International Journal of Computer and Information Technology (ISSN: 2279 – 0764)
Volume 02– Issue 02, March 2013

Fuzzy Logic Models for Selection of Machining Parameters in CAPP Systems

Saleh M. AMAITIK
Industrial and Manufacturing Systems Engineering Department
Benghazi University
Benghazi, Libya

Abstract—**Fuzzy logic is a mathematical theory of inexact reasoning that allows us to model the reasoning process of humans in linguistic terms. It is very suitable in defining the relationship between the system inputs and the desired system outputs. This paper presents fuzzy logic models to select machining parameters (cutting speed and feed rate) in automated process planning (CAPP) systems. Each model utilizes two-input and two-output variables which are partitioned into several fuzzy sets according to their minimum and maximum values allowed to control the model. A set of fuzzy rules have been constructed for each model, based on the knowledge extracted from machining data handbooks. Once the rules are evaluated the variables are defuzzified and converted into the corresponding output variables (cutting speed and feed rate). An example is given to demonstrate and verify the application of the developed fuzzy models. The results obtained are compared with the corresponding ones obtained from machining data handbook and shown good fit.**

Keywords- Fuzzy logic; machining parameters; process planning; CAPP

I. INTRODUCTION

In a Computer Aided Process Planning (CAPP) system, the machining parameters have to be selected automatically. The approaches used in the existing computerized selection systems for the machining parameters fall into one of the four categories, namely data storage and retrieval, empirical method, expert system and mathematical modeling. The storage and retrieval procedure requires a large amount of memory space for storing data, and the data it provides are often too conservative and not optimal. The systems based on empirical approaches reduce the data to an empirical form whereas the expert system approach uses the stored data or the empirical equations along with a knowledge base [1]. The mathematical modeling is using optimization algorithms with constraints. It is difficult for traditional optimization algorithms to solve this problem because of the problems of convergence speed and accuracy [2]. Recently, process planners have started using artificial intelligent techniques, such as neural networks, fuzzy logic and genetic algorithms to select the machining parameters and have made some progress [2, 3, 4, 5].

Very little literature is available in application of fuzzy logic in process planning [6]. El-Baradie [4] is one of the first to suggest a fuzzy logic model for machining data selection. He described the development stages of a fuzzy logic model for metal cutting. The model is based on the assumption that the relationship between the hardness of a given material and the recommended cutting speed is an imprecise relationship, and can be described and evaluated by the theory of fuzzy sets. The model has been applied to data extracted from the Machining Data Handbook, and a very good correlation was obtained between the handbook data and that predicted using the fuzzy logic model. Wong et al [7] have suggested a new fuzzy model for machinability data selection, which is different from El Baradie [4]. The model suggested by El Baradie [4] was a one-input–one-output fuzzy relationship by considering the depth of cut as a discrete parameter. Whilst Wong et al. [7] showed the feasibility of incorporating the depth of cut as one of the continuous parameters required to determine the cutting speed. Hashmi et al [8] have developed a fuzzy logic model used to select cutting speeds for three different materials in drilling operation. The relationship between a given material hardness and drilling speed was described and evaluated by fuzzy relation for different cutting tool materials and different hole diameters and feed rates.

In this research work, several fuzzy logic models are developed to select machining parameters in drilling and milling type operations. Each model can utilize two input variables, two output variables, five fuzzy sets, nine workpiece materials, and two tool materials combinations. In order to explain the steps involved in the development of these models, there are three basic components of fuzzy models which have to be described. These components are fuzzification of input and output variables, fuzzy rules applications, and defuzzification of the output variables. The following sections will explain detailed steps on how these components of the fuzzy model are implemented.

II. FUZZIFICATION OF INPUT AND OUTPUT VARIABLES

Fuzzification is a mathematical procedure for converting an element in the universe of discourse into the membership value of a fuzzy set. Fuzzification dividing the input and output variables into fuzzy regions (sets). The first step of fuzzification process is to define the fuzzy sets in the input and output variables. The possible domain interval of both the inputs and outputs are divided into a number of regions in such away that they overlap each other. The length of region may differ for each variable and one membership function is assigned to each region [9, 10].

