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Estimation of surface roughness on Ti-6Al-4V in high speed micro end milling by ANFIS model

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Titanium and its alloys are a few of the most suitable materials in medical applications due to their biocompatibility, anticorrosion and desirable mechanical properties compared to other materials like commercially pure Nb & Ta, Cr-Co alloys and stainless steels. High speed micro end milling is one of the favorable methods for accomplishing micro features on hard metals/alloys with better quality products delivering efficiently in shorter lead and production times. In this paper, experimental investigation of machining parameters influence on surface roughness in high speed micro end milling of Ti-6Al-4V using uncoated tungsten carbide tools under dry cutting conditions and prediction of surface roughness using adaptive neuro- fuzzy inference system (ANFIS) methodology has been presented. Using MATLAB tool box - ANFIS approach four membership functions - triangular, trapezoidal, gbell, gauss has been chosen during the training process in order to evaluate the prediction accuracy of surface roughness. The model's predictions have been compared with experimental data for verifying the approach. From the comparison of four membership functions, the prediction accuracy of ANFIS has been reached 99.96% using general bell membership function. The most influential factor which influences the surface roughness has the feed rate followed by depth of cut.

Keywords: Micro end milling, ANFIS, Ti-6Al-4V, Surface roughness

1 Introduction

Micro-end-milling process is one of the most widely used process in machining titanium and its alloys for aerospace, automotive, biomedical, marine, die and mold making functions because of its resistance to corrosion and high specific strength. Today in this competitive world of industry 4.0, industrial design and manufacturing of the products is done using advanced technologies and processes to meet the customer need, demand and satisfaction within a short span of time. High speed micro-end-milling is one such process which delivers efficient and better-quality products with shorter lead and production times at low costs. Titanium and its alloys are excellent for their combination of relatively low densities, high strengths and facture toughness, low modulus of elasticity, better fatigue strength, high melting point, low thermal expansion coefficient and thermal conductivity, high electrical resistivity, high intrinsic shock resistance, high ballistic resistance-to-density ratio, nonmagnetic, exceptional corrosion and erosion resistance to chlorides, sea water, sour and oxidizing media[1-3].

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Product quality is one of the product output in which surface of desired material plays a major role. It may impact the wear resistance, friction, corrosion, light reflection, coating, lubrication, withstanding stresses and temperature and fatigue conditions on the machined surface. Surface roughness is measured using surface profilometers with contact stylus and by non-contact type like white light interferometry at fixed intervals. Micro-milling operation is a very important process for making slots, pockets, moulds, and dies in the industry. Micro end milling process is used for roughing and finishing operations. The challenge in machining titanium alloys was chiefly the high tool wear associated with the reactivity of titanium with tool materials and its low thermal conductivity. However, there were many challenges faced and are continuous during high speed machining operation because of many factors like cost, work materials, cutting tool materials, heat affected zones, work piece surface integrity, feed rate, spindle speed, depth of cut, tool breakage, tool wear, tool run-out, tool chatter, tool deflection, tool geometry, vibration of the work piece and tool material, machine motion errors, chip formation, material non-homogeneity of both the tool and work piece[1-3]. Hardness, strength, microstructure and heat treatment affect the surface generated on work material in micro-end-milling process. To achieve the desired surface quality, it is tedious to choose the machining parameters because of uncontrollable factors comes into play while machining. In order to meet the product features performance and quality, particularly the machining area emphasizes on a large number of factors that were complex to deal and delivering it out successfully can be done by following and adopting the prediction methodologies recommended by researchers.

Alauddin *et al.*[4] investigated the effect of cutting parameters on the surface roughness using response surface methodology. Contours of the surface-roughness outputs were constructed in planes containing two of the independent variables for higher material remove rate with compromising on surface roughness. They found that feed effect was very dominant in both the models. Chou *et al.*[5] proposed the grey-fuzzy control scheme to control the turning process with constant cutting force under various cutting conditions. They found that the taguchi-genetic method is a useful tool for searching for the optimal control parameters of the optimal grey-fuzzy control scheme in turning operations. Ozel *et al*.[6] investigated the functioning of CBN tools under different cutting conditions using neural network model. They found that with known forces, estimation of the flank wear is possible by algorithms. Benardos *et al*.[7] using taguchi- design of experiments method presented a neural network modeling approach for estimation of surface roughness in face milling and they found that it can be implemented successfully. Balazinski *et al.*[8] compared the usability of three artificial intelligence (AI) methods to predict tool wear by means of known cutting force components in turning. They found that the neuro-fuzzy system, the structure (number of rules) and the number of iterations do not have an important influence on system performance and the operator does not have to know the results of preliminary tests i.e. it is so short for the neuro- fuzzy system that it can be easily optimized and implemented on the factory floor.

