DEVELOPMENT OF FUZZY LOGIC MODEL FOR CUTTING PARAMETERS INFLUENCE ON THE CUTTING FORCE AND THE CHIP THICKNESS RATIO DURING TURNING OF ALUMINUM ALLOY 1350-O

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ABSTRACT

In turning operation, numerous parameters are utilized to analyze machinability. Parameters, for instant, tool wear, tool life, cutting temperature, machining force components, power consumption, surface roughness, and chip thickness ratio are frequently utilized. The goal of this work is to model the effect of cutting parameters (cutting speed, depth of cut and feed rate) on the machining force and chip thickness ratio during turning ductile aluminum 1350-O. Four fuzzy logic models were built to model the relationship between cutting parameters and the three force components of machining force and the chip thickness ration. The inputs to all fuzzy logic models are cutting speed, depth of cut and feed rate. Whereas, the output for first, second, third and fourth models are cutting force, passive force, feed force and chip thickness ratio, respectively. All fuzzy models showed good match to the experimental data and the computed correlation coefficients were larger than or equal 0.9998. Those models were used to optimize the cutting process and give the optimum cutting parameters.

KEYWORDS : Machining forces, chip thickness ratio, fuzzy logic regression, optimization, turning operation.

تطوير نموذج المنطق الضبابي لنمذجة تأثير متغيرات القطع على قوة القطع ونسبة سمك النحاتة أثناء خراطة سبيكة الألومنيوم *1350-O*

مهند محمد الخفاجي

الخلاصة:

لتحليل قابلية التشغيل في عملية الخراطة يتم دراسة متغيرات متعددة مثل تآكل عدة القطع وعمر أداة القطع ودرجة حرارة القطع ومركبات قوى القطع واستهلاك الطاقة وخشونة السطح ونسبة سمك النحاتة. الهدف من البحث هو بناء نموذج لدراسة تأثير متغيرات القطع (سرعة القطع وعمق القطع ومعدل التغذية) على قوة التشغيل ونسبة سمك النحاتة. تم بناء أربعة نماذج المنطق الضبابي، ثلاثة نماذج استخدمت لتمثيل العلاقة بين متغيرات القطع ومركبات قوة التشغيل والرابع استخدم لتمثيل العلاقة بين متغيرات القطع ونسبة سمك النحاتة. ان المدخلات لجميع نماذج المنطق الضبابي هي سرعة القطع وعمق القطع ومعدل التغذية. بينما المخرجات لنموذج الأول والثاني والثالث والرابع هي قوة القطع وقوة الغير فعالة وقوة التغذية ونسبة سمك النحاتة، على التوالي. جميع النماذج التي تم بنائها أظهرت تطابق جيد مع النتائج العملية وكان معامل الارتباط لها اكبر من (0.9998). استخدمت هذه النماذج التي تم بنائها للحصول على أفضل قيم لمتغيرات القطع .

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INTRODUCTION

The turning operation is one of the important cutting operation that used to produce different types of cylindrical products such as solid shafts, hollow shafts, profile shafts, threads, etc. Because of its important, many researchers considered the parameter that affecting the process, either to produce a good finished product, increase the tool life or both. In addition, they are taking into account the power consumption reduction and the production time.

The machining force (F_u) in turning operation is a 3D vector represented by three components, namely, the cutting force (F_c) which is in the cutting direction, the passive force (F_p) in the radial direction and feed force (F_f) in the feed direction. The cutting force has the greatest value in the machining force components. Many researchers considered these components and taking into accounts the effect of cutting parameters. Stachurski, et al. [2012] modeled the cutting force using a power polynomial during turning C45 Steel. Astakhov and Xiao [2008] presented mathematical models to compute the cutting forces for two materials, AISI bearing steel E52100 and aerospace aluminum alloy 2024 T6. Agustina, et al. [2013] applied a design of experiment to analyze the effect of cutting parameters on the cutting force when turning aluminum alloy (UNS A97075) in dry conditions. They investigated the influence of micro groove shape and size on the cutting temperature, cutting force and tool wear. C.X.Yue, et al. [2009] build a 3D model using Abaqus/Explicit to simulate the cutting process of PCBN tool cylindrical cutting hardened steel GCr15. In their model the cutting force, cutting temperature, surface residual stresses and the side flow were investigated.

The chip thickness ratio (CTR) gives significant indication for the cutting process stability. It can be defined as the ratio between the chip thickness to the undeformed chip thickness and is always higher than unity $(CTR > 1)$. From the definition, the higher CTR means the chip is thicker and this is because of the restriction to the chip movement accordingly leads to increase in the machining energy and vice versa. Santos, et al. [2015] investigated the behavior of the machining force (Fu), chip thickness ratio (CTR), and chip disposal when turning ductile (1350-O grade) and of high strength (7075-T6 grade) aluminum alloys at various cutting conditions. Astakhov & Shvets, [2004] considered the effect of cutting parameters on the chip compression ratio.

