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A Fuzzy Approach for Selecting Optimal End Milling Parameters

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Abstract

In this paper, a fuzzy modeling technique is used for the selection of end milling parameters for a required surface roughness (*Ra*) with maximum material removal rate (*MRR*). Spindle speed (*N*), feed rate (*fr*) and depth of cut (*d*) are the inputs and outputs are MRR and SR. Three different levels of each input parameter were used to curry out the experimental work under dry conditions. Optimal sets of parameters were identified using artificial neural network (ANN) for prediction followed by genetic algorithm (GA) multi-objective for optimization. Fuzzy logic model (FLM) was then used to develop a fuzzy rule base in the form of IF-THEN rules for the selection of cutting parameters. The performance of the developed model was evaluated through a validation test. The results show that the average errors of the FLM are 2.463% and 6.08% for *Ra* and *MRR* respectively, which is less than 10%.

Keywords

Artificial Neural Network, Genetic Algorithm, Multi-objective, Fuzzy Logic Model

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1. Introduction

Determination of optimal machining parameters is a continuous engineering task in order to achieve the desired product quality with high productivity at low cost [1].

Quality and productivity are two important but conflicting criteria in any machining operation. The improvement of one factor is not possible without the worsening of the other one [2]. Indeed, an increase in productivity results in reduction of machining time which may results in quality loss. On the contrary, an improvement in quality results in reduction in machining time thereby, reducing productivity. Therefore, it is essential to optimize quality and productivity simultaneously by selecting the most appropriate (optimal) machining settings [3]. In this perspective, this work considers surface roughness (SR) and material removal rate (MRR) as the machining process responses to be optimized.

Surface roughness and material removal rate are two important aspects in machining because these two factors greatly influence the process performances [3].

Surface roughness (SR) is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost [4], [5].

Material removal rate (MRR) indicates the processing time of the workpiece and greatly influences the production rate and cost [3].

Both the surface roughness and material removal rate greatly vary with the change of cutting process parameters, namely feed, depth of cut, and cutting speed. Feed and depth of cut have upper limitations related to the maximal mechanical load that can be applied on the tool, thereby defining a mechanical barrier. Cutting speed has an upper limitation related to the maximal thermal load that the tool can withstand, thereby defining a thermal barrier. Therefore, the

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selected cutting tool sets limitations on cutting parameters for a certain workpiece material [3], [6].

The selection of the cutting parameters in a machining operation is a key step to achieve high efficiency and productivity. In practice, the machining parameters are usually selected based on the machine tool operators or/and part programmer's judgment and experience, machining handbooks or trial-and-error method. These methods are not accurate enough and in many cases, production systems run under inefficient operating conditions [6-8]. Therefore, proper selection of process parameters is an essential issue for manufacturing industries in order to improve cutting efficiency, process at low cost and produce high-quality products [9].

Multi-objective approach which consider simultaneously surface roughness and material removal rate as process responses have been reported in milling parameters optimization. A non-exhaustive list is given below.

[10] used Taguchi method to optimize the process parameter in the milling process for AISI steel. L_9 orthogonal design was selected to form the experimental design for response parameters. The experiments were conducted by using ball end mill cutter. Process parameters were varied to study their effect on material removal rate and surface roughness. Collected results were analyzed by the main effect plot and interaction plot. Finally, process parameters were optimized to achieve the maximum MRR and minimum Ra. The confirmation test reveals a good agreement between prediction and experimental results.

The research work presented by [11] determines the setting of process parameters of focused ion beam (FIB) micro-milling for achieving a specific combination of MRR and surface roughness on cemented carbide. The experiment has been conducted according to the L_{16} orthogonal array of Taguchi technique. Beam current, extraction voltage, angle of beam incidence, dwell time and percentage overlap between beam diameters have been considered as process variables. Multi-objective optimization for material removal rate and surface roughness has been carried out using genetic algorithm toolbox of matlab. The percentage errors between experimental and empirical values have been found to be less than 10% for both MRR and surface roughness.

In their work, [12] defined an approach to determine the best cutting parameters leading to minimum surface roughness and maximum material removal rate by using various milling machine parameters such as spindle speed, feed rate, and depth of cut. Machining operations were conducted on Al (2024-T4) plates using a CNC End milling and the response characteristics were studied. In this experimentation the L_9 orthogonal array was selected based on the DOF. ANOVA has been performed and compared with Taguchi method. The optimization process and methodology were found to have the potential to be applied for cutting parameters optimization problems during actual industrial machining process.

