BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 67, No. 4, 2019
DOI: 10.24425/bpasts.2019.130178

Experimental investigation of cryogenically treated HSS tool in turning on AISI1045 using fuzzy logic – Taguchi approach

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Abstract. This work depicts the effects of deep cryogenically treated high-speed steel on machining. In recent research, cryogenic treatment has been acknowledged for improving the life or performance of tool materials. Hence, tool materials such as the molybdenum-based high-speed tool steel are frequently used in the industry at present. Therefore, it is necessary to observe the tool performance in machining; the present research used medium carbon steel (AISI 1045) under dry turning based on the L_9 orthogonal array. The effect of untreated and deep cryogenically treated tools on the turning of medium carbon steel is analyzed using the multi-input-multi-output fuzzy inference system with the Taguchi approach. The cutting speed, feed rate and depth of cut were the selected process parameters with an effect on surface roughness and the cutting tool edge temperature was also observed. The results reveal that surface roughness decreases and cutting tool edge temperature increases on increasing the cutting speed. This is followed by the feed rate and depth of cut. The deep cryogenically treated tool caused a reduction in surface roughness of about 11% while the cutting tool edge temperature reduction was about 23.76% higher than for an untreated tool. It was thus proved that the deep cryogenically treated tool achieved better performance on selected levels of the turning parameters.

Key words: cryogenic, fuzzy, roughness, Taguchi, temperature, turning.

1. Introduction

Machining is one of the most primary and essential processes of manufacturing. Today, manufacturing industries need to meet the demand of the society by correspondingly increasing their productivity. Turning is the fundamental machining process to remove the metal from the outer surface of the rotating workpiece with the help of a cutting tool. The cutting tool plays a vital role in any machining process and is selected based on its quality and the cost of processing. It is inevitable to use high-speed steel in the machining industries because it is economically suitable for many tools [1]. The conventional heat treatment method is widely used to improve tool life [2]. Recently, the cryogenic treatment process has become supplementary to conventional heat treatments. In the cryogenic treatment process, the temperature ranges from −80°C to −140°C whereas shallow cryogenic treatment (SCT) and deep cryogenic treatment (DCT) are in the range of −140°C to −196°C [3, 4]. A study has been conducted on deep cryogenic treatment at −196°C and shallow cryogenic treatment at −110°C on a high-speed steel molybdenum (M2) single point cutting tool in the turning of hot rolled annealed AISI 1045 medium carbon steel. The researchers reported that the DCT tool is better than the SCT tool or an untreated tool [5].The deep cryogenically treated tool improvement in tool life that is 50% higher than that of the shallow cryogenically treated tool is achieved by less cutting forces and smaller vibrations during the process [6]. A number of studies have investigated the effect on the performance of the tool at constant cutting speed, feed rate and depth of cut on AISI 1020 steel using the untreated high-speed tool and cryogenically treated high-speed tool in the turning operation. The results show that the cryogenically treated high-speed tool has a better surface finish of the machined part, low power consumption and less tool wear [7].

It was reported that the experiments on the turning operation using the deep cryogenic treatment of the P-40 grade tungsten carbide cutting tool insert reveal that the surface roughness of the machined component was 20% less than that of the untreated inserts, while the cutting force was reduced by 11% [8]. The research has been carried out in an orthogonal turning process on tungsten carbide inserts (P-25) subjected to two levels of cryogenic temperature: −110°C (shallow treatment) and −196°C (deep treatment). The results show that the cryogenically treated inserts performed significantly better than the untreated (UT) tool. Also, substantial improvement in tool life was recorded in deep cryogenically treated inserts as compared to shallow cryogenically treated inserts [9]. Recently, a number of researchers attempted cryogenic machining in metal cutting operations and reported better surface roughness and increased tool life in machining [10–14]. The investigators used the Taguchi method to employ a unique design of the orthogonal array to study the effects of machining parameters through a number of experiments. In recent times, this approach has been widely used in several industrial fields and research works. The Taguchi L_9 Orthogonal Array (OA) method has been applied to evaluate

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Manuscript submitted 2018-05-13, revised 2018-10-01, initially accepted for publication 2018-10-24, published in August 2019

the performance of deep cryogenically treated tools on turning Hastelloy C22 of surface roughness (R_a). The results indicated that the significant factor for surface roughness was the feed rate, with a contribution percentage of 87.64%. It is the most dominant factor that affects the machining performance and the cryogenically treated tools with surface roughness improved by 72.3% [15]. In general, the fuzzy inference system deals with the process of making the map bridge between particular inputs and an output, using fuzzy logic. The logic to solving the technique is based on inexact human reasoning to handle statistical data and linguistic knowledge [16–19]. Fuzzy interface has developed seven input multi-response variables to convert equivalent single objective optimization and the problem solved by the Taguchi method. It is recommended as the approach offers continuous quality improvement and offline quality control of a process or product in any manufacturing or production environment [20]. The neuro-fuzzy inference system consists of a cryogenically treated AISI M2 high-speed tool with hot rolled annealed steel stock (C-45) as the work material. The estimation of flank wear is made based on the results that the predictions are typically decided predominantly by the investigation of the untreated tool and cryogenically treated tool correlation coefficients of 0.994 and mean errors of 2.47% [21]. Only limited research works were reported about this experiment methodology on optimization using the multi-input-multiple-output (MIMO) fuzzy logic-Taguchi approach in the performance of the turning process using the DCT tool. This work concentrates on the DCT tool performance in the operation of medium carbon steel as expressed through the responses, namely, surface roughness and cutting tool edge temperature, found to be the best turning parameters identified using the methodology. This approach was applied to avoid the assumptions, uncertainty, limitations and imprecision of the machining process.

2. Experimental methods

2.1. Workpiece material. A round bar of 50 mm in diameter and 150 mm in length of medium carbon AISI 1045 steel was selected as the workpiece in the experiments, and its chemical composition is shown in Table 1. The work material is frequently used the in machinery and axles in the automotive industry [22].