The input variables in this research work are material hardness, hole diameter, depth of cut, and thread pitch. The output variables are cutting speed and feed rate. Table I presents the inputs, outputs, and the domain intervals of the variables used in the developed fuzzy models as well as the range of each variable. The universe of input and output variables have been partitioned according to their minimum and maximum values allowed controlling the models. Table II shows the fuzzy sets of the variables and their associated values and labels. The number of fuzzy sets for each input and output variable is five sets. Each fuzzy set has a defined linguistic term and specified range which can be modified to control the fuzzy model.

Although scientific publications have suggested many different types of membership functions of fuzzy logic, standard membership functions are used in most practical applications [11]. In this research work, a triangular membership function is used for all input and output variables. It is defined by the following equation:

$$Triangle(x,a,b,c)=\begin{cases} 0 & (x\le a) \\ \dfrac{x-a}{b-a} & (a\le x\le b) \\ \dfrac{c-x}{c-b} & (b\le x\le c) \\ 0 & (c\le x) \end{cases}. \qquad (1)$$

It has three parameters 'a' (minimum), 'b' (middle), and 'c' (maximum) that determine the shape of the triangle. Figures 1 shows a triangular membership function of a fuzzy set. Figures 2 and 3 show the membership functions for the input and output variables of the developed fuzzy models.

TABLE I. DOMAIN INTERVALS OF INPUT AND OUTPUT VARIABLES

Variable	**Range**	**Unit**
Input variables		
Material hardness	$0 \rightarrow 550$	BHN
Hole diameter	$0 \rightarrow 80$	Mm
Depth of cut	$0 \rightarrow 10$	Mm
Thread pitch	$0 \rightarrow 4.5$	Mm
Output variables		
Cutting speed	$0 \rightarrow 250$	m/min
Feed rate	$0 \rightarrow 1.5$	mm/rev or mm/tooth

III. FUZZY RULES KNOWLEDGE BASE

A fuzzy model uses fuzzy rules, which are linguistic IF-THEN statements involving fuzzy sets and fuzzy inference. Fuzzy rules play key role in representing expert modeling knowledge and experience and in linking the input variables of fuzzy models to output variables. The most used type of fuzzy rules is known as Mamdani fuzzy rules [9, 11]. A simple but representative Mamdani fuzzy rule describing the selection of cutting speed in drilling operation is given as:

IF Material Hardness is *Soft* **AND** Hole Diameter is *Medium* **THEN** Cutting Speed is *High.*

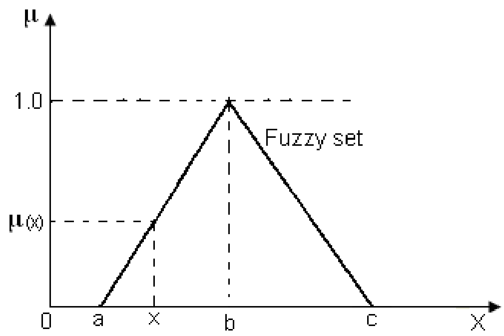


Figure 1. A triangular membership function of a fuzzy set

TABLE II. FUZZY SETS OF INPUT AND OUTPUT VARIABLES

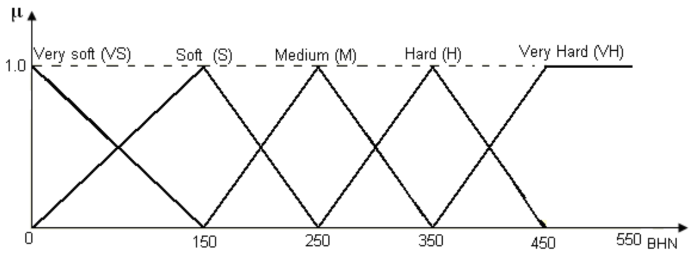
Fuzzy set	Range a	Range b	Range c	Symbol
Material hardness				
Very soft	0	0	150	VS
Soft	0	150	250	S
Medium	150	250	350	M
Hard	250		450	H
Very hard	350	450	550	VH
Hole diameter				
Very small	0	0	6	VS
Small	0	6	13	S
Medium	6	13	26.5	M
Large	13	26.5	55	L
Very large	26.5	55	80	VL
Depth of cut				
Very small	0	0	1	VS
Small	0	1	2.5	S
Medium	1	2.5	4	M
Large	2.5	4	6	L
Very large	4	6	10	VL
Thread pitch				
Very short	0	0	0.5	VS
Short	0	0.5	1.5	S
Medium	0.5	1.5	2.5	M
Long	1.5	2.5	3.5	L
Very long	2.5	3.5	4.5	VL

Where material hardness and hole diameter are input variables and cutting speed is output variable. "Soft", "Medium", and "High" are fuzzy sets, and the first two are called input fuzzy sets while the last one is called output fuzzy set. The variables as well as linguistic terms, such as High can be represented by mathematical symbols.

