

Decision Making based on Fuzzy Approach for End Milling Parameters Selection when Machining SS400 Steel using HSS Co8 Tool

Paul Sawadogo, Pai-Chung Tseng, Hsueh-Yu Liao

Abstract— In this paper, a fuzzy modeling technique is used for the selection of end milling parameters for a required surface roughness (SR) with maximum material removal rate (MRR). Feed rate (Fr), radial depth of cut (Dr) and axial depth of cut (Da) are the inputs and outputs are MRR and SR. Three different levels of each input parameter were used to carry out the experimental work: Fr = 100; 200; 300 mm/min, Dr = 0.1; 0.2; 0.3 mm, Da = 3; 3.5; 4 mm. Optimal sets of parameters were identified using artificial neural network (ANN) coupled with genetic algorithm (GA). Fuzzy logic model (FLM) was 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 and shows that FLM is a successful tool for end milling parameters selection with closer relationship with the experimental results. The accuracy of the developed model is around 98%.

Keywords— Artificial Neural Network, End milling, Fuzzy Logic Model, Genetic Algorithm

1 INTRODUCTION

One of the practical problem in machining is selecting the proper cutting conditions for a given operation.

Machining is a manufacturing process in which a sharp cutting tool is used to cut away material to leave the desired part shape [1]. Machining, also referred to as cutting, metal cutting, or material removal, is the dominant manufacturing shaping process. It is both a primary as well as secondary shaping process [2].

End milling is an important and common machining operation, because of its versatility and capability to produce various profiles and curved surfaces. The cutter can remove material on both its end and its cylindrical cutting edges [3]. Applications of end milling process can be found in many industries ranging from large aerospace manufacturers to small tool and die shops. Reason for its popularity include the fact that it may be used for the rough and finishing machining of such features as slots, pockets, peripheries, and faces of components [4].

SS 400 steel is most frequently used material during design of mechanical mechanism/parts (hardness 160 HB). 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 steel has most economic value for structure parts and is excelling in welding and machinability and can be subjected to various heat treatments.

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In machining operations, the cutting conditions such as cutting speed, feed rate, depth of cut, features of tools and work piece materials affect the process efficiency and performance characteristics [5]. The selection of optimum machining parameters is difficult and relies heavily on the operator experience and the machining hand books provided by the cutting tool manufacturer for the targeted material. Hence, the optimization of machining parameters is of greater importance where the economy as well as quality of the machined part plays a key role [6].

Optimization involves determining optimal process parameters in order to optimize an objective function. Some of the essential objective functions in machining include minimizing the cost of production, surface roughness, cutting force, tool wear, and flank wear, as well as maximizing metal removal rate, production rate, and tool life [7]. However, the improvement of one objective function is not possible without the worsening of at least one of the other objective function.

This work aims to optimize multi-objective functions (e.g. minimizing surface roughness and maximizing metal removal rate) in end milling of SS 400 steel using high speed steel HSS Co8 end mill.

In the case of multiple objectives, there does not necessarily exist such a solution that is the best with respect to all objectives because of incommensurability and conflict among objectives. A solution may be best in one objective but worst in other objectives. Therefore, there usually exists a set of solutions for the multiple objective cases which cannot simply be compared with each other. Decision should be made among this set of solutions also called alternatives in

order to choose the one that best fits with our goals, objective, desires, values, and so on.

At present, decisions concerning the cutting parameters used in machining operation are based on experience. So, it needs a tool that will allow to select the most appropriate machining parameters in order to improve cutting efficiency, process at low cost, and produce high-quality products.

A non-exhaustive presentation of development of decision making systems for machining operations is given in the following.

A decision making model for the selection of die sinking Electrical Discharge Machining (EDM) parameters was developed, in order to achieve green EDM [8]. A combination of Taguchi and fuzzy TOPSIS methods has been used to solve multi-response parameter optimization problems. An experimental investigation was carried out based on Taguchi L9 orthogonal array to analyze the sensitivity of green manufacturing attributes to the variations in process parameters such as peak current, pulse duration, dielectric level and flushing pressure. An analytical model was developed for optimizing the process parameters. A fuzzy-based algorithm was introduced for prediction of material removal rate (MRR), Tool wear ratio (TWR) and surface roughness (R_z , R_k) in the EDM and ultrasonic-assisted EDM (US/EDM) processes [9]. Discharge current, pulse duration and ultrasonic vibration of tool are the input variables and outputs are MRR, TWR, R_z and R_k . A fuzzy rule-based system was developed to provide a more precise and easy selection of EDM and US/EDM input parameters, respectively for the required MRR, TWR, R_z and R_k which leads to better machining conditions and decreases the machining cost. The effect of various EDM input parameters as well as the influence of different tool geometry on material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR) has been investigated in machining of Inconel 718 by using copper electrode [10]. Pulse on time, pulse off time, peak current, flushing pressure and electrode tool geometry were considered in this work. Tool geometry for the electrodes was circle, square, rectangle and triangle. Four different levels for the five input parameters were planned as per the L16 orthogonal array. Multi-objective optimization technique of desirability approach was used to optimize the parameters and the significance of each parameter was analyzed by analysis of variance (ANOVA). Finally, Fuzzy Logic Model (FLM) was used to better understand the input and the output response. With the desirability approach, it was sought to optimize the values of copper electrode for maximum MRR, and minimum TWR and SR. Hybrid algorithms employing neural network embedded with genetic algorithm and particle swarm optimization technique were developed to predict machining quality for a given set of process parameters in CNC turning process [11]. Experiments were designed based on Taguchi Design of Experiments (DoE) and conducted with cutting speed, feed rate, depth of cut and nose radius as the