Another work conducted by [13] presented an approach for determination of the best cutting parameters leading to minimum surface roughness and maximum Material Removal Rate in machining Cast Iron on Machining Centre. The machining parameters selected are spindle speed, feed and depth of cut. Experiments were conducted at four levels of machining parameters. Surface roughness was measured by using talysurf and material removal rate is calculated. A neural network was generated to predict the surface roughness values. The network created is exported to the multi objective genetic algorithm program written in MATLAB software. The results reveal a good agreement between experimental and predicted values.

[3] proposed application of Principal Component analysis (PCA) coupled with Taguchi method to solve multi-attribute optimization of CNC end milling operation. The experimental work sought to evaluate the optimal result for selection of spindle speed (S), feed rate (f) and depth of cut (d) in order to achieve good surface roughness (Ra value) and high material removal rate (MRR) during the CNC end milling process. The test workpieces are made of Aluminum of size 95 mm x 75 mm x 10mm rectangular plate. Different plates of same dimension and material are used for each experimental run. The experimental work was carried out based on Taguchi's L_9 Orthogonal Array (OA) design. From the study and analyses, the proposed method has been found efficient for solving multi-attribute decision making problem i.e., for multi-objective product as well as process optimization; for continuous quality improvement.

Although these systems can accurately determine the optimal cutting parameters for a desired surface roughness, they do not provide a quick and easy means for the selection of the cutting parameters on the production floor environment. So, it is necessary to move the optimization research to the implementation of a tool that will assist manufacturing engineers in the selection of the cutting parameters.

In this work, it is proposed to apply fuzzy logic (FL) technique to develop an automated manufacturing support system for the selection of end milling parameters for a given surface roughness assuring at the same time a maximal material removal rate (MRR). Artificial neural network (ANN) will be used to predict the process responses based on the process parameters (spindle speed, feed rate and depth of cut). Optimization of the machining parameters will be achieved with genetic algorithm (GA). Finally, an FL inference system will be used as a decision making mechanism to assist the user in the selection of the best process parameters. The system will estimate the optimal machining parameters, namely, spindle speed, feed rate and depth of cut for a given surface roughness with maximal material removal rate.

This paper is organized as follow: Section 2 presents the experimental procedure and provides the results obtained from the experiment. In section 3, the model development procedure and the optimization method are described. Also the prediction and the optimization results are analyzed. Conclusion is drawn in section 4.

2. Experimental Procedure

In this study, a series of end milling operations was conducted on a vertical CNC milling machine (VICTORTEC VNC M5200 HSP) under dry conditions. Three cutting parameters, namely, spindle speed (*N*), feed rate (*fr*), and depth of cut (*d*), each with three levels were used as controllable factors. The cutting parameters are presented in Table 1.

Table 1. Cutting parameters and levels.

Parameters	Level 1	Level 2	Level 3
Spindle speed *N* (rpm)	6000	6500	7000
Feed rate *fr* (mm/min)	100	200	300
Depth of cut *d* (mm)	3	3.5	4

Twenty seven (27) end milling operations were performed to take on all possible combinations of cutting parameters. For the purpose of this study, finishing operation was considered. Therefore, single pass, linear cuts were executed with a cutting length l = 5 mm. The radial depth of cut, also called width of cut, w = 0.1 mm.

The workpiece is a prismatic part of 120x90x20 mm. Two slots have been previously machined in order to allow the cutting tool to access the cutting zone.

The workpiece material used for the experiments is a low carbon SS 400 steel, most frequently used material during design of mechanical mechanism/parts. In JIS (Japanese Industrial Standard), "SS" stands for Structural Steel and 400 grade which is similar to AISI 1018. Typical carbon steel material, SS 400 has most economic value for structure parts and is excelling in welding and machinability and can be subjected to various heat treatments. The material composition is following: carbon (C), not controlled; silicon (Si), not controlled; manganese (Mn), not controlled; phosporus (P), ≤ 0.05%; sulphur (S), ≤ 0.05%.