Table 1
Composition of AISI 1045 steel

C	Mn	S	P	Si	Cr	Ni	Mg
0.424	0.797	0.014	0.015	0.169	0.018	0.005	0.002

Where: C – carbon, Mn – manganese, S – sulfur, P – phosphorus, Si – silicon, Cr – chromium, Ni – nickel and Mg – magnesium.

2.2. Tool material. The tool material used is M2 high-speed steel [23]. The square tool has a size of 12 mm × 12 mm × 50 mm ground on the cutter grinder, to achieve the nomenclature as per IS: 3019–1973 standards. The terminology of the cutting tool is provided in Table 2 and the composition is as follows: carbon – 0.974%, silicon – 0.115%, chromium – 3.955%, vanadium – 1.891%, tungsten – 6.509% and molybdenum – 4.950%.

Table 2
Cutting tool terminology and composition

γ	γ_1	α	α_1	Φ	φ_1	Nose radius
10°	12°	5°	5°	15°	15°	0.4 mm

Where: γ – back rake, γ_1 – side rake, α_1 – end clearance, α – side clearance, φ – side cutting edge and φ_1 – end cutting edge.

2.3. Cryogenic treatment. The HSS M2 tool was treated with the deep cryogenic treatment by lowering the temperature from room temperature to −196°C in liquid nitrogen and holding it at that temperature for 24 hours and then raising it back to room temperature. The tool was cooled down and heated up slowly at the rate of 0.5°C/min to avoid thermal shocks in the tool. Following cryogenic treatment, the tool was subjected to single-cycle tempering at 200°C for 2 hours [24], followed by the cryogenic process of the thermal cycle, as shown in Fig. 1.

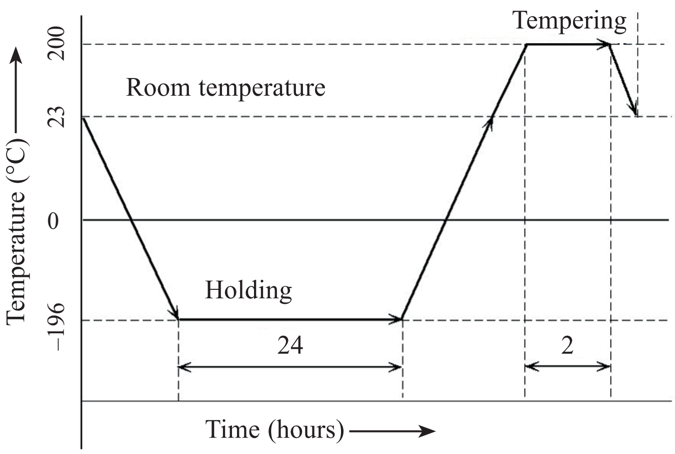

Fig. 1. Cryogenic process

2.4. Turning and observation. The experimental methodology adopted in the present work is shown in Fig. 2. The tests were conducted as per that methodology. The turning was carried out under dry conditions using the Kirloskar (Turn master 35) lathe machine, and the experimental setup is shown in Fig. 3. The experiments were based on the Taguchi (L_9) orthogonal array to attain a response. The process parameters used in this test and the respective levels are shown in Table 3. Their levels are selected within the intervals as recommended [25]. The outcome of surface roughness measurements (arithmetic average roughness R_a) for each cutting condition was measured using the Mitutoyo (SJ210) roughness meter. Online measurement of the cutting tool edge temperature (θ) was made using an Amprobe (IR-750) infrared (IR) pyrometer. The measured response values are presented in Table 4.

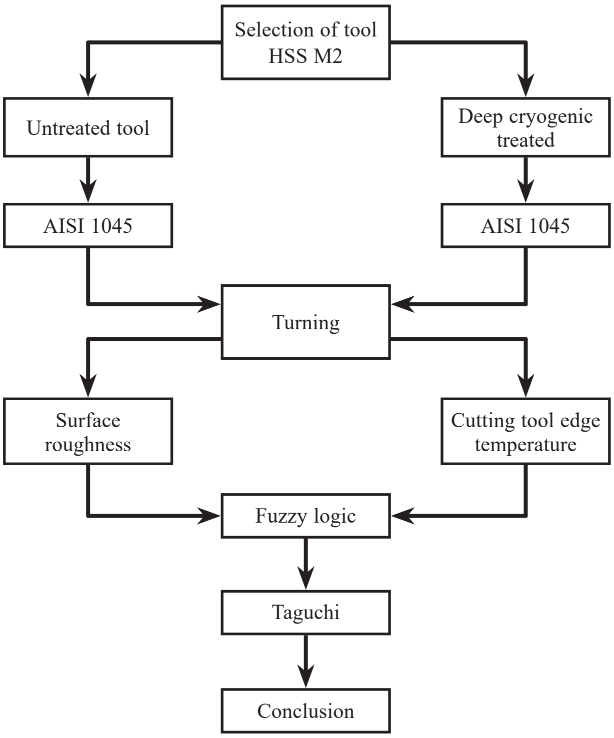

Fig. 2. Experiment methodology

Table 3
Process parameters and their levels

Notation	Cutting parameters	Levels		
		1	2	3
A	Cutting speed (v) (rpm)	382	414	446
B	Feed rate(s) (mm/rev)	0.125	0.135	0.145
C	Depth of cut (t) (mm)	0.4	0.45	0.5

Table 4
Response values

Untreated tool		Deep cryogenically treated tool	
R_a (μm)	θ (°C)	R_a (μm)	θ (°C)
3.162	45.65	2.824	34.80
3.294	65.40	2.990	41.10
3.346	68.40	3.243	55.50
2.625	69.75	2.518	59.17
2.743	70.35	2.550	65.50
2.796	91.20	2.596	80.00
2.520	100.00	2.440	95.00
2.539	95.00	2.480	87.00
2.579	103.00	2.490	102.00

2.5. Fuzzy logic and Taguchi approach. The fuzzy logic (FL) system commonly has four components: a fuzzifier process, fuzzy rule base, inference engine and a defuzzifier process (defuzzification). Fuzzification is a process of mapping from a crisp input universe of discussion into the fuzzy interval (0, 1) that depicts the membership of fuzzy input variables. The rule