process parameters and surface roughness and power consumption as objectives. Signal-to-noise (S/N) ratios of responses were calculated to identify the influence of process parameters using analysis of variance (ANOVA). The developed model can be used for deciding the machining parameters to attain quality with minimum power consumption and hence maximum productivity. In [6], a new approach to selection of machining parameters in turning of Inconel 718 by using an intelligent technique was illustrated. The machining parameters are optimized based on the multi-objectives which are limiting the cost and quality of the machining process. The machining experiment has been conducted using uncoated carbide tool under dry machining condition. Using the experimental responses mathematical models were developed for the objective functions as well as constraints in the multi-objective optimization. The multiple attribute decision making (MADM) method is used to select a single solution from the optimized results which are a set of non-dominated solutions for their multi-objective optimization. The MADM method helped to evaluate and rank the machining parameters. The higher rank solution was selected as the best solution for the machining of Inconel 718 in that respective environment. Multi-objective optimization techniques in high speed machining of Inconel 718 using carbide cutting tool were presented [7]. A set of non-dominated solutions were obtained using non-sorted genetic algorithm for multi-objective functions. A multi-criteria decision making (MCDM) concept based on technique for order preference by similarity to ideal solution (TOPSIS) was used for selecting a single solution from non-dominated solutions. TOPSIS determine the shortest distance to the positive-ideal solution and the greatest distance from the negative-ideal solution. Six objective functions (e.g. minimizing surface roughness, flank wear, cutting force and power consumption as well as maximizing tool life and material removal rate) were considered as attributes against the process variables of cutting speed, feed, and depth of cut. The higher-ranked solution was selected as the best solution for the machining of Inconel 718 in its respective environment. An optimization method has been developed for effectively performing simultaneous optimization of well-known surface quality characteristics like arithmetic average (R_a), average distance between the highest peak and lowest valley (R_z) and maximum height of the profile (R_t) in turning of EN 1.4404 austenitic, EN 1.4462 standard duplex and EN 1.4410 super alloy stainless steels [12]. Taguchi approach was coupled with fuzzy-multiple attribute decision making (FMADM) methods for achieving better surface quality in constant cutting speed face turning. The results were further analyzed using analysis of means (AMON) and analysis of variance (ANOVA). The difference in machinability among machined stainless steels was additionally reported through presenting chip breaking chart. In 2, intelligent hybrid decision making tools were applied to find the optimal process parameters in CNC

turning of EN 31. The CNC turning was investigated by considering the performance measures, material removal rate (MRR), tool wear (TW) in terms of spindle speed, feed rate, and depth of cut as control factors. The experiment was conducted as per the design of experiments, and then artificial neural network (ANN) was applied to predict the models for the chosen output responses. The models were tested for its adequacy using ANOVA analysis and chosen for subsequent optimization of the process parameters using evolutionary techniques like genetic algorithm (GA).

The main issue of these works is the use of evolutionary (non-conventional) optimization techniques to solve multi-objective optimization problems in machining processes. Evolutionary optimization techniques are the new trend for optimization of the machining process parameters. Today machining problems are more complex so that single optimization techniques have limited values to fix the optimal cutting conditions. Evolutionary techniques are particularly suitable to solve multi-objective optimization problems because they deal simultaneously with a set of possible solutions. Furthermore, referring to previous works, researches on multi-objective optimization of end milling parameters when machining SS400 using HSS co8 tool are not given.

This paper addresses the development of a decision making system based on fuzzy logic reasoning to identify and select the best combination of cutting parameters (e.g. feed rate, axial depth of cut, and radial depth of cut) from several optimal alternatives in order to minimize surface roughness while maximizing the production rate. The optimization system was based on artificial neural network (ANN) coupled with genetic algorithm (GA). Based on fuzzy rules, inference were drawn on output grade and membership values in order to arrive at a final decision.

The objective of this work is to allow better and user friendly selection of cutting parameters in end milling operations.

This paper is organized as follow: Section 2 presents some theoretical concepts related to the subject of this paper. Section 3 presents the experimental work procedure. In section 4, the optimization method and results are presented. Section 5 describes the fuzzy logic modeling procedure. In section 6, results and analysis are presented. Finally, conclusions are drawn in section 7.

2 THEORETICAL CONCEPTS

2.1 Artificial Neural Networks

Artificial neural network (ANNs) consist of a number of elementary units called neurons. A neuron is a simple processor which takes one or more inputs and produces an output. Each input into a neuron has an associated weight that

determines the “intensity” of the input. The processes that a neuron performs are: multiplication of each of the input by its respective weight, adding up the resulting numbers of all the inputs and determination of the output according to the result of this summation and an activation function [13].

