Innovative Systems Design and Engineering
ISSN 2222-1727 (Paper) ISSN 2222-2871 (Online)
Vol.5, No.2, 2014
www.iiste.org

Selection of Optimum Cutting Speed In End Milling Process Using Fuzzy Logic

Prof. Dr. Nabeel Kadim Abid Al-Sahib [1], Hasan Fahad Abdulrazzaq[2*]

1. Thi-Qar University, Al-Jadriya , Baghdad, Iraq
2. Al-Khawarizmi College of Engineering, Baghdad University, Al-Saidiya , Baghdad, Iraq

* E-mail of the corresponding author: hasanfahad1989@gmail.com

Abstract

The machining process shows ambiguous behavior and often cannot be linearly extrapolated in a wide range. It cannot be modeled effectively using theories and equations. The classical method for selection of machining parameters, such as cutting speed is based on data from machining hand books for machining parameters or on the experience of the operator or CNC programmer. The parameters chosen in most situations are highly conservative to protect over- matching errors from tool failures, such as deflection, breakage, etc. In this paper, a model to find the optimum cutting speed for end milling operation was built using Fuzzy Logic, this model is user-friendly and compatible with the automation concept of a flexible and computer integrated manufacturing systems. It allows the operator, even unskilled, to find the optimal cutting speed for an efficient machining process that can lead to an improvement of product quality, increase production rates and thus reducing product cost and total manufacturing costs. The developed fuzzy logic model showed a good prediction to select the optimum cutting speed , with a mean absolute error of around 4.5% from the optimum machining parameters in the Machining Data Handbook.

Keywords: Fuzzy Logic, End Milling Process, CNC, FL, Optimum Cutting Speed Selection.

1. Introduction

Selection of optimal process parameter values for a dedicated machining operation is typical but yet a tedious task in the modern computer-aided manufacturing (CAM) environment. With today's demanding productivity and profitability in manufacturing industry, machining has increasingly needed to be performed optimally. Thus, the selection of machinability data plays an important role on machine performance in terms of productivity, reliability and product quality [2]. The optimized machinability data is obtained from a skilled machinist who has years of experience. Machining Data Handbook (MDH) [7] has been used as a good reference for machinists to perform a machining process. Besides that, the mathematical and empirical modeling also had been practiced as another method to predict the optimal machinability parameters and showed good results. However, there are still some problems with these practices. Thus, some common artificial intelligence technologies, such as fuzzy logic (FL), and models using hybrids of these had been employed into modeling of a machining process [2].

Using machining data handbook for the choice of cutting conditions for material hardness that lies in the middle of a group is simple and straight forward. But there exists a degree of vagueness in boundary cases, where two choices of cutting speeds are applicable for one choice of material hardness. In this situation, the skilled operator makes a decision on the appropriate cutting speed, based on his experience. However, this method of data selection by individual operators is not very desirable, because it may vary from operator to operator. Therefore, it is desirable to have an operator independent data selection system for choosing machining operation [3].

While the output variables of the machining operation depend on the cutting conditions, the decision concerning the selection of the cutting parameters have an important influence on the cost and quality of the production. Increasing cutting speed and feed will lead to decreasing machining time and cost, at the same time, this increasing will lead to tool wear which leads to increasing machining cost. For this reason, an optimum cutting speed is needed, optimum speed which balances these opposing factors and results in minimum cost per piece, figure 1 shows the relationship between cutting speed and cost.

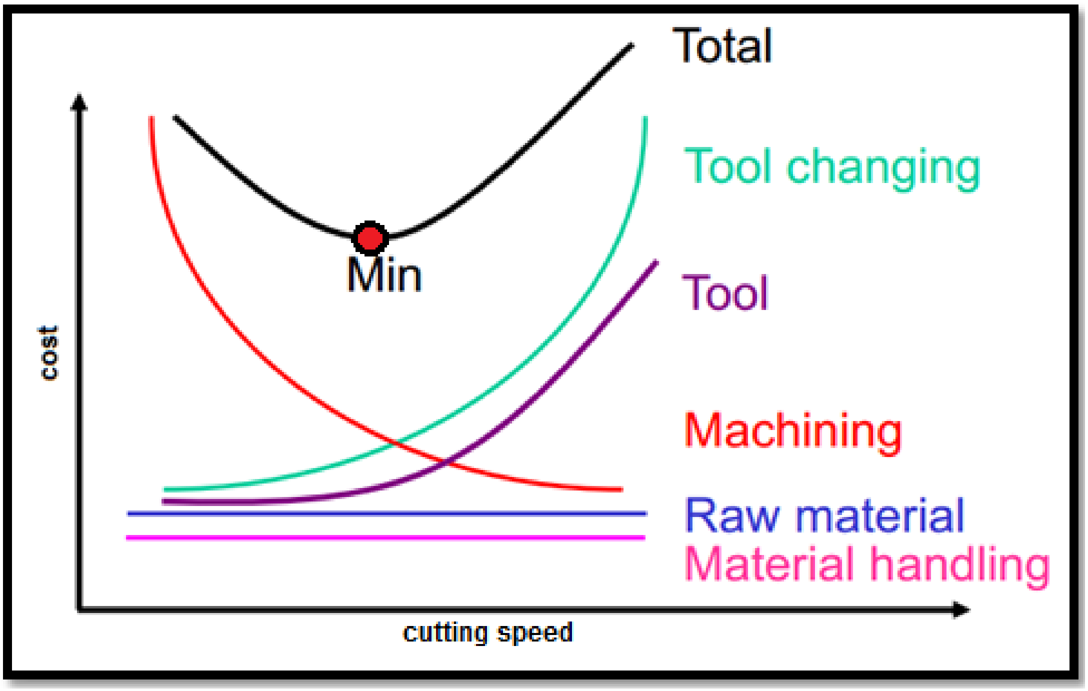

Figure 1 Cutting speed and cost relationship [5].

So, finding the optimum cutting will lead to reduce machining cost and total cost , which can be determined as in equation (1) [4] :

$$\mathbf{C_u = C_m + C_n + C_c + C_t} \quad (1)$$

Where :

- $\mathbf{C_u}$: The total unit (per piece) cost.
- $\mathbf{C_t}$: The tool cost per piece.
- $\mathbf{C_n}$: The cost associated with non-machining time.
- $\mathbf{C_m}$: The machining cost.
- $\mathbf{C_c}$: The cost of tool changing.

Due to the increased use of CNC machines and severe competition between the makers, the importance of precise optimization cutting conditions has increased, fuzzy logic can be applied to any process in which a human being plays an important role which depends on his subjective assessment [1] , and FL will be used here to develop a model for finding the optimum cutting speed.