Achiche *et al.*[9] applied fuzzy knowledge - genetic algorithm (FL-GA) method for tool wear monitoring application. They found that for shop floor control FL-GA method was the shortest among other methods proposed. Kwon *et al.*[10] developed a fuzzy adaptive modeling technique to estimate surface roughness under process variations in CNC turning. They found that using fuzzy adaptive predictor i.e. fuzzy rule base enables the implementation of human expert knowledge into the inference mechanism; hence modifications to control rules can be made coherent to the process variations. Lo[11] applied ANFIS technique to estimate the surface roughness considering the machining input parameters after the end milling process. They found 96 % accuracy rate for triangular membership function when compared to others. Huang *et al.*[12] studied the estimation of surface roughness using input machining parameters by neural network associated with sensing technology. They found that it was suitable for fixed work material and fixed tool and they suggested further investigations with more input parameters should be done. Susanto *et al.*[13] for tool wear scrutinizing proposed a fuzzy logic approach and found more than 90% accuracy during a t-test at alpha value of 0.05. Brezocnik *et al*.[14] based on input machining parameters proposed the integrated genetic programming and genetic algorithm approach for estimation of surface roughness in end-milling and found suitable accuracy. Benardos *et al.*[15] presented a review on approaches based on artificial intelligence (AI), machining theory, designed experiments and experimental investigation for estimation of surface roughness and drawn advantages and disadvantages of individual approach. Sokolowski[16] analyzed burr height modeling, thermal deformation monitoring and cutting tool wear using fuzzy logic (FL) application and practically implemented in machine monitoring and diagnostics which was fruitful.

Jiao *et al.*[17] developed fuzzy adaptive network (FAN) model to predict surface roughness in turning operations and compared the result with multiple regression analysis, depicting FAN model is best. Zuperl *et al.*[18] developed an approach to study the effect of cutting forces in ball-end milling process using back propagation neural network model. *Fu et al.*[19]established an intelligent tool condition monitoring system by applying a unique fuzzy neural hybrid pattern recognition system for tool wear classification. They found that the developed hybrid neuro fuzzy networks have a simplified structure and produces better and more transparent models than a general fuzzy system. Oktem *et al.*[20] for determining optimum cutting parameters to minimize surface roughness in end milling considered the feed forward neural network and genetic algorithm in MATLAB.

Ghosh *et al.*[21] developed a neural network-based sensor fusion model for tool condition monitoring for prediction of tool wear in CNC milling. They found that for critical machining operations better power and force-based TCM can be used which is costly and for general machining industry low cost power-based TCM or SPL-current-based TCM can be used. Uros *et al.*[22] proposed ANFIS model for prediction of flank wear from cutting force signals in end-milling process and found high accuracy at low computational time. Ho *et al.*[23] proposed ANFIS model for estimation of surface roughness in end milling process using hybrid Taguchi-genetic learning algorithm (HTGLA). They found that HTGLA based analysis out performed than ANFIS approach. Samantha[24] considered the ANFIS approach with genetic algorithms for surface roughness prediction in machining and in comparison, the ANFIS results outperformed than ANN model.

Chandrasekaran *et al.*[25] reviewed different soft computing techniques for predicting the performance and optimizing the different machining processes such as turning, milling, drilling and grinding machining processes. Pontes *et al.*[26] reviewed different research papers on usage of artificial neural networks for modeling surface roughness in machining processes and concluded that how researchers define network architectures, error measures, training algorithms and results validation. Ratava *et al.*[27] presented an adaptive fuzzy control system approach method to increase cutting efficiency for steel rough turning and avoid the onset of instability. Asilturk*et al.*[28] used multiple regression and artificial neural network approaches to predict the surface roughness in AISI 1040 steel. They found that ANN is a dominant tool than multiple regression because of its capacity of learning, speed and simplicity Zuperl *et al.*[29] discussed the application of neural adaptive control strategy in high speed end milling operations to maintain material removal rate and prevent the tool breakage, excessive tool wear and the problem of controlling the cutting force. Natarajan *et al.*[30] compared the ANFIS methodology and ANN- back propagation models for prediction of surface roughness in end milling and found ANFIS outperformed than ANN model. Suganthi *et al.*[31] considered the ANFIS and back propagation (BP) of ANN models for estimation of multiple quality responses in micro-EDM operations. They found that ANFIS model outperforms BP-based ANN when compared with observed values. Aydin *et al.*[32] considered ANFIS with particle swarm optimization (PSO) learning for modeling and prediction of both surface roughness and cutting zone temperature in turning of AISI304 austenitic stainless steel with coated tungsten carbide tools. Azmi *et al.*[33] utilized multiple regression analysis (MRA) and neuro-fuzzy modelling for validating the estimation and monitoring of carbide tool wear during end milling of glass fibre-reinforced polymer composites. Huang *et al.*[34] developed steps for an intelligent neural-fuzzy inference system, making the neural networks and fuzzy logic more efficient in developing the decision-making IF-THEN and are much clearer in calculating the algorithm for an in-process surface roughness monitoring system in end milling operations. Jian Wei *et al.*[35] investigated the importance of selection of spindle speed in high speed milling of titanium alloys of curved surface. Salman *et al.*[36] evaluated the challenges lying in improving machinability of the titanium and nickel based alloys. Maher *et al.*[37] used ANFIS methodology to predict surface roughness in correlation with cutting forces in end milling operation. Maher *et al.*[38] utilized ANFIS methodology for prediction and comparison of surface roughness, cutting speed and heat affected zone values with measured values in order to improve the performance of wire EDM process. Wu[39] utilized ANFIS and ANN methods to develop the standard relation between the effects of processing parameters and coating properties in plasma spraying process. Chakradhar *et al.*[40] investigated estimation of surface roughness using artificial neural network (ANN), group method data handling (GMDH) and multiple regression analysis (MRA) in high speed micro end milling of titanium alloy (grade-5).

