9- Severity of failure

Severity of failure	Damage
Very high	More than five billion per year
High	Between one and five billion per year
Moderate	Between half a million to one billion per year
Low	Between one hundred to five hundred million per year
Very low	Less than one hundred million per year

Table 10- Failure frequency of system parts

Failure frequency of system parts	Frequency of failure occurrence
Very high	More than five years
High	Between three and five years
Moderate	Between one and two years
Low	Between six and twelve months
Very low	Less than six months

Table 11- Impact rate

Impact rate	Value
Very high	0-0.1062
High	0.1-0.25
Moderate	0.25-0.5
Low	0.5-0.75
Very low	0.75-1

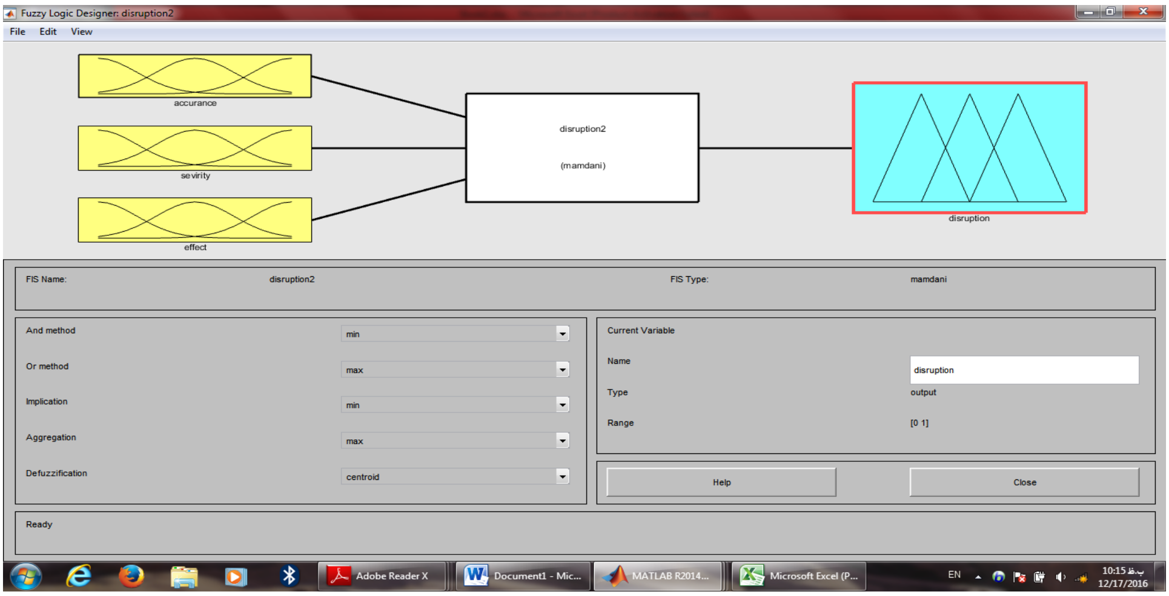

Figure 3. Inputs and Output structure in Matlab (according to equation 12)

After defining the input and output variables, fuzzy rules were developed for 125 inference rules; “if ... then” examples of the developed rules are as follows:

1- If the frequency of occurrence is very low, severity is low and impact rate is high, then disruption is very low.
2- If the frequency of occurrence is moderate, severity is low and impact rate is low, then disruption is low.
3- If the frequency of occurrence is low, severity is very high and impact rate is high, then disruption is high.…

Show implement these rules in the form of graphics are presented in Figure 4.