2. Literature Survey

Many methods are used by related journal to optimize cutting speed and machining parameters in CNC machining :

El-Baradie (1995) **[1]**, 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 was 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. (2003) **[2]**, suggested a new fuzzy model for machinability data selection, which is different from El Baradie [1]. The model suggested by El Baradie [1] was a one-input–one-output fuzzy relationship by considering the depth of cut as a discrete parameter. Whilst Wong et al**.** [2] showed the feasibility of incorporating the depth of cut as one of the continuous parameters required to determine the cutting speed.

Hashmi et. al. (2000) **[3]**, 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.

3. Objectives of The Work

1. Building a model using Fuzzy Logic to find the optimum cutting speed for the end milling operation.
2. Comparing the results obtained from Fuzzy Logic model with the practical values of optimum cutting speed in MDH (Machining Data Handbook).

4. Fuzzy System

Fuzzy logic is one of the powerful artificial intelligence techniques. Fuzzy logic does has the capability to converse, reason and make rational decisions in an environment of imprecision, uncertainty and vagueness of information or knowledge. Besides, fuzzy logic is able to perform a wide variety of physical and mental tasks without any measurements and any computations. Furthermore, fuzzy logic can be easily combined with classic control techniques and can be operated in coordination . These capabilities helped the researchers to break through the computational bottlenecks of traditional expert systems [6].

4.1 Fuzzy Sets

Fuzzy sets are the functions which map a value that may possibly be a member of the set to a number between zero and one indicating its degree of membership function. Theory of fuzzy sets can be further explained using equation (2), where fuzzy set of A of universe X is defined by function $\mu A\ (x)$ (membership function of set A):

$$\mu A\ (x): X \rightarrow [0, 1] \tag{2}$$

where $\mu A\ (x) = 0$ if x is totally not in A; $0 < \mu A\ (x) < 1$ if x is partly in A and $\mu A\ (x) = 1$ if x is totally in A. Membership function shown in figure 2 is very useful for modeling and quantifying the meaning of symbols. However, the steps of recognizing the fuzzy attributes and drafting the fuzzy set into membership function are a crucial task which will affect the effectiveness and efficiency of the developed model. Common membership function shapes are triangle, trapezoid and bell shapes. Triangle membership function with shoulder applied for each end of fuzzy sets was used throughout this research for easily represented and minimum computing power [6] .

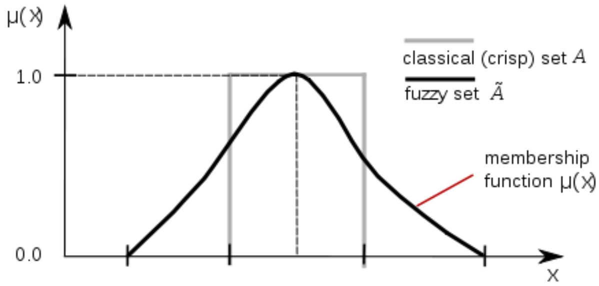

Figure 2 Membership function of a fuzzy set [5]

4.2 Fuzzy Rules

Fuzzy rule is very important due to its ability to capture human knowledge. Fuzzy "IF THEN" rule is commonly used for describing the relationship between the input and output of a fuzzy system. A fuzzy IF-THEN rule is of the form:

IF X1 = A1 and X2 = A2 ... and Xn = An THEN Y = B

where *Xn* and *Y* are linguistic variables, and *An* and *B* are linguistic terms. The 'IF part' of the rule is the antecedent or premise, while the 'THEN part' is the consequent or conclusion.

Example of the single-input and single-output fuzzy rule is as follow:

IF the material hardness is *soft,***THEN** the cutting speed is *high.*

A complex system will have conventional complex rules such follow:

IF the material hardness is *extremely soft* **AND** the radial depth of cut is *extremely shallow* **AND** the cutter diameter is *extremely small,* **THEN** the cutting speed is *extremely fast* **AND** the feed rate is *extremely low*.

The number of fuzzy rules is calculated from multiplication of the number of fuzzy sets for each input variables [6] .

4.3 Fuzzy Inference

Fuzzy inference is based on the human knowledge and common sense; it is intuitive and easy to understand. It can be described as a process that will map the given input to its corresponding output based on constructed fuzzy rules by using the theory of fuzzy sets. Fuzzy inference has three main steps initiated by fuzzification, followed by rules applications (some people address this as inference mechanism) and then defuzzification. Fuzzification involves the translation of crisp inputs into linguistic fuzzy sets. Here, the truth degree of which these crisp inputs belong to each of the appropriate linguistic fuzzy sets will be determined. Then, the translated inputs will undergo the inference mechanism that applies the fuzzy rules. There are two common methods in rule applications which are max-min method and max product. The difference between them is the aggregation of the rule. They are using truncation (max min method) and multiplication(max-product) of the output fuzzy set with the yielded result. The defuzzification process is defined as the conversion of a fuzzy quantity, represented by a membership function, to a precise or crisp value. There are two commonly used defuzzification methods: the center of gravity method and the mean of maxima method. In the **center of gravity** (COG) method, calculation of the y-coordinate of the center of gravity of the fuzzy set B' is done. And this is done according to [6] :

$$\mathrm{y}' = \mathrm{cog}(B') = \frac{\sum_{j=1}^{F} \mu_{B'}(y_j) y_j}{\sum_{j=1}^{F} \mu_{B'}(y_j)} = \frac{\int_Y \mu_{B'}(y) y \, dy}{\int_Y \mu_{B'}(y)} \tag{3}$$

The first part of the above equation is used for discretized domains Y , whereas the second part is used for continuous domains Y . In the **mean of maxima** (MOM) method, we find all points where $\mu\ B'$. (y) is at its maximum. Then take the mean of all these points. In mathematical notation, at last the equation of MOM is:

$$\mathrm{y}' = \mathrm{mom}(B') = \mathrm{cog}\left(\left\{\mathrm{y} \middle| \mu_{B'}(\mathrm{y}) = \max_{\mathrm{y} \in Y} \mu_{B'}(\mathrm{y})\right\}\right). \tag{4}$$

In a way, the MOM method selects the 'most probable' output. It is often used with inference based on fuzzy implications. On the other hand, the COG method is usually used together with Mamdani inference [6] .

5. Work Procedures

This work includes finding and selecting the optimum cutting speed in end milling process using fuzzy logic, the procedure of the work is as follows :

5.1 Materials and Methods

The proposed fuzzy model in this paper is able to predict cutting speed for peripheral end milling process at a given radial depth of cut and hardness of workpiece material. In this study, Wrought Carbon Steel has been used as the workpiece material while carbide and High Speed Steel as the cutting tools.

5.2 Data Collection

Data were extracted from Machining Data Handbook (MDH) [7] for peripheral end milling process of wrought carbon steels using carbide and high speed steel tools. The data from MDH were in the form of grouped data. Therefore, a few testing sets were generated from each group of the data in a manner that well described the group. The method of testing data set generation from group data specifically applies to parameters of hardness of material (85-125 BHN, 125-175 BHN, 175-225 BHN and 225- 275BHN) and cutter diameter of (d = 10 mm,). Then, the radial depth of cut, d which is dependent on cutter diameter (0.5 mm, 1.5 mm, d/4 and d/2) was converted into a definite number.