A comparative study was made to know the influence of spindle speed, feed and depth of cut on surface roughness of Ti-6Al-4V-titanium alloy. They found that prediction accuracy of artificial neural network is higher than other techniques. Chakradhar[41] investigated the influence of machining parameters in high-speed micro-end milling of titanium alloy (grade-2) using uncoated tungsten carbide micro end mills to understand the cutting mechanism and surface roughness formation. They found that micro-milling at high spindle speeds, low depth of cut, and low feed rate ensures the high quality of surface finish and lower cutting forces.

However, there is a need for an approach that will allow the evaluation of the surface roughness value before the machining of the part and which, at the same time, can be easily used in the production-floor environment contributing to the minimization of required time and cost. Moreover, it could be used for the determination of the appropriate cutting conditions in order to achieve specific surface quality. From the efforts of researchers, new techniques have been developed and application of soft computing like mathematical models, statistical analysis tools, fuzzy logic and artificial neural network models in various disciplines resulted in estimation of desired outputs. To predict the surface roughness in high speed micro end milling of titanium and its alloys by membership functions (MF's) approach is limited. This paper discusses the adaptive-network based fuzzy inference system (ANFIS) approach because of its simplicity, speed and capacity of learning to examine the prospect and effectiveness of predicting surface roughness. In construction of this model, machining output variable surface roughness and input variables such as cutting speed, feed and axial depth of cut were considered. In this model, four different MF's. - triangular, trapezoidal, gbell & gauss was adopted during the training process of ANFIS using Matlab tool box in order to evaluate the prediction accuracy of surface roughness. The results signify that the gbell MF has a higher correct rate of surface roughness prediction rather than the triangular MF, trapezoidal MF & gauss MF.

2 ANFIS Model

ANFIS uses input data and output data set given by the end user for constructing fuzzy inference system (FIS) whose MF parameters are regulated using either a back propagation algorithm alone or in combination with a least squares type of method. ANFIS structural design is shown in Fig. 1. The design consists of five layers, namely, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. Adaptive nodes, denoted by squares represent the parameter sets that are adjustable in these nodes, whereas fixed nodes denoted by circles represent the parameter sets that are fixed in the system[10,11,17,22,23,25,34,40]. The flow chart of surface roughness prediction by ANFIS methodology is shown in Fig. 2.

In fuzzy inference system, two inputs x and y and one output g were considered. For a first-order sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as:

Rule 1: If (x is C_1) and (y is D_1)then

$$g_1=a_1x+b_1y+k_1 \quad \ldots (1)$$

Rule 2: If (x is C_2) and (y is D_2)then

$$g_2 = a_2x + b_2y +k_2 \quad \ldots (2)$$

where, a_1, a_2, b_1, b_2, k_1 and k_2 are linear parameters and C_1, C_2, D_1 and D_2 are nonlinear parameters.

3 Experimental Details

High-speed micro-end-milling was carried out on titanium alloy- Ti-6Al-4V-Grade-5 of dimensions 60 mm X 40 mm X 4 mm with a two-flute uncoated tungsten carbide end mill cutter of diameter size 500 µm with a helix angle of 30°. Experimental tests were conducted at high speed micromachining centre at Indian Institute of Technology Bombay (IIT-Bombay) as shown in Fig. 3. Spindle speeds were considered as 30,000, 60,000 & 90,000 rpm i.e. a cutting speed range of 47, 94 and 141 m/min. Feed considered was 2, 4 & 6 µm/tooth. The feed rate was 2, 4, 6, 8, 12 &18 mm/sec that results in the feed/tooth/rev or maximum undeformed chip thickness of 2, 4 & 6 µm. The depth