The milling cutter used is a solid four flutes cobalt-bearing high speed steel HSS Co8 type M42 end mill (hardness = 62-64 HRC) having diameter of 6 mm with Titanium Aluminum Nitride (TiAlN) coating. M42 is a molybdenum-series high-speed steel alloy with an additional 8% cobalt, widely used in metal manufacturing industries because of its superior hot hardness, higher strength and wear resistance as compared to more conventional high-speed steels. TiAlN forms a hard aluminum oxide layer in hot (>800°C), dry machining applications. This further reflects the heat back into the chip and away from the tool and workpiece. The tool material composition is following: carbon (C) 1.08%, chromium (Cr) 3.75%, molybdenum (Mo) 9.6%, tungsten (W) 1.6%, vanadium (V) 1.15%, cobalt (Co) 8.25%.

The roughness average, R_a, was measured off-line using a two dimensional stylus profilometer (Kosaka L SE 3500 K). The measurement was performed for a cutoff length of 0.25 mm, a sampling length equal to cutoff × 5 = 1.25 mm, and a speed of 0.2 mm/s. Five measurements were taken on each machined surface and the average value was calculated.

MRR is determined using the following expression:

$$MRR = d \times w \times f \times z \times N \quad (1)$$

where f is the feed per tooth (mm), N is the spindle speed (rpm), w is the width of cut (mm), and z is the number of flutes on the tool.

The machining data are presented in Table 2.

Table 2. Machining data.

No	*N* (rpm)	*fr* (mm/min)	*d* (mm)	*Ra* (µm)	*MRR* (mm^3/min)
1	6000	100	3	0.548	29.52
2	6000	100	3.5	0.584	34.44
3	6000	100	4	0.586	39.36
4	6000	200	3	0.622	59.76
5	6000	200	3.5	0.624	62.72
6	6000	200	4	0.65	79.68
7	6000	300	3	0.67	89.28
8	6000	300	3.5	0.68	104.16
9	6000	300	4	0.73	119.04
10	6500	100	3	0.534	29.64
11	6500	100	3.5	0.582	34.58
12	6500	100	4	0.608	39.52
13	6500	200	3	0.546	59.98
14	6500	200	3.5	0.596	69.979
15	6500	200	4	0.644	79.976
16	6500	300	3	0.58	89.7
17	6500	300	3.5	0.654	104.65
18	6500	300	4	0.7	119.6
19	7000	100	3	0.474	29.98
20	7000	100	3.5	0.5	34.98
21	7000	100	4	0.606	39.98
22	7000	200	3	0.522	59.99
23	7000	200	3.5	0.558	69.99
24	7000	200	4	0.64	79.99
25	7000	300	3	0.56	89.88
26	7000	300	3.5	0.594	104.86
27	7000	300	4	0.658	119.84

3. Analytical Procedure

3.1. Development of the ANN-Based Prediction Model

The development of the successful model of ANN principally depends on the process of trial and error with some factors to consider [15]. In this study, the Matlab ANN toolbox will be used for the development of the ANN model. Based on the ANN toolbox of Matlab software, the influencing factors are the network algorithm, the transfer function, the training function, the learning function, and the performance function. In addition, the following other factors that can influence the effectiveness of the model are also considered: the network structure, the number of training data, the number of testing data, and the data normalization [14-15].

By limiting the trial-and-error process with one hidden layer, several networks were designed and tested. The Levenberg-Marquadt (LM) algorithm was used for training the algorithm. Hyperbolic tangent sigmoid transfer function (tansig) and linear (purelin) transfer functions have been used for the activation function in the hidden and the output layers respectively. The following network structures have been designed and tested: 3-3-1, 3-6-1 and 3-7-1.

The network of structure 3-7-1 was found to be the most suitable for the present study as it had the lowest mean square error of 2.11248e-21. The regression coefficient (R) was found to be 9.99999e-1, which is close to 1, thus, indicating a strong correlation between the experimental outputs and network outputs. The ANN prediction results are shown in table 3.

Table 3. ANN prediction.