5.3 Implementation

MATLAB 7.14.0.739 (R2012a), had been used as the tool for the implementation of the prototype models. Mean Absolute Percentage Error (MAPE) was used as the measurement for performance. Fine tuning fuzzy models were done to enhance the initial fuzzy models design as well as to improve the capability in solving the problems. Figure 3 describes the procedure of finding optimum cutting speed.

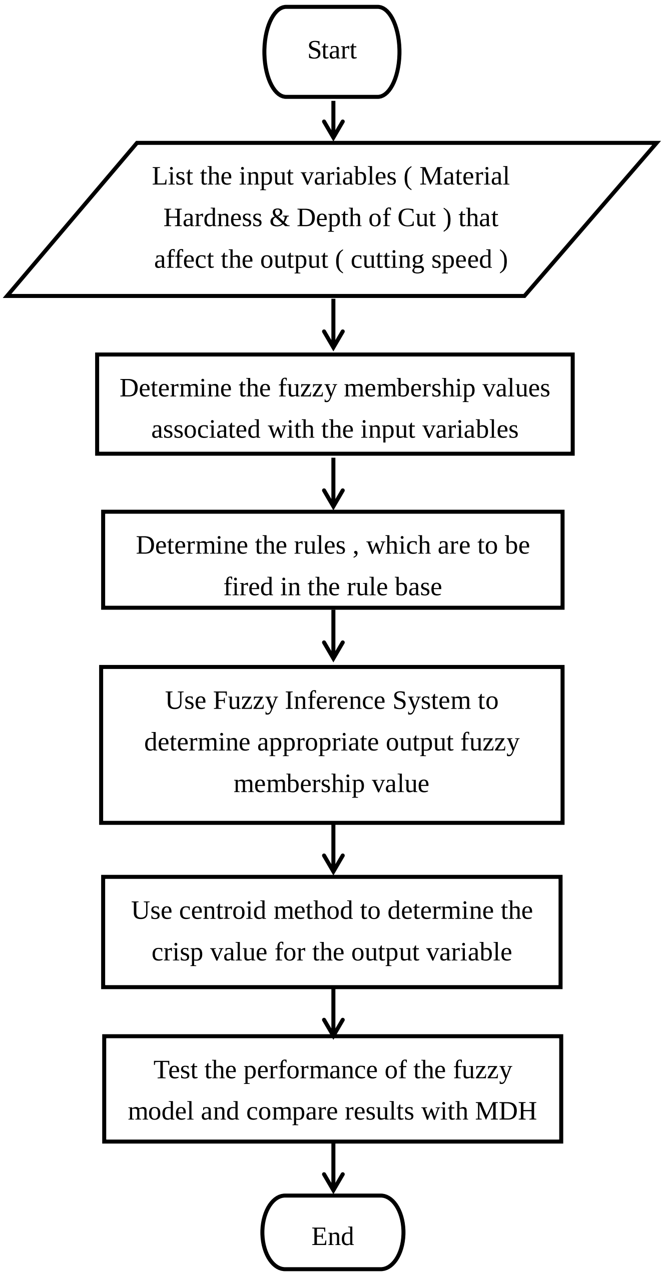

Figure 3 Flowchart of finding optimum cutting speed using fuzzy logic.

5.4 Membership Functions For Fuzzy Variables

The Speed Fuzzy (SF) model uses multi input- single output fuzzy variables for the selection of optimum cutting speed, as shown in figure 4 . The multi inputs are **material hardness** (BHN) and **depth of cut** (DOC), and the output is the optimum **cutting speed** (CS) . The fuzzy expressions for the inputs and output are shown in Table 1 . The model is applied for peripheral (end milling) operation for wrought carbon steels using different types of tools.

Table 1 Linguistic Labels for Inputs and Output Variables

Inputs		Output
Material Hardness (BHN)	Depth Of Cut (mm)	Cutting Speed (m/min)
Very Soft (VS)	Very Shallow(VSh)	Extremely Low (EL)
		Very Low (VL)
Soft (S)	Shallow (Sh)	Low (L)
		Med Low (ML)
Medium (M)	Medium (Med)	Medium Speed (MS)
		Med High (MH)
Hard (H)	Deep (D)	High (H)
		Very High (VH)
Very Hard (VH)	Very Deep (VD)	Extremely High (EH)

Different applications of the fuzzy control technique use a specific shape of the fuzzy set. There is no standard method of choosing the proper shape of the fuzzy sets of the control variables. Trial and error methods are usually exercised [3]. In this model, an equal sided triangular shape membership function is selected for both inputs BHN, DOC and for the cutting speed, as shown in figures 5 , 6 and 7.

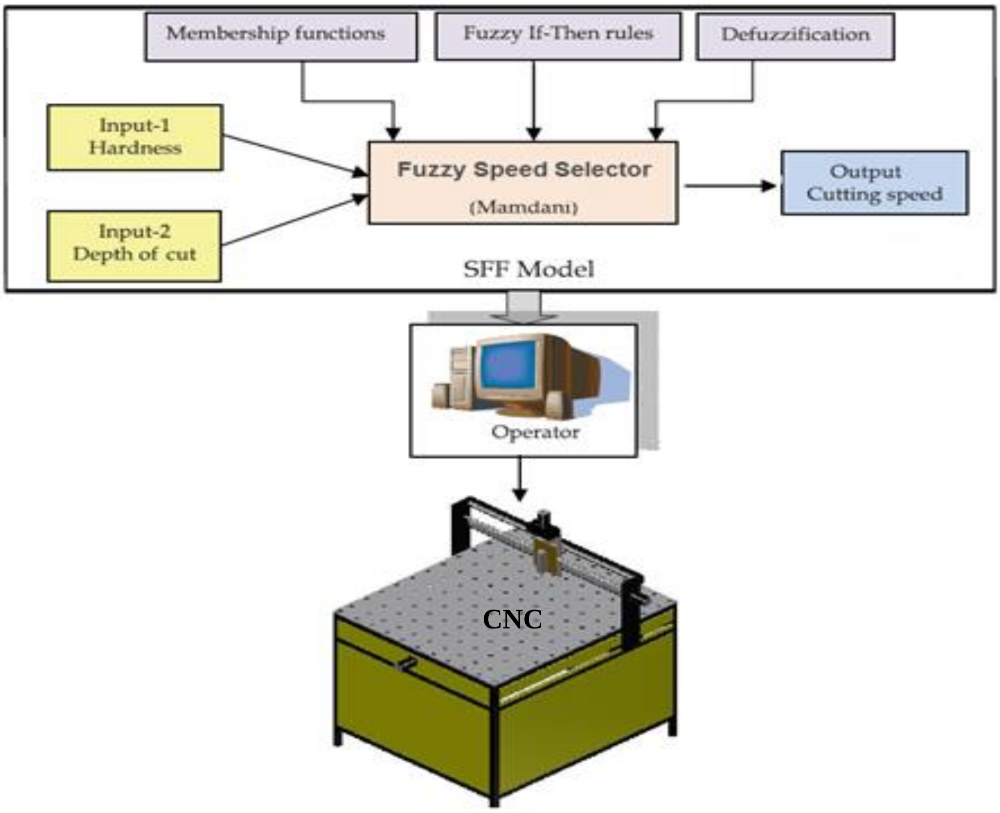

Figure 4 Structure of the Speed Fuzzy model.

