JJMIE

Volume 10 Number 1, March.2016
ISSN 1995-6665
Pages 67- 74

Jordan Journal of Mechanical and Industrial Engineering

A Fuzzy Approach for Modeling and Design of Agile Supply Chains using Interpretive Structural Modeling

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Received 9 Feb 2015 Accepted 16 Oct 2015

Abstract

Supply chain agility has opened new perspectives for efficient and intelligent manufacturing. In the arena of intense global competition, analysis of supply chain enablers and their interactions between one another decide the levels of agility. Previous research studies have effectively used Interpretive Structural Modeling (ISM) to study the relationships between identified enablers with the aid of Structural Self Interaction Matrix (SSIM), Reachability Matrix (RM) & Graph Theoretic Approach (GTA). In the present paper, fuzzy agility evaluation is deployed to spot and rank Agile Supply Chain Attributes (ASCA) of ISM identified driver enablers. The fuzzy system addressed uses linguistic variables, MATLAB & fuzzy Technique for Order Preferences by Similiarity to Ideal Solution (TOPSIS) methods for the tabulation of Fuzzy Agility Index (FAI), Fuzzy Merit Important Index (FMII) and ranking the scores of ASCA. This attempt may provide firms with engrossed information in the design of agile supply chains which will be dominant competitive vehicles in future.

Keywords: *Intelligent Manufacturing, Interpretive Structural Modeling, Structural Self Interaction Matrix, Fuzzy Agility Index, Fuzzy Merit Important Index, MATLAB.*

1. Introduction

The prime focus of any supply chain is to organize internal and external resources of an economic enterprise comprehensively. Off late, success measures for manufacturing firms were thought of as lower production costs, shorter production times, shorter lead times, lesser inventory, reliable delivery times, higher quality and better customer satisfaction. In recent past, success levels are mostly determined by balancing demand, supply and production and, hence, the concept of supply chain has emerged. Managing a supply chain effectively is a generative complex problem, with the growing levels of uncertainty and complex interrelationships. An efficient integration of production and distribution functions into a unified flexible entity is vital for competitive advantage. Most studies focused on traditional, analytical and orthodox methods for identifying critical ASCA. The present attempt, however, is to model the agility problem using fuzzy systems. The hypothesis of the present paper is that fuzzy modeling is an appropriate tool for a supply chain to become responsive, adaptive and flexible.

Complex and dynamic interactions between supply chain entities lead to a considerable uncertainty in planning. Uncertainty tends to propagate the supply chain up and down. Many proposed strategies for mitigating this bullwhip effect have a history of successful application . This effect leads to inefficiencies in supply chains since it increases the cost for logistics, and it lowers its competitive ability [1]. According to Faisal *et al*. [2], an Agile Supply Chain (ASC) should acquire characteristics such as market sensitiveness, virtual integration, network integration and process alignment which provides the opportunity to understand the dynamics among the enablers of agility in a supply chain. Here, the GTA approach has been used to analyze supply chain agility from the perspective of key enablers as obtained from ISM. Mehdi abbasi *et al*. [3] have used ISM as a tool for the determination of the optimal manufacturing strategy by using expert opinion technique and also applied the seven step algorithm and MICMAC analysis to analyze the elements in a complicated supply chain system. Iyer and mohammed sagheer [4] focused on risk prioritization in public-private partnership projects. ISM, here, is used to prepare a hierarchical structure as well as to study the interrelationships of these risks that would enable decision makers to take appropriate steps. Kannan govindhan [5] attempted ISM in logistics where the model was used to identify and summarize relationships among the specific

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attributes for selecting the best among the various third party logistic providers. Ching-torng lin [6] applied Fuzzy logics based on agility providers to determine the ranking of sub enablers deduced from ISM by calculating the fuzzy agility index comprising attribute rating and weights aggregated by average. Mir Aryanezhad [7] employed fuzzy topsis method using right and left scores to calculate the final ranking score among the selected sub enablers.

