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Fuzzy Approach to Measure Manufacturing Agility along with Developing Fuzzy Inference Systems in MATLAB

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ABSTRACT

Agility is the ability of an organization to respond quickly and successfully to change. The integration of information system/technologies, people, business processes and facilities is the basis of an agile enterprise. Due to the ill-defined and vague indicators which exist within agility measurement, most measures are described subjectively by linguistic terms which are characterized by ambiguity and multi-possibility, and the conventional assessment approaches cannot suitably nor effectively handle such measurement. However, fuzzy logic provides a useful tool for dealing with decisions in which the phenomena are imprecise and vague. For measuring agility we use “IF (Fuzzy antecedents) THEN (Fuzzy consequent)” rules. In this paper, fuzzy inference systems (FIS) are designed, in several steps: fuzzification, aggregation of antecedents, inferencing, composition, and defuzzification. The key idea of our model in measurement is the involvement of all distinct dimensions and corresponding operational parameters in the determination of the overall agility. The proposed scheme is illustrated through an example.

Keywords: *Agility, Fuzzy Inference System, Fuzzy logic, expert knowledge, Agility measurement*

1. INTRODUCTION

As globalization of market raises competitive pressures, one essential requirement for the survival of organization is their capability to meet competition. Market needs cause unceasing changes in the life cycle, shape, quality and price of products. Ever-changing is one of firms' major characteristics in this new competitive era. Agile manufacturing (AM) has been increasingly viewed as a winning strategy (Goldman et al., 1995; Gerwin, 1993). AM is an integration of technologies, people, facilities, information systems and business processes (Tsourveloudis et al., 2002; Van Hoek et al., 2001; Yang et al., 2002). Agile manufacturing is defined as the capability of surviving and prospering in a competitive environment of continuous and unpredictable change by reacting quickly and effectively to changing markets, driven by customer-designed high-quality, high-performance, products and services (Fliedner et al., 1997; Katayama et al., 1999; Gupta, 2004).

Agility is not only the outcome of technological achievement, advanced organizational and managerial structure and practice, but also a product of human abilities, skills and motivations (Forsythe, 1997; Dove, 2001). In real world applications, precise data concerning agility factors are not available or very hard to be extracted. In addition, decision makers prefer natural language expressions such as “high”, “low”, “average”, etc., rather than numerical values in assessing agility. Mathematical models have difficulties in dealing with the direct measurement of agility. Algebraic formulae fail in putting together the various components of agility. It is important to take into account the ideas people have about the quantification of the observable parameters of notion. The key idea is to model human inference to arrive at a value of agility. Fuzzy-set theory and fuzzy logic, constitutes a natural framework for the representation and manipulation of uncertainty (Zadeh, 1983). The proposed measuring approach involves all the founding concepts of agility expressed, for the sake of analysis, in ten dimensions or divisions (Yusuf and Gunasekaran, 1999) with respective agility attributes or enablers. The overall agility is calculated by applying fuzzy logic to individual agility scores in each division. The value of agility is given by an approximate reasoning method taking into account the knowledge that is included in simple **IF-THEN** rules.

Section 2 gives the implementation details of the approach along with the fuzzy concepts followed by an example to illustrate the developed framework in Section 3. Section 4 provides a summary conclusion of the key contributions.

2. IMPLEMENTATION DETAILS OF THE APPROACH

The proposed measuring approach involves all the founding concepts of agility expressed, for the sake of analysis, in ten divisions/dimensions (Beach, 2000; Fliedner et al., 1997; Yusuf and Gunasekaran, 1999; Sharp et al., 1999; Gunasekaran, 1999; Sharifi et al., 1999). Table 1 shows the agility dimensions along with the respective attributes.

The initial step in the implementation of the suggested approach is to develop a Fuzzy Inference System (FIS) for the problem domain of study. In this paper, FIS are designed, in several steps: fuzzification, aggregation of antecedents, inferencing, composition, and defuzzification Fuzzy inference systems emulate the reasoning process of a human expert within the required knowledge domain and are built for the purpose of exploiting the experience and problem-solving capabilities of experts available to others (Ross, 1995). Figure 2 shows the FIS developed in Matlab Software.

2.1 Fuzzy Perspective

The knowledge can be represented in the form of "**if <*antecedent*> then <*consequent*>**" rules, where the implication operator and the connectives among antecedents are fuzzy. These rules include statements that are close to natural language and can be extracted via knowledge-acquisition methodologies (Zimmermann, 1980), such as interviews or questionnaires or from the experts.