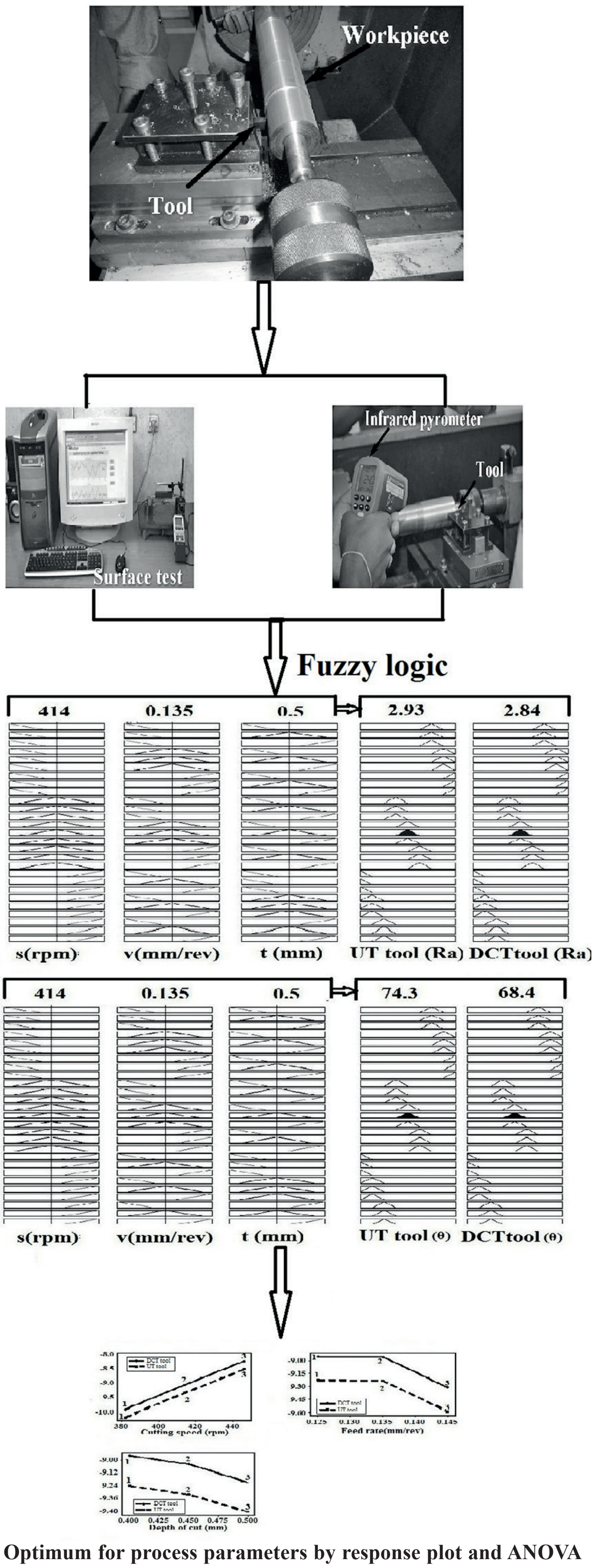

Fig. 3. Experiment setup

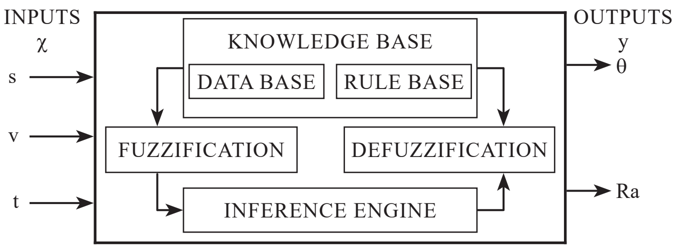

Fig.4. Fuzzy modelling

base contains the IF-THEN rules that embody linguistic reasoning [26]. An inference engine applies the rule base to the fuzzy sets to obtain a fuzzy outcome. The process of the fuzzy inference system (FIS) involves membership functions, fuzzy logic operators, and IF-THEN rules. The structure of a FIS consists of three components: a rule base containing a selection of fuzzy rules; a database defining the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism performing the inference procedure upon the rules to derive an output. The process parameters of the IF-THEN rules, referred to as antecedents in fuzzy modelling, define a fuzzy region of the input space, while the output parameters used as consequents specify the corresponding output in fuzzy modelling (Fig. 4).

There exist two types of fuzzy inference systems: the Mamdani fuzzy inference system (MFIS) and the Sugeno fuzzy inference system (SFIS). Both have been widely used in a variety of applications. MFIS is generally more widely used [27], mostly because it provides reasonable results with a relatively simple structure, and also due to the intuitive and interpretable nature of the rule base. MFIS can be used directly for both multi-input-single output (MISO) systems and multi-input-multi-output (MIMO) systems.

Fuzzy knowledge base systems can be formed by means of expert knowledge or automatic generation of rules-based measured data. Irrespective of the manner of formation, the knowledge base has a system with input and output, and knowledge base R contains n rules in the following form:
[R1, R2, R3... R n].
Where each n^{th} rule has the following form:
IF x is A THEN y is B
alternatively, in a mathematical form:
[IF (premise) THEN (consequent)] $\eta_{i=1}$.
Where A and B are linguistic values defined by fuzzy sets on ranges x and y, respectively. The IF-part of the rule "x is A" is called the antecedent or premise, while the THEN-part of the rule "y is B" is called the consequent. The input to an IF-THEN rule is the current value for the input variable, and the output is defuzzified. In the present work, an attempt has been made to develop a FIS model for the prediction of surface roughness and cutting temperature in the turning process using an integrated multi-input-multi-output (MIMO) FIS.

The primary stage in FL is the selection of appropriate shapes of the MF for developing an algorithm to select the machining parameters. The MF is a graphical representation of the magnitude of the participation of each parameter. It associates a weighting with each of the inputs that are processed, defines the functional overlap between inputs, and ultimately determines an output response. For the prediction of output parameters such as surface roughness and cutting tool edge temperature, the turning process is modelled using three input parameters, such as cutting speed, feed rate and depth of cut.