Fuzzy logic can be used for relating the system inputs and outputs. It widely used to build up rule based expert systems in complicated process modelling that are difficult to be modeled analytically under various assumptions Kovac, et al., [2014], Fuzzy logic may be used to construct process models based on the knowledge and expertise of human operators. Hence, the main characteristic of fuzzy logic is to handle any complicated problem and reflect the human thinking style. With regards to the purpose, it is shown in literature review that fuzzy logic can be handy tools in representing and modeling a machining process for most purposes. Based on the literature, it could be figured that fuzzy logic is found in modeling of machining process to resolve machining problems such as predicting surface roughness in term of machining performance, optimizing tool life in machining process, control machining parameter of machining process, collection of machining parameters, and monitoring tool maximize and wear Adnan, et al., [2013]. Kovac, et al., [2014] constructed multi inputs-multi outputs fuzzy inference system to model the relationship between cutting parameters (cutting speed, depth of cut, feed rate and flank wear) as inputs and provide two outputs (tool life and cutting temperature) in face milling. Kuram and Ozcelik, [2003] used the fuzzy logic regression to predict the thrust force and surface roughness as responses to vegetable based cutting fluids (VBCFs) in drilling operation. Tanikić, et al. [2016] optimize the cutting parameters to get optimum cutting temperature using fuzzy logic and response surface method. Datta and Majumder [2010] developed multi objective evolutionary algorithm based optimization technique, to optimize cutting parameters (cutting speed, feed, and depth of cut) in turning operation. Genetic algorithm (GAs) technique applied to optimize cutting parameters for two conflicting objectives (operation time and tool life). Li, et al. [2012] used the adaptive network fuzzy inference system (ANFIS) and support Vector machine (SVM) to model the tool wear and cutting parameters in high speed milling of Inconel 718.

This work aims to construct fuzzy logic based model to compute the effect of cutting parameters (cutting speed, depth of cut and feed rate) on the machining force (F_u) and chip thickness ratio (CTR) during turning ductile aluminum 1350-O.

EXPERIMENTAL DATA

The experimental data used in this work are taken from Santos, et al., [2015]. The workpieces are cylindrical extruded bars from aluminum alloy 1350-O in the annealed condition with additive elements given in Table 1. The experiments where conducted on CNC lath machine ROMI Multiplic 35D using 6% concentration of soluble oil with 360 l/h. The cutting tool used has an ISO designation of (TCGT16T308-AZ HTi10) which is cemented carbide inserts recommended for aluminum alloy. The tool holder used in the experiments is manufactured by Mitsubishi has designation of (STGCR2020K16Z). Tool geometries were as follows: relief angle, $\alpha_0 = 7°$; rake angle, $\gamma_0 = 15°$, and approach angle, $\chi_r = 90°$, these angles were measured after mounting the insert on the tool holder. A force dynamometer and a signal amplifier manufactured by Kistler Company both have model no. (9265B) and (5019B), respectively. An USB 6251 data acquisition board from National Instruments controlled by LabVIEW® 9.0 software were used for recording the data. After the cutting conditions are reaching a steady-state level, the data recorded at 6kHz sample rate for 10s period. The system was calibrated before using it. The machining parameters that considered in this work are cutting speed (v_c) depth of cut (a) and feed rate (f). For each parameter five level were specified, for cutting speed, v_c, (117, 200, 400, 600, and 683 m/min), for depth of cut, a, (0.38, 1.00, 2.50, 4.00, and 4.62 mm) and for feed rate, f, (0.170, 0.200, 0.275; 0.350; and 0.380 mm/rev). The measured data for each experiment are cutting force, F_c, passive force, F_p, feed force, F_f, and chip thickness ratio, CTR. The experimental data used in this work shown in

Table 2. The experiments no 8, 9, 10 and 11 shown in the table are repeated, the average of their outputs was taken in the modeling.

FUZZY LOGIC MODELING

A fuzzy modelling like other modelling technique provides mapping from input to output. To construct a fuzzy model, first the expert knowledge in the verbal form, based on the relation between sets of input-output variables, is translated into if-then rules. Parameters of this structure, such as membership functions and weights of rules, can be tuned by using input and output data Marza and Seyyedi, [2009].

It is difficult or impossible to effectively model complicated natural operations or built systems by using a conventional nonlinear numerical procedure with limited preceding knowledge. Fortunately, for situations such as these, fuzzy modeling is very sensible and may be used to create a model for the such system using the "limited" available information. Batch least squares, recursive least squares, gradient method, learning from example (LFE), modified learning from example (MLFE), and clustering method are some of the algorithms available for developing a fuzzy model Ross, [2004]. All these algorithms assume automatic construction to the fuzzy inference system.

In this work, manual method is used to build the fuzzy inference system, using MS Excel and MATLAB software. At first the membership function for the input parameters are constructed using triangular membership which can be represented by three parameters a, b and c and given by (1) Zhao, et al., [2002]

$$f(x,a,b,c) = \max\left\{min\left\{\frac{x-a}{b-a}, \frac{c-x}{c-b}\right\}, 0\right\} \quad (1)$$

This stage of the fuzzy inference system called fuzzification. The membership function for cutting speed, depth of cut and feed rate shown in Fig. 1. These are input parameters in the fuzzy system. Each membership has five sets that defined as very low (VL), low (L), medium (M), high (H) and very high (VH). These linguistic presentations will be used to set the fuzzy rules. Four Mamdani fuzzy logic models were built to relate the input parameters to the responses output which are F_c, F_p, F_f and CTR. The membership functions for the outputs responses are shown in Fig. 2. They all divided into nine sets defined as very very low (VVL), very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH) and very very high (VVH). It should be noted that all membership functions are generated with half overlapping automatically by using Matlab fuzzy toolbox and they tuned manually to give the best fitting. The second stage in fuzzy logic inference system construction is building the fuzzy rules. The fuzzy reasoning system consist from a group of $IF — THEN$ statements, in this case take three inputs (V_c, a and f) and one output for each model (F_c, F_p, F_f and CTR). Consequently, the final form of rule base system is:

$$R_1\colon\ IF\ V_c\ is\ A_i\ AND\ a\ is\ B_i\ AND\ f\ is\ C_i\ THEN\ output\ is\ D_i \tag{2}$$