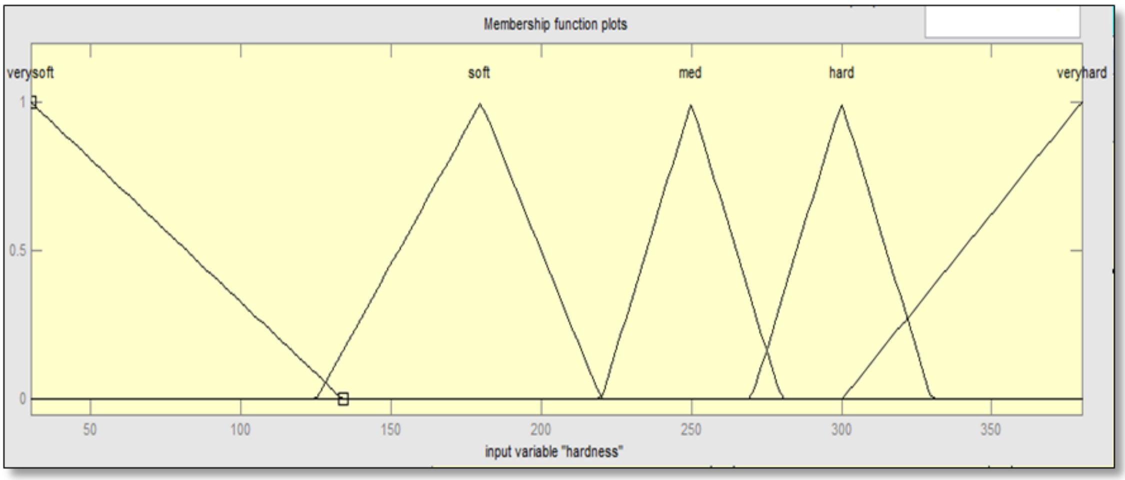

Figure 5 Membership functions for Hardness of material (BHN).

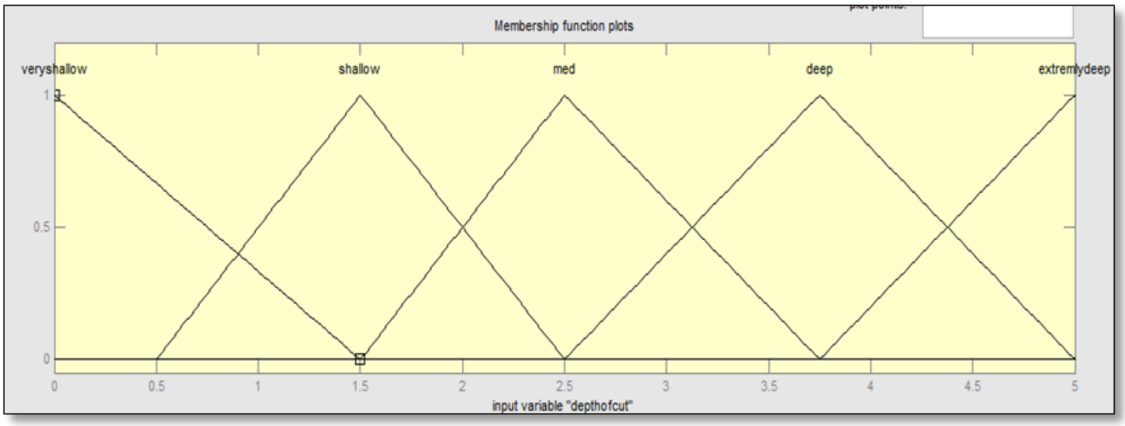

Figure 6 Membership functions for depth of cut (DOC).

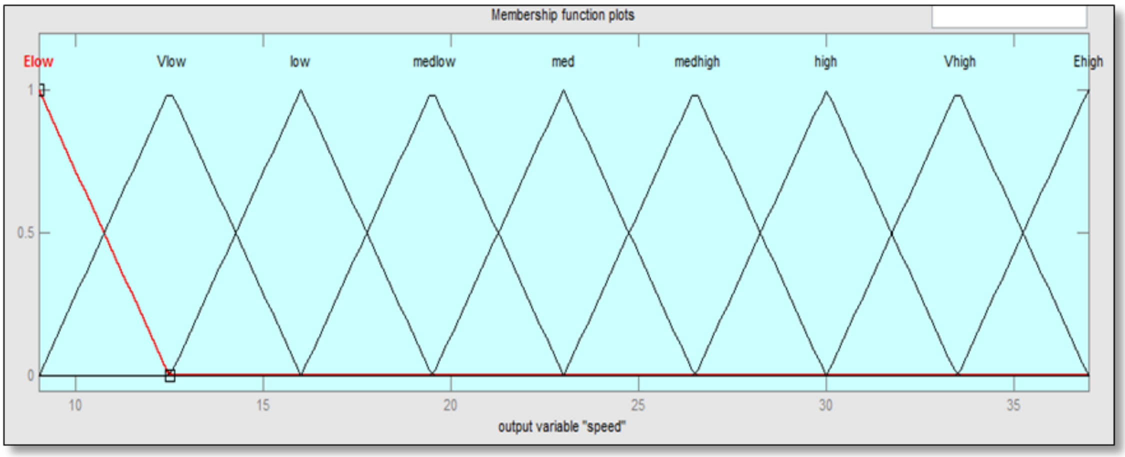

Figure 7 Membership functions for output cutting speed.

5.5 Fuzzy Rules

The point of fuzzy logic is to map an input space to an output space, and the basic mechanism for doing this is a set of IF-THEN rules with the application of fuzzy operator (AND or OR) . These if-then rules are used to formulate the conditional statements that comprise fuzzy logic. By using the rules, the fuzzy inference system (FIS) formulates the mapping form. Mamdani's fuzzy inference system, which is used in this work, is the most commonly seen fuzzy methodology. The relationship between the input variables and the output variables is characterized by if-then rules defined based on experimental, expert and engineering knowledge. The two common methods for the FIS engine are the **Max-Min** method and the **Max-Product** method. The difference between them is the aggregation of the rules. The first uses truncation, and the last uses multiplication of the output fuzzy set. Both methods are tested and the Max-Min method gives more reliable and more accurate results, therefore, it is used in calculations of the fuzzy system. In this study, there are two input variables; hardness of material and depth of cut each of five fuzzy sets, and then the fuzzy system of a minimum of 5 x 5 = 25 rules can be defined. Figure 8, shows a part of the rules in linguistic form. By using these rules, the input-output variables in a network representation can be drawn as in Figure 9 .