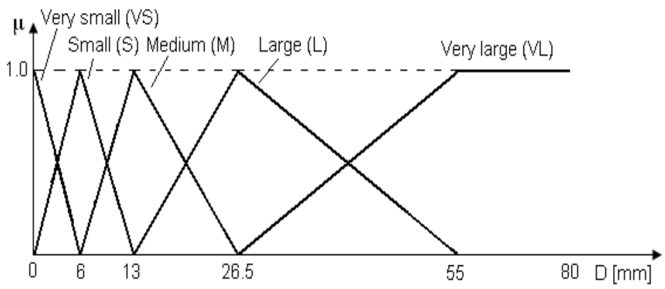
Thus, a Mamdani fuzzy rule for a fuzzy model involving two input variables and two output variables can be described as follows:

IF X_1 is A **AND** X_2 is B **THEN** Y_1 is C, Y_2 is D

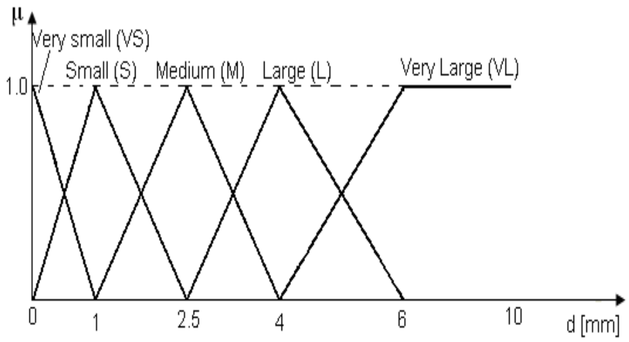
Where X_1 and X_2 are input variables, and Y_1 and Y_2 are output variables. A, B, C, and D are fuzzy sets, and AND is a fuzzy logic operator. The IF-part "X_1 is A AND X_2 is B" is called the rule premise, whereas the remaining part, THEN-part "Y_1 is C, Y_2 is D", is called the rule conclusion.



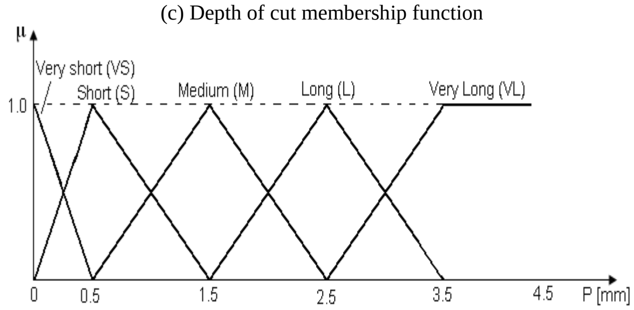
(a) Material hardness membership function