The fuzzy expressions for different input parameters are shown in Table 3. In Fig. 5a, the fuzzy sets of cutting speed

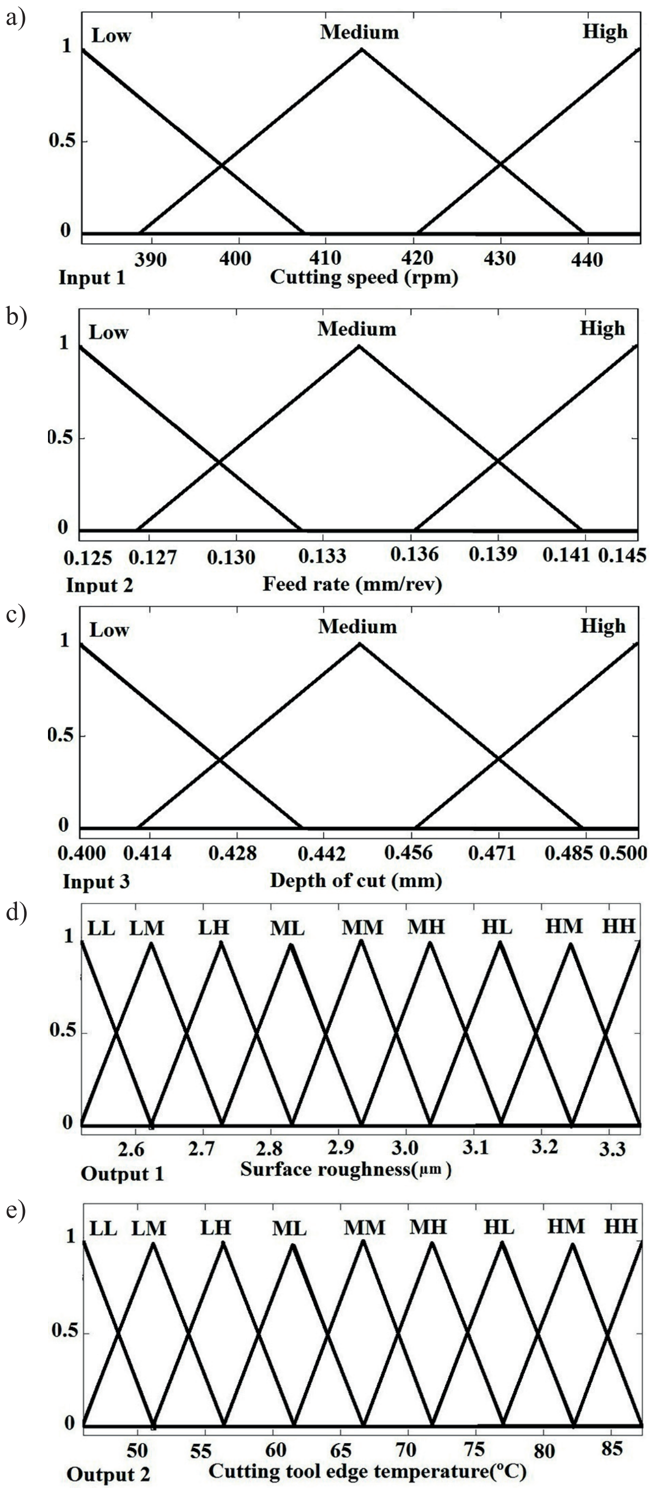

Fig. 5. Membership functions

(rpm) are Low (L), Medium (M) and high (H), the degree of membership is equal to 1, the corresponding currents will be 382, 414 and 446, respectively, and the cutting speed values will be used in experiments. This way, the feed rate (mm/rev) stands at 0.125, 0.135 and 0.145, respectively (Fig.5b), and the depth of cut (mm) is 0.4, 0.45 and 0.5, respectively (Fig. 5c), to be used for the experiments. Each experiment will result in specific output parameters that are to be classified into the corresponding fuzzy set of the output variable. More precise results can be obtained by using a greater number of MF.

Hence, the nine MF selected for each fuzzy set are defined by a separate membership function. The number of MF used for the output responses is nine: Low-Low (LL), Low Medium (LM) and Low-High (LH), Medium Low (ML), Medium Medium (MM), Medium-High (MH), High-Low (HL), High Medium (HM) and High-High (HH). The output response of the fuzzy processes can only be viewed in fuzzy values that have to be defuzzified.

The MF used for output response of surface roughness and temperature are presented in Fig. 5d and 5e. Fuzzy logic uses MF representation, and there are many shapes of MF available, such as the triangular, trapezoidal or Gaussian one. Triangular membership has been used.

The concept of fuzzy reasoning for a three-input and two-output FL unit is described as follows: the fuzzy rule base consists of a group of IF-THEN statements with three inputs: x_1 (cutting speed), x_2 (feed rate) and x_3 (depth of cut) and two outputs: y_1 (surface roughness) and y_2 (cutting tool edge temperature). Thus the form of rule-based systems with multiple inputs and multiple outputs is:

Inputs: x_1 is A_i and x_2 is B_i and x_3 is C_i

Output: y_1 is D_i and y_2 is E_i

R1: x_1 is A_1 and x_2 is B_1 and x_3 is C_1 THEN y_1 is D_1 and y_2 is E_1

R2: x_1 is A_2 and x_2 is B_2 and x_3 is C_2 THEN y_1 is D_2 and y_2 is E_2

Ri: x_1 is A_i and x_2 is B_i and x_3 is C_i THEN y_1 is D_i and y_2 is E_i

Where x_1, x_2 and x_3 are variables describing the process status and representing the input size of a fuzzy system, while y_1 and y_2 are the outputs of a fuzzy system. L, M, H, LL, LM, LH, ML, MM, MH, HL, HM and HH are linguistic values defined by fuzzy sets in ranges x_1, x_2, x_3, y_1 and y_2, respectively. A fuzzy-based 27-rule matrix has been shown in Table 5.