A fuzzy *conditional statement* or a fuzzy if/then rule is an expression of the type

$$\text{IF } X_1 \text{ is } A_1 \text{ AND } \ldots \text{ AND } X_N \text{ is } A_N \text{ THEN } Y \text{ is } B \quad (1)$$

$$\text{denoted} \quad (A_1 \text{ AND } A_2 \text{ AND} \ldots \text{ AND } A_N) \rightarrow B \quad (2)$$

where $A_1, A_2 \ldots, A_N$ and B and are values of the linguistic variables $X_1, X2, \ldots X_N$ and Y.

The key idea of our model is the involvement of all distinct factors and corresponding operational parameters in the determination of the overall agility. This is implemented via multi-antecedent fuzzy IF-THEN rules, which are conditional statements that relate the observations concerning the allocated factors (IF-part) with the value of agility (THEN-part). Consider that A_i , $i = 1, \ldots, N$, is the set of agility divisions (here $N = 10$), and LA_i the linguistic value of each division. Then, the expert rule for overall value of enterprise agility can be formulated as follows

$$\textbf{IF } A_1 \textbf{ is } LA_1 \textbf{ AND} \ldots \textbf{AND } A_N \textbf{ is } LA_N \textbf{ THEN EA is } LEA \quad (3)$$

where *LEA* represents the set of linguistic values for enterprise agility EA. All linguistic values *LAi* and *LEA* are fuzzy sets, with certain membership functions as shown in Figure.1. **An example** of such a rule is shown in Figure 3.

The meaning of the fuzzy conditional ($A \rightarrow B$) is given by a fuzzy relation

$$\mu_R(x, y) = \mu_A(x) \ominus \mu_B(y), \quad x \in X, y \in Y \quad (4)$$

where $\ominus$ represents any fuzzy implication. Fuzzy relations play a major role in fuzzy or approximate reasoning. The most frequently used inference method, the *Compositional Rule of Inference* (CRI) proposed by Zadeh (1983), is based on the composition of fuzzy relations. An example of fuzzy implication follows.

Let A, A^* be fuzzy sets on X, B, B^* be fuzzy sets on Y, and the statements

Implication: If X is A then Y is B (Expert Rule)

Conclusion: Y is B^* (Consequence).

Note that A and A^* and are simply different fuzzy sets of the same universal set; the same is true for B and B^*. In the above inference schema, an observation is combined with an expert rule providing the consequence, which in turn is the advice to the decision maker. The conclusion B^* can be obtained from the CRI by taking the composition of the observation and the fuzzy conditional as follows:

$$B^* = A^* \mathrm{o} (A \rightarrow B) \quad (5)$$

where "o" is the max-min composition. In the membership function domain, the CRI is

$$\mu_{B^*}(y_j) = \mathrm{V}_i[\mu_{A^*}(x_i) \wedge \mu_{A \rightarrow B}(x_i, y_j)],$$
$$i = 1,2,\ldots\ldots.,I$$
$$j = 1,2,\ldots\ldots.,J \quad (6)$$

where $\mu_{B^*}(y_j)$ is the membership grade of the jth element of B^*, $\mu_{A^*}(x_i)$ is the membership grade of the ith element of A^*, $\mu_{A \rightarrow B}(x_i, y_j)$ is the membership grade of the ijth element of the implication relation $A \rightarrow B$, and V, $\wedge$ denote maximum and minimum, respectively. The outcome is in the form of a modified membership function which is subsequently *defuzzified*.

2.2 The Measurement Algorithm

The overall measurement algorithm can be summarized in the following structural steps:

***Step 1*:** Select the implication operator and the "AND" connective: Choose the form and the mathematical meaning of the rules that fit the practical system of interest. Use conjunction operators to interpret the dependencies of agility dimensions or attributes.

Step 2: Match the observations (inputs) with the antecedents of the rules.

***Step* 3:** Select and apply an approximate reasoning method: Associate the observations with the available knowledge and compute the value of 'Agility Index'.

3. AN EXAMPLE

In the previous section, we discussed the fuzzy formulation of ten agility dimensions which are observed in various hierarchical levels. Figure 2 is graphical representation of the proposed methodology, where manufacturing agility is given as the logical synthesis of all types.