Where A_i, B_i, C_i and D_i are the linguistic values defined by fuzzy sets on the ranges, V_c, a, f and the output, respectively. These described by fuzzy memberships defined earlier. Whereas, the output represents the mentioned responses (F_c, F_p, F_f and CTR)

The fuzzy rules were build using excel visual data presentation shown in

Table 3. This way helps to visually constructing the fuzzy rules after sorting the experiments in ascending manner depending on the output data. As it is shown in

Table 3 the colored bars describe the rule how should be built, for instance, the experiment no 1 shows that the cutting speed is M, the depth of cut is VL, the feed rate is M and the cutting force is VVL. So, the rule will be

$$if\ V_c\ is\ M\ and\ a\ is\ VL\ and\ f\ is\ M\ then\ F_c\ is\ VVL \tag{3}$$

All rules for four models are created in the same way and their weights are one. These weights are tuned to give the best fit to the responses. As mentioned in advance four fuzzy logic models have been built in this work, the rules and the rules weights (w) for F_c,F_f, F_p and CTR are given in Table 4,Table 5,Table 6 and Table 7, respectively.

The rules implications used in this work is the MIN function. Using Mamdani implication method, each rule in the former set of rules can be viewed as a fuzzy implication, in order that the ith rule can be explained as:

$$\mu_{D_i} = \min[\mu_{A_i}(V_c), \mu_{B_i}(a), \mu_{C_i}(f)] \tag{4}$$

The fuzzy rule aggregation method used in all four models is MAX function, the rule implication and aggregation equation can be described as:

$$\mu_{R_i} = \max\left[min\left[\mu_{A_i}(V_c), \mu_{B_i}(a), \mu_{C_i}(f)\right]\right] \tag{5}$$

This is called Mamdani (max-min) inference system (Ross, 2004). The final stage in fuzzy modeling is the defuzzification to get the desired crisp output. The centroid method is used as the defuzzification of the four models can be given as (Kovac, et al., 2014):

$$y^* = \frac{\sum y \cdot \mu_{R_i}(y)}{\sum \mu_{R_i}(y)} \tag{6}$$

Where y^* is the defuzzified (crisp) output, this output corresponds to the specified model. In other words, it is either F_c, F_p, F_f or CRT.

RESULTS AND DISCUSSION

The correlation coefficient R have been used to measure how the models' outputs are close to the experimental data. The correlation coefficient can be expressed as Marza & Seyyedi, [2009]:

$$R = \frac{n \sum x_i\, y_i - \sum x \sum y}{\sqrt{[n \sum x_i^2 - (\sum x_i)^2][n \sum y_i^2 - (\sum y_i)^2]}} \tag{7}$$

The correlation coefficients for all models are calculated using (7). They were 0.99996, 0.99999, 0.99998 and 0.9999761 for F_c, F_p, F_f and CTR responses, respectively. Fig. 3, Fig. 4, Fig. 5 and Fig. 6 show the outputs of the constructed fuzzy logic models against the experimental data for F_c, F_f, F_p and CTR, respectivly. The F_u is the resultant of the three components as mentioned in advance could be calculated from

$$F_u = \sqrt{F_c^2 + F_p^2 + F_f^2} \tag{8}$$

Fig. 7 shows the machining force computed from the fuzzy logic models output versus machining force computed from experimental data. The correlation coefficient R for F_u is 0.99998. Comparing the results of the fuzzy models with the results given in Santos, et al., [2015]. Table 8 shows the square correlation coefficient for the machining force and the chip thickness ratio for the current work and the result from Santos, et al., [2015]. From Table 8 the fuzzy models showed good results and can be used for prediction and optimization purpose.

All fuzzy logic models are fitting the experimental data and can be used for prediction purposes. These models where used to optimize the cutting parameters. A Matlab function has been built to find the optimum machining parameters that give the minimum machining force F_u and minimum chip thickness ration CTR. The function generates three vectors. The first one store 100 elements for cutting speed V_c in the rang [117,683], the second vector has 100 elements for the depth of cut a in the rang [0.38, 4.62] and the third vector present the feed rate f in the range [0.17, 0.35]. In addition, the function creates two three dimensional arrays with (100,100,100) in size. The first array stores the result of machining force that computed from the combination of the three input vectors, at the same time the CTR is computed and stored in the second array. The minimums of the two arrays are the optimum for both machining force and CTR, and the corresponding parameter represent the optimum cutting conditions. The optimum cutting conditions are shown in Table 9 with their corresponding optimum machining force and optimum chip thickness ratio. It can be seen both the optimum value of V_c and a are same for F_u and CTR, whereas, the feed rate is differing slightly.

CONLUSION

The results of this work showed that the fuzzy logic models can be used to model machining operation, farther more can be used to model any process with any number of independent variables.

In additions, the method used to build the fuzzy rule is effective and can be used to simplify the construction of fuzzy inference system. This method can be developed to create fuzzy regression algorithm in future works.