(b) Hole diameter membership function



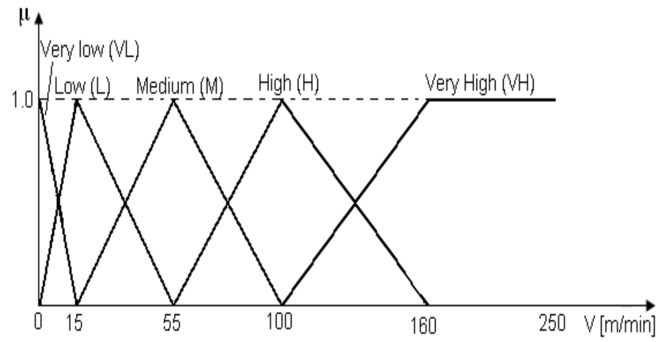
(c) Depth of cut membership function



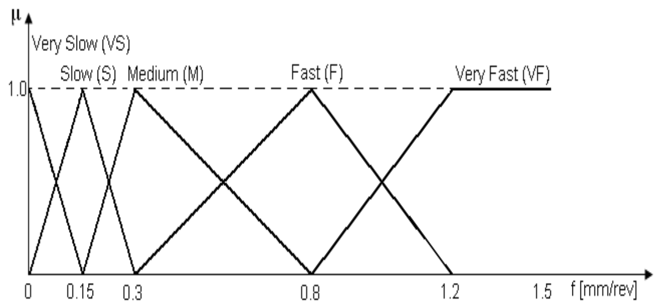
(d) Thread pitch membership function

Figure 2. Membership functions for input variables

A set of fuzzy rules have been constructed for each fuzzy model, based on the knowledge extracted from machining data handbooks [12]. In this research work, nine fuzzy models have been developed as shown in Table III. Each model can utilize two input variables, two output variables, five fuzzy sets, nine workpiece materials, and two tool materials combinations. With these numbers of parameters, each fuzzy logic model needs a maximum number of rules about 450 rules. For the purpose of explanation on how these rules are utilized, Table 4 shows the fuzzy rules in a tabulated form used to select cutting speed and feed rate for twist drilling of carbon steel workpiece with high speed steel tool.



(e) Cutting speed membership function



(f) Feed rate membership function

Figure 3. Membership functions for output variables

TABLE III. SUMMARY OF DEVELOPED FUZZY LOGIC MODELS

Fuzzy logic model	Input variables	Output variables
Twist drilling model	Hole diameter Material hardness	Cutting speed Feed rate
Spade drilling model	Hole diameter Material hardness	Cutting speed Feed rate
Center drilling, Counterboring, and countersinking model	Hole diameter Material hardness	Cutting speed Feed rate
Reaming model	Hole diameter Material hardness	Cutting speed Feed rate
Boring model	Depth of cut Material hardness	Cutting speed Feed rate
Tapping model	Thread pitch Material hardness	Cutting speed Feed rate
End milling	Depth of cut Material hardness	Cutting speed Feed rate
Side milling	Depth of cut Material hardness	Cutting speed Feed rate
Plane milling	Depth of cut Material hardness	Cutting speed Feed rate

Table IV shows the example of tabulated rules between work material hardness (*bhn*) and hole diameter (*d*) and the corresponding cutting speed and feed rate. The first column denotes the fuzzy sets for the workpiece material hardness (VS, S, M, H, VH) starting from very soft to very hard. The first row denotes the fuzzy sets for hole diameter varying from very small to very large (VS, S, M, L, VL). The contents of the table are the outputs yielded, which are the cutting speed (*v*) and feed rate (*f*) for this model. The AND used in the rules will apply to the fuzzy AND operation. A few examples of fuzzy rules (from Table IV) in a Mamdani form are presented as follows:

R_1: IF bhn is Very soft AND d is Very small

THEN v is Medium, f is Very slow

R_2: IF bhn is Soft AND d is Small

THEN v is Medium, f is Very slow

R_3: IF bhn is Soft AND d is Large THEN v is Low, f is Fast

TABLE IV. FUZZY RULES TABLE FOR TWIST DRILLING CARBON STEEL WORKPIECE WITH HSS TOOL

Material Hardness (*bhn*)		Hole diameter (*d*)				
		Very small	Small	Medium	Large	Very large
Very soft	*v*	M	M	M	M	M
	f	VS	S	M	F	F
Soft	*v*	L	L	L	L	L
	f	VS	S	M	F	F
Medium	*v*	L	L	L	L	L
	f	VS	S	M	M	V
Hard	*v*	VL	VL	VL	VL	VL
	f	VS	S	S	M	F
Very hard	*v*	VL	VL	VL	VL	VL
	f	VS	S	S	M	M

IV. FUZZY INFERENCE

Fuzzy inference is sometimes called fuzzy reasoning. It is used in a fuzzy rule to determine the rule outcome from the given rule input information. Fuzzy rules represent modeling knowledge or experience. When specific information is assigned to input variables in the rule premise, fuzzy inference is needed to calculate the outcome for output variables in the rule conclusion. In other words, for the general Mamdani fuzzy rule, the question about fuzzy inference is the following: Given $X_i = \alpha_i$, for all of *i*, where α_i are real numbers, what should Y_i be? For fuzzy modeling, after fuzzifying X_i at α_i and applying fuzzy logic AND operation on the resulting membership values in the fuzzy rule, we attain a combined membership value, μ, which is the outcome for the rule premise. Then, the question is how to compute "Then-part" in the rule. Calculating "THEN" is called *fuzzy inference*. Specifically, the question is: Given μ, how should Y_i be computed? [9].