The activation function defines the output of a neuron in terms of the activity level at its input. The basic types of activation functions are threshold function, piecewise-linear function and sigmoid function which is by far the most common form of activation function used in the construction of artificial neural networks [14].

The significant functions of neural network are tackling non-linearity and mapping input-output information. The different types of neural networks in practice are back propagation neural network, counter propagation neural network, and radial basis function neural network [11].

In [11], Back propagation neural network (BPNN) is a multiple layers ANN with input layer, output layer and some hidden layers between the input and output layers. Its learning procedure is based on gradient search with least mean squared optimality criteria. Once the input data is fed to the nodes in the input layer (o_i), this will be fed to nodes (j) in the hidden layer through weighting factors (w_{ji}).

The net input to node j :

$$\text{net}_j = \sum_i w_{ji} o_i - b_j \quad (1)$$

where b_j is the bias over node j .

The output to the node j :

$$o_j = \frac{1}{1 + e^{-\text{net}_j}} \quad (2)$$

Similarly the outputs from nodes in the hidden layer are fed into nodes in the output layer. This process is called feed forward stage. After feed forward, the calculation output (o_{pk}) can be obtain from nodes in the output layer. In general, the output o_{pk} will not be the same as the desired known target t_{pk} . Therefore, the average system error is:

$$E = \frac{1}{2p} \sum_p \sum_k (t_{pk} - o_{pk})^2 \quad (3)$$

The error is then back propagated from nodes in the output layer to nodes in the hidden layer using gradient search method $\Delta p w_{kj} = -\eta (\partial E / \partial w_{kj}) = \eta \delta_k o_j$. Delta value for output layer is $\delta_k = o_k(1 - o_k)(t_k - o_k)$. Delta value for hidden layer is $\delta_j = o_j(1 - o_j) \sum_k w_{kj} \delta_k$.

This process is called back propagation stage. After all examples are trained the system will collect adjusted weights according to $\Delta w_{ji} = \sum_p w_{ji}$.

Updating of weights is done according to:

$$w_{ji}(n + 1) = w_{ji}(n) + \Delta w_{ji} \quad (4)$$

Supervised training works by showing the network a series of matching input and output examples. The network will adjust its weights according to the training algorithm to accommodate each training example. The weights from the “memory” of the network are the points where it stores the information about the problem that is trying to solve [13].

The Levenberg-Marquardt algorithm selected for training the ANNs is a variation of the classic back propagation algorithm that, unlike other variations that use heuristics, relies on numerical optimization techniques to minimize and accelerate the required calculation, resulting in much faster training [15]. More specially, the direction in which the search is made is described by: $x_{k+1} = x_k - A_k^{-1} g_k$,

where A_k is the Hessian matrix of the error function at the current values of weights and biases and g_k is the gradient of the error function. Since the error function has the form of a sum of squares, the Hessian matrix can be approximated as $A = J^T J$

and the gradient as $g = J^T e$,

where J is the Jacobian matrix, which contains first derivatives of the network errors which respect to the weights and biases, and e is a vector of network errors. Finally, the search direction is given by $x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e$.

2.2 Genetic algorithm (GA)

GA technique is based on the natural process of evolution to solve optimization and search problems. There are three main operators in GA which are reproduction, crossover and mutation. To apply GA in optimization of machining process parameters, the process parameters are encoded as genes by binary encoding [16]. The steps to apply GA in optimization of machining are as follow: (i) the process parameters are encoded as genes by binary encoding; (ii) A set of genes is combined together to form a chromosome, which is used to perform the basic mechanisms in the GA, such as crossover and mutation; (iii) crossover is the operation to exchange some part of two chromosomes to generate new offspring, which is important when exploring the whole search space rapidly; (iv) mutation is applied after crossover to provide a small randomness to new chromosomes; (v) To evaluate each individual or chromosome, the encoded process parameters are decoded from the chromosomes and are used to predict machining performance measures; (vi) the fitness or objective function is a function needed in the optimization process and the selection of the next generation in the GA; (vii) After a number of iterations of the GA, optimal results of process

parameters are obtained by comparison of values of objective functions among all individuals [17], [18].

2.3 Fuzzy logic

Fuzzy logic is a discipline that has been successful in automated reasoning of expert systems [19]. Fuzzy logic has great capability to capture human commonsense reasoning, decision making and other aspects of human cognition. It overcomes the limitations of classical logical systems, which impose inherent restrictions on representation of imprecise concepts [20]. Uncertainty, vagueness, ambiguity, and impreciseness are some of problems found in relationships between inputs and outputs of real world systems, and this can be tackled effectively by utilizing treatment of fuzzy logic [21]. Fuzzy logic uses linguistic terms to develop reasonable relationships between input and output variables. There are three main stages during the development of the model: formation of membership function (fuzzification), definition of the expert rules, and selecting defuzzification method [22].

2.3.1 Fuzzification

Fuzzification is a kind of process in which the input data, precise or imprecise, is converted into a kind of linguistic form which is easily perceptible by the human minds, for example very short, highly hard etc. [21]. The ranges of input and output values from the optimized data set which are crisp values will be divided into several groups of fuzzy subsets and linguistic terms assigned to them. A fuzzy membership function is then assigned to each fuzzy subset. A membership function characterizes the fuzziness in a fuzzy set whether the elements in the set are discret or continuous in graphical form. There is an infinite number of methods to graphically describe the fuzziness: triangular, trapezoidal, Gaussian are some types of membership function (MF) shapes [9]. Some of them are illustrated on Fig. 1(a-c).