Table 1 the alloying elements for the

Component name	Fe	Si	Cu	Zn
%	0.4	0.1	0.05	0.05

Table 2 Machining experiment results taken from (Santos, et al., 2015)

No	Input			Measured			
	$V_c(\frac{m}{min})$	a (mm)	f $(\frac{mm}{rev})$	$F_c(N)$	$F_p(N)$	$F_f(N)$	CTR
1	117	2.5	0.275	783	170	640	8.3
2	200	4	0.2	792	45.7	324	9.83
3	200	4	0.35	1230	75.1	441	7.14
4	200	1	0.2	197	47.5	74.1	5.58
5	200	1	0.35	311	72.3	108	3.24
6	400	4.6	0.275	980	60	650	7.09
7	400	2.5	0.17	416	54.6	280	6.51
8	400	2.5	0.275	594	83.4	415	6.79
9	400	2.5	0.275	611	89.2	425	7.27
10	400	2.5	0.275	646	92.5	482	6.79
11	400	2.5	0.275	661	102	540	7.27
12	400	2.5	0.38	768	123	584	5.82
13	400	0.38	0.275	35	27.1	9.55	2.67
14	600	4	0.2	682	37.6	234	5.92
15	600	4	0.35	986	23.1	230	5.33
16	600	1	0.2	145	18	41.3	3.42
17	600	1	0.35	236	31.2	52.7	2.95
18	683	2.5	0.275	493	49.4	297	4.42

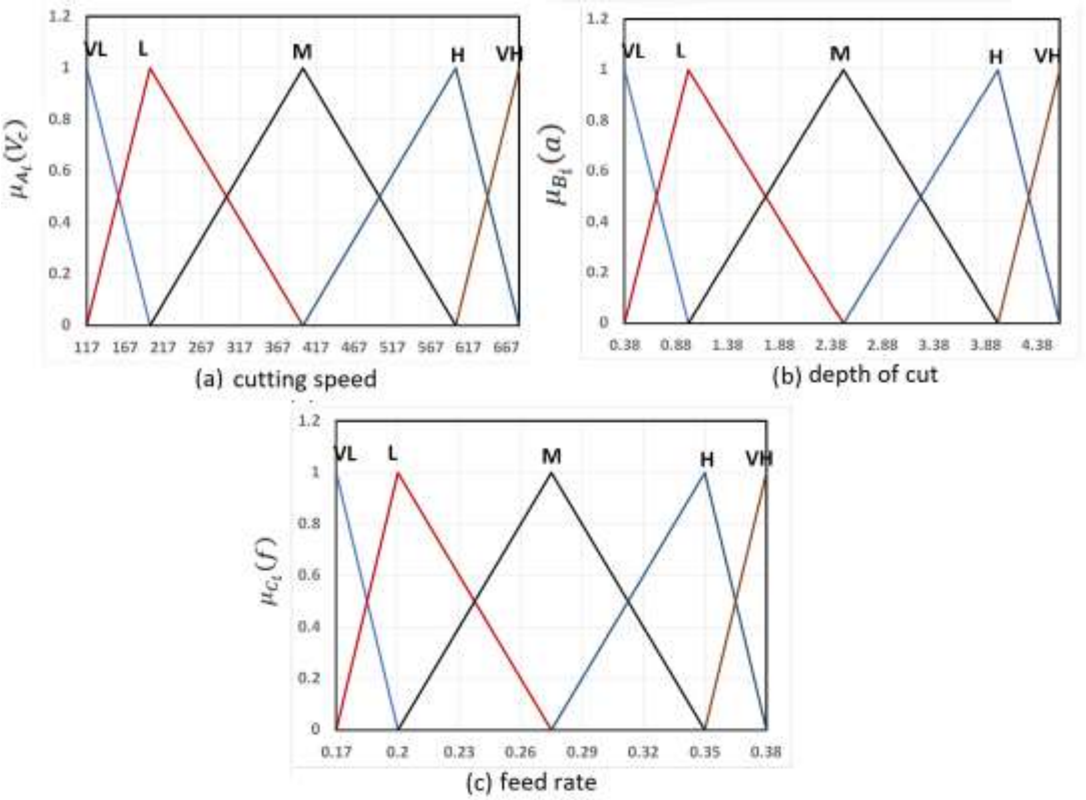

Fig. 1. Membership functions for the input parameters (a) cutting speed (b) depth of cut (c) feed rate