A number of fuzzy inference methods can be used to accomplish this task. In this research work, the Max-Min inference method is used. In this method, all the fuzzy AND operations are applied into all the input's value of the corresponding fuzzy sets. Applying a fuzzy AND operation will yield a result that is the minimum of the fuzzy value of the number of input variables. The aggregation of the rule will be the truncation of the output fuzzy set. This method is applied to all rules to obtain the final result which gives the final shape of the output fuzzy membership function after aggregation of all the rules, respectively. Then the union operation is applied to all the output fuzzy sets to yield the final fuzzy set [10].

V. DEFUZZIFICATION OF OUTPUT VALUES

Defuzzification is a mathematical process used to convert a fuzzy set or fuzzy sets to a real number. It is necessary step because fuzzy sets generated by fuzzy inference in fuzzy rules must be somehow mathematically combined to come up with one single number as the output of a fuzzy model [10].

Every fuzzy model uses a defuzzifier, which is simply a mathematical formula, to achieve defuzzification. For fuzzy models with more than one output variable, defuzzification is carried out for each of them separately but in a very similar fashion. In most cases, only one defuzzifier is employed for all output variables, although it is theoretically possible to use different defuzzifiers for different output variables.

In this research work, the centroide or center of area (COA) is used as a defuzzifier for all output variables of the developed models. In COA defuzzification the crisp value u* is taken to be the geometrical center of the output fuzzy value $\mu_{out}(u)$, where $\mu_{out}(u)$ is formed by taking the union of all fuzzy rule contributions. The center is the point which splits the area under the $\mu_{out}(u)$ curve into two equal parts. The defuzzified output is defined as:

$$u^* = \frac{\sum_{i=1}^{N} u_i \mu_{out}(u_i)}{\sum_{i=1}^{N} \mu_{out}(u_i)} \quad (2)$$

Where the summation is carried over (discrete) values of the universe of discourse u_i sampled at N points. COA is a well-known and often used defuzzification method [10].

VI. FUZZY LOGIC ALGORITH

In this research work, nine fuzzy models have been developed for selection of machining parameters. Each model utilizes two input variables and two output variables. Each input and output variable is partitioned into five fuzzy regions (sets). A fuzzy rule base for each fuzzy model is generated and saved in separate files. The rule base contains a maximum number of rules about 450 rules for each model. The Max-Min inference method is used as the fuzzy inference engine, and the center of area method is used as a defuzzifier for the output variables. The fuzzy logic algorithm developed in this research work is based on four main steps summarized as follows:

A. Fuzzification of Input Values

Fuzzify the input values of X_1, X_2, … X_n variables using the fuzzification formula of triangular membership function:

$$\mu_{FSI_i}(x_j) = \begin{cases} 1 - \dfrac{|x_j - a_i|}{b_i - a_i} & (a_i \le x_j \le b_i) \\ 1 - \dfrac{|c_i - x_j|}{c_i - b_i} & (b_i \le x_j \le c_i) \\ 0 & otherwise \end{cases} \quad .(3)$$

Where

$\mu_{FSI_i}(x_j)$ are the degree of membership value of input variables X_j to the fuzzy set FSI_i.

X_j are the input variables to the fuzzy model (j = 1, 2, …., n, n = number of input variables).

a_i are the minimum values of the fuzzy set FSI_i.

b_i are the middle values of the fuzzy set FSI_i.

c_i are the maximum values of the fuzzy set FSI_i.

FSI_i are the fuzzy sets associated with the input variables X_j (i = 1, 2, ….., m, m = number of fuzzy sets for X_j variable).

B. Fuzzy Inference

Pass the fuzzified values to the fuzzy rules knowledge base through the inference method used. The evaluation form for possible rules can be written as follows;

IF X_1 is FSI_1 **AND** X_2 is FSI_2 **AND** ………X_n is FSI_m **THEN** Y_1 is FSO_1, Y_2 is FSO_2, …….., Y_p is FSO_q

Where
Y_j are the output variables of the fuzzy model (j = 1, 2, .., p, p = number of output variables.

FSO_i are the fuzzy sets associated with the output variables Y_j (i = 1, 2, ……., q, q = number of fuzzy sets for Y_j variable).

Use the Max-Min inference method (i.e. the min "$\wedge$" interpretation of AND). The degree of fulfillment of each fired rule can be calculated as follows;

$$DOF_k = \mu_{FSI_1}(x_1) \wedge \mu_{FSI_2}(x_2) \wedge ....\mu_{FSI_m}(x_n).$$

Where k is the number of fired rules contributed for output variable calculation.