Following this, the implication function modifies the fuzzy set to a degree specified by the antecedent. The most common way to modify the fuzzy output set is truncation using the minimum function. Each rule from the previous set of rules can be viewed as a fuzzy implication; thus the i^{th} rule can be defined as:

$$\mu R_i = \mu(A_i \wedge B_i \wedge C_i = E_i)(x_1 x_2 x_3, y_1, y_2)$$

$$[\mu A_i(x_1) \wedge \mu B_i(x_2) \wedge \mu C_i(x_3)] = \mu D_i(y_1) \wedge \mu E_i(y_2).$$

It has used the Mamdani minimum implication operator, whereby the implication operator takes as an input the MF of an antecedent $\mu A_i(x_1) \wedge \mu B_i(x_2) \wedge \mu C_i(x_3)]$ while $\mu D_i(y_1) \wedge \mu E_i(y_2)$ is the consequent. Every rule has a weight (number between 0 and 1) which is applied to the number given by the antecedent.

Finally, a defuzzification method is used to transform the fuzzy output into a non-fuzzy value y_1 and y_2. Defuzzification is carried out by using the centroid defuzzification method. It produces the center area of the potential distribution of the inference output. It is one of the most frequently used defuzzification methods using the centroid of the area under the membership function for calculation by means of Equation 1:

$$y_1 = \frac{\sum_{i=1}^{n} (y_1)\mu D_i(y_1)}{\sum_{i=1}^{n} \mu D_i(y_1)} \wedge y_2 = \frac{\sum_{i=1}^{n} (y_2)\mu D_i(y_2)}{\sum_{i=1}^{n} \mu D_i(y_2)} \tag{1}$$

where y_1 and y_2 are defuzzified outputs, μD_i and μE_i are aggregated membership functions while y_1 and y_2 are output variables.

The non-fuzzy values y_1 and y_2 give the output value in a numerical form. For example, the cutting speed is 414 rpm and feed rate is 0.135 mm/rev with depth of cut(t) of 0.5 mm; the values of the cutting condition obtained for surface roughness for untreated and deep treated tool are 2.93 µm and 2.84 µm and the cutting tool edge temperatures are 74.3°C and 68.4°C, whereby the MATLAB fuzzy logic tool used for this calculation, and the calculated result is that fuzzy rules have

Table 5
27-rule matrix

Surface roughness				Cutting tool edge temperature			
Premise			Consequent	Premise			Consequent
v (rpm)	s (mm/rev)	t (mm)	Ra (µm)	v (rpm)	s (mm/rev)	t (mm)	θ (°C)
L	L	L	HL	L	L	L	LL
L	L	L	HM	L	L	L	LM
L	L	L	HH	L	L	L	LH
L	M	M	ML	L	M	M	ML
L	M	M	MM	L	M	M	MM
L	M	M	MH	L	M	M	MH
L	H	H	LL	L	H	H	HL
L	H	H	LM	L	H	H	HM
L	H	H	LM	L	H	H	HH
M	L	M	HL	M	L	M	LL
M	L	M	HM	M	L	M	LM
M	L	M	HH	M	L	M	LH
M	M	H	ML	M	M	H	ML
M	M	H	MM	M	M	H	MM
M	M	H	MH	M	M	H	MH
M	H	L	LL	M	H	L	HL
M	H	L	LM	M	H	L	HM
M	H	L	LH	M	H	L	HH
H	L	H	HL	H	L	H	LL
H	L	H	HM	H	L	H	LM
H	L	H	HH	H	L	H	LH
H	M	L	ML	H	M	L	ML
H	M	L	MM	H	M	L	MM
H	M	L	MH	H	M	L	MH
H	H	M	LL	H	H	M	HL
H	H	M	LM	H	H	M	HM
H	H	M	LH	H	H	M	HH

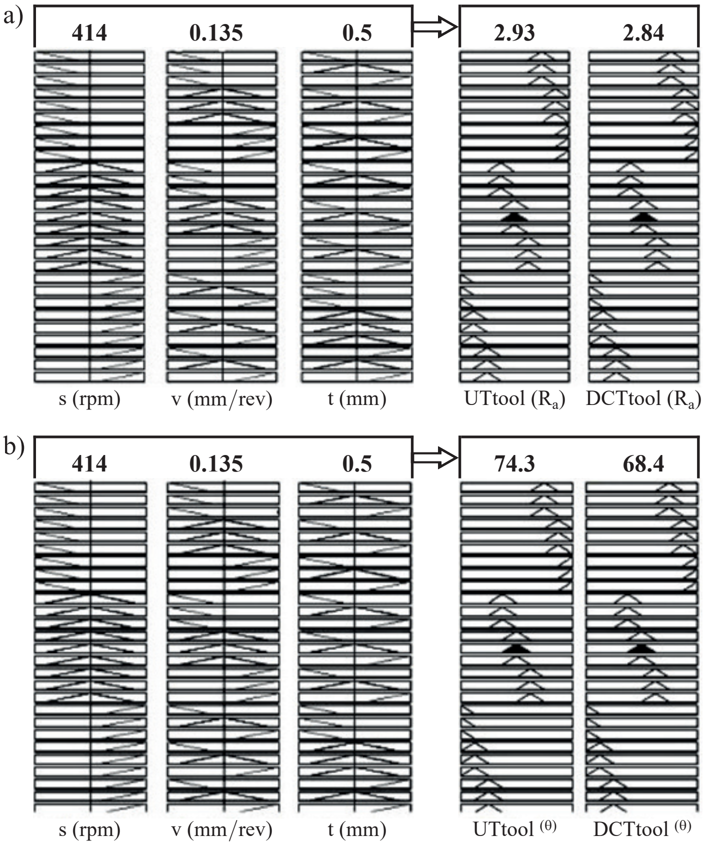

Fig. 6. Rule matrix

been explored for fuzzy reasoning based rule matrix, as shown in Fig. 6a, b.

A comparison of the experimental results and the predicted results by the MIMO fuzzy logic for surface roughness and cutting tool edge temperature has been made. The model shows good agreement between the untreated and deep cryogenically treated tool by the percentage of relative error for surface roughness at –3.499%; the cutting tool edge temperature stands at 4.832%. At the same time, the deep cryogenically treated tool has an improved Ra of –6.332% and θ is –0.230%. In this study, the modelling of the turning parameters is carried out using MIMO fuzzy logic; the analyses of the experimental process parameters are carried out by means of the Taguchi approach. The effects of the process parameters on the responses were analyzed using MINI TAB statistical software. This approach, based on the quality characteristics, can be prospective in the S/N ratio value, namely the-lower-the-better, the-nominal-the-better, and the-higher-the-better. The objective is to produce samples with minimum surface roughness and lower cutting tool edge temperature. Therefore, the the-lower-the-better criterion of the quality characteristic should be appropriate for surface roughness.