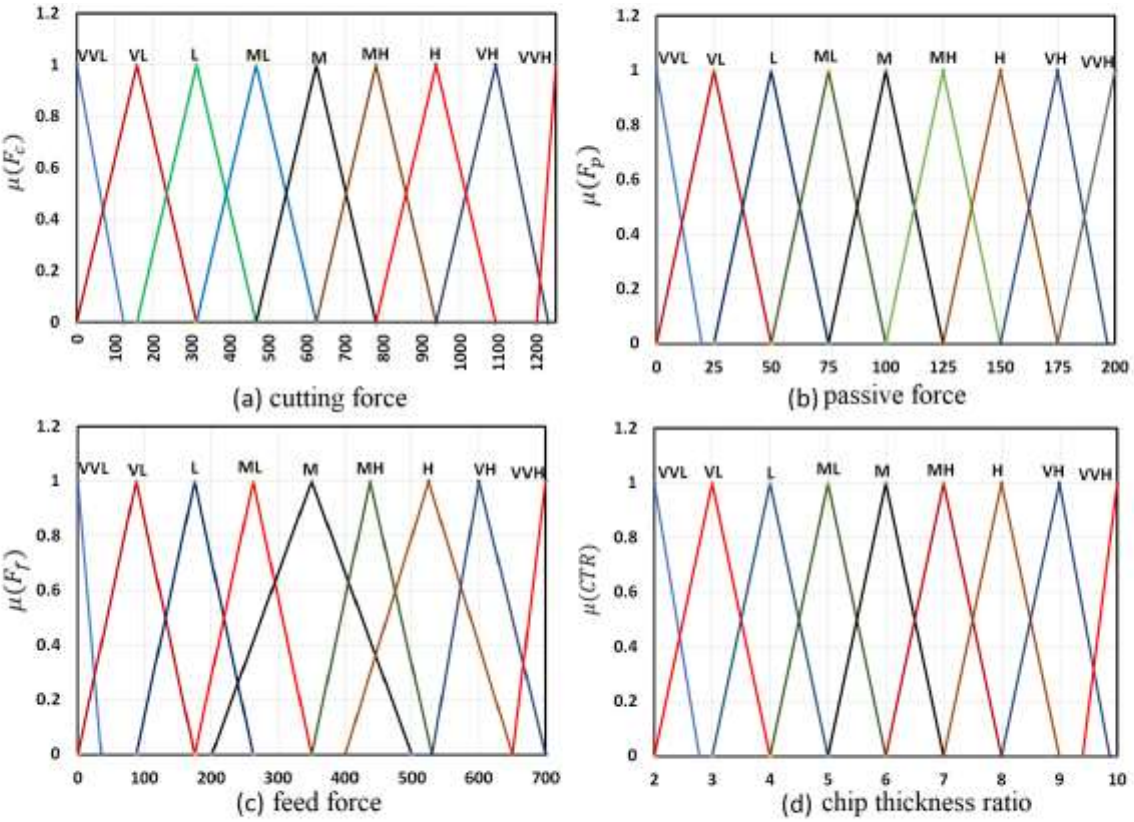

Fig. 2. Output membership functions (a) cutting force (b) passive force (c) feed force (d) chip thickness ratio

Table 3 arranged results data for cutting force

	Vc	a	f	Fc (N)
1	400	0.38	0.275	35
2	600	1	0.2	145
3	200	1	0.2	197
4	600	1	0.35	236
5	200	1	0.35	311
6	400	2.5	0.17	416
7	683	2.5	0.275	493
8	400	2.5	0.275	594
9	400	2.5	0.275	611
10	400	2.5	0.275	646
11	400	2.5	0.275	661
12	600	4	0.2	682
13	400	2.5	0.38	768
14	117	2.5	0.275	783
15	200	4	0.2	792
16	400	4.6	0.275	980
17	600	4	0.35	986
18	200	4	0.35	1230

Table 4 cutting force fuzzy logic model rules and their weights

No	V_c	a	f	F_c	w
1.	M	VL	M	VVL	1
2.	H	L	L	VL	1
3.	H	L	L	VVL	0.32
4.	L	L	L	VL	1
5.	L	L	L	L	0.26
6.	H	L	H	L	1
7.	H	L	H	L	0.67
8.	L	L	H	L	1
9.	L	L	H	ML	0.018
10.	M	M	VL	ML	1
11.	M	M	VL	L	0.275
12.	VH	M	M	ML	1
13.	VH	M	M	M	0.17
14.	M	M	M	M	1
15.	M	M	M	MH	0.06
16.	H	H	L	MH	0.55

No	V_c	a	f	F_c	w
17.	H	H	L	M	1
18.	M	M	VH	MH	1
19.	M	M	VH	M	0.005
20.	VL	M	M	MH	1
21.	VL	M	M	H	0.07
22.	L	H	L	MH	1
23.	L	H	L	H	0.115
24.	M	VH	M	H	1
25.	M	VH	M	VH	0.4
26.	H	H	H	H	1
27.	H	H	H	VH	0.5
28.	L	H	H	VVH	0.5

Table 5 feed force fuzzy logic model rules and their weights

No	V_c	a	f	F_f	w
1.	M	VL	M	VVL	1
2.	H	L	H	VL	0.14
3.	L	L	L	VL	0.85
4.	L	L	H	VL	1
5.	L	L	H	L	0.2
6.	H	H	H	L	1
7.	H	H	H	ML	1
8.	H	H	H	M	0.06
9.	H	H	L	L	1
10.	H	H	L	ML	1
11.	H	H	L	M	0.08
12.	M	M	VL	ML	0.5
13.	M	M	VL	M	0.06
14.	VH	M	M	ML	1
15.	VH	M	M	M	0.18
16.	L	H	L	ML	1
17.	L	H	L	M	1
18.	M	M	M	M	0.2
19.	M	M	M	MH	1
20.	M	M	M	H	1
21.	L	H	H	M	0.5
22.	L	H	H	MH	1
23.	L	H	H	H	1

No	V_c	a	f	F_f	w
24.	M	M	VH	VH	1
25.	M	M	VH	H	0.15
26.	VL	M	M	VH	0.2
27.	VL	M	M	VVH	1
28.	M	VH	M	VVH	1
29.	H	L	L	VL	0.08
30.	H	L	L	VVL	1
31.	H	L	H	VVL	1
32.	L	L	L	VVL	1
33.	M	VH	M	VH	0.15