Suppose, that for a given manufacturing plant we have five linguistic variations of the variables involved in the fuzzy rules, namely, *Low(L), About Low(AL),Average(A), About High(AH)* and *High(H).* Their membership functions in X are denoted by where μ_T : X→ [0, 1], where T= {*L,AL,A,AH,H*}. For simplicity and without loss of generality, we define the membership functions in the unit interval [0, 1] as shown in Figure 1.

By representing the discrete membership functions of the linguistic values with $\mu_T(x)$ / x, $x \in X$ where $\mu_T(x)$ is the membership grade of point x, we have

μ_L = [1/.00	1/.1	.7/.20	0.5/.25	0.2/.3	0/.4]	
μ_{AL} = [0/.10	0.7/.2	1/.25	0.7/0.3	0/.40]		
μ_A = [0/.25	0.2/.3	0.6/.4	1/.5	0.6/.6	0.2/.7	0/0.75]
μ_{AH} = [0/.60	0.4/.65	0.7/.70	1/.75	0.7/.80	0/.90]	
μ_H = [0/.65	0.2/.70	0.5/.75	0.7/.8	1/.9	1/1]	

We assume that for the given production system we have the observations of Table 1.

We now present the implementation details of the algorithm for Integration Dimension. The implementation details given below closely follow the procedural details given in Dubois and Prade (1982) and Tsourveloudis and Phillis (1998).

1. *From the observations, obtain the membership functions for each observed linguistic label. Use linguistic hedges to suitably modify semantic variations observed in the linguistic labels.*

For the Integration Dimension, assume that the values of the related attributes i.e., Concurrent execution of activities (A_{I1}), Enterprise integration (A_{I2}) and Information accessible to employees (A_{I3}) are as follows, given by Table 1.

O: Concurrent execution of activities is *About High* (*AH*) AND Enterprise integration is *More or less High* (*MLH*) AND Information accessible to employees *Average* (*A*)

which compactly can be written as

O: A_{I1} is *AH* AND A_{I2} is *MLH* AND A_{I3} is *A*

or more simple as O: *AH* AND *MLH* AND *A* (7)

It is known (Zadeh, 1976) that for the fuzzy modifies "more or less" hold that

More or Less High=DIL(H) = $H^{0.5}$ or equivalently $\mu_{MLH}(x) = \mu_H^{0.5}(x), x \in X$

and consequently

More or Less High = [0/.65 .45/.7 .7/.75 .83/.8 1/.9 1/1]

The rule with which observation O matches best is

If A_{I1} is *AH* AND A_{I2} is *H* AND A_{I3} is *A*

or compactly *AH* AND *H* AND *A* →*H* (8)

The above rule contains the information we use to deduce the value of Integration Dimension because its antecedents (A_{I1} is *AH* AND A_{I2} is *H* AND A_{I3} is *A*) are closer to the observation (A_{I1} is *AH* AND A_{I2} is *MLH* AND A_{I3} is *A*) than any others rule in rule base.

2. *Determine the membership function for the antecedent of each factor.*

The minimum operator, which usually represents the intersection of fuzzy sets, does not allow for any compensation among those sets. The compensatory operation is essentially a convex combination of the unions (U) and intersection (∩) for the antecedent rule so that the discrete membership observation O is

$$\mu_{AH\ AND\ MLH\ AND\ A}(x) = (1-\gamma)\ \mu_{AH \cap MLH \cap A}(x) + \gamma\ \mu_{AH \cup MLH \cup A}(x),\ x \in X,\ \gamma \in [0, 1] \quad (9)$$

where 'γ' is the grade of compensation and indicates where the actual operator is located between the actual operator is located between the class union (full compensation, γ = 1) and intersection (no-compensation, γ = 0) of the connected sets (Zimmermann, 1980). Intersection and union are represented by the minimum (=Λ) and maximum (=V) operators, respectively, and for γ=0.4, yields

$\mu_{AH\ AND\ MLH\ AND\ A}$ = [0/.25 .08/.3 .24/.4 .4/.5 .24/.6 .16/.65 .4/.7 .4/.75 .33/.8 .4/.9 .4/1]

Example: ((1-.4) (.7Λ.45 Λ.2) + 0.4(.7 V .45 V.2))/.7 = ((.6) (.2) + 0.4(.7))/.7 = .4/.7