A triangular MF is described by three parameters a , b , c and given by the expression

$$f(x;a,b,c) = \max\left\{\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right\} \quad (5)$$

where the parameters a and c locate the “feet” of the triangle and the parameter b locates the “peak” as shown in Fig.1a.

A trapezoidal MF has a shape of a truncated triangle. These may again be symmetrical or asymmetrical in shape. A trapezoidal MF is described by four parameters a , b , c and d , and given by the expression

$$f(x;a,b,c,d) = \max\left\{\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right\} \quad (6)$$

where the parameters a and d locate the “feet” of the trapezoid and b and c locate the “shoulder” as shown in Fig. 1b. A

trapezoidal MF can have either narrow “shoulder” or wide “shoulder” [23].

A Gaussian MF is given by the expression

$$f(x;\sigma,c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (7)$$

where the parameter c locates the distance from the origin and σ indicates the width of the curve as shown in Fig. 1c.

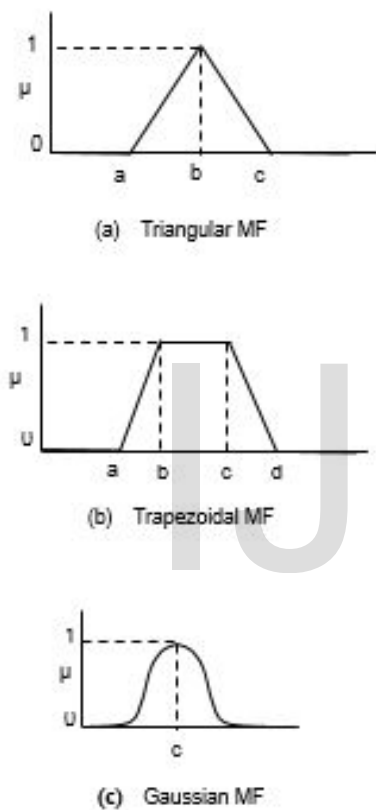


Fig.1. Some types of membership functions.

There is no standard method of choosing the proper shape of membership function for the fuzzy sets of control variables. Trial and error methods are usually exercised [9].

2.3.2 Fuzzy rules generation

The relationship between inputs and outputs is defined by a set of linguistic statements in the form of IF-THEN. Each statement represents a fuzzy rule. The IF part is called premises part and comprised of conditions or clauses connected to one another with logical operators such as AND, OR, and NOT. The THEN part is the conclusion part and corresponds to a conjunction of actions. Considering two fuzzy sets A and B with membership functions $\mu_A(u)$ and

$\mu_B(u)$ respectively, the fuzzy operators [24] are defined in the following.

The AND operator corresponds to the intersection of the two sets A and B whose membership function is given by

$$\mu_{A \cap B}(u) = \min \{ \mu_A(u), \mu_B(u) \} \quad (8)$$

The OR operator corresponds to the union of the two sets A and B whose membership function is given by

$$\mu_{A \cup B}(u) = \max \{ \mu_A(u), \mu_B(u) \} \quad (9)$$

The NOT operator corresponds to the complement of a fuzzy set which is defined as the fuzzy set of the same universe with membership function

$$\mu_{A^c}(u) = 1 - \mu_A(u) \quad (10)$$

In this paper one of these rules could be IF feed rate is VL and axial depth of cut is S and radial depth of cut is L THEN surface roughness is VL and MRR is L (S = small, L = large, VL = very large). The set of rules constitutes the fuzzy rule base of the system.

2.3.3 Defuzzification

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. In general there are several methods for defuzzifying fuzzy sets. Centroid of area is the most widely adopted defuzzification strategy which is reminiscent of the calculation of expected values of probability distribution [9]. The crisp value of the output corresponds to the x -coordinate of the center of gravity of the aggregate output.

$$Z_0 = \frac{\int x \mu_i(x) dx}{\int \mu_i(x) dx} \quad (11)$$

where Z_0 is the defuzzified output, μ_i is the membership function and x is the output variable [25].

A fuzzy inference or reasoning mechanism allows mapping a given input to an output, using fuzzy logic. The mapping provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in membership functions, logical operators and if-then rules. Fuzzy inference process comprises the following parts:

- Fuzzification of the input variables. This step is concerned with taking the inputs and determining the degree to which they belong to each of the appropriate fuzzy sets via membership functions.

- Application of the fuzzy operator (AND or OR) in the antecedent (the IF part of the rule). If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. This number is then applied to the output function. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single truth value.
- Implication from the antecedent to the consequent (the THEN part of the rule). Every rule must be weighted by a number between 0 and 1. After proper weighting has been assigned to each rule, the implication method is implemented. A consequent is a fuzzy set represented by a membership function, which weights appropriately the linguistic characteristics that are attributed to it. The consequent is reshaped using a function associated with the antecedent (a single number). The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Implication is implemented for each rule.
- Aggregation of the consequents across the rules. The fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Aggregation only occurs once for each output variable, just prior to final step, defuzzification. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable.
- Defuzzification. A crisp value is extracted from the fuzzy output. The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number.