Table 6 passive force fuzzy logic model rules and their weights

No	V_c	a	f	F_p	w
1.	H	L	L	VVL	1
2.	H	L	L	VL	0.34
3.	H	H	H	VL	1
4.	H	H	H	VVL	0.39
5.	M	VL	M	VL	1
6.	M	VL	M	L	0.06
7.	H	L	H	VL	1
8.	H	L	H	L	0.24
9.	H	H	L	L	1
10.	H	H	L	VL	1
11.	L	H	L	L	1
12.	L	H	L	VL	0.14
13.	L	L	L	VL	0.07
14.	L	L	L	L	1
15.	VH	M	M	L	1
16.	VH	M	M	VL	0.02
17.	M	M	VL	L	1
18.	M	M	VL	ML	0.15
19.	M	VH	M	ML	0.48
20.	M	VH	M	L	1
21.	L	L	H	ML	1
22.	L	L	H	L	0.08
23.	L	H	H	ML	1
24.	M	M	M	M	1
25.	M	M	VH	M	0.08
26.	M	M	VH	MH	1
27.	VL	M	M	VH	1
28.	VL	M	M	H	0.13
29.	M	M	M	ML	0.335

Table 7 Chip thickness ratio fuzzy logic model rules and their weights

No	V_c	a	f	CTR	w
1.	M	VL	M	VVL	1
2.	M	VL	M	VL	0.26
3.	H	L	H	VL	1
4.	H	L	H	VVL	0.2
5.	L	L	H	VL	1
6.	L	L	H	L	0.2
7.	H	L	L	L	0.5
8.	H	L	L	VL	1
9.	VH	M	M	L	1
10.	VH	M	M	ML	0.52
11.	H	H	H	ML	1
12.	H	H	H	M	0.33
13.	L	L	L	ML	0.5
14.	L	L	L	M	1
15.	M	M	VH	M	1
16.	M	M	VH	ML	0.15
17.	H	H	L	ML	0.06
18.	H	H	L	M	1
19.	M	M	VL	M	1
20.	M	M	VL	MH	1
21.	M	M	M	MH	1
22.	M	VH	M	MH	1
23.	M	VH	M	H	0.065
24.	L	H	H	H	0.11
25.	L	H	H	MH	1
26.	VL	M	M	H	1
27.	VL	M	M	VH	0.35
28.	L	H	L	VVH	1

Table 8 Fuzzy models R^2 versus R^2 from (Santos, et al., 2015).

	R^2 for F_u	R^2 for CTR
Fuzzy model of this work	0.999961	0.999952
Results from (Santos, et al., 2015)	0.9901	0.9907

Table 9 the optimum parameters and their corresponding optimum values from F_u and CTR

	$V_c\left(\frac{m}{min}\right)$	$a(mm)$	$f\ (\frac{mm}{rev})$	Optimum value
F_u	397.1414	0.38	0.2755	46.6 N
CTR	397.1414	0.38	0.3136	2.63

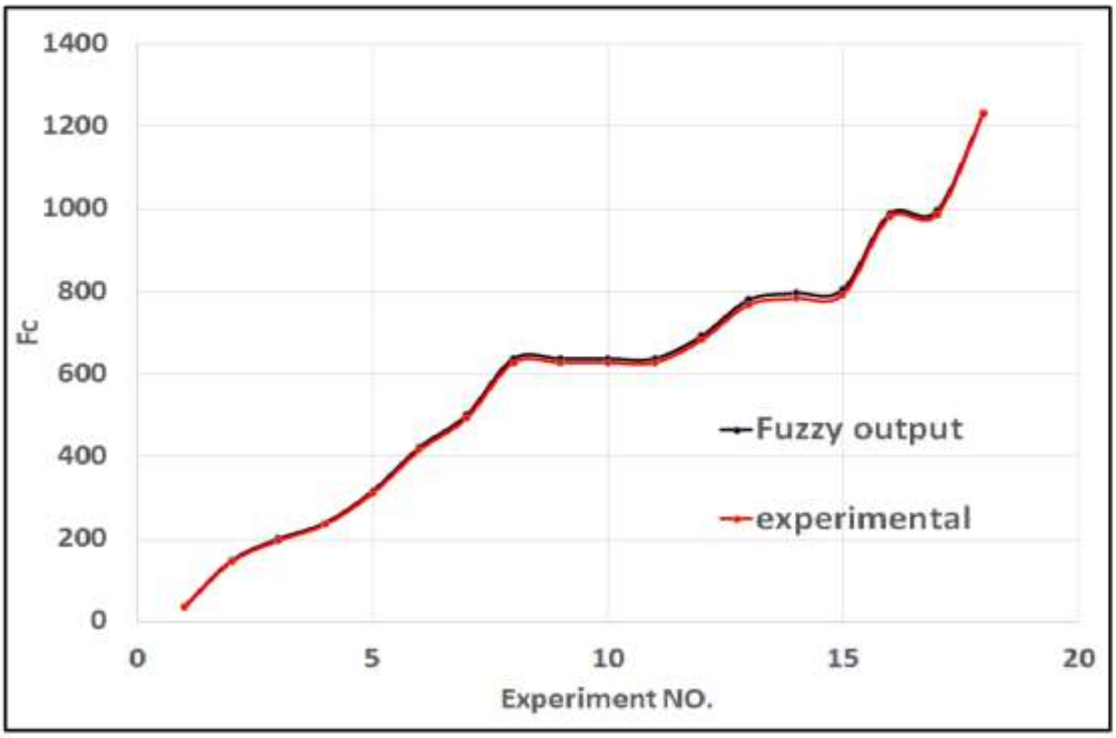

Fig. 3. The fussy logic models outputs against the experimental data for cutting force.