Figure 8 Part of fuzzy rules in linguistic form.

1. If (hardness is veryhard) and (depthofcut is veryshallow) then (output1 is medhigh) (1)
2. If (hardness is veryhard) and (depthofcut is shallow) then (output1 is med) (1)
3. If (hardness is veryhard) and (depthofcut is med) then (output1 is Vlow) (1)
4. If (hardness is veryhard) and (depthofcut is deep) then (output1 is Vlow) (1)
5. If (hardness is veryhard) and (depthofcut is extremlydeep) then (output1 is Elow) (1)
6. If (hardness is hard) and (depthofcut is veryshallow) then (output1 is medhigh) (1)
7. If (hardness is hard) and (depthofcut is shallow) then (output1 is medlow) (1)
8. If (hardness is hard) and (depthofcut is med) then (output1 is low) (1)
9. If (hardness is hard) and (depthofcut is deep) then (output1 is low) (1)
10. If (hardness is hard) and (depthofcut is extremlydeep) then (output1 is low) (1)
11. If (hardness is med) and (depthofcut is veryshallow) then (output1 is Ehigh) (1)
12. If (hardness is med) and (depthofcut is shallow) then (output1 is medhigh) (1)
13. If (hardness is med) and (depthofcut is med) then (output1 is med) (1)
14. If (hardness is med) and (depthofcut is deep) then (output1 is med) (1)
15. If (hardness is med) and (depthofcut is extremlydeep) then (output1 is medlow) (1)
16. If (hardness is soft) and (depthofcut is veryshallow) then (output1 is Vhigh) (1)
17. If (hardness is soft) and (depthofcut is shallow) then (output1 is med) (1)

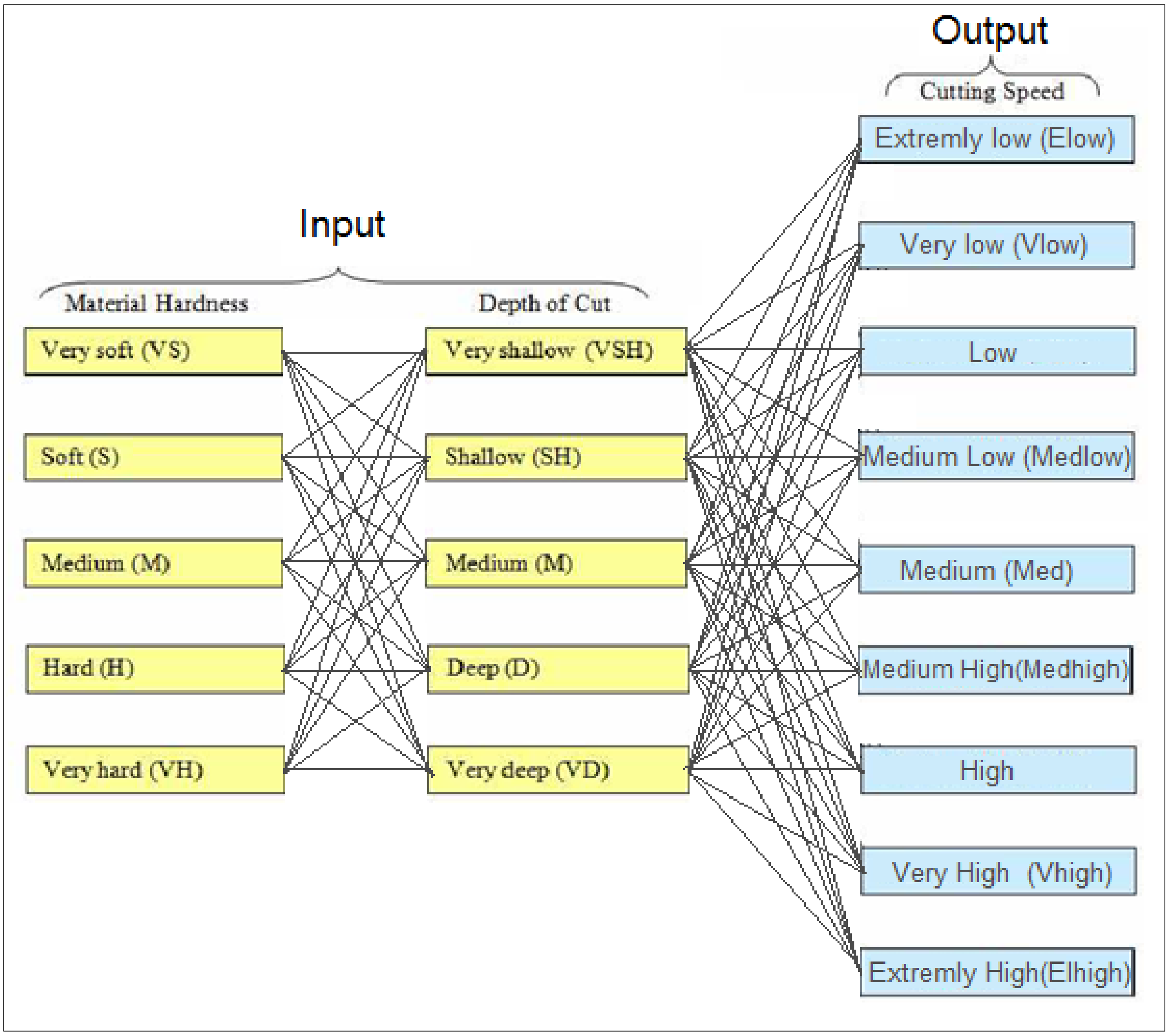

Figure 9 Network representation for Fuzzy Cutting Speed Selector

5.5 Defuzzification

Defuzzification is the process of transforming the fuzzy quantities into crisp quantities, as shown in Figure 10. There are several methods used for defuzzifying the fuzzy output functions: **the centroid method**, the **centre of sums**, **the max-membership function**, **the centre of largest area**, and **the first of maxima** or **the last of maxima**. The selected defuzzification method is significantly affecting the speed and accuracy of the fuzzy model. The centroid method provides more linear and more reliable results by taking the union of the output of each fuzzy rule and this method is used in this study.