No	*N* (rpm)	*fr* (mm/min)	*d* (mm)	Exp R_a (µm)	ANN Pred.	Error
1	6000	100	3	0.548	0.548	-1.95E-11
2	6000	100	3.5	0.584	0.584	-2.17E-11
3	6000	100	4	0.586	0.589	-0.00344
4	6000	200	3	0.622	0.566	0.056023
5	6000	200	3.5	0.624	0.624	-4.03E-12
6	6000	200	4	0.65	0.65	-1.55E-11
7	6000	300	3	0.67	0.67	5.43E-11
8	6000	300	3.5	0.68	0.68	-2.26E-12
9	6000	300	4	0.73	0.73	4.31E-11
10	6500	100	3	0.534	0.534	-5.49E-11
11	6500	100	3.5	0.582	0.582	2.51E-11
12	6500	100	4	0.608	0.622	-0.01436
13	6500	200	3	0.546	0.546	-3.15E-11
14	6500	200	3.5	0.596	0.596	-2.61E-13
15	6500	200	4	0.644	0.644	-8.23E-12
16	6500	300	3	0.58	0.664	-0.0837
17	6500	300	3.5	0.654	0.654	4.18E-13
18	6500	300	4	0.7	0.7	1.73E-11
19	7000	100	3	0.474	0.474	-4.01E-11
20	7000	100	3.5	0.5	0.5	-1.43E-10
21	7000	100	4	0.606	0.606	7.14E-11
22	7000	200	3	0.522	0.485	0.03713
23	7000	200	3.5	0.558	0.558	-9.32E-12
24	7000	200	4	0.64	0.64	4.55E-11
25	7000	300	3	0.56	0.646	-0.08635
26	7000	300	3.5	0.594	0.632	-0.03766
27	7000	300	4	0.658	0.646	0.012178

3.2. GA-Based Optimization

The performance of GA is dependent on the optimal setting of population size (or initial population, Ps), crossover probability (Pc) and mutation probability (Pm) [11]. For this study, the initial population size has been set to 20. The pareto fraction, which is a fraction of population size has been set to 0.35. For the crossover ratio, 1.0 has been taken. The crossover function has been set for intermediate. The limit of the number of iterations has been set to 1000 to prevent the premature termination of GA before getting the set of optimal solutions.

The two conflicting objectives are minimization of surface roughness and maximization of MRR. The regression analysis for surface roughness and MRR was performed using Excel 2013 software. The regression equations are following:

$$Ra = 0.555452362 - 5.05235E\text{-}05 \times N + 0.000545406 \times fr + 0.077191972 \times d \quad (2)$$

$$MRR = -70.15344444 + 0.34945 \times fr + 19.91733333 \times d \quad (3)$$

where d is the depth of cut (mm), fr is the feed rate (mm/min), N is the spindle speed (rpm), MRR is the material removal rate (mm^3/min), and Ra is the roughness average (µm).

The multiple coefficient of determination, R^2, is 84% and 98% for surface roughness and MRR respectively, indicating that the multiple regression equation fit the sample data. The small value of the significance factor, 2.42341E-09 and 8.13148E-23 for Ra and MRR respectively, indicates that the multiple regression equations have good overall significance.

Programming has been performed using the inbuilt MATLAB functions of genetic algorithm for the multi-objective optimization. The input parameters have been provided with the limits shown in table 1. Equations (2) and (3) have been utilized for multi-objective optimization.

Multi-objective problems have not a unique solution. It is the finding of the optimal process parameters to achieve the desired level of response [12]. The set of optimal results generated by GA for this study is given in table 4. The number of iterations simulated by MATLAB is 194.

Table 4. Optimization results.

No	*N* (rpm)	*fr* mm/min)	*d* (mm)	*Ra* (µm)	*MRR* (mm^3/min)
1	6808.997	100.099	3.001	0.498	24.589
2	6781.368	159.276	3.106	0.539	47.362
3	6521.717	214.741	3.353	0.642	86.444
4	6477.678	258.675	3.837	0.665	96.672
5	6400.248	287.919	3.789	0.682	105.929
6	6385.74	300	4	0.705	114.351

3.3. Development of the Fuzzy Inference System

The development of the fuzzy model involves three main stages: fuzzification (formation of membership function), definition of the expert rules, and selecting defuzzification method [16].

In the fuzzification process, the ranges of input and output values from the optimized data set which are crisp values are divided into several groups of fuzzy subsets and linguistic terms assigned to them [16]. A fuzzy membership function is then assigned to each fuzzy subset. A membership function (MF) is a curve that maps elements in a set to their membership value (or degree of membership) between 0 and 1. There are numerous types of membership functions: triangles, trapezoids, bell curves, Gaussian, and sigmoidal functions. In selecting the membership functions trial and error methods are usually exercised [16-18]. Triangular MF have been used to map input and output elements in this work. The linguistic terms used are VS (very smooth), S (smooth), M (medium), MR (medium rough), R (rough), VL (very low), L (low), MH (medium high), H (high), and VH (very high).