Similarly, $\mu_{AH\ AND\ H\ AND\ A}(x) = (1-\gamma)\ \mu_{AH \cap H \cap A}(x) + \gamma\ \mu_{AH \cup H \cup A}(x),\ x \in X,\ \gamma \in [0, 1]$

$\mu_{AH\ AND\ H\ AND\ A}$ = [0/.25 .08/.3 .24/.4 .4/.5 .24/.6 .16/.65 .4/.7 .4/.75 .28/.8 .4/.9 .4/1]

3. *Compute the normalized membership function for the antecedent rule by dividing each membership grade value (obtained from step 2 above) by the largest membership grade value of the entire membership function.*

In order to achieve meaningful inference and since all the linguistic values we use are normal fuzzy sets (∋ x such that $\mu(x) = 1$), we compute the normalized membership function for the antecedent rule by dividing each membership grade value by the largest membership grade value of the entire membership function. In the present example, the normalized membership function of the observation O is obtained by dividing each membership grade value with the largest value i.e. 0.4 in $\mu_{VH\ AND\ AH.}$

Observation: $\mu_{VH\ AND\ AH}$ =
[0/.25 .2/.3 .6/.4 1/.5
.6/.6 .4/.65 1/.7 1/.75 .83/.8 1/.9 1/1]

Example: (.08/.4)/.3 = .2/.3

4. *Compute the entries for the relation matrix.*

The relation matrix 'relates' each fuzzy rule antecedent with its associated consequent using an appropriate implication operator. The implication operator selected is a function of the conjunction $\mu_{H\ AND\ AH}(x)$, $x \in X$, and the consequent $\mu_H(y)$, $y \in Y$ over X×Y which in the membership domain is given by

$R_{AH\ AND\ H\ AND\ A \rightarrow H}(x,y)$

$$R_{\rightarrow}(x,y) = (1-\mu_{AH\ AND\ H\ AND\ A}(x)\ V\ \mu_H(y) \quad (10)$$

From this equation, we compute the relation matrix, as follows

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ .92 & .92 & .92 & .92 & 1 & 1 \\ .76 & .76 & .76 & .76 & 1 & 1 \\ .6 & .6 & .6 & .7 & 1 & 1 \\ .76 & .76 & .76 & .76 & 1 & 1 \\ .84 & .84 & .84 & .84 & 1 & 1 \\ .6 & .6 & .6 & .7 & 1 & 1 \\ .6 & .6 & .6 & .7 & 1 & 1 \\ .72 & .72 & .72 & .72 & 1 & 1 \\ .6 & .6 & .6 & .7 & 1 & 1 \\ .6 & .6 & .6 & .7 & 1 & 1 \end{bmatrix}$$

Example: R_{11}= (1- $\mu_{AH\ AND\ H\ AND\ A}$(.25) V μ_H(.65) = (1-0) V 0 = 1

5. *Using the normalized membership function for the antecedent (from step 3) and the relation matrix (from step 4), obtain the membership function for the consequent, i.e., the Integration Dimension using the Zadeh (1983) 'max-min' compositional rule of inference.*

This frequently used approximate reasoning method is described by the following inference pattern.

O AH AND MLH AND A (Observation)

Expert Rule R AH AND H AND A →H
(Existing Knowledge from fuzzy rule base)

A_I' O o R (Conclusion)

where "o" denotes max-min composition defined by Zadeh (1976) as

$$A_I' = \max (O \Lambda R) \quad (11)$$

which gives the membership function of Integration Domain of agility

$A_I' = (.72/.65 \quad .72/.7 \quad .72/.75 \quad .72/.8 \quad 1/.9 \quad 1/1)$

Example: $((0 \wedge 1) \vee (.2 \wedge .92) \vee (.6 \wedge .76) \vee (1 \wedge .6) \vee (.6 \wedge .76) \vee (.4 \wedge .84) \vee (1 \wedge .6) \vee (1 \wedge .6) \vee (.83 \wedge .72) \vee (1 \wedge .6) \vee (1 \wedge .6))/.65 = (0 \vee .2 \vee .6 \vee .6 \vee .6 \vee .4 \vee .6 \vee .6 \vee .72 \vee .6 \vee .6)/.65 = 0.72/.65$

6. Defuzzify the membership function for the consequent using the standard Center-of Area method to obtain the numeric contribution value for Integration Domain of agility.