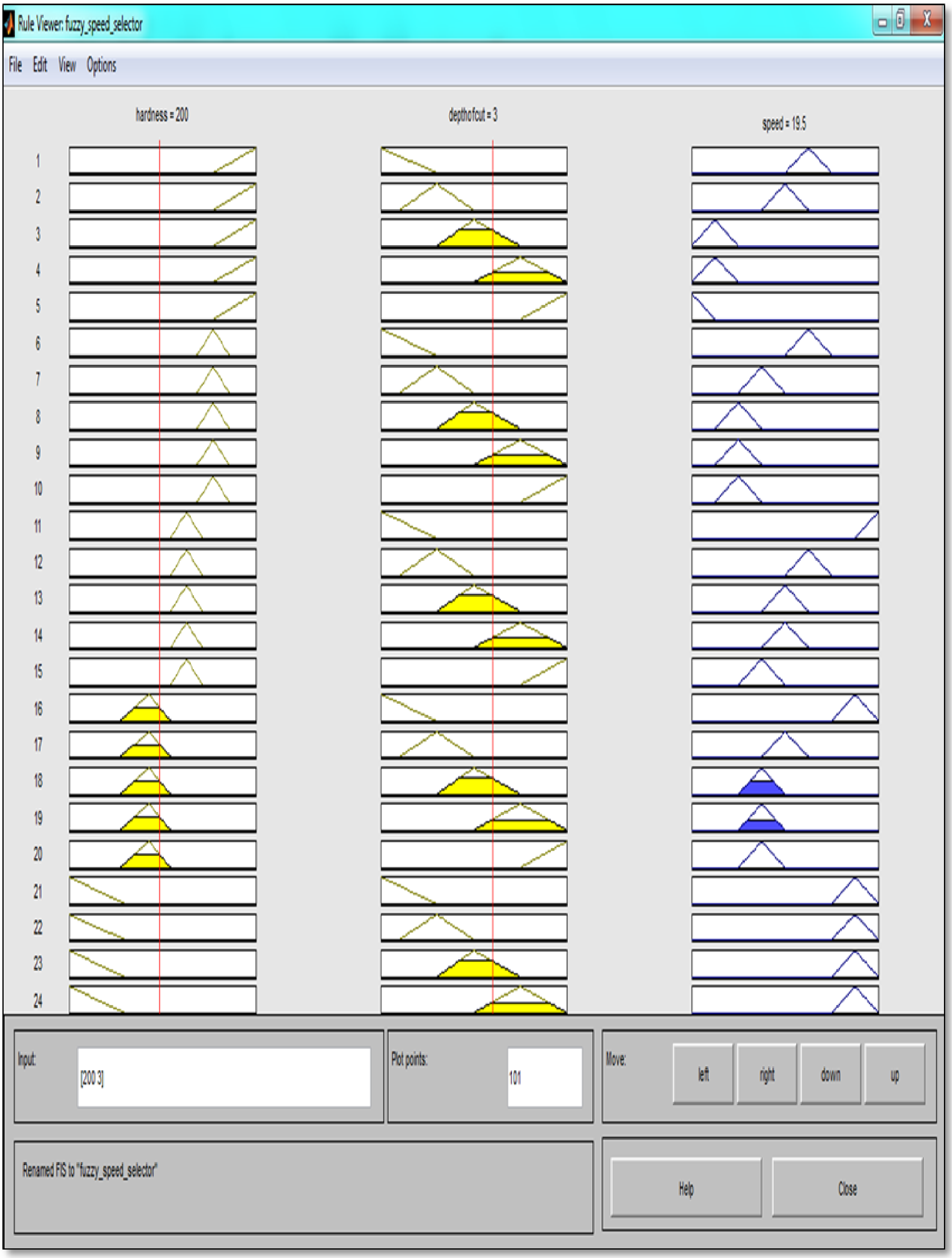

Figure 10 Fuzzy Rules for Fuzzy Cutting Speed Selector

6. Results and Discussion

In this section, the performance of the Speed Fuzzy (SF) model is compared with machining data handbook in finding and selecting the output cutting speed which can result in a lower cutting force, a longer tool life, and better surface finish.

The proposed system is expected to contribute in the selection of optimal cutting speed that will assist process planners, production engineers , CNC programmers, and machinists with easy access to data necessary for effective machining process.

Speed Fuzzy (SF) selector is used to predict the optimum cutting speed using data extracted from the Machining Data Handbook (MDH) [7] .

A user-friendly viewer of the SF model enabling a time saving and easy way for operator for interring the inputs and getting the output. Fine tuning fuzzy model is done to enhance the initial fuzzy models design as well as to improve the capability in solving the problems. The viewer is used to generate the input-output samples.

The values are tabulated in Tables 2 and 3 . These tables show the validation of the predicted values of cutting speed found by the SF model with the optimum values of Machining Data Handbook.

Forty different values of wrought carbon steel hardness from (135-380) BHN and depth of cut from (1-5) mm with a cutter diameter of 10 mm are selected for this comparison.

For demonstration purpose, two tool types are used: uncoated brazed carbide (Carbide) tool and high speed steel (HSS) tool.

The SF model is applied to obtain the output cutting speed, and the values are then compared with MDH [7] . The absolute error percentage is calculated for each value, and the mean absolute percentages errors (MAPEs) are obtained for the 40 samples.

The mean absolute percentage error is almost 4% when using high speed steel tool and it is almost 4.5% for carbide tool. The density of the selected samples can be increased, in order to get better results.

6.1 Case Study1: High Speed Steel Tool

The SF model is applied to HSS tool to obtain the output speed, and the values are compared with MDH [7], as shown in table 2 .

The Mean Absolute Percentage Error for FS model applied to high speed steel tool **= 4.173257 %** .

The relationship between the various variables in the model of HSS tool (material hardness, depth of cut and cutting speed) is shown in form of surfaces in figure 12.

Table 2 Comparison of the results from SF model with MDH for high speed steel tool

No.	Material hardness (BHN)		Depth of cut (mm)	Cutting speed (m/min)		
				MDH table	Fuzzy speed selector	Abs error %
1	135-185 Wrought Austenitic Stainless steels	135	0.5	34	33.5	1.470
2			1.5	24	23.0	4.166
3			2.5	21	19.6	6.666
4			5.0	18	19.5	8.333
5		180	0.5	34	33.5	1.470
6			1.5	24	23.0	4.166
7			2.5	21	19.5	7.142
8			5.0	18	19.5	8.333
9	225—275 Wrought carbon steels Annealed or cold drawn	225	0.5	37	35.6	3.783
10			1.5	27	26.6	1.481
11			2.5	24	23.0	4.166
12			5.0	21	19.5	7.142
13		260	0.5	37	35.8	3.243
14			1.5	27	26.6	1.481
15			2.5	24	23.0	4.166
16			5.0	21	19.5	7.142
17	225—275 Hot rolled, normalized, annealed, cold drawn or quenched and tempered	225	0.5	34	35.6	4.705
18			1.5	26	26.6	2.307
19			2.5	23	23.0	0.000
20			5.0	20	19.5	2.500
21		260	0.5	34	35.8	5.294
22			1.5	26	26.6	2.307
23			2.5	23	23.0	0.000
24			5.0	20	19.5	2.500
25	275-325 Wrought medium-carbon alloy steels Normalized or quenched and tempered	275	0.5	26	26.5	1.923
26			1.5	20	19.5	2.500
27			2.5	17	17.0	0.000
28			5.0	15	16.0	6.666
29		310	0.5	26	26.5	1.923
30			1.5	20	20.1	0.500
31			2.5	17	15.9	6.470
32			5.0	15	15.3	2.000
33	320-380 Wrought α +α -β titanium alloys Solution treated and aged	320	0.5	26	26.5	1.923
34			1.5	23	22.0	4.347
35			2.5	12	12.9	7.500
36			5.0	9	10.7	18.888
37		380	0.5	26	26.5	1.923
38			1.5	23	23.0	0.000
39			2.5	12	12.5	4.166
40			5.0	9	10.1	12.222