Fuzzy rules define the relationship between inputs and outputs by a linguistic statement in the form of if-then. The if-part, also referred to as the antecedent describes a condition and the then-part, also referred to as the consequent, a conclusion that can be drawn when the condition holds. The set of rules constitutes the fuzzy rule base of the system. The number of rules is determined by the partition of the fuzzy inputs [18]. The complete list of rules is displayed in Table 5.

Table 5. List of rules.

Rule no.	Antecedents		Consequents		
	Ra	***MRR***	***N***	***fr***	***D***
1	VS	VL	VH	VL	VL
2	S	L	H	L	L
3	M	M	MH	M	M
4	MR	MH	M	MH	H
5	R	H	L	H	MH
6	VR	VH	VL	VH	VH

A fuzzy inference or reasoning mechanism is required to allow mapping a given input to an output, using fuzzy logic. There are four fuzzy reasoning methods to obtain the inference result from a system: Mamdani's strategy, Larsen's strategy, Tsukamoto's strategy, and Takagi and Sugeno's strategy. These methods vary in ways of determining outputs [19, 20]. In this work, Mamdani mechanism which is based on MAX-MIN operator inferring has been used.

The output response of the fuzzy process can be view only in fuzzy values. Crisp values need to be extracted from the fuzzy output sets. Defuzzification refers to the method in which a crisp value is extracted from a fuzzy set as a representative value. There are several defuzzification techniques; however, only five are practical: the center-of-area (COA), center-of-gravity (COG), height defuzzification (HD), center-of-largest-area (COLA), mean-of-maximum (MOM). Although the choice is somewhat subjective, the center of area (COA) method (also referred to as the center-of-gravity or centroid method) is the most commonly used defuzzification technique as it is very accurate. It is based on the computation of the position of divisive axis between the left and right half area under the curve of the membership function [16, 17, 19, 20].

Using fuzzy logic toolbox of Matlab software, the estimated parameters of the fuzzy system are presented in Table 6, Table 7 and Table 8 for spindle speed, feed rate and depth of cut respectively. The error between the estimated and the optimal values is obtained by the following equation:

$$\text{Error} = \frac{\mathit{Optimal\ value} - \mathit{Estimated\ value}}{\mathit{Optimal\ value}} \times 100 \qquad (4)$$

Table 6. Estimated spindle speed of the fuzzy system.

No	*Ra*	*MRR*	*Opt. N*	*Est. N*	Error (%)
1	0.498	24.589	6808.997	6800	0.13213
2	0.539	47.362	6781.368	6700	1.1998
3	0.642	86.444	6521.717	6590	-1.047
4	0.665	96.672	6477.678	6470	0.11853
5	0.682	105.929	6400.248	6420	-0.3086
6	0.705	114.351	6385.74	6390	-0.0667
Average error (%)					0.0047

Opt. N = optimal spindle speed, Est. N = estimated spindle speed.

Table 7. Estimated feed rate of the fuzzy system.

No	*Ra*	*MRR*	*Opt. fr*	*Est. fr*	Error (%)
1	0.498	24.589	100.099	119	-18.882
2	0.539	47.362	159.276	158	0.80113
3	0.642	86.444	214.741	211	1.7421
4	0.665	96.672	258.675	254	1.80729
5	0.682	105.929	287.919	282	2.05579
6	0.705	114.351	300	295	1.66667
Average error (%)					-1.8016

Opt. fr = optimal feed rate, Est. fr = estimated feed rate.

Table 8. Estimated depth of cut of the fuzzy system.

No	*Ra*	*MRR*	*Opt. d*	*Est. d*	Error (%)
1	0.498	24.589	3.001	3.03	-0.966
2	0.539	47.362	3.106	3.15	-1.417
3	0.642	86.444	3.353	3.42	-1.998
4	0.665	96.672	3.837	3.88	-1.121
5	0.682	105.929	3.789	3.66	3.4046
6	0.705	114.351	4	3.95	1.25
Average error (%)					-0.141

Opt. d = optimal depth of cut, Est. d = estimated depth of cut.

3.4. Results and Analysis

Experimental investigations were carried out to validate the prediction of the fuzzy system for N, fr and d. The estimated parameters of the fuzzy system were fed to the CNC milling machine and end milling operations were conducted. The validation values of surface roughness and material removal rate were compared to the optimal values. The percentage error between the validation values and the optimal value was estimated based on equation (4) and displayed in Table 9 and Table 10 for surface roughness and material removal rate respectively.