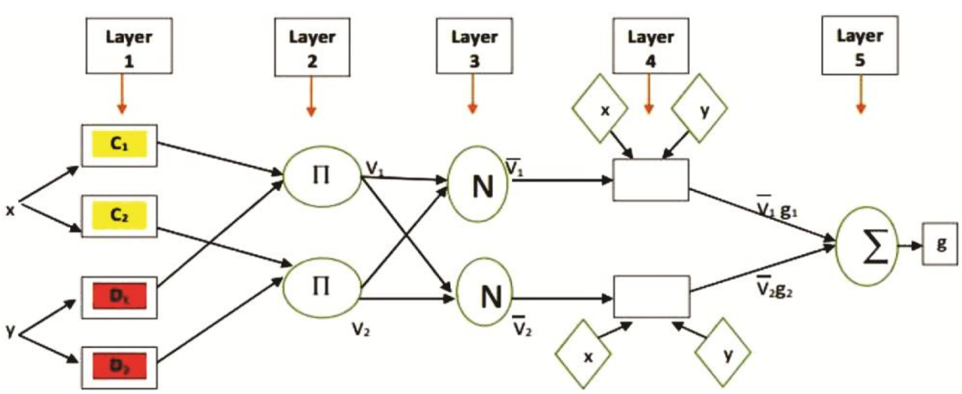

Fig. 1 — ANFIS architecture

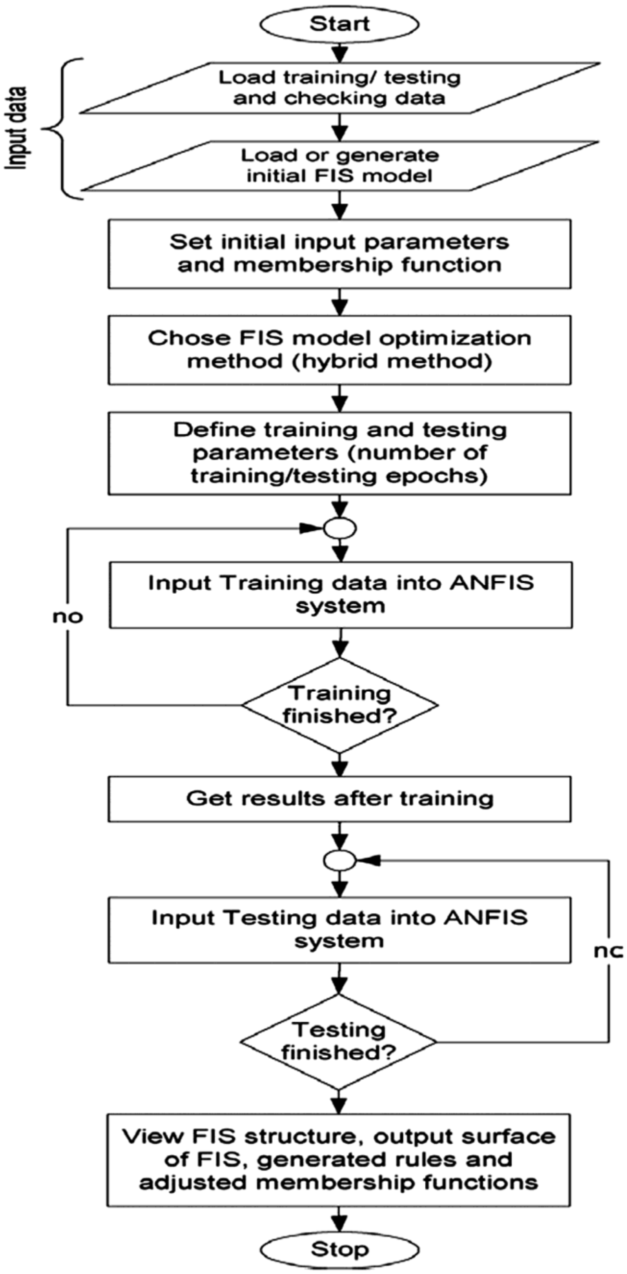

Fig. 2 — Flow chart for prediction of surface roughness by ANFIS[21]

of cut consideration was 0.02, 0.04 & 0.06 mm. Design of experiments with 3 parameters (spindle speed, feed rate, depth of cut) varying on 3 levels in all the possible combinations were considered. Total 54 experiments (27 x (2 -1) material and tool type) i.e. 2 repetitions were carried out after every 9 series of tests with new end mill for verification and observation of machining output parameters. Surface roughness of the micromilled slots was examined using non-contact type white light

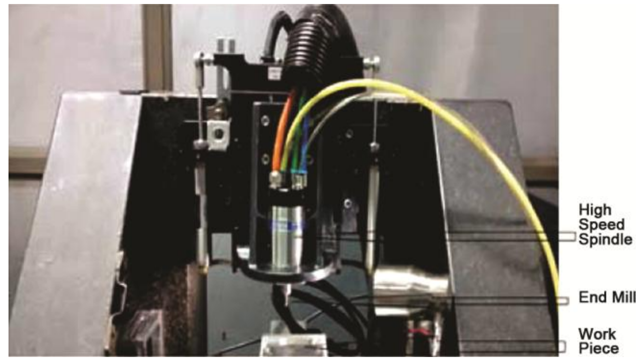

Fig. 3 — Micro milling Machine.

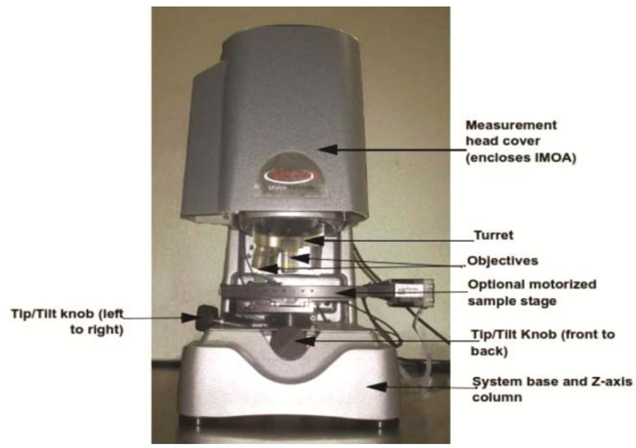

Fig. 4 — White light interferometry (WYKO NT 9100®)

interferometry (WYKO NT 9100) as shown in Fig 4. The vertical measurement range of instrument is 0.1 nm to 10 mm, optical resolution is 0.49µm min and RMS repeatability is 0.05 nm. The average of surface roughness values measured at 6 equidistant locations on each slot is used for the analysis. Surface roughness examined image of 2D & 3D was shown in Figs 5 & 6. The measured values of surface roughness were shown in Table1.