In practice, a number in [0,1] may be more preferable than a membership function, in order to represent 'Integration Domain of agility'. The procedure that converts a membership function into a single point-wise value is called defuzzification. Here, defuzzification is done by using the standard *Center-of Area* method out of the various defuzzification methods available (Ross, 19950). The defuzzification procedure is notationally given as

$$\text{def } A_I' = \frac{\sum_{i=1}^{6} x_i \, \mu_{A\,I}(x_i)}{\sum_{i=1}^{6} \mu_{A\,I}(x_i)} \tag{12}$$

$$= \frac{.72 \times .65 + .72 \times .7 + .72 \times .75 + .72 \times .8 + 1 \times .9 + 1 \times 1}{.72 + .72 + .72 + .72 + 1 + 1} = 0.8172$$

7. Repeat steps 1 through 6 to compute the remaining dimensions affecting the overall agility.

In a likewise manner (following steps 1 through 6 above) the following numeric values are achieved for the remaining dimensions.

A_C'= [0/.6	.4/.65	.7/.7	1/.75	.7/.8	0/.9]			
A_T'= [0/.25	.2/.3	.6/.4	1/.5	.6/.6	.2/.7	0/.75]		
A_Q'= [0/.65	.7/.7	1/.75	.7/.8	0/.9]				
A_{CH}'= [.6/.7	.6/.75	.7/.8	1/.9	1/1]				
A_E'= [0/.65	.45/.7	.7/.75	.83/.8	1/.9	1/1]			
A_P'= [0/.65	.2/.7	.5/.75	.7/.8	1/.9	1/1]			
A_M'= [0/.25	.7/.3	.7/.4	1/.5	.7/.6	.7/.7	0/.75]		
A_W'= [0/.6	.4/.65	.7/.7	1/.75	.7/.8	0/.9]			
A_{TB}'= [0/.25	.22/.3	.62/.4	1/.5	.62/.6	.22/.7	0/.75]		

The respective crisp values after defuzzification are

def A_C'=0.7357	def A_{TB}'=0.7216	def A_T'=0.5
def A_Q'=0.75	def A_{CH}'=0.8538	def A_P'=0.875
def A_M'=0.5	def A_E'=0.85527	def A_W'=0.7357

The combined effect of these results is the input to the manufacturing agility model and the membership function of the overall enterprise agility for the system under study is

EA= [0/.6 .42/.65 .7/.7 1/.75 .68/.8 0/.9]

and the defuzzified value is 0.7344. This shows that agility level of the organization is *'Almost High'* which can be improved. For an overall picture, Figure 4 shows software implementation of the proposed methology: the MATLAB Surface Viewer.

4. CONCLUDING REMARKS

Agility is ability to respond to unpredictable changes with quick response and profitability. The proposed measurement framework is **direct, adaptive, holistic** and **knowledge-based**. From a technical point of view the proposed framework has the following advantages:

- It is adjustable by the user. Within the context of fuzzy logic one can define new variables, values, or even rules and reasoning procedures.
- It contributes to the acquisition and the representation of expertise concerning agility through multiple antecedent IF-THEN rules.
- It provides successive aggregation of the agility levels as they are expressed through the already known agility types.
- Another purpose of this research was to implement the above-mentioned model in a software

environment that allows **graphical user interface programming (GUI),** in order to relieve from having complex programming skills. The input data, the membership functions and the fuzzy rules can be changed “on the fly” by modifying data within the GUI interface, without the requirement of writing complex program code.

Finally, there are some limitations to this fuzzy logic approach. The membership functions of linguistic variables depend on the managerial perception of the decision-maker. Thus, the decision-maker must be at a strategic level in the company in order to realize the importance, possibility and trends of all aspects, such as strategy, marketing and technology. Furthermore, competitive situations and requirements vary from company to company; hence, companies have to establish their unique membership function by fitting in with their specific environment and considerations.