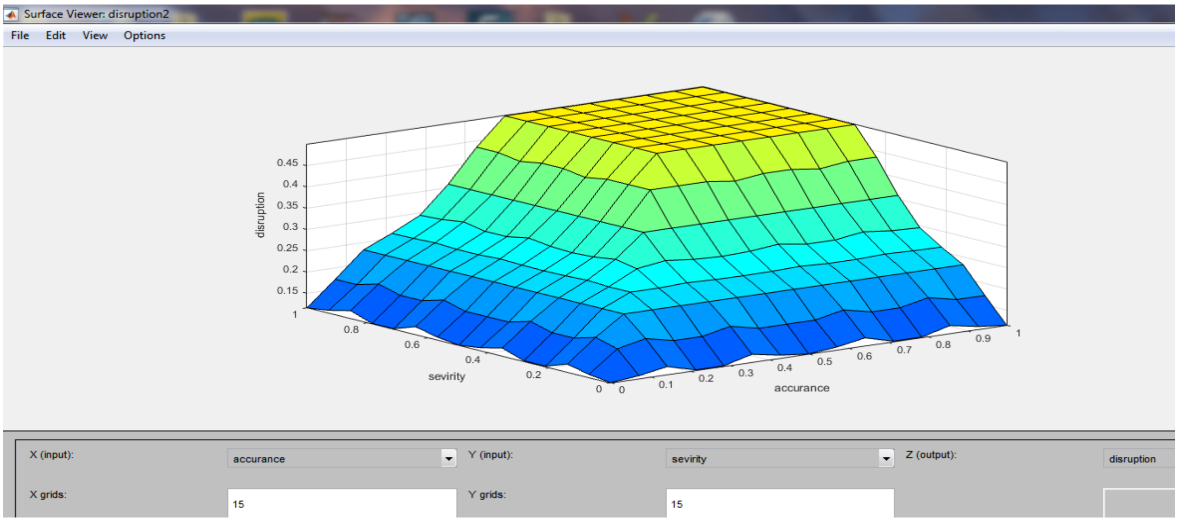

Figure 4: Surface viewer

After the formation of the model, values for the frequency of occurrence, severity and impact rate (weight) were used in the qualitative analysis as input variables. After fuzzy processing, disruption fuzzy values were produced, which are shown in Table 12.

Table 12 -Fuzzy logic result

Disruption	input1	input2	input3	output	Normalized output
c1	VH	L	0.208325	0.26	0.229277
c2	MO	L	0.215592	0.19	0.167549
c3	H	MO	0.213378	0.248	0.218695
c4	L	VH	0.190368	0.256	0.22575
c5	L	H	0.172337	0.18	0.15873

The next step is identifying strategies for dealing with the disruption. For this purpose, we interviewed experts. After qualitative analysis of the information, we used the PROMETHEE technique for quantifying the results and determining the most appropriate strategy for dealing with each of the disruptions. After the interviews were performed, we identified four strategies for confronting the disruption (Table 13).

Table 13- Disruption mitigation strategies

A1	Control and endurance
A2	Flexibility
A3	Avoidance
A4	Transfer and Assignment

So, for selecting the strategies we use the PROMETHEE method, in which calculated weights were computed by the Fuzzy Logic model (output) for criteria weights. At first, we defined p (a, b) or f (a, b) for each of the criteria (determined by DM).
$D_j = g_j(a) - g_j(b)$
All criterions:

$$F(a,b) = \begin{cases} 1 & if \quad dj > 0 \\ 0 & if \ dj \ \leq 0 \end{cases} \tag{13}$$

Table 14 presents the results of interviews with experts.

Tables 14 –Initial matrix

AVERAGE					
	c1	c2	c3	c4	c5
A1	4	3.4	4.2	2	2.4
A2	2	4.4	2.8	2	2
A3	1.4	2.8	1.2	3.6	1.6
A4	4.4	1.4	4.6	1.4	4.8

Next, we obtained the overall preference indices for each alternative pair by using this formula: π (a,b)=$\sum w_j \ f_j$ (a,b). Results of the PROMETHEE model are shown in Tables 15-20.

Table 15. Results of the PROMETHEE model for the first disruption (c1)

C1	Q^+	Q^-	Q
A1	0.46	0.23	0.23
A2	0.23	0.46	-0.23
A3	-	0.69	-0.69
A4	0.69	-	0.69

Considering the results, it is clear that A4 has top priority in ranking suppliers followed by A1, A2, and A3, respectively (A4 > A1 > A2 > A3).