4 Results & Discussion

Spindle speed, feed rate and depth of cut were considered as input parameters, which affects the surface roughness in the high-speed micro end milling process. Four different MF's - triangular, trapezoidal, gbell, gauss were implemented throughout the training process of ANFIS using the Matlab tool box to evaluate the estimation accuracy of surface roughness. Experimentally surface roughness observations were done and it was used as training data and testing data in ANFIS methodology to verify the estimated accuracy. In this approach 18 training and 9 testing data sets were used. Among the 9 testing

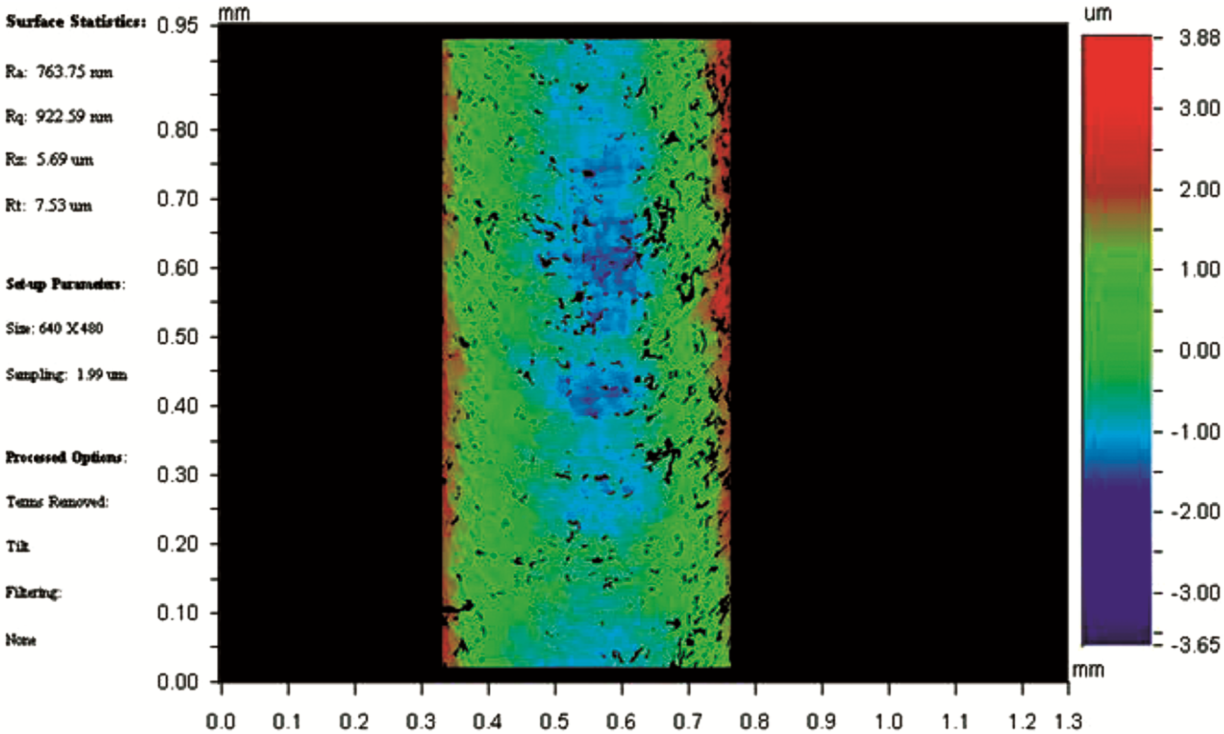

Fig. 5 — 2D Surface roughness at 90,000 rpm

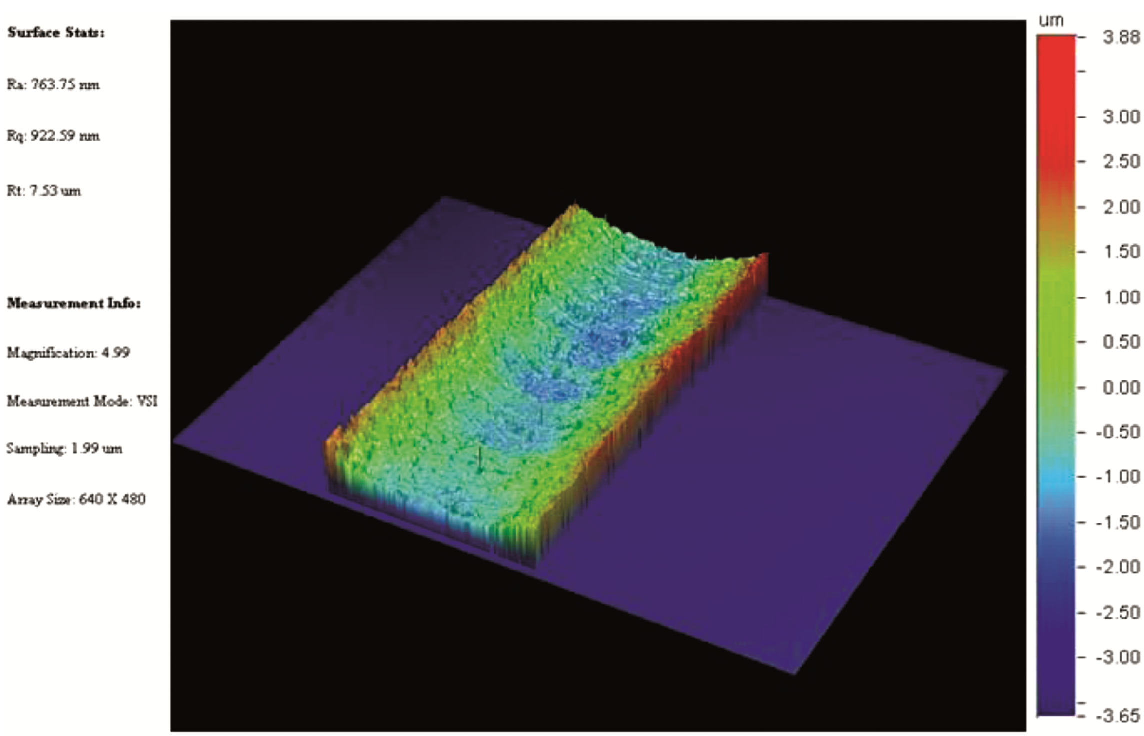

Fig. 6 — 3D Surface roughness at 90,000 rpm

data in ANFIS, for 30,000 rpm the testing data feed rate was different but for 60,000 rpm and 90,000 rpm the settings of the depth of cut and feed rate were same as those used in the training sets. Figs (7-18) show the fuzzy rule MF's of triangular, trapezoidal, gbell and gauss in ANFIS.

In the course of aiming in ANFIS, 18 sets of experimental data were used to manage 30 cycles of learning. The compared experimental and estimated MF's values of the surface roughness after training by ANFIS are shown in Table 2. The three machining parameters of any one of the 9 sets of test data has to be entered in ANFIS after training then an output value was obtained from the calculation results. This output value was the predicted value of surface roughness. Estimated