The fuzzy output $\mu(Y_j)$ is the union (max $\vee$) of the contributions DOF_k and can be written as follows;

$$\mu(Y_j) = \mu_{FSO_1}(y_1) \vee \mu_{FSO_2}(y_2) \vee ......\mu_{FSO_m}(y_p).$$

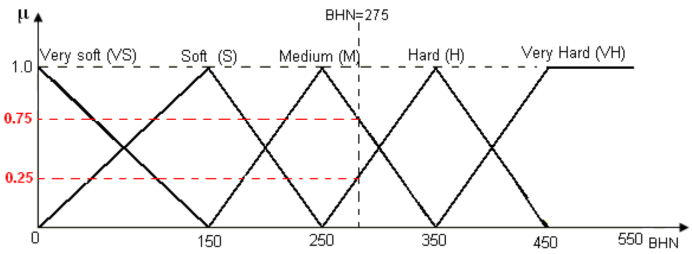
C. Defuzzification of Output Values

The crisp numbers for Y_1, Y_2, ……., Y_p can be calculated using the center of area defuzzification method as follows;

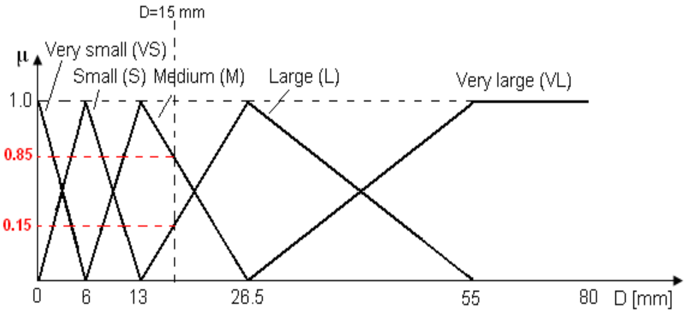
$$Y_j = \frac{\sum Y_j \mu(Y_j)}{\sum \mu(Y_j)} \quad (4)$$

VII. Machining Parameters Selection Example

To demonstrate the application of the proposed fuzzy models, an example is being presented to select cutting speed and feed rate for twist drilling of carbon steel workpiece with high speed steel tool. Consider the situation where work material hardness, *BHN*, is equal to 275 and hole diameter, *D*, is equal to 15 mm. Using the fuzzification formula of triangular membership function, the crisp material hardness value of 275 belongs to fuzzy set Medium to a degree of 0.75 and to fuzzy set Hard to degree of 0.25. Similarly, crisp hole diameter value of 15 belongs to fuzzy set Medium to degree of 0.85 and to fuzzy set Large to degree of 0.15, see Figure 4.



(a) Material hardness membership function



(b) Hole diameter membership function

Figure 4. Fuzzification of the input values

These fuzzified values are then passed to the fuzzy rules knowledge base through the inference method used. The only rules that will have degree of fulfillment, DOF (it is a measure of the degree of similarity between the input and the premise of the rule) greater than zero will fire up. In the case of this example the following four rules will fire up (see Table IV).

R_1 **IF** *bhn* is **M** and *d* is **M THEN** *v* is **L**, *f* is **M**

R_2 **IF** *bhn* is **M** and *d* is **L THEN** *v* is **L**, *f* is **M**
R_3 **IF** *bhn* is **H** and *d* is **M THEN** *v* is **VL**, *f* is **S**
R_4 **IF** *bhn* is **H** and *d* is **L THEN** *v* is **VL**, *f* is **M**

Using the Max-Min inference method of DOF (i.e. the min (^) interpretation of AND), each rule contributes the machining parameters values. The degree of fulfillment of each rule can be calculated as follows (see Figure 4 for evaluation steps);

R_1: $DOF_1 = \mu_{medium}(275) \wedge \mu_{medium}(15) = 0.75 \wedge 0.85 = 0.75$. Contributes Low to cutting speed and Medium to feed rate. Similarly, rules R_2, R_3, and R_4 can written as

R_2:$DOF_2 = \mu_{medium}(275) \wedge \mu_{large}(15) = 0.75 \wedge 0.15 = 0.15$. Contributes Low to cutting speed and Medium to feed rate.