While several studies have steered the making of an ASC [2 - 7], a potential gap in combining them for extracting ASC driver enablers through ISM and prioritizing ASCA using Fuzzy approach ought to lend justification to this novel endeavor. The present paper is organized as follows: In section 2, ISM, SSIM, and RM model are developed; in section 3, estimation of fuzzy agility index and ranking of ASCA using fuzzy TOPSIS method are presented, followed by Results in section 4 and Conclusions in section 5.

2. ISM Methodology

ISM is a model that transforms unclear, poorly articulated models of systems into well-defined models. It is palpable that for a complex problem under consideration, a number of factors may be related and the direct and indirect relationships between the factors describe the situation far more accurately than the individual factor taken in isolation. ISM develops insights into collective understandings of these relationships. ISM starts with the identification of variables relevant to the problem and extends with a group problem solving technique by choosing a contextually relevant subordinate relation. Having decided on the element set and the contextual relation, SSIM is developed based on a pairwise comparison of variables. SSIM is later converted into a binary matrix called as the RM. Prominent ASC enablers referred in past literature are exhibited in Table 1.

Table 1. ASC Enablers

S.No	ASC Enablers	Reference
1.	Managerial control, Deliverability, Quality	[8]
2.	Organization role	[5]
3.	Strategic planning	[9]
4.	Cooperative behavior of chain members	[10]
5.	Information sharing, Reliability of information	[11]
6.	Production methodology, Time management	[12]

2.1. *SSIM Matrix*

Listed enablers and their interrelationships identified through interactive studies are depicted in Table 2 using 4 cyphers namely V, A, X and O were:

V: enabler i will augment enabler j;
A: enabler i will be augmented by the enabler j;
X: enabler i and j will augment each other;
O: enabler i and j are unrelated.

Table 2. Formation of SSIM matrix

S.No	ASC Enablers	Reference	10	9	8	7	6	5	4	3	2
1	Managerial control	[8]	V	A	O	V	O	O	O	A	O
2	Organizational role	[5]	A	O	O	O	X	O	O	X	
3	Quality	[8]	A	O	O	A	X	O	O		
4	Production methodology	[12]	V	V	A	O	X	O			
5	Deliverability	[8]	A	A	X	O	O				
6	Cooperative behavior of chain members	[10]	X	A	V	O					
7	Information sharing	[11]	X	V	V						
8	Strategic planning	[9]	A	O							
9	Time management	[12]	V								
10	Reliability of information	[11]									

2.2. *Reachability Matrix*

From the deduced SSIM matrix, the RM can be framed using alpha variables tabulated with binary numbers as shown in Table 3. This renders a methodology to calculate the driver and dependence values by summing up rows and columns respectively. The SSIM is transformed into a binary matrix, called RM by substituting 1 and 0 on behalf of V, A, X, O based on the following syntax.

- If the (i, j) entry in the SSIM is V, then the (i, j) entry in the RM becomes 1 and the (j, i) entry becomes 0.
- If the (i, j) entry in the SSIM is A, then the (i, j) entry in the RM becomes 0 and the (j, i) entry becomes 1.
- If the (i, j) entry in the SSIM is X, then the (i, j) entry in the RM becomes 1 and the (j, i) entry also becomes 1.
- If the (i, j) entry in the SSIM is O, then the (i, j) entry in the RM becomes 0 and the (j, i) entry also becomes 0.
- From the RM, the driver power of each element is obtained by the summation of 1's in the corresponding row. Similarly, dependence power of each element is obtained by the summation of 1's in the corresponding column.

Table 3. Reachability matrix

S.No.	ASC Enablers (ASC_i)	10	9	8	7	6	5	4	3	2	1	*Driver*
1	Managerial control	1	0	0	1	0	0	0	0	0	1	**3**
2	Organizational role	0	0	0	0	1	0	0	1	1	0	**3**
3	Quality	0	0	0	0	1	0	0	1	1	1	**4**
4	Production methodology	1	1	0	0	1	0	1	0	0	0	**4**
5	Deliverability	0	0	1	0	0	1	0	0	0	0	**2**
6	Cooperative behavior of chain Members	1	0	1	0	1	0	1	1	1	0	**6**
7	Information sharing	1	1	1	1	0	0	0	1	0	0	**5**
8	Strategic planning	0	0	1	0	0	1	1	0	0	0	**3**
9	Time management	1	1	0	0	1	1	0	0	0	1	**5**
10	Reliability of Information	1	0	1	1	1	1	0	1	1	0	**7**
	Dependence	**6**	**3**	**5**	**3**	**6**	**4**	**3**	**5**	**4**	**3**	