surface roughness average error was around 9.74% for triangular MF, 1.46 % for trapezoidal MF, 0.04 % for general bell MF and 0.37 % for gauss MF as shown in Table 2. When general MF was utilized accuracy of 99.96% obtained because of the wide range of machining parameter selection. When the gauss MF adopted the accuracy was 99.63%. When the triangular & trapezoidal MF's adopted the accuracy was 90.26 % and 98.54 %.
These results indicate that the training of ANFIS with the general bell MF obtained a higher accuracy rate in the prediction of surface roughness than other MF's used. The effect of input parameters on output

Table 1— Experimental results of surface roughness.

Spindle Speed (rpm)	Feed (μm/ tooth)	Feed Rate (mm/sec)	Depth of cut (mm)	Surface Roughness (nm)
30000	2	2	0.02	126
30000	2	2	0.04	178
30000	2	2	0.06	192
30000	4	4	0.02	209
30000	4	4	0.04	227
30000	4	4	0.06	272
30000	6	6	0.02	406
30000	6	6	0.04	493
30000	6	6	0.06	545
60000	2	4	0.02	115
60000	2	4	0.04	121
60000	2	4	0.06	135
60000	4	8	0.02	225
60000	4	8	0.04	313
60000	4	8	0.06	474
60000	6	12	0.02	493
60000	6	12	0.04	532
60000	6	12	0.06	620
90000	2	6	0.02	144
90000	2	6	0.04	153
90000	2	6	0.06	188
90000	4	12	0.02	270
90000	4	12	0.04	520
90000	4	12	0.06	746
90000	6	18	0.02	808
90000	6	18	0.04	842
90000	6	18	0.06	862

parameter is shown in Figs 19 & 20. The fuzzy rule function architecture of ANFIS is shown in Fig. 21. Experimental values of surface roughness Ra plotted with input variables results were shown in Fig. 22. At 30, 000 rpm machining conditions i.e. from 1 to 9 the