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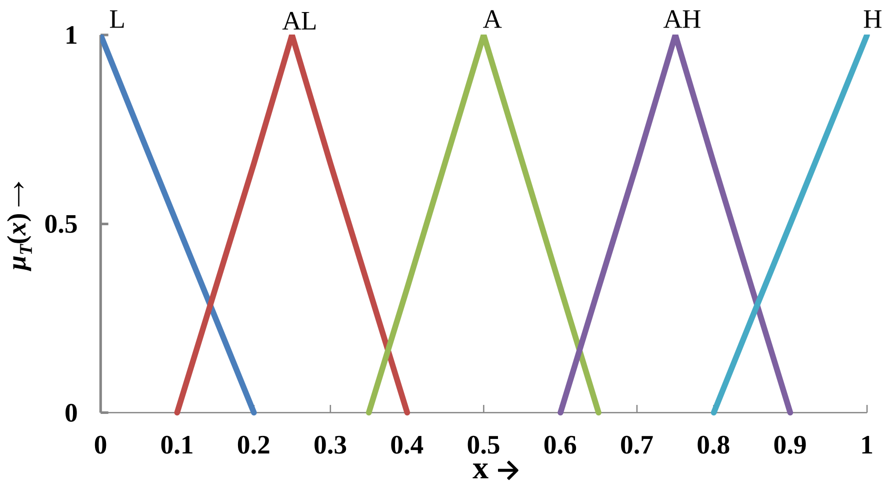

Fig.1: Membership functions of the linguistic values: L=low, AL= about low, A=average, AH=about high, and H=high.

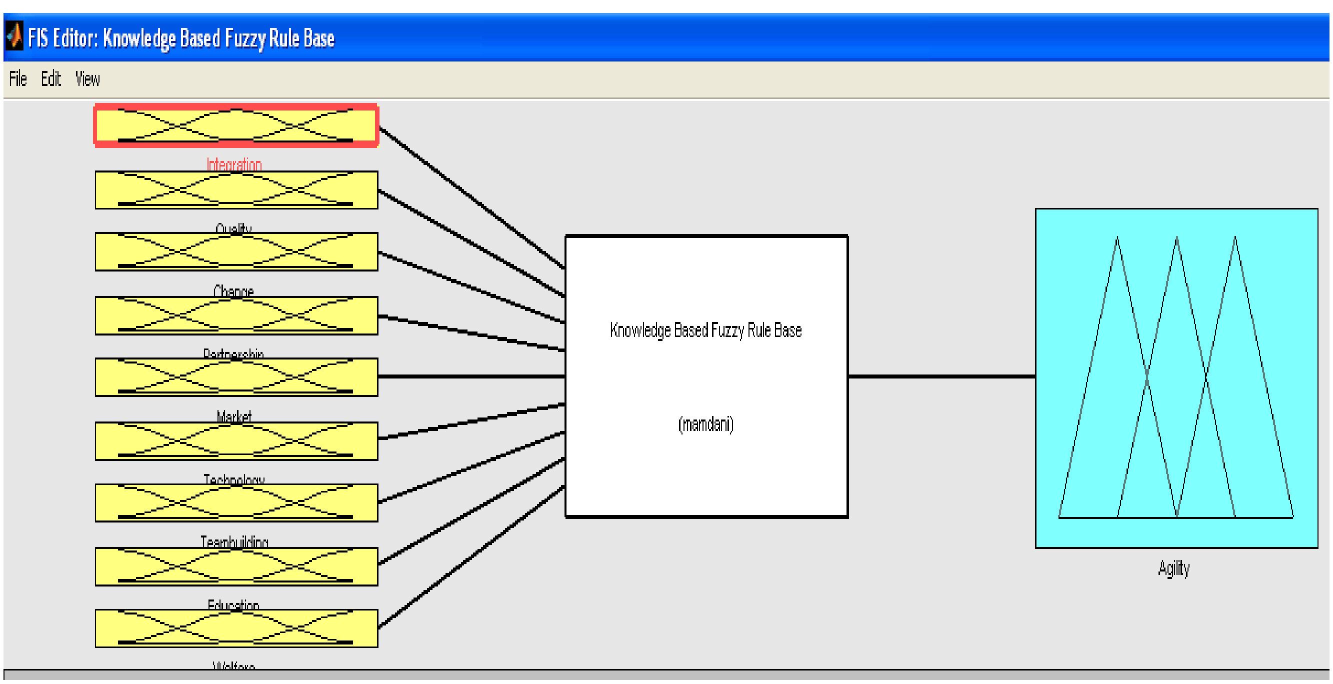

Fig. 2: Fuzzy Inference System (FIS) developed in MATLAB.