Mamdani and Sugeno are the most common types of inference system.

3 EXPERIMENTAL WORK

3.1 Experiment set up

In this research work, end milling operations were conducted in a Victortec VNC M5200 HSP CNC milling machine under dry conditions and constant spindle speed of 6000 rpm. For the purpose of this study, finishing operation was considered. The monitoring system comprised:

- A Kistler 925 BA three component piezoelectric dynamometer with a KISTLER type 5233A amplifier

and National Instruments NI PXIe-1073 DAQ for cutting force measurement;

- An acoustic emission (AE) KISTLER 8152B121 sensor and National Instruments SCB 68A DAQ for AE signal collection from the machining operation.
- A computer with LABVIEW 2013 software for data processing and recording.

During the experiment, the dynamometer was fixed on the machine table. AE sensor was fixed on the work-piece which in turn was fixed on the dynamometer. By following the cutting path, cutting operations are performed on the right side of each slot previously machined on the workpiece. The experiment set up is shown in Fig. 2.

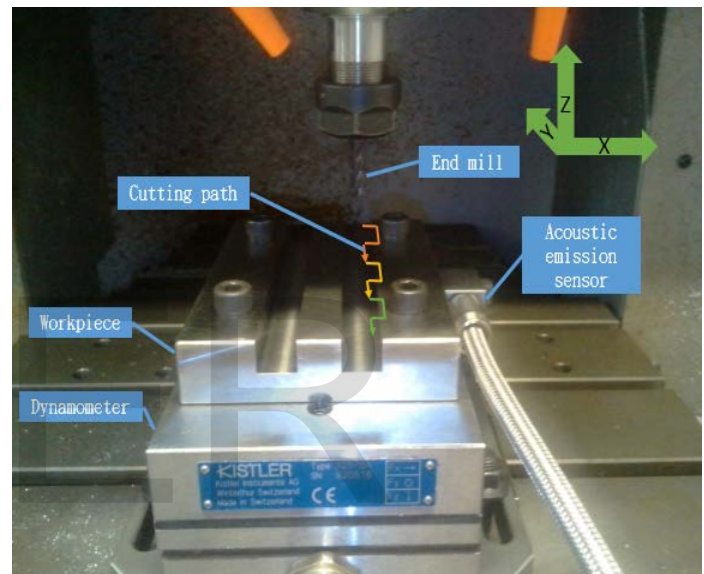


Fig. 2. Experimental set up.

3.2 Workpiece material

The material used for the experiments was a low carbon SS 400 steel (SS for Structural steel), most frequently used material during design of mechanical mechanism/parts (hardness 160HB). The material composition is following: carbon (C), not controlled; silicon (Si), not controlled; manganese (Mn), not controlled; phosphorus (P), $\leq 0.05\%$; sulphur (S), $\leq 0.05\%$.

3.3 Cutting tool material

The milling cutter used was a solid four flutes cobalt-bearing high speed steel HSS Co8 type M42 end mill (hardness = 62-64 HRC) having diameter of 6mm. 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. 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%.

threshold (e.g. 0.3µm). The optimization results are shown in Table 1.

3.4 Cutting conditions

The selected cutting conditions for the experiment were following:

- Spindle speed (rpm): 6000.
- Feed rate (mm/min): 100; 200; 300.
- Axial depth of cut (mm): 0.1; 0.2; 0.3.
- Radial depth of cut (mm): 3; 3.5; 4.

Single pass, linear cuts were executed.

3.5 Surface roughness measurement

The mean surface roughness Ra was measured with a two dimensional Kosaka L SE 3500 K profilometer. Five measurements were taken on each machined surface and the average value was calculated.

3.6 Production rate

MRR is the most commonly used optimization criterion of production rate in milling process. MRR is determined using the product of the cross-sectional area of the cut and the feed rate [1]. In the case of our study, MRR can be computed by the following expression:

$$MRR = Fr \times Da \times Dr \quad (9)$$

where *MRR* is the material removal rate (mm³/min), *Da* is the axial depth of cut (mm), *Dr* is the radial depth of cut (mm), and *Fr* is the feed rate (mm/min).

4 OPTIMIZATION

At the completion of the prediction model training, the optimization process was initiated and the top ten MRR parameter sets were then reported by the optimization system. A 28-14-1-1 network architecture was used to design the neural network. The number of epoch was 500. The transfer functions which has been used were tansig (hyperbolic tangent sigmoid transfer function) and purelin (linear transfer function) in hidden and output layers respectively. Training the network was made with the help of back propagation and Levenberg-Marquardt algorithms. The optimization problem was searching the parameter combination including feed rate, radial depth of cut, and axial depth of cut which lead to low surface roughness with maximum material removal rate. In addition, the optimization problem was solved under the constraint that the surface roughness which is predicted by ANNs must beneath the designed surface roughness