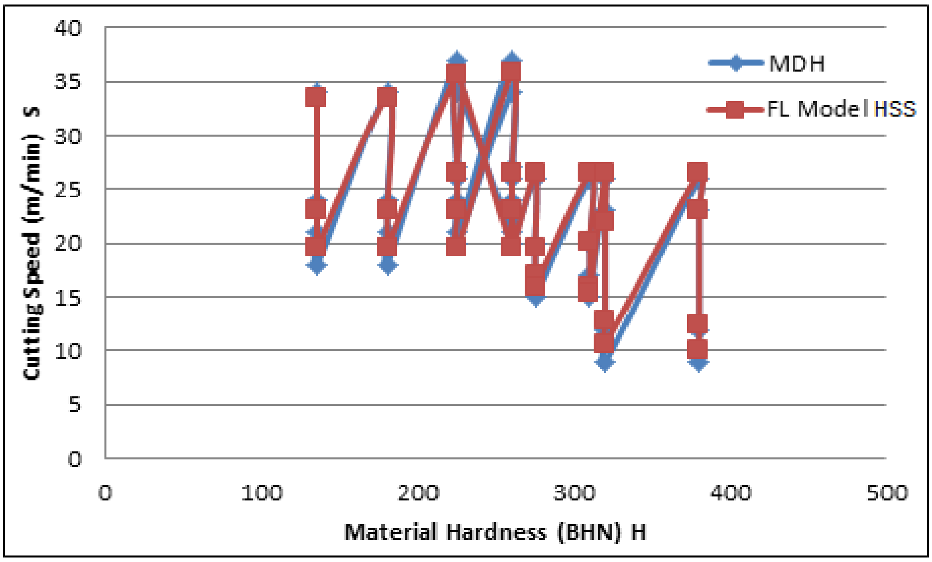

Figure 11 Cutting speed for High Speed Steel tool found by fuzzy model and compared with MDH.

Figure **11** shows the results from Table **2** in a graphical representation. From this figure, it can be seen that the fuzzy cutting speed obtained by the SF model lies close to the recommended values from the MDH.

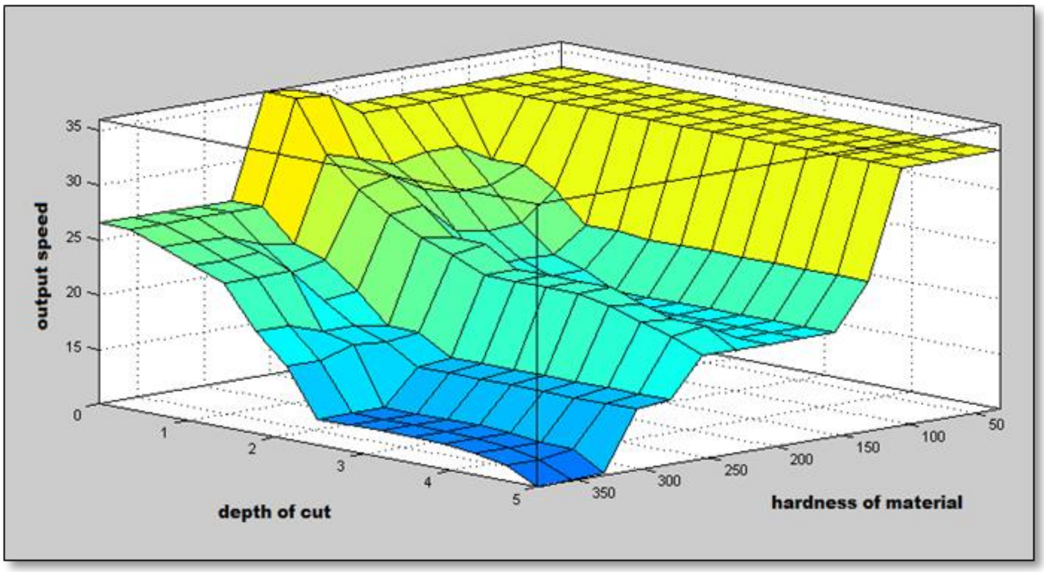

Figure 12 Surfaces represent the relationship between the variables

6.2 Case Study2: Carbide Tool

The SF model is applied to carbide tool to obtain the output speed, and the values are compared with MDH, as shown in table 3 .

Table 3 Comparison of the results from SF model with MDH for Carbide tool

No.	Material hardness (BHN)		Depth of cut (mm)	Cutting speed (m/min)		
				MDH table	Fuzzy speed selector	ABS Error %
1	135-185 Wrought Austenitic Stainless steels	135	0.5	110	111.0	0.909
2			1.5	82	81.8	0.243
3			2.5	72	71.2	1.111
4			5.0	67	71.2	6.268
5		180	0.5	110	111.0	0.909
6			1.5	82	83.5	1.829
7			2.5	72	71.2	1.111
8			5.0	67	71.2	6.268
9	225—275 Wrought carbon steels Annealed or cold drawn	225	0.5	140	135.0	3.571
10			1.5	105	98.8	5.904
11			2.5	90	85.0	5.555
12			5.0	85	85.0	0.000
13		260	0.5	140	135.0	3.571
14			1.5	105	98.8	5.904
15			2.5	90	85.0	5.555
16			5.0	85	85.0	0.000
17	225—275 Hot rolled, normalized, annealed, cold drawn or quenched and tempered	225	0.5	130	135.0	3.846
18			1.5	100	98.8	1.200
19			2.5	85	85.0	0.000
20			5.0	81	85.0	4.938
21		260	0.5	130	135.0	3.846
22			1.5	100	98.8	1.200
23			2.5	85	85.0	0.000
24			5.0	81	85.0	4.938
25	275-325 Wrought medium-carbon alloy steels Normalized or quenched and tempered	275	0.5	95	98.8	4.000
26			1.5	72	71.2	1.111
27			2.5	62	61.3	1.129
28			5.0	58	57.5	0.862
29		310	0.5	95	93.0	2.105
30			1.5	72	70.3	2.361
31			2.5	62	57.5	7.258
32			5.0	58	56.2	3.103
33	320-380 Wrought α +α -β titanium alloys Solution treated and aged	320	0.5	69	70.8	2.608
34			1.5	60	60.6	1.000
35			2.5	38	43.6	14.736
36			5.0	30	41.0	36.666
37		380	0.5	69	71.2	3.188
38			1.5	60	57.4	4.333
39			2.5	38	43.7	15.000
40			5.0	30	34.2	14.000

Mean Absolute Percentage Error (MAPE) for FS model applied to carbide tool = **4.553682%** .