2.3. Classification of Enablers

From the findings of RM in the form of driver and dependence power of each ASC enabler, a graph is drawn were each element is plotted as a point using the conventional x-y coordinate system as depicted in Figure 1 in order to classify the four quadrants for the ease of viewing and analyzing. First quadrant consists of 'Autonomous enablers' posessing weak driver power and weak dependence. The 'Dependant enablers' constitute the second quadrant which has a weak driver power but a strong dependence. The third quadrant represents the 'Linkage enablers' that has a strong driving power and a strong dependence power. The fourth quadrant entails 'Driver enablers' having a strong driver power but a weak dependence. As per past research done on ISM, the driver enablers were often inferred for the improvement of agility levels as they have the potential to influence the other 3 quadrants. Accordingly, Driver enablers 4, 7, 9 were sidelined as per classification done similar to the one by Mandal *et al*. [13] and Faisal *et al* [14].

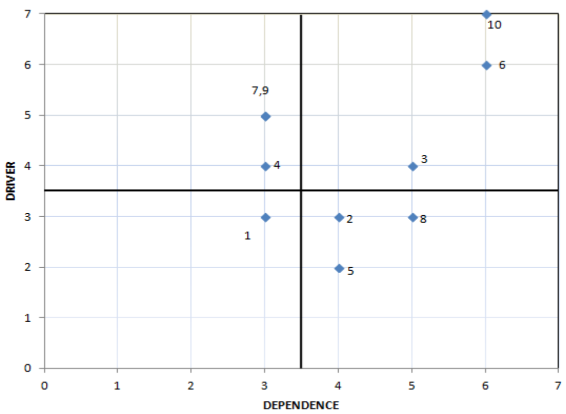

Figure 1. Classification of enablers

3. Fuzzy Modeling

Fuzzy logic is a technique suitable for dealing with uncertainty and subjectivity, which becomes an interesting supplementary approach to manage the performance of supply chains. It helps to deal with parameters that are difficult to express in a quantitative or a numerical measure and is used in making decisions with imprecise data. Due to its availability for representing uncertain values, fuzzy numbers are extensively used in many applications. In order to rank fuzzy numbers, one fuzzy number needs to be deployed, evaluated and compared with its counterparts or the median. Henceforth, to reduce the vagueness of the problem under study and to have a deep focus on ISM speckled driver enablers, Fuzzy agility evaluation is used on the basis of fuzzy logic systems.The evaluation can be done by classifying the sub enablers or attributes from driver enabler and by ranking them to improve supply chain agility.

Opulent review of related literature reveals that fuzzy logic has been applied for analyzing and monitoring the performance of supply chains, in developing models for strategy related performance outcomes and in developing methods for ranking fuzzy numbers for decision making from the viewpoints of users [15]. It has also served as a versatile tool in Multiple Criteria Decision Making (MCDM), arraying TOPSIS methods with fuzzy weighted averages [16]. Fuzzy logics have also been functional in the calculation of agility index in supply chains [6], designing optimal network for supply chain with fuzzy mathematical programming [17] and fractional programming for estimating fuzzy weighted averages in decision analysis [18].

3.1. Fuzzy Model Construction

3.1.1. Exploring ASCA Of ISM Identified Driver Enablers

The driver enablers identified from ISM were taken up for further studies and with the help of wide-ranging past literature, the ASCA pertaining to each of the driver enablers were surfaced as shown in Table 4.