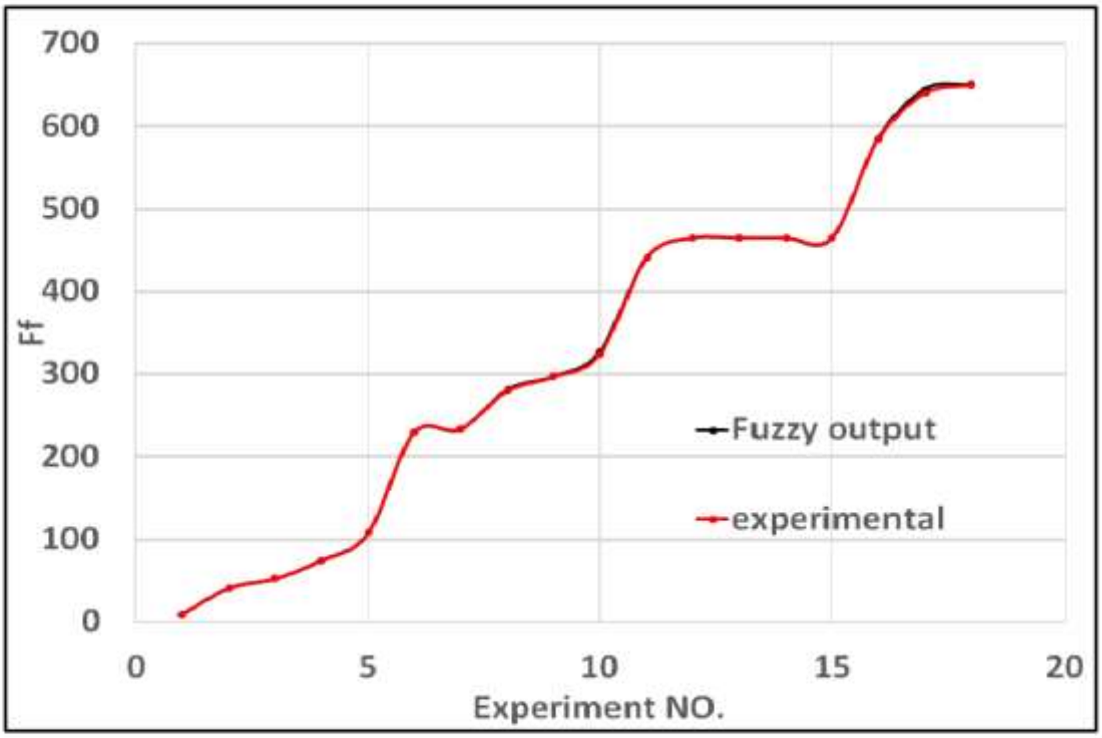

Fig. 4. The fussy logic models outputs against the experimental data for feed force.

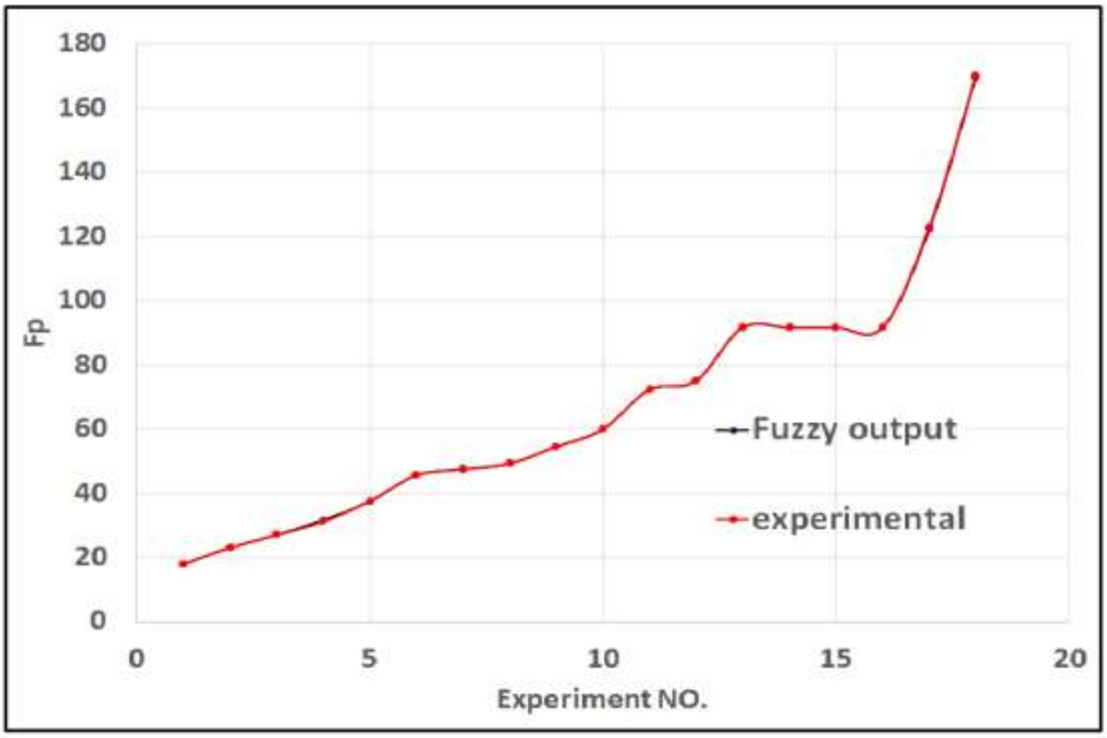

Fig. 5. The fussy logic models outputs against the experimental data for passive force