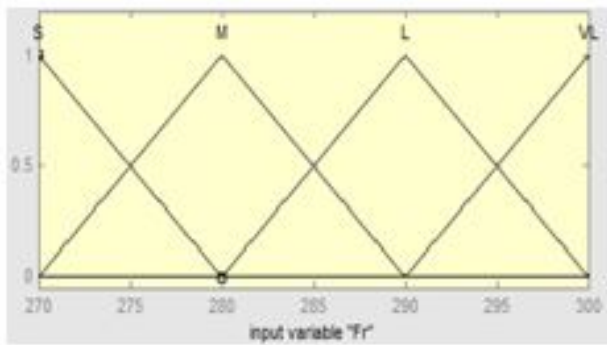
TABLE 1
 OPTIMIZATION RESULTS

No	Fr mm/min	Dr mm	Da mm	MRR mm ³ /min	SR µm
1	300	0.30	4	360	0.214427
2	300	0.30	3.9	351	0.202190
3	290	0.30	4	348	0.198691
4	290	0.30	3.9	339.300	0.190468
5	290	0.29	4	336.400	0.187266
6	280	0.30	4	336	0.185556
7	280	0.30	3.9	327.600	0.179304
8	280	0.29	4	324.800	0.173065
9	270	0.30	4	324	0.173100
10	270	0.3	3.9	315.900	0.161437

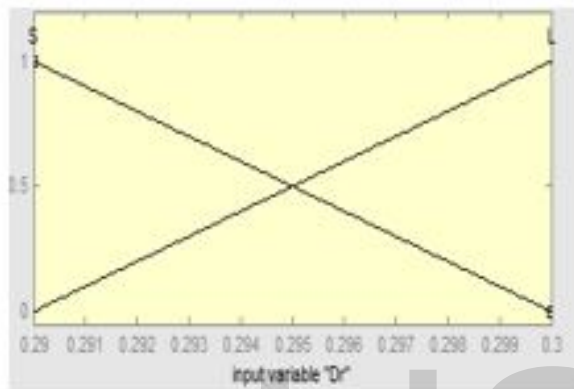
mm = millimeter, min = minute, µm = micrometer

5 FUZZY LOGIC MODEL (FLM)

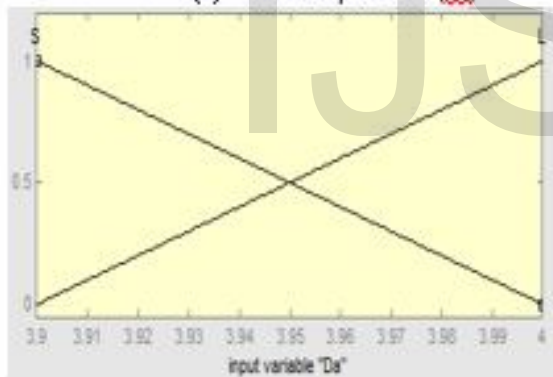
Matlab R2013a fuzzy logic tool box was used to build the FLM of end milling process. After a number of trials, the input and output values are fuzzified using triangular and trapezoidal membership functions respectively. The membership functions are designed based on Equations 5 and 6 and presented in Fig. 3(a-c) and Fig. 4(a, b). The fuzzy reasoning was based on AND operator, Mamdani inference system, min (minimum) implication and max (maximum) aggregation method. The notation used for fuzzy subsets were as follow: VS (very small), S (small), M (medium), L (large), and VL (very large).



(a) Feed rate (Fr)

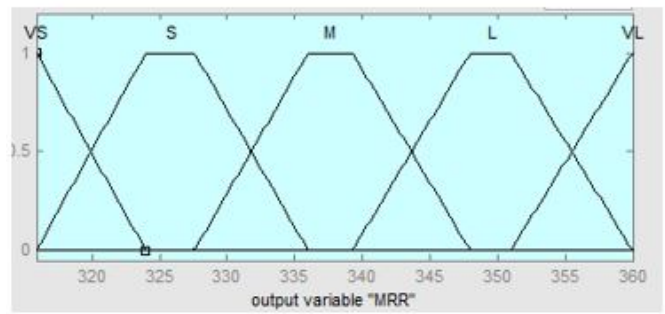


(b) Radial depth of cut (D_r)

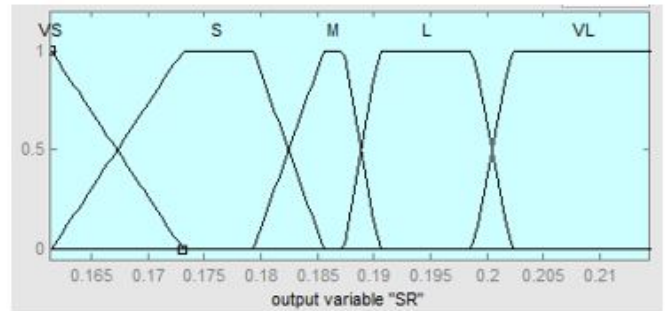


(c) Axial depth of cut (D_a)

Fig. 3. Input variable Membership function plots.



(a) Material removal rate (MRR)



(b) Surface roughness (SR)

Fig. 4. Output variable membership function plots.

The relationship between input and output is characterized by a set of linguistic statements, one experiment resulting in one fuzzy rule. For this work, 10 fuzzy rules were established as shown in Table 2. All rules have a weight of 1. Finally, the fuzzy values obtained from the fuzzy rules were converted into crisp outputs using centroid defuzzification method.