R_3:$DOF_3 = \mu_{hard}(275) \wedge \mu_{medium}(15) = 0.25 \wedge 0.85 = 0.25$. Contributes Very Low to cutting speed and Slow to feed rate.

R_4:$DOF_4 = \mu_{hard}(275) \wedge \mu_{large}(15) = 0.25 \wedge 0.15 = 0.15$. Contributes Very Low to cutting speed and Medium to feed rate.

The fuzzy outputs $\mu(v)$ and $\mu(f)$ are the union (max) of these four contributions for each parameter; that is

$$\mu(v) = \mu_{low}(v) \vee \mu_{low}(v) \vee \mu_{verylow}(v) \vee \mu_{verylow}(v)$$
$$\mu(f) = \mu_{medium}(f) \vee \mu_{medium}(f) \vee \mu_{slow}(f) \vee \mu_{medium}(f).$$

Selecting crisp numbers for cutting speed, v^* and feed rate, f^* representative of $\mu(v)$ and $\mu(f)$ is the process of defuzzification. Using COA defuzzification, the crisp outputs of the cutting speed, v^* and feed rate, f^* are obtained as follows;

$$v^* = \frac{\sum v.\mu(v)}{\sum \mu(v)}, \quad f^* = \frac{\sum f.\mu(f)}{\sum \mu(f)} \qquad (5)$$

According to the input values of material hardness, *BHN* = 275 and hole diameter, *D*=15 mm, it is found that the cutting speed v^* =13.56 m/min and feed rate f^* = 0.2 mm/rev. The corresponding values of cutting speed and feed rate obtained from Machining Data Handbook [12, 13] are v = 15 m/min and f = 0.22 mm/r. These values show a good correlation between Machining Handbook recommended values of cutting speed and feed rate and those predicted by fuzzy logic model.