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Table 4. ASCA

ASC Driver Enablers (ASC_i)	ASCA of Driver Enablers ($ASCA_{ij}$)	Reference
Production methodology (ASC_4)	Fully automated inspection systems ($ASCA_{41}$)	[12]
	Management's interest towards investment on FMS concepts($ASCA_{42}$)	[12]
	Application of Lean manufacturing principles for waste elimination ($ASCA_{43}$)	[12]
	IT application to exercise better vendor and supplier management[11] ($ASCA_{44}$)	[12]
Information sharing (ASC_7)	Infrastructure support for information sharing($ASCA_{71}$)	[11]
	End to end connectivity ($ASCA_{72}$)	[11]
	Honesty in sharing the information ($ASCA_{73}$)	[11]
	Undistorted communication ($ASCA_{74}$)	[11]
Time management (ASC_9)	Scheduled activities ($ASCA_{91}$)	[12]
	IT based communication system ($ASCA_{92}$)	[12]
	Training programme on time management concepts ($ASCA_{93}$)	[12]
	Adoption of time compression technologies ($ASCA_{94}$)	[12]

3.1.2. Fuzzy Ratings & Weights Using Linguistic Levels

Fuzzy evaluation is used to find and elicit the negative factors in the supply chain to improve the agility levels. Using linguistic levels, shown in Table 5 [19], the corresponding ratings and weights given by the 5 identified experts as exhibited in Table 6 and Table 7 was instrumental in the tabulating the aggregate rating and weights.

3.1.3. Aggregating Fuzzy Ratings & Weights for Estimating FAI

The aggregate mean of fuzzy ratings and weights (Rij and Wij) were estimated using equations 1 & 2 where E denotes experts and n the number of experts for the ASC enabler i and ASC attribute j, the summary of which is exhibited in Table 8.

$$\mathrm{Rij} = \mathrm{E1} + \mathrm{E2} + \mathrm{E3} + \cdots \mathrm{En}/\mathrm{n} \quad (1)$$

$$\mathrm{Wij} = \mathrm{E1} + \mathrm{E2} + \mathrm{E3} + \cdots \mathrm{En}/\mathrm{n} \quad (2)$$

Table 5. Linguistic Levels

For Ratings		For Weights	
Linguistic variables	Fuzzy numbers	Linguistic variables	Fuzzy numbers
Worst (W)	(0, 0.05, 0.15)	Very Low (VL)	(0, 0.05, 0.15)
Very Poor (VP)	(0.1, 0.2, 0.3)	Low (L)	(0.1, 0.2, 0.3)
Poor (P)	(0.2, 0.35, 0.5)	Fairly Low (FL)	(0.2, 0.35, 0.5)
Fair (F)	(0.3, 0.5, 0.7)	Medium (M)	(0.3, 0.5, 0.7)
Good (G)	(0.5, 0.65, 0.8)	Fairly High (FH)	(0.5, 0.65, 0.8)
Very Good (VG)	(0.7, 0.8, 0.9)	High (H)	(0.7, 0.8, 0.9)
Excellent (E)	(0.85, 0.95, 1.0)	Very High (VH)	(0.85, 0.95, 1.0)