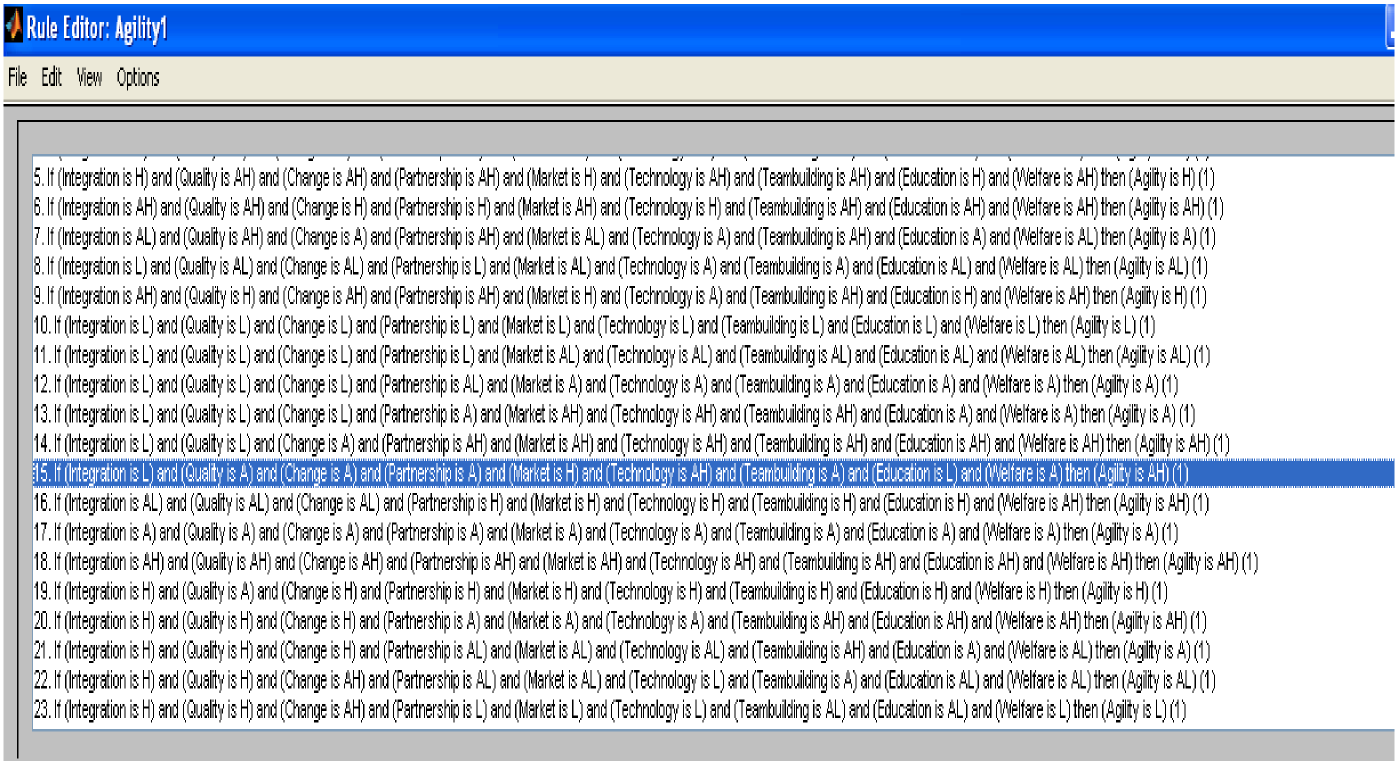

Fig.3: A part of the Agility rule base within the software (MATLAB)