Because the Ra value decreased in the machined components, it reveals a good finish or quality index. The cutting tool edge temperature was based on the the-lower -the-better criterion as it helps to reduce the wear and thereby increase tool life [28–29]. The S/N ratio values calculated for surface roughness and cutting tool edge temperature using Equation 2 are shown in Table 6.

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right). \tag{2}$$

Here, y_i is the observed data at the i^{th} experiment and n is the number of experiments.

Table 6
S/N ratio values of surface roughness and cutting tool edge temperature

Untreated tool				Deep cryogenically treated tool			
Ra (μm)	S/N (dB)	θ (°C)	S/N (dB)	Ra (μm)	S/N (dB)	θ (°C)	S/N (dB)
3.14	–9.94	47.9	–33.6	3.04	–9.7	37.4	–31.5
3.24	–10.2	52.8	–34.5	3.14	–9.9	43.2	–32.7
3.31	–10.4	60	–35.6	3.21	–10	51.6	–34.3
2.83	–9.04	67.2	–36.6	2.74	–8.8	60	–35.6
2.93	–9.34	74.3	–37.4	2.84	–9.1	68.4	–36.7
3.04	–9.66	81.5	–38.2	2.94	–9.4	76.8	–37.7
2.73	–8.72	101	–40.1	2.64	–7.9	99.4	–38.6
2.55	–8.13	88.7	–39	2.47	–8.1	85.2	–39.4
2.73	–8.72	101	–40.1	2.64	–8.4	99.5	–40

3. Results and discussion

3.1. Effect of untreated tool on surface roughness and cutting tool edge temperature. The response values for the untreated tool are illustrated in Table 4. It is clear that the minimum surface roughness value was attained at a higher level of speed, lower level of feed rate and a higher level of depth of cut. Therefore, a higher level of cutting speed to eliminate built-up edges [30] and feed rate increases the amount of material near the contact, and the load on the tool is increased. The depth of cut increases the volume of uncut chip, thus increasing the force leading to a deformed shape at the tool edge [31].

Moreover, the lower cutting tool edge temperature was achieved at a low cutting speed (s), a low feed rate (v) and a low depth of a cut (t). For that reason, extremely slow cutting speeds are opted for to store the elastic energy of the deformed material as strain energy [32]. The feed rate and depth of cut are less affected because of the smaller contact area of the tool. In machining, a material layer being cut appears to be cut off, and the squeezing action on the component by the cutting tool edge is blunt and intensified, thus increasing the friction, due to increasing flank wear [33].

3.2. Effect of deep cryogenically treated tool on surface roughness and cutting tool edge temperature. The response valves for the deep cryogenically treated tool is shown in Table 4. It is observed that the smallest values for surface roughness and cutting tool edge temperature are obtained through the untreated