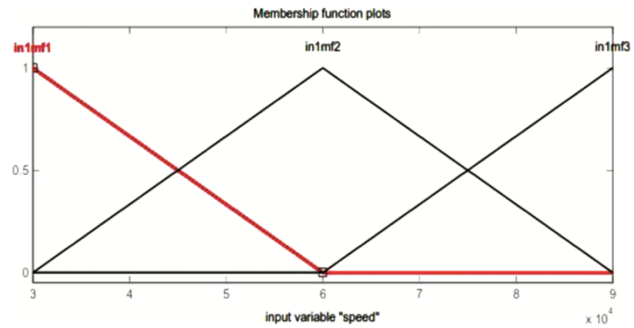

Fig. 7 — Triangular MF -spindlespeed

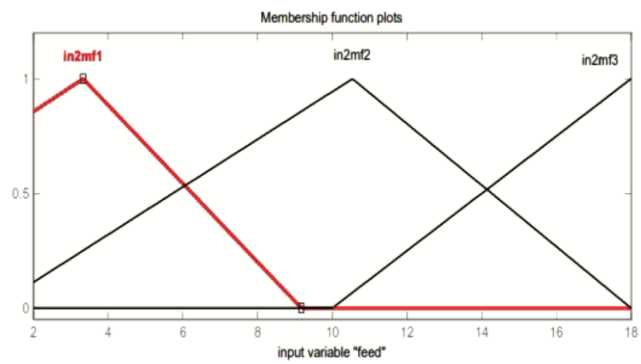

Fig. 8 — Triangular MF - feedrate

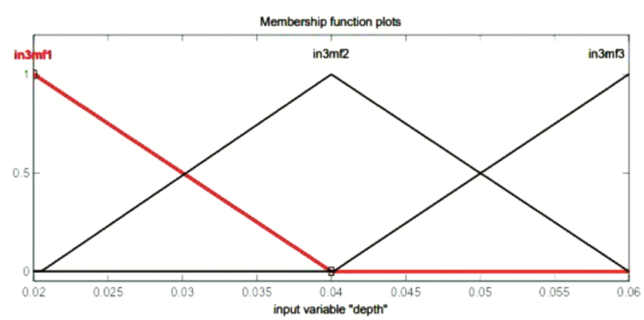

Fig. 9 —Triangular MF - depthof cut

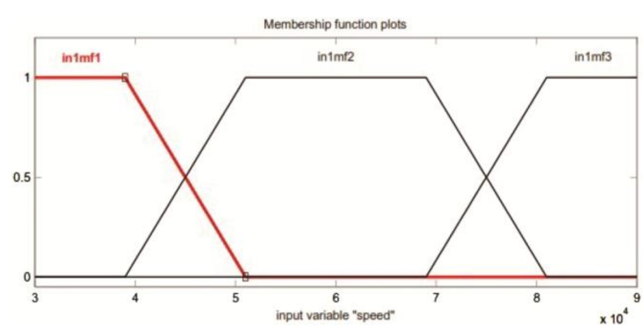

Fig. 10 — Trapezoidal MF - spindle speed

surface roughness was increased by 23 % as shown in Fig. 22. At 60, 000 rpm machining conditions i.e. from 1 to 9 the surface roughness was increased by 18.52 % as shown in Fig. 22. At 90, 000 rpm machining conditions i.e. from 1 to 9 the surface roughness was increased by 16.6 % as shown in Fig. 22. It was observed that at particular depth of cut and feed rate comparisons among different spindle speeds i.e. from 30,000-90,000 rpm the surface roughness slightly decreased and there after surface roughness increased gradually. 3D–Area of the estimated and measured readings of nine sets of

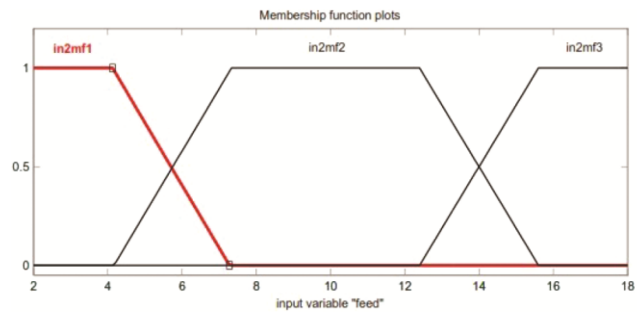

Fig. 11 — Trapezoidal MF -feedrate.

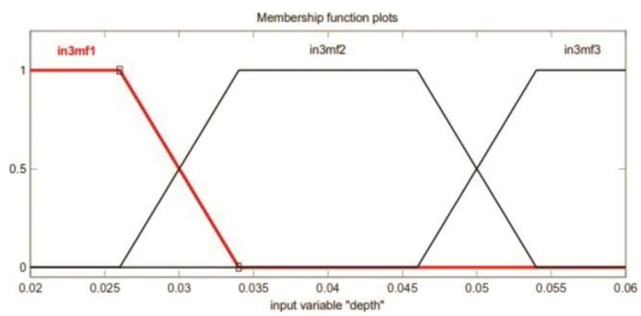

Fig. 12 — Trapezoidal MF - depth ofcut.

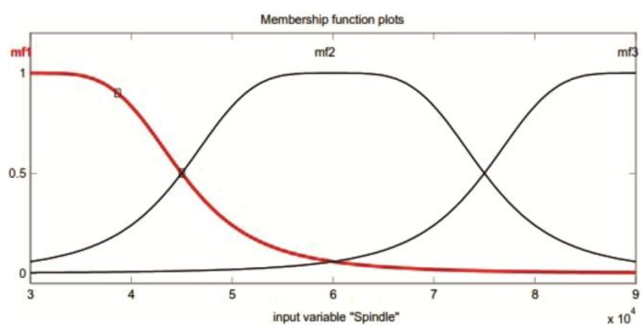

Fig. 13 — General bell MF -spindlespeed.