Table 16. Results of the PROMETHEE model for the second disruption (c2)

C2	Q^+	Q^-	Q
A1	0.34	0.17	0.17
A2	0.51	-	0.51
A3	0.17	0.34	-0.17
A4	-	0.51	-0.51

Considering the results, it is clear that A2 has top priority in ranking suppliers, and A1, A3, A4have the second, third and fourth ranks, respectively (A2 > A1 > A3 > A4).

Table 17. Results of the PROMETHEE model for the third disruption (c3)

C3	Q^{+}	Q^{-}	Q
A1	0.44	0.22	0.22
A2	0.22	0.44	-0.22
A3	-	0.66	-0.66
A4	0.66	-	0.66

Based on the results, A4 has top priority in ranking suppliers followed by A1, A2, and A3, respectively (A4 > A1 > A2 > A3).

Table 18. Results of the PROMETHEE model for the fourth disruption (c4)

C5	Q^{+}	Q^{-}	Q
A1	0.46	0.46	0
A2	0.46	0.46	0
A3	0.69	-	0.69
A4	-	0.69	-0.69

As shown in Table 18, A3 has top priority in ranking suppliers, and A4, A1, A2 rank second, third and fourth, respectively (A3 > A4 > A1 = A2).

Table 19. Results of the PROMETHEE model for the fifth disruption (c5)

C5	Q^{+}	Q^{-}	Q
A1	0.32	0.16	0.16
A2	0.16	0.32	-0.16
A3		0.48	-0.48
A4	0.48		0.48

Table 19 shows that A4 has top priority in ranking suppliers followed by A1, A2, and A3, respectively (A4 > A1 > A2 > A3).

Table 20. Results of the PROMETHEE model

Total	Q^{+}	Q^{-}	Q
A1	2	1.24	0.76
A2	1.57	1.67	-0.1
A3	0.86	2.15	-1.29
A4	1.83	1.2	0.63

Results showed that A4 has top priority in ranking suppliers, and A1, A2, A3 rank second, third and fourth, respectively (A4 > A1 > A2 > A3)(Table 20).

5. Conclusion

Supply chains are increasingly susceptible to disruptions, and thus, investigating policies for control/mitigation is becoming a necessity for companies and a crucial field for research. This paper used the hybrid model as a tool to trace the prevailing disruption; also, strategies were addressed and compared with regard to the type of disruptions. The work described here presents a proposal for applying a decision model to the final vendor-rating phase of a process of strategy selection. These problems are often influenced by uncertainty in practice, and in this situation, the fuzzy approach is an appropriate tool for dealing with such problems. Based on the proposed model, interaction between the disruption and its effects on performance factors can be determined by the fuzzy DEMATEL. According to the output and D+R and D-R values, was seen that the fourth disorder is the most influential factor on the system and the other factors were the fifth, second, third and first disorders, respectively.

This study proposed weighting in the fuzzy inference system (as an input for calculating disruption value) based on the implementation of the fuzzy DEMATEL technique. Therefore, we used the outputs of the fuzzy inference system as weights in the PROMETHEE model.

The results showed that for the first disorder, transfer and assignment strategy was the most appropriate solution, also for the second, third, fourth and fifth disorders, respectively; Flexibility, transfer and assignment, avoidance, transfer and assignment strategies were the most appropriate strategy, and finally in general and considering the relationships between disorders, transfer and assignment strategy was the most appropriate strategy.

The proposed method is very flexible. This method enables us to assess and determine the outranking orders of strategies and thus, to rate the different strategies. This rating method can be used in combination with mathematical programming and other methods for selecting the most appropriate strategies. Because supply chain disruptions have different impacts on firm performance and supply chain performance outcomes, supply chain managers would be facing a challenging decision on how to address firm performance vs. supply chain performance from a perspective of risk management.

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