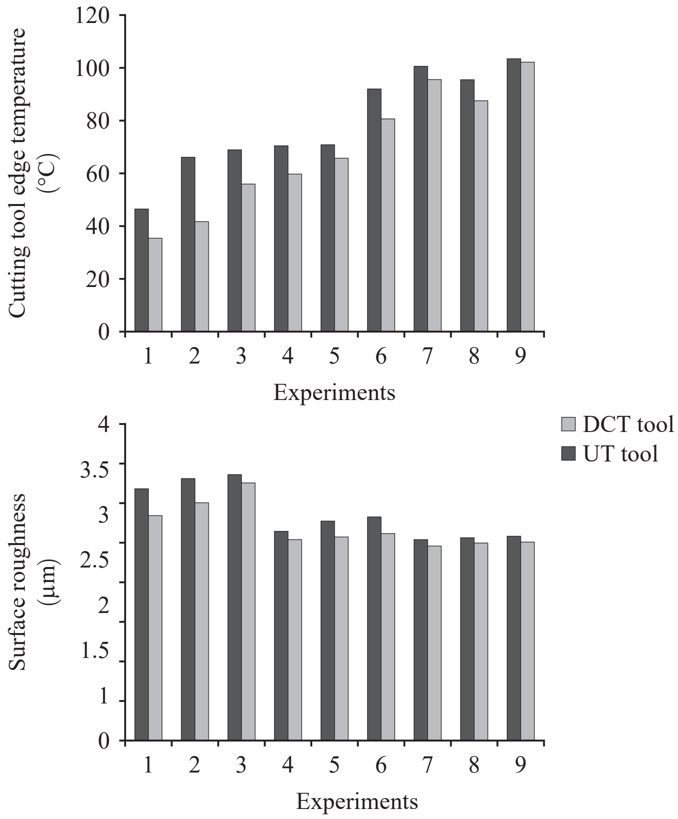

Fig. 7. Performance comparison

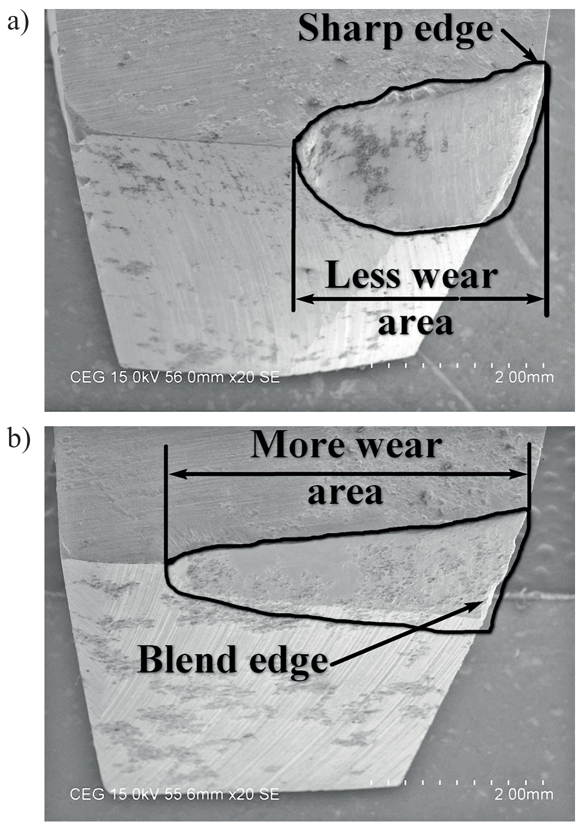

Fig. 8. a) DCT tool, b) UT tool after machining

tool for the same combination. However, the deep cryogenically treated tool's performance has improved by up to 11%, and cutting tool edge temperature reduction was about 23.76% over that of the untreated tool. For that reason, using the deep cryogenic treatment leads to enhancement of the precipitation of fine carbides during subsequent tempering [34]. The strain energy in the martensite lattice increases at a lower temperature. The consequent carbon atoms migrate and form clusters. During subsequent heating back to room temperature or even tempering, these clusters act as nuclei for the formation of ultrafine carbides [35–37]. The carbides that form are uniformly distributed throughout the microstructure. Because of this, the tool is hard. It also increases the tool's performance during machining. The performance comparison of the UT tool and DCT tool in cutting tool edge temperature and surface roughness is shown in Fig. 7. Figure 8a, b shows the wear morphology of both tools after turning. It is observed that the worn-out region in the flank surface of the deep cryogenically treated tool is smaller than that of the untreated tool under the same cutting conditions.

3.3. Optimization of process parameters using responses. The multi-input-multi-output fuzzy inference system for the signal-to-noise ratio is calculated using the the-higher-the-better rule to get the optimum parametric combination. As per the calculation, the S/N ratio values should be selected among three levels of parameters to arrive at optimum results. Figure 9a–c

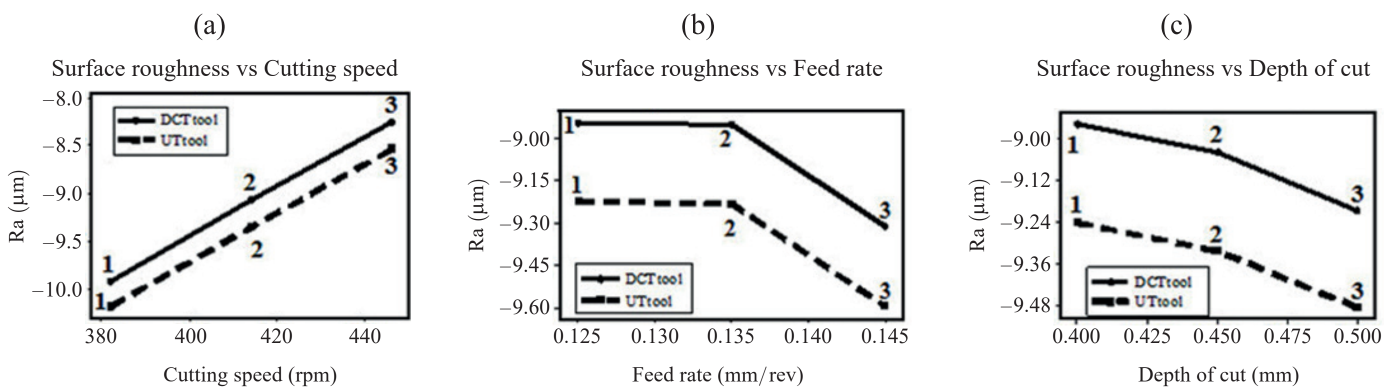

Fig. 9. Signal-to-noise ratio graph for surface roughness

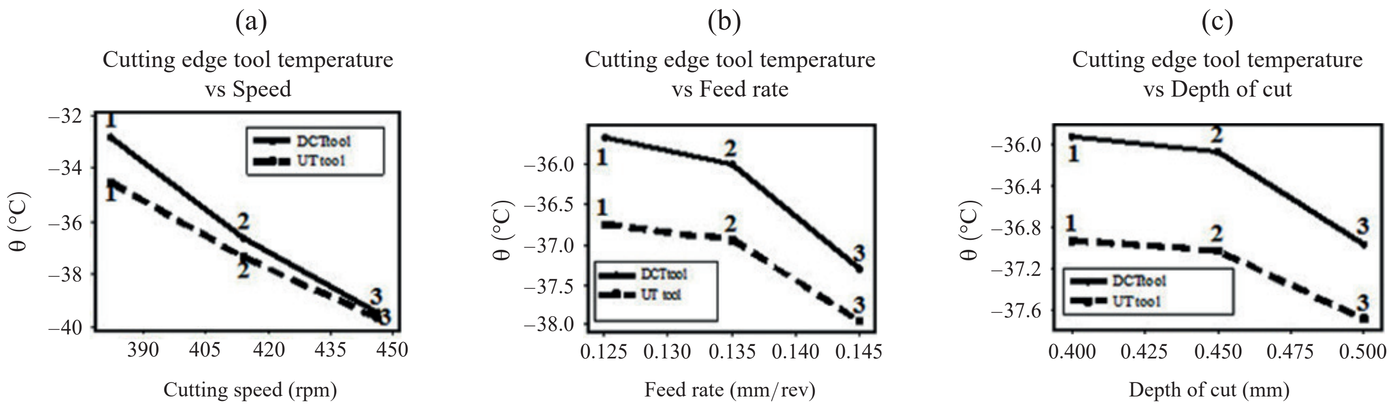

Fig.10. Signal-to-noise ratio graph for cutting tool edge temperature

and 10a–c outline the main effects of surface roughness and cutting tool temperature. The Figures also display the effect of the machining parameters and their interaction with surface roughness and cutting tool temperature. They reveal that both tools produce similar trends. The minimum surface roughness combination is A3B1C1, i.e. 446 rpm cutting speed (A3), 0.125 mm/rev feed rate (B1) and 0.4 mm depth of cut (C1). Table 7 shows the values of surface roughness mainly influenced by the cutting speed (v) followed by feed rate (s) and depth of cut (t).