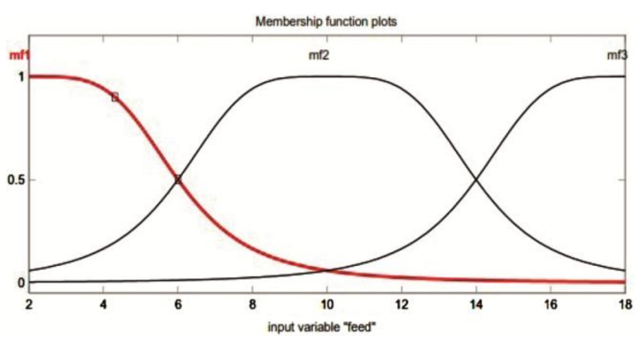

Fig. 14— General bell MF - feedrate

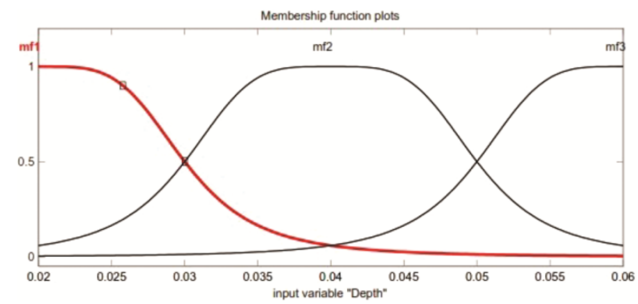

Fig. 15 — General bell MF - depthofcut

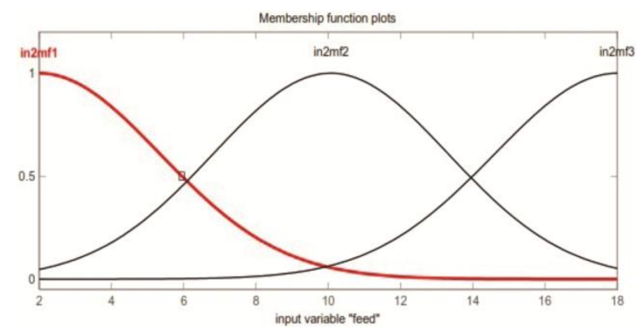

Fig. 16 — Gauss MF - spindlespeed

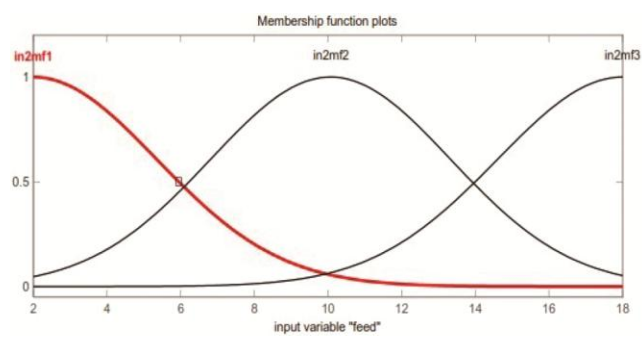

Fig. 17 — Gauss MF of feed rate

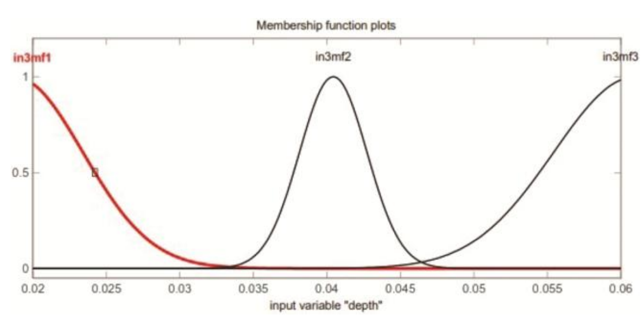

Fig. 18 — Gauss MF - depth of cut

Table 2 — Experimental and predicted values comparison for surface roughness.

Exp. No	Spindle Speed (rpm)	Feed Rate (mm/sec)	Depth of cut (mm)	Surface Roughness (nm)	Triangular MF Predicted Error (%)	Trapezoidal MF Predicted Error (%)	Gbell MF Predicted Error (%)	Gauss MF Predicted Error (%)
1	30000	4	0.04	227	248.13 9.30	236.23 4.06	226.73 0.11	226.24 0.33
2	30000	4	0.06	272	232.41 14.55	278.44 2.36	271.96 0.01	270.63 0.50
3	60000	4	0.04	121	138.95 14.83	126.23 4.32	120.96 0.03	120.23 0.63
4	60000	8	0.06	474	434.63 8.30	474.87 0.18	473.94 0.01	473.02 0.20
5	60000	12	0.02	493	540.85 9.70	493.61 0.12	492.89 0.02	491.42 0.32
6	60000	12	0.04	532	485.36 8.76	532.32 0.06	531.73 0.05	530.62 0.25
7	90000	6	0.06	188	174.11 7.38	191.61 1.92	187.91 0.04	187.26 0.39
8	90000	12	0.06	746	680.58 8.76	746.21 0.02	745.44 0.07	742.98 0.40
9	90000	18	0.04	842	892.98 6.05	842.78 0.09	841.51 0.05	839.11 0.34

Average Error 9.74 1.46 0.04 0.37

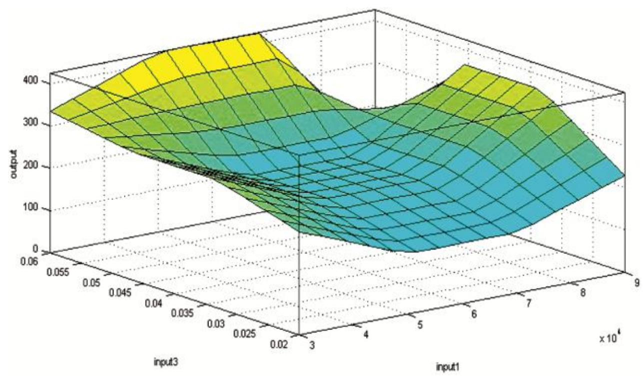

Fig. 19 — 3D view of surface roughness for inputs spindle speed and depth of cut