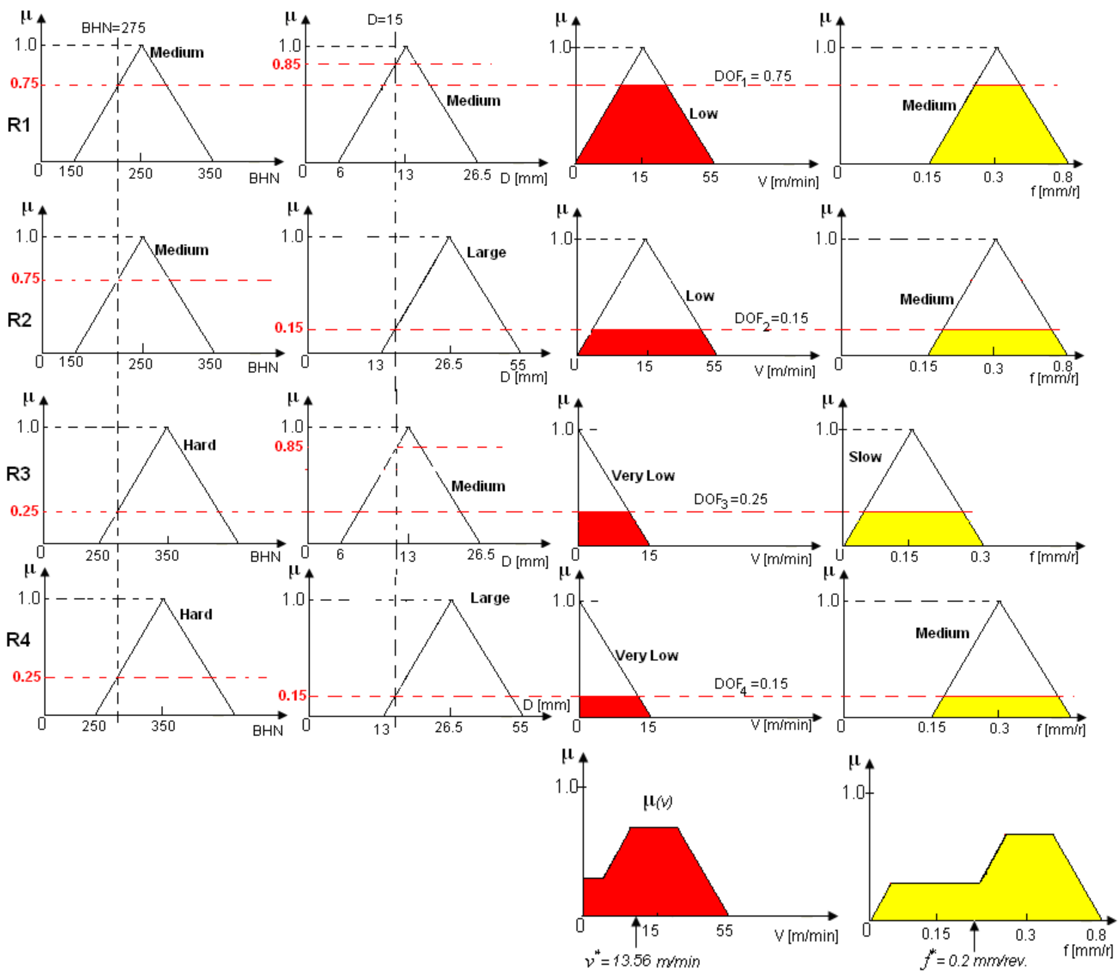


Figure 5. Evaluation of the fuzzy algorithm of the example

VIII. CONCLUSIONS

This paper presented several fuzzy logic models for selecting machining parameters (cutting speed and feed rate) in drilling and milling type machining operations. Indeed, the proposed fuzzy models have been implemented in a CAPP system developed by the author in [14]. The results obtained showed that fuzzy logic approach can provide a promising approach for automated knowledge acquisition and can be advantageously used in the building of new generation CAPP systems. This is due to its ability to cope with the dynamic changes of manufacturing systems. In addition, fuzzy logic approach utilizes the knowledge of machining data and avoids complex optimization procedures hence it may be more acceptable to process planners.

ACKNOWLEDGMENT

The author would like to express his gratefulness and appreciation to Libyan Ministry of Higher Education and Scientific Research and Benghazi University for their support.

REFERENCES

[1] Shunmugam, M.S., Reddy, S.V. & Narendran, T.T., “Selection of optimal conditions in multi-pass face-milling using a genetic algorithm”. Int. J. Mach. Tools and Manuf., 40, 401-414, 2000.

[2] Liu, Y. & Wang, C., “A modified genetic algorithm based optimization of milling parameters”. Adv. Manuf. Tech.,15, 296-799, 1999.

[3] Chen, Y.-T. & Kumara, S.R.T., “Fuzzy logic and neural networks for design of process parameters: a grinding process application”. Int. J. Prod. Res., 36, 395-415, 1998.

[4] EL Baradie, M. A., “A fuzzy logic model for machining data selection”, Int. J. Mach. Tools and Manuf., 37, 1353-1372, 1995.

[5] Wong, S.V. & Hamouda, A. M., “Machinability data representation with artificial neural networks". Journal. Mater. Process. Technol., 138, 538-544, 2003.

[6] Singh, N., & Mohanty, B. K., “A fuzzy approach to multi-objective routing problem with application to process planning in manufacturing systems”. Int. J. Prod. Res., 29, 1161-l 170, 1991.

[7] Wong, S.V., Hamouda, A.M.S. & EL Baradie, M.A., “Generalized fuzzy model for metal cutting data selection”. J. Mater. Process. Technol., 89-90, 310-317, 1999.

[8] Hashmi, K., Graham, I.D. & Mills, B., “Fuzzy logic based data selection for drilling process”. J. Mater. Process. Technol., 108, 55-61, 2000.

[9] Ying, H., “Fuzzy control and Modeling: Analytical foundations and applications, IEEE, New York, 2000.

[10] Tsoukalas, L.H. & Uhrig, R.E., “Fuzzy and neural approaches in Engineering”, John Willey & Sons, Inc., New York, 1997.

[11] Berkan, R.C. & Sheldon, L.T., “Fuzzy systems design principles: building fuzzy IF-THEN rule bases”, IEEE Press, New York, 1997.

[12] “Machining Data Handbook”, 3rd ed., 1–2. Metcut Research Associates Inc., Cincinnati, 1980.

[13] Boaisha, S. M. & Amaitik, S.M., "Forecasting Model Based on Fuzzy Time Series Approach", Proceedings of the 10th International Arab Conference on Information Technology - ACIT 2010, Benghazi, Libya, December 14-16, 2010.

[14] Amaitik, S.M. & Kilic, S.E., “An intelligent process planning system for prismatic parts using STEP features”. The International Journal of Advanced Manufacturing Technology 31 (9), 978-993, 2006.