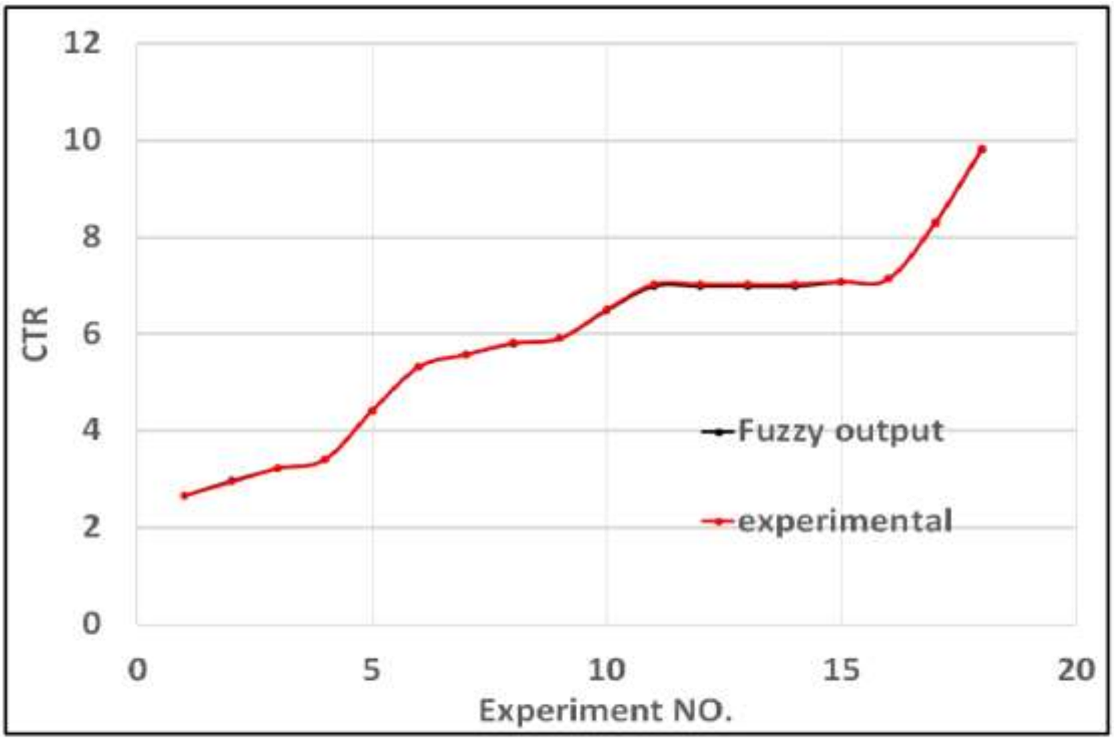

Fig. 6. The fussy logic models outputs against the experimental data for chip thickness ratio

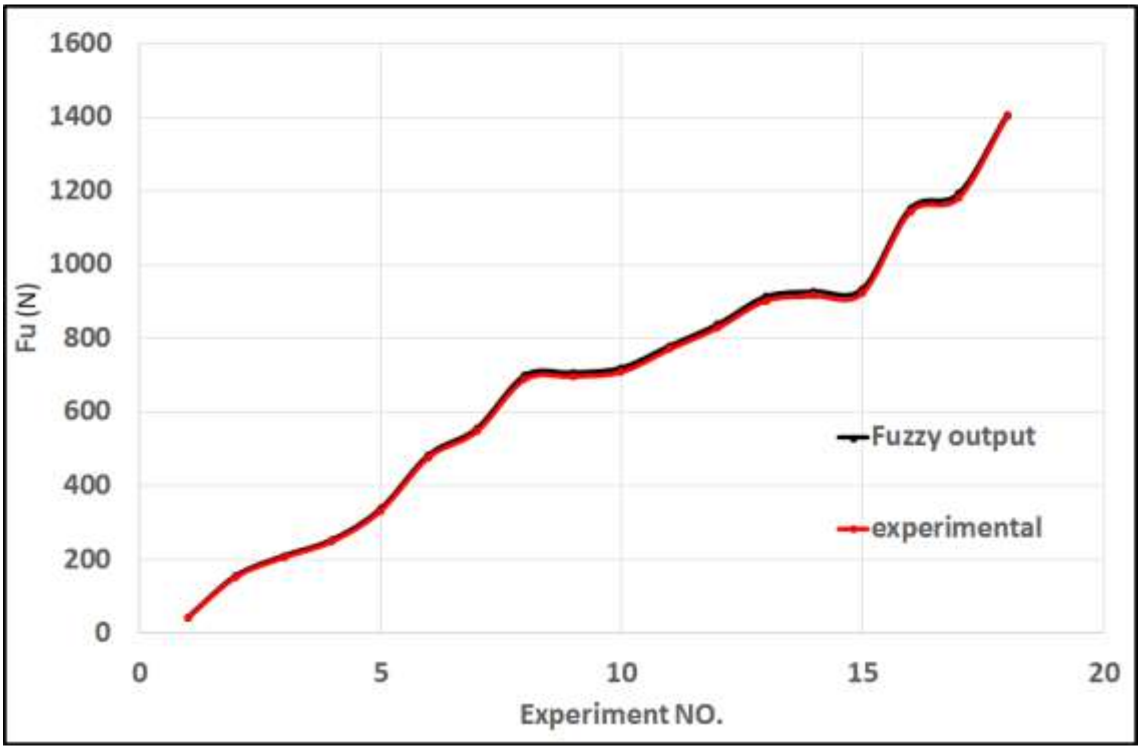

Fig. 7. the machining force computed form the fuzzy outputs against machining force computed from experimental data

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