Graphical representation of the fuzzy logic reasoning procedure for test 1 for prediction of MRR and SR is shown in Fig.5. Rows represent the 10 rules and columns are three-input/two-output variables. The location of triangles indicates the determined fuzzy sets of each input/output value. The height of the colored area of each triangle corresponds to the fuzzy membership value for that fuzzy set. For test 1, the input value of feed rate is 300 mm/min which belongs to VL, radial depth of cut is 0.30 mm which belongs to L, and axial depth of cut is 4 mm which belongs to L. By applying the fuzzy reasoning mechanism, the fuzzy outputs MRR and SR belong to VL. The defuzzified outputs that give the final MRR and SR values are calculated from the combined colored area shown in the bottom of MRR and SR columns in Fig. 5 (MRR = 357mm³/min and SR = 0.208 μ m). The remaining modeling results are shown in Table 3.

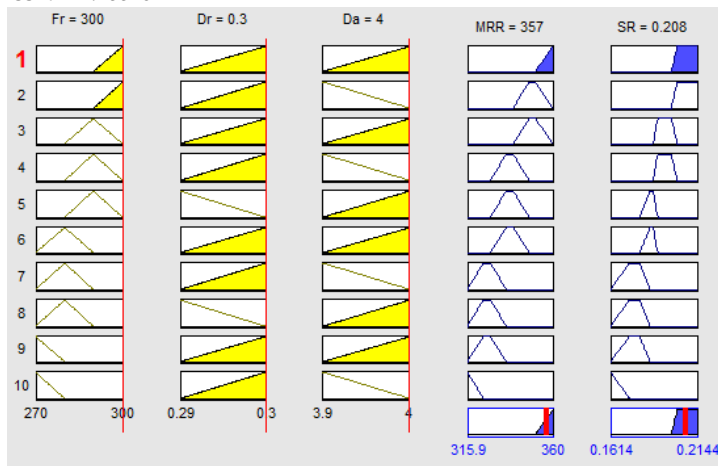


Fig. 5. Graphical representation of rule 1 for prediction of MRR and SR.

TABLE 2
FUZZY EXPRESSION OF INPUT AND OUTPUT PARAMETERS

No	IF					THEN		
	Fr	Con	Dr	Con	Da	MRR	Con	SR
1	VL	and	L	and	L	VL	and	VL
2	VL	and	L	and	S	L	and	VL
3	L	and	L	and	L	L	and	L
4	L	and	L	and	S	M	and	L
5	L	and	S	and	L	M	and	M
6	M	and	L	and	L	M	and	M
7	M	and	L	and	S	S	and	S
8	M	and	S	and	L	S	and	S
9	S	and	L	and	L	S	and	S
10	S	and	L	and	S	VS	and	VS

6 RESULTS AND ANALYSIS

Experimental investigations were carried out to validate the FLM for MRR and SR. Firstly, the optimal input values (table 1) are given to the FLM and the outputs are noted (table 3). The prediction error between fuzzy model values and optimal values were calculated using equations 12 and 13.

$$MRR_E = \frac{MRR_{FLM} - MRR_{Opt}}{MRR_{FLM}} \times 100 \quad (12)$$

$$SR_E = \frac{SR_{FLM} - SR_{Opt}}{SR_{FLM}} \times 100 \quad (13)$$

where MRR_E is the prediction error for MRR, MRR_{Opt} is the optimal value of MRR, MRR_{FLM} is the fuzzy model value of MRR; SR_E is the prediction error for SR, SR_{Opt} is the optimal value of SR and SR_{FLM} is the fuzzy model value of SR.

TABLE 3
COMPARISON BETWEEN OPTIMAL AND FLM VALUES

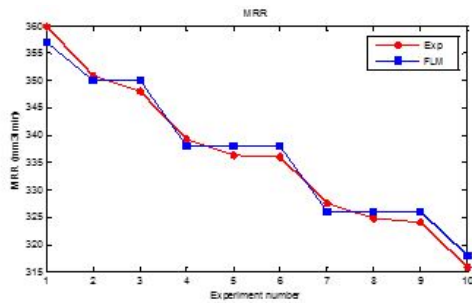
No	Optimization results		FLM prediction		Error (%)	
	MRR	SR	MRR	SR	MRR	SR
1	360	0.214427	357	0.208	-0.84	-3.08
2	351	0.202190	350	0.208	-0.28	2.79
3	348	0.198691	350	0.195	0.57	-1.89
4	339.3	0.190468	338	0.195	-0.38	2.32
5	336.4	0.187266	338	0.185	0.47	-1.22
6	336	0.185556	338	0.185	0.59	-0.30
7	327.6	0.179304	326	0.175	-0.49	-2.45
8	324.8	0.173065	326	0.175	0.36	1.10
9	324	0.173100	326	0.175	0.61	1.08
10	315.9	0.161437	318	0.165	0.66	2.15
Average error (%)					0.52	1.91

Secondly, the optimal parameters were used to perform validation end milling operations and the surface roughness was measured. Similarly, errors between the validation results and FLM prediction were calculated and shown in Table 4.