Table 6. Ratings of ASCA assigned by experts using linguistic levels

ASC_i	$ASCA_{ij}$	E1	E2	E3	E4	E5
ASC_4						
	$ASCA_{41}$	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)	**F**(0.3,0.5,0.7)
	$ASCA_{42}$	**F**(0.3,0.5,0.7)	**F**(0.3,0.5,0.7)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)
	$ASCA_{43}$	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)	**F**(0.3,0.5,0.7)	**G**(0.5,0.65,0.8)	**VG**(0.7,0.8,0.9)
	$ASCA_{44}$	**P**(0.2,0.35,0.5)	**F**(0.3,0.5,0.7)	**P**(0.2,0.35,0.5)	**F**(0.3,0.5,0.7)	**F**(0.3,0.5,0.7)
ASC_7						
	$ASCA_{71}$	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)
	$ASCA_{72}$	**G**(0.5,0.65,0.8)	**VG**(0.7,0.8,0.9)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)	**VG**(0.7,0.8,0.9)
	$ASCA_{73}$	**G**(0.5,0.65,0.8)	**VG**(0.7,0.8,0.9)	**G**(0.5,0.65,0.8)	**F**(0.3,0.5,0.7)	**F**(0.3,0.5,0.7)
	$ASCA_{74}$	**G**(0.5,0.65,0.8)	**VG**(0.7,0.8,0.9)	**G**(0.5,0.65,0.8)	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)
ASC_9						
	$ASCA_{91}$	**E**(0.85,0.95,1.0)	**F**(0.3,0.5,0.7)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)	**VG**(0.7,0.8,0.9)
	$ASCA_{92}$	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)	**F**(0.3,0.5,0.7)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)
	$ASCA_{93}$	**F**(0.3,0.5,0.7)	**VG**(0.7,0.8,0.9)	**VG**(0.7,0.8,0.9)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)
	$ASCA_{94}$	**F**(0.3,0.5,0.7)	**G**(0.5,0.65,0.8)	**E**(0.85,0.95,1.0)	**G**(0.5,0.65,0.8)	**G**(0.5,0.65,0.8)

Table 7. Weights of ASCA assigned by experts using linguistic levels

ASC_i	**$ASCA_{ij}$**	**E1**	**E2**	**E3**	**E4**	**E5**
ASC_4		**H**(0.7,0.8,0.9)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)	**H**(0.7,0.8,0.9)	**VH**(0.85,0.95,1.0)
	$ASCA_{41}$	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)	**FH**(0.5,0.65,0.8)	**FH** (0.5,0.65,0.8)	**H**(0.7,0.8,0.9)
	$ASCA_{42}$	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)
	$ASCA_{43}$	**M**(0.3,0.5,0.7)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)	**FH**(0.5,0.65,0.8)	**M**(0.3,0.5,0.7)
	$ASCA_{44}$	**M**(0.3,0.5,0.7)	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)
ASC_7		**FH**(0.5,0.65,0.8)	**H**(0.7,0.8,0.9)	**FH**(0.5,0.65,0.8)	**FH**(0.5,0.65,0.8)	**FH**(0.5,0.65,0.8)
	$ASCA_{71}$	**VH**(0.85,0.95,1)	**H**(0.7,0.8,0.9)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)
	$ASCA_{72}$	**H**(0.7,0.8,0.9)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)
	$ASCA_{73}$	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)	**FH**(0.5,0.65,0.8)	**FH** (0.5,0.65,0.8)	**H**(0.7,0.8,0.9)
	$ASCA_{74}$	**M**(0.3,0.5,0.7)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)	**FH**(0.5,0.65,0.8)	**M**(0.3,0.5,0.7)
ASC_9		**M**(0.3,0.5,0.7)	**M**(0.3,0.5,0.7)	**L**(0.1,0.2,0.3)	**FH**(0.5,0.65,0.8)	**FH**(0.5,0.65,0.8)
	$ASCA_{91}$	**H**(0.7,0.8,0.9)	**VH**(0.85,0.95,1.0)	**VH**(0.85,0.95,1.0)	**H**(0.7,0.8,0.9)	**VH**(0.85,0.95,1.0)
	$ASCA_{92}$	**H**(0.7,0.8,0.9)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)
	$ASCA_{93}$	**M**(0.3,0.5,0.7)	**H**(0.7,0.8,0.9)	**M**(0.3,0.5,0.7)	**M**(0.3,0.5,0.7)	**M**(0.3,0.5,0.7)
	$ASCA_{94}$	**H**(0.7,0.8,0.9)	**FH**(0.5,0.65,0.8)	**FH**(0.5,0.65,0.8)	**FH** (0.5,0.65,0.8)	**FH**(0.5,0.65,0.8)