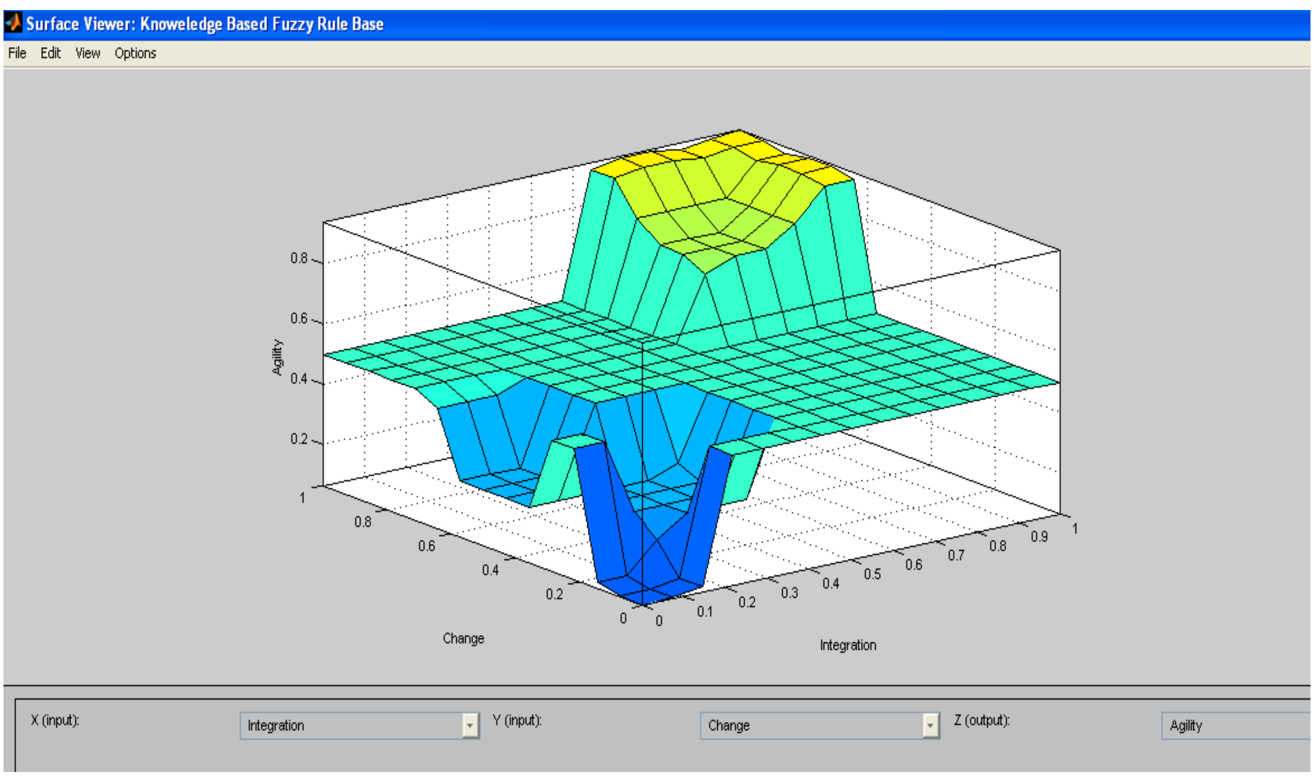

Fig. 4: Software Implementation of the Proposed Methology: the MATLAB Surface Viewer.

Table I: Linguistic Data for Agility Dimension

Decision Domain Agility Dimensions	Related Attributes	Notations	Observed values
Integration(A_I)	Concurrent execution of activities	A_{I1}	AH
	Enterprise Integration	A_{I2}	More or less High
	Information accessible to employees	A_{I3}	A
Competence(A_C)	Multi-venturing capabilities	A_{C1}	AH
	Developed business practice difficult to copy	A_{C2}	H
Team Building(A_{TB})	Empowered individuals working in teams	A_{TB1}	AH
	Cross functional teams	A_{TB2}	H
	Teams across company borders	A_{TB3}	AH
	Decentralised decision making	A_{TB4}	More or less High
Technology(A_T)	Technology awareness	A_{T1}	AH
	Leadership in the use of current technology	A_{T2}	AL
	Skill and knowledge enhancing technologies	A_{T3}	A
	Flexible production technology	A_{T4}	H
Quality(A_Q)	Quality over product life	A_{Q1}	A
	Products with substantial value-addition	A_{Q2}	AH
	First-time right design	A_{Q3}	AL
	Short development cycle times	A_{Q4}	AH
Change(A_C)	Continuous improvement	A_{C1}	AH
	Culture of change	A_{C2}	VH
Partnership(A_P)	Rapid partnership formation	A_{P1}	AH
	Strategic relationship with customers	A_{P2}	H
	Close relationship with suppliers	A_{P3}	H
	Trust-based relationship with customers/suppliers	A_{P4}	A
Market(A_M)	New product introduction	A_{M1}	AH
	Customer-driven innovations	A_{M2}	L
	Customer satisfaction	A_{M3}	More or less Average
	Response to changing market requirements	A_{M4}	A
Education(A_E)	Learning organization	A_{E1}	More or less High
	Multi-skilled and flexible people	A_{E2}	H
	Workforce skill upgrade	A_{E3}	AH
	Continuous training and development	A_{E4}	H
Welfare(A_W)	Employee satisfaction	A_{W1}	AH