Table 9. Comparison between optimal and validation values of surface roughness.

No	Estimated parameters			Opt. *Ra*	Val. *Ra*	Error (%)
	N	*fr*	*d*			
1	6800	119	3.03	0.498	0.51	-2.41
2	6700	158	3.15	0.539	0.535	0.742
3	6590	211	3.42	0.642	0.6	6.542
4	6470	254	3.88	0.665	0.635	4.511
5	6420	282	3.66	0.682	0.651	4.545
6	6390	295	3.95	0.705	0.699	0.85
Average error (%)						2.463

Opt. *Ra* = optimal surface roughness, Val. *Ra* = validation surface roughness.

Table 10. Comparison between optimal and validation values of material removal rate.

No	Estimated parameters			Opt. *MRR*	Val. *MRR*	Error (%)
	N	*fr*	*d*			
1	6800	119	3.03	24.589	36.057	-46.639
2	6700	158	3.15	47.362	49.77	-5.084
3	6590	211	3.42	86.444	72.162	16.521
4	6470	254	3.88	96.672	98.552	-1.945
5	6420	282	3.66	105.929	103.212	2.565
6	6390	295	3.95	114.351	116.525	-1.901
Average error (%)						-6.08

Opt. *MRR* = optimal material removal rate, Val. *MRR* = validation material removal rate.

Plots of optimal and validation values of surface roughness and material removal rate are provided on Figures 1 and 2 respectively.

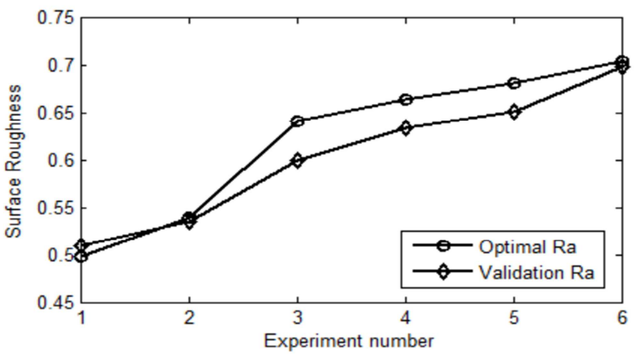

Figure 1. Plot of optimal and validation surface roughness.

It can be observed from figures 1 and 2 that the overall validation data are closer with the optimal data generated by GA multi-objective optimization process. The average errors between the optimal and estimated values are 2.463% and 6.08% for surface roughness and material removal rate respectively, due to errors in machining, measurement and modeling.

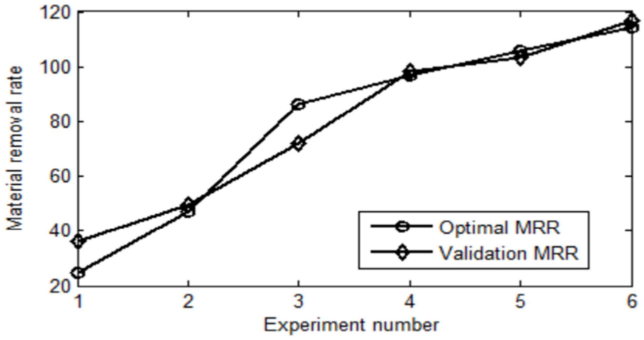

Figure 2. Plot of optimal and validation material removal rate.

4. Conclusion

This work attempts to develop a fuzzy logic-based system for end milling parameters selection in the production floor environment. The experimentation was carried out under dry conditions using SS400 steel for the workpiece and HSS Co8 as tool material. Three cutting parameters, namely spindle speed (*N*), feed rate (*fr*) and depth of cut (*d*) were considered in this work. The optimal sets of parameters are identified using artificial neural network followed by genetic algorithm. Fuzzy rules are then generated for the selection of end milling parameters for the required surface roughness.

The validation experiment shows a closed relationship between validation and optimal data since the average error of the system is 2.463% for surface roughness and 6.08% for material removal, which is less than 10%.

By investigating more cutting tool and workpiece material combinations, one may build a database for a variety of cases in order to design an expert system which provides assistance to operators in selecting machining parameters for a given surface roughness. Such a system helps to save production time and facilitates increased automation of manufacturing processes.

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