Table 8. Average of Ratings and Weights

ASC_i	ASCAij	Average RatIngs (Rij)	Average WeightS (WIJ)
ASC_4			(0.79,0.89,0.96)
	$ASCA_{41}$	(0.53,0.68,0.82)	(0.62,0.74,0.86)
	$ASCA_{42}$	(0.42,0.59,0.76)	(0.54,0.68,0.82)
	$ASCA_{43}$	(0.57,0.7,0.84)	(0.42,0.59,0.76)
	$ASCA_{44}$	(0.26,0.44,0.62)	(0.62,0.74,0.86)
ASC_7			(0.54,0.68,0.82)
	$ASCA_{71}$	(0.65,0.77,0.88)	(0.82,0.920.98)
	$ASCA_{72}$	(0.58,0.71,0.84)	(0.82,0.920.98)
	$ASCA_{73}$	(0.46,0.62,0.78)	(0.62,0.74,0.86)
	$ASCA_{74}$	(0.61,0.74,0.86)	(0.42,0.59,0.76)
ASC_9			(0.34,0.5,0.66)
	$ASCA_{91}$	(0.57,0.71,0.84)	(0.79,0.89,0.96)
	$ASCA_{92}$	(0.53,0.68,0.82)	(0.54,0.68,0.82)
	$ASCA_{93}$	(0.54,0.68,0.82)	(0.38,0.56,0.74)
	$ASCA_{94}$	(0.53,0.68,0.82)	((0.54,0.68,0.82)

3.1.4. Associating FAI with agility levels

Fuzzy Agility Index (FAI) is an information fusion composed of aggregate fuzzy ratings and weights [18] and is mathematically defined as presented in equation 3. Arithmetical findings reveal an FAI value of (0.5035,0.6770,0.8038) which can be associated with natural language Agility Level (AL) expression shown in Table 9, to estimate the FAI of the case with the employability of Euclidean distance method. Assuming U_{FAI} and U_{ALi} represents membership functions of FAI and natural language agility i, respectively, the distance between FAI and AL is calculated using equation 4 and designed using MATLAB as depicted in Figure 2.

$$FAI = \sum_{j=1}^{n}(Wij)(Rij)/\sum_{j=1}^{n} Wij \quad (3)$$

$$d(FAI, ALi) = \left\{\sum_{x\in p} U_{FAI}(x) - U_{AL_i}(x))^2\right\}^{1/2} \quad (4)$$

Table 9. Agility Levels

Slowly Agile (S)	(0.0,0.1,0.2)
Low Agile (LA)	(0.1,0.2,0.3)
Slightly Agile (SA)	(0.2,0.3,0.4)
Fairly Agile (F)	(0.3,0.4,0.5)
Agile (A)	(0.4,0.5,0.6)
High Agile (HA)	(0.5,0.6,0.7)
Very Agile (VA)	(0.6,0.7,0.8)
Extremely Agile (EA)	(0.7,0.8,0.9)
Definitely Agile (DA)	(0.8,0.9,1.0)