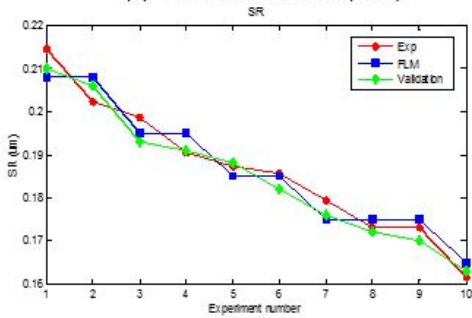
TABLE 4
COMPARISON BETWEEN FLM AND VALIDATION VALUES

No	SR _{FLM}	SR _{VAL}	Error (%)
1	0.208	0.21	0.95
2	0.208	0.206	0.97
3	0.195	0.193	-1.03
4	0.195	0.191	2.09
5	0.185	0.188	1.59
6	0.185	0.182	-1.64
7	0.175	0.176	0.56
8	0.175	0.172	-1.74
9	0.175	0.17	-2.94
10	0.165	0.163	-1.22
Average error (%)			1.47

The average error of the FLM is around 0.52% for MRR and 1.47% for SR which is due to errors in machining, measurement and modeling. Comparison of experimental results and fuzzy prediction as well as fuzzy 3D plots of MRR and SR are illustrated in Fig. 6(a, b), 7(a-c) and 8(a-c). Fig. 6(a, b) show that the fuzzy predicted values are very closer with the experimental values of MRR and SR. Fig. 7(a-c) and Fig. 8(a-c) indicate that surface roughness is improved (minimum surface roughness) when low input parameters are used while the improvement of material removal rate (maximum MRR) resides in the use of high input parameters.

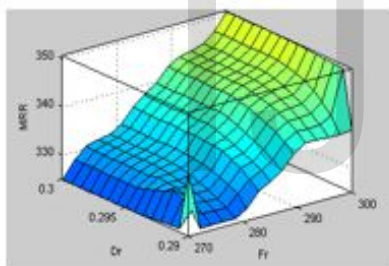


(a) Material removal rate (MRR)

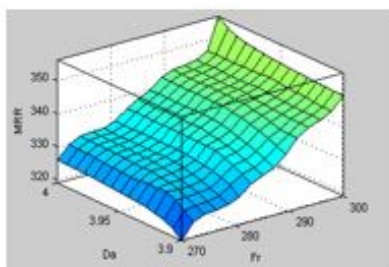


(b) Surface roughness (SR)

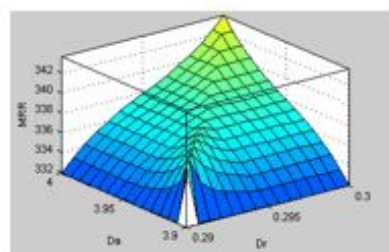
Fig.6. Comparison of fuzzy and experimental values (Exp = experimental results; FLM = fuzzy logic prediction data; Validation = validation test data).



(a) MRR versus Fr and Dr

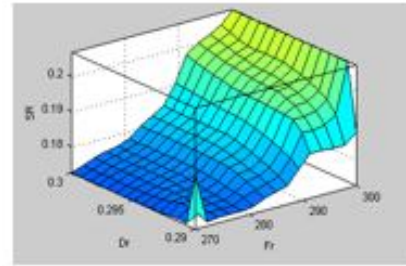


(b) MRR versus Fr and Da

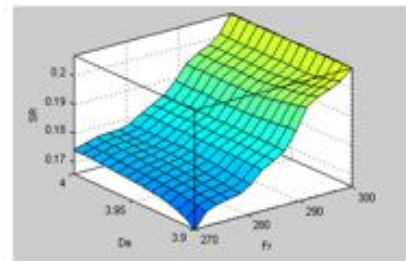


(c) MRR versus Da and Dr

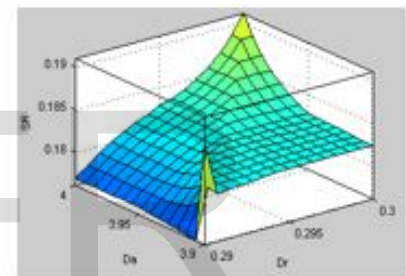
Fig. 7 Fuzzy surfaces of MRR



(a) SR versus Fr and Dr



(b) SR versus Fr and Da



(c) SR versus Fr and Da

Fig. 8 Fuzzy surfaces of SR

7 CONCLUSION

In this paper, a fuzzy system for the selection of end milling process parameters has been presented. Workpiece and cutting tool materials were SS400 steel and HSS Co8 respectively. The optimal sets of parameters were identified using artificial neural network coupled with genetic algorithm. Fuzzy rules were then generated for the selection of end milling parameters for the required material removal rate and surface roughness. Observations of experiments results lead to the following conclusion:

- Fuzzy modeling technique provides a very precise and easy selection of end milling parameters. Validation and comparison of fuzzy results with experimental values proved the high accuracy of the model (around 98%).
- Material removal rate and surface roughness increase with an increase in cutting parameters. Consequently, surface roughness is improved (minimum surface

roughness) when low cutting parameters are used while the improvement of material removal rate (maximum MRR) resides in the use of high cutting parameters. Furthermore, surface roughness predominantly depends on feed rate.

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