Figure 13, show the results from Table 3 in a graphical representation. From this figure, it can be seen that the fuzzy cutting speed obtained by the SF model lies close to the recommended values from the Machining Data Handbook.

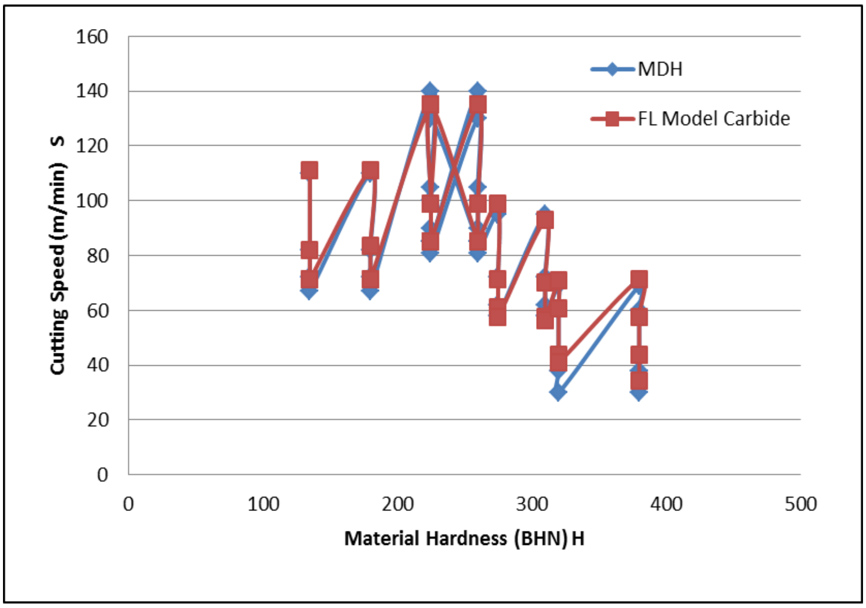

Figure 13 Cutting speed for Carbide tool found by fuzzy model and compared with MDH.

The relationship between the various variables in the model of Carbide tool (material hardness, depth of cut and cutting speed) is shown in form of surfaces in figure 14 .

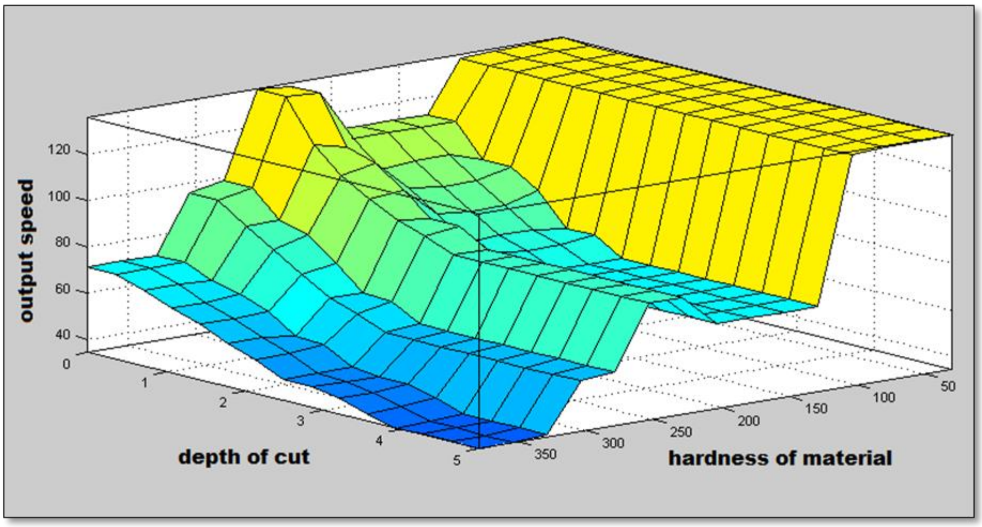

Figure 14 Surfaces represent the relationship between the variables

7. General Discussion

Predicted cutting speed showed not much deviation from the validation data. Overall performance of the FL model in predicting the cutting speed is very good; which is able to produce average 4.17% MAPE for HSS tool, and 4.55% MAPE for Carbide tool.

8. Conclusions and Future Directions

The conclusions resulting from the current study are summarized as follows:

1. In this study, A fuzzy logic using expert rules is used to predict the cutting speed . The fuzzy inference engine used in the model has successfully formulated the input-output mapping, enabling an effective and easy approach for selecting the optimal cutting speed. This approach can be easily expanded to handle more tool-workpiece materials combinations and it is not limited to milling process only and can be used for other machining processes, like turning, drilling, etc.

2. The SF model is user-friendly and compatible with the automation concept of a flexible and computer integrated manufacturing systems. It allows the machinist , even unskilled, to find the optimal cutting speed for an efficient machining process that can lead to an enhancement of the product quality, increasing of the production rates and thus reducing production cost and the total manufacturing costs.

Based on the work presented in this paper, the following recommendations can be suggested for further future investigations:

1. The present study of finding optimum cutting speed using fuzzy logic, can be extended by adding other parameters in input variables, such as diameter of milling cutter which affects the output cutting speed.
2. In addition to cutting speed , other machining parameters also can be calculated using fuzzy logic, such as feed rate .
3. Selection of optimum machining parameters can also be applied in the other machining processes, such as turning , drilling and grinding.

References

1. EL Baradie, M. A. , (1995), *A Fuzzy Logic Model for Machining Data Selection*, Int. J. Mach. Tools and Manuf., 37, PP. 1353-1372 .
2. Wong, S. V. and Hamouda, A. M., (2003), *Machinability Data Representation with Artificial Neural Networks*, Journal. Mater. Process. Technol., 138, PP. 538-544.
3. Hashmi, K., Graham, I.D. and Mills, B., (2000), *Fuzzy Logic Based Data Selection for Drilling Process*. J. Mater. Process. Technol., 108, PP. 55-61.
4. Serope Kalpajian and Steven R. Schmid, (2007), *Manufacturing Processes for Engineering Materials*, 4/e, Pearson Education, Inc.
5. [Online], [Cited: Sep 14, 2013.], available at : http://www.wikipedia.org/
6. Berkan, R.C. and Sheldon, L.T., (1997), *Fuzzy Systems Design Principles: Building Fuzzy IF-THEN Rule Bases*, IEEE Press, New York.
7. Metcut Research Associates,(1980), Institute of Advanced Manufacturing Sciences, Inc., *Machining Data Handbook*, 3rd ed. vol. 1 and 2.