Table 7
S/N ratio mean values for R_a

Untreated tool				Deep cryogenically treated tool			
Levels	(A)	(B)	(C)	Levels	(A)	(B)	(C)
1	–10.1	–9.2	–9.2	1	–9.9	–8.9	–8.9
2	–9.3	–9.2	–9.3	2	–9	–8.9	–9
3	–8.5	–9.5	–9.4	3	–8.2	–9.3	–9.2
Delta	1.6	0.3	0.2	Delta	1.6	0.3	0.2
Rank	1	2	3	Rank	1	2	3

Figure 10a–c shows that the optimum process parameters achieved for the minimum cutting tool edge temperature combination are A1B1C1. i.e. 382 rpm cutting speed (A1), 0.125 mm/rev feed rate (B1) and 0.4 mm depth of cut (C1).

Table 8 shows the values of cutting tool edge temperature; it reveals that speed is the most influential factor followed by feed rate and depth of cut.

Table 8
S/N ratio mean values for θ

Untreated tool				Deep cryogenically treated tool			
Levels	(A)	(B)	(C)	Levels	(A)	(B)	(C)
1	–35	–37	–37	1	–33	–36	–36
2	–37	–37	–37	2	–37	–36	–36
3	–40	–38	–38	3	–40	–37	–37
Delta	5.1	1.2	0.7	Delta	6.6	1.6	1
Rank	1	2	3	Rank	1	2	3

3.4. Analysis of variance for surface roughness. The ANOVA results for surface roughness are given in Table 9. The speed of the untreated tool contributes 89%, and deep cryogenically treated tool contributes 88%, which is the most significant parameter. The feed rate and depth of cut of the deep cryogenically treated tool are 5.6%, and 6.1%, and for the untreated tool they stand at 1.98% and 1.4%, respectively. Ra decreases with an increase in cutting speed and decrease in feed rate and depth of cut. It is observed that the deep cryogenically treated tool obtained less contribution percentage than the untreated tool because of less distortion on the cutting edge due to enhanced hardness through the deep cryogenic treatment [38]. From the ANOVA, it is clear that the cutting speed is the most significant factor followed by feed rate and depth of cut.

Table 9
ANOVA for surface roughness of untreated and deep cryogenically treated tools

Untreated tool				
Source	DF	Seq SS	Adj MS	PC %
Cutting speed	2	4.18	2.09	89.0
Feed rate	2	0.26	0.129	6.1
Depth of cut	2	0.1	0.049	1.4
Residual error	2	0.17	0.084	
Total	8	4.7		
Deep cryogenically treated tool				
Source	DF	Seq SS	Adj MS	PC %
Cutting speed	2	4.11	2.06	88.0
Feed rate	2	0.26	0.13	5.6
Depth of cut	2	0.09	0.05	1.98
Residual error	2	0.18	0.09	
Total	8	4.65		

DF – degrees of freedom, Seq SS – sequential sum of squares, Adj MS – adjusted mean squares and PC % – percentage contribution ratio

3.5. Analysis of variance for cutting tool edge temperature. The ANOVA of the cutting tool edge temperature for both the cutting tools is presented in Table 10; it is noted that the DCT tool contributes 90% and the untreated tool contributes 91% of the cutting speed. The feed rate and depth of cut of the deep cryogenically treated tool is at 5%, and 3%, and of the untreated tool 6% and 1%, respectively. This reveals that the values of the cutting tool edge temperature increase with an increase in the cutting speed followed by feed rate and depth of cut. It can be observed that the deep cryogenically treated tool achieved smaller values than the untreated tool. For that reason, the cutting tool edge is sharper to prevent heat accumulation in the forefront due to an increase in hardness and wear resistance generated by the cryogenic treatment [39]. From the ANOVA, it is clear that the cutting speed is the most dominant factor followed by feed rate and depth of cut.

Table 10
ANOVA for cutting temperature of untreated and deep cryogenically treated tools

Untreated tool				
Source	DF	Seq SS	Adj MS	PC %
Cutting speed	2	40.23	0.12	91.00
Feed rate	2	2.53	1.27	6.00
Depth of cut	2	1.02	0.51	1.31
Residual error	2	0.62	0.31	
Total	8	44.41		
Deep cryogenically treated tool				
Source	DF	Seq SS	Adj MS	PC %
Cutting speed	2	67.74	33.868	90
Feed rate	2	4.51	2.257	5
Depth of cut	2	1.91	0.954	3
Residual error	2	1.00	0.498	
Total	8	75.15		

4. Conclusions

The multi-input-multi-output fuzzy logic based on the Taguchi approach was employed to determine the optimum combination of process parameters with the desired quality characteristics (the-lower-the-better surface roughness and cutting tool edge temperature) in the turning of AISI 1045 steel under dry conditions using untreated and deep cryogenically treated tools. The following conclusions have been drawn:

1) The deep cryogenically treated tool has a positive effect on surface roughness and cutting tool edge temperature. At the same time, the deep cryogenically treated tool achieved lower surface roughness of up to 11% and also lower cutting tool edge temperature of up to 23.76% as compared with the untreated tool.
2) The optimum process parameters for lower surface roughness as determined by the Taguchi signal-to-noise ratio are (A3 B1 C1), i.e. cutting speed of 446 rpm (A3), the feed rate of 0.125 mm/rev (B1) and depth of cut of 0.4 mm (C1). Meanwhile, it is found that the optimum process parameters for smaller cutting temperature are (A1 B1 C1), i.e. cutting speed of 382 rpm (A1), the feed rate of 0.125 mm/rev (B1) and depth of cut of 0.4 mm (C1).
3) From the ANOVA results, it is found that the cutting speed is the most significant factor for the responses, followed by feed rate and depth of cut. It was clear that the deep cryogenically treated tool provides a significant improvement in the performance of machining.
4) The implemented methodology of experimental approach is simple and effective in developing a robust, versatile and flexible process. The same is recommended for application in industrial cryogenic machining and for future research.

Acknowledgements. The authors would like to thank Cryoteknics and Systems, Hosur, Tamil Nadu, India.

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