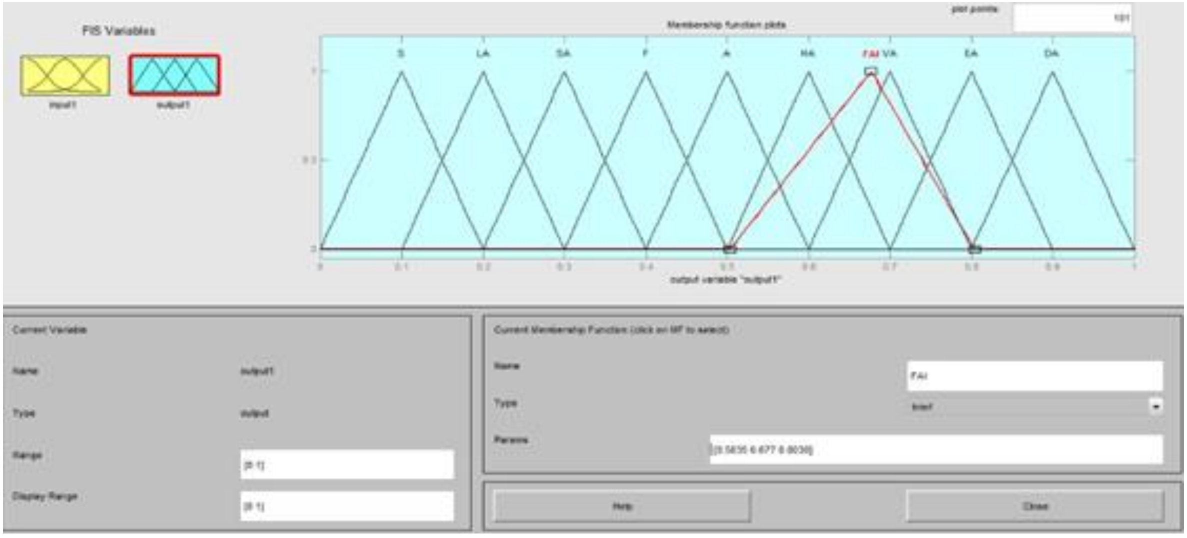

Figure 2. Distance measures in MATLAB

The results of the distances between FAI and AL formulated using equation 4 are exhibited in Table 10. As per the support given by previous researchers [19], the closest natural expression with the smallest distance is identified. Accordingly, the minimum value of the focused case is 0.0436 which clearly indicates the system to be 'very agile'.

3.1.5. Estimating FMII

The degree of contribution of supply chain agility for a factor decreases with decreasing FMII and thus leverages in identifying principal obstacles. To avoid the effect of neutralization, FMII is defined as shown in equation 5 and summarized in Table 11.

$$\mathrm{FMII} = \mathrm{Rij}(\,.\,)[(1,1,1) - (\mathrm{Wij})] \quad (5)$$

3.1.6. Calculating Right, Left and Ranking Scores using Fuzzy TOPSIS

The proposed fuzzy TOPSIS method mainly accounts for systematic evaluation and ranking of attributes from the integrated rating and weights and the performance values. Supposing FMII scores to resemble aij,bij and cij, the left score [UL(FMII)], right score [UR(FMII)] and the ranking score [UT(FMII)] of ASCA were obtained using equation 6,7 & 8, respectively, where i denotes ASC enabler and j denotes ASC attribute as shown in Table 11.

$$\mathrm{UL(FMII)} = \mathrm{(LS)ij} = \mathrm{(bij)}/1 + \mathrm{(bij)} - \mathrm{(aij)} \quad (6)$$

$$\mathrm{UR(FMII)} = \mathrm{(RS)ij} = \mathrm{(cij)}/1 + \mathrm{(cij)} - \mathrm{(bij)} \quad (7)$$

$$\mathrm{UT(FMII)} = [\mathrm{UR(FMII)} + 1 - \mathrm{UL(FMII)}]/2 \quad (8)$$

Table 10. FAI Distance summary

d(FAI,S)	d(FAI,LA)	d(FAI,SA)	d(FAI,F)	d(FAI,A)	d(FAI,HA)	d(FAI,VA)	d(FAI,EA)	d(FAI,DA)
0.5700	0.4702	0.3705	0.2709	0.1720	0.5188	0.0436	0.1343	0.3252

Table 11. Fuzzy Merit Important Indexes and Ranking scores of ASCA

ASCAij	Rij	(1.0,1.0,1.0) (-)Wij	Fuzzy Merit- Important Indexes Rij (.) (1.0,1.0,1.0) (-) Wij	Left and right scores [UL,UR]	Ranking scores [UT]
ASCA41	(0.53,0.68,0.82)	(0.14,0.26,0.38)	(0.0742,0.1768,0.3116)	(0.1603,0.2745)	0.5571
ASCA42	(0.42,0.59,0.76)	(0.18,0.32,0.46)	(0.0756,0.1888,0.3496)	(0.1696,0.3011)	0.5657
ASCA43	(0.57,0.7,0.84)	(0.24,0.41,0.58)	(0.1368,0.287,0.4872)	(0.2495,0.4059)	0.5782
ASCA44	(0.26,0.44,0.62)	(0.14,0.26,0.38)	(0.0364,0.1144,0.2356)	(0.1061,0.2101)	0.552
ASCA71	(0.65,0.77,0.88)	(0.02,0.08,0.18)	(0.013,0.0616,0.1584)	(0.0587,0.1444)	0.542
ASCA72	(0.58,0.71,0.84)	(0.02,0.08,0.18)	(0.0116,0.0568,0.1512)	(0.0543,0.1381)	0.5419
ASCA73	(0.46,0.62,0.78)	(0.14,0.26,0.38)	(0.0644,0.1612,0.2964)	(0.1469,0.2610)	0.5570
ASCA74	(0.61,0.74,0.86)	(0.24,0.41,0.58)	(0.1464,0.3034,0.4988)	(0.2622,0.4172)	0.5775
ASCA91	(0.57,0.71,0.84)	(0.04,0.11,0.21)	(0.0228,0.0781,0.1764)	(0.0740,0.1606)	0.5433
ASCA92	(0.53,0.68,0.82)	(0.18,0.32,0.46)	(0.0954,0.2176,0.3772)	(0.1939,0.3252)	0.5656
ASCA93	(0.54,0.68,0.82)	(0.26,0.44,0.62)	(0.1404,0.2992,0.5084)	(0.2581,0.4204)	0.5811
ASCA94	(0.53,0.68,0.82)	(0.18,0.32,0.46)	(0.0954,0.2176,0.3772)	(0.1939,0.3252)	0.5656

4. Results and Discussion

Malignancies disfavoring an agile enterprise challenge the managers and policy makers. The evaluation of agility is gaining extreme importance as it is an indicator of the organisational excellence. A few researchers contributed approaches for measuring agility in past, but since conventional agility measurement has always been associated with vagueness and complexity, the fuzzy logic approach is used in the study [12]. The proposed model provides an opportunity to understand the dynamics among the enablers and attributes of an ASC. Unlike many of MCDM methods, the proposed fuzzy TOPSIS method is easy to use, and it considers the decision-maker's preference and enjoys a low computational volume and flexibility [7]. A few notable results drawn from identifying and investigating the interactions between crtitical attributes; these are:

- ISM classification of enablers reveals that Production Methodology (ASC_4), Information Sharing (ASC_7) and Time Management (ASC_9) are the driver enablers where the firm should place high precedence.
- The outcomes of FAI tabulations classifies the existing system to be 'very agile' and exemplifies the margins of difference on desired agility levels.
- Fuzzy TOPSIS prioritization of ASCA of ISM acknowledged driver enablers, emphasizes that the priority should start from End to end connectivity ($ASCA_{72}$) which has the minimum ranking score of 0.5419 and progress onwards till Training programme on time management concepts ($ASCA_{93}$) which has the maximum ranking score of 0.5811.

5. Conclusions

The agility paradigm has become an important avenue in modern manufacturing. World class organizations are attempting to gain competitive advantage by impinging agile concepts in their supply chain. Achieving agility lies in designing agile friendly processes and, thus, firms need to concentrate on their supply chains and their enablers in the attempt of redressing themselves as responsive supply chains[20]. Ample opportunities exist for the growth of this field due to its multi-functional and interdisciplinary focus [21]. The present study aimed to develop a quantitative analysis framework for organizations to identify their weakness in supply chains. ISM and fuzzy theory has been effectively utilized to handle the imprecision and vagueness of ASC enablers and ASC attributes congruently. The study addresses the question of how to measure and improve supply chain agility as we can't manage what we can't measure. The uniqueness of the model is in bridging the traditional concepts of ISM with the non-traditional concepts of fuzzy arithmetics. This trial has doubtlessly presented a model for future managers to spot uncertainties in business and demonstrated an unprecedented application of fuzzy logic systems. In lines of novelty, the model will opine the following features:

- The model is a scientific approach to identify ASC enablers and roots itself with betterment plans by generating ASC attributes.
- The FAI provides a holistic picture of agility and, thus, helps managers to perform gap analysis between existing agility levels and desired levels of the subject under limelight.
- The model facilitates supply chain managers for swift and effective MCDM.
- Considering and investigating the roots of agility enablers could show directions for further research. Targeting the relationships between these enablers and its capabilities could set the platform for the design of a perfect agile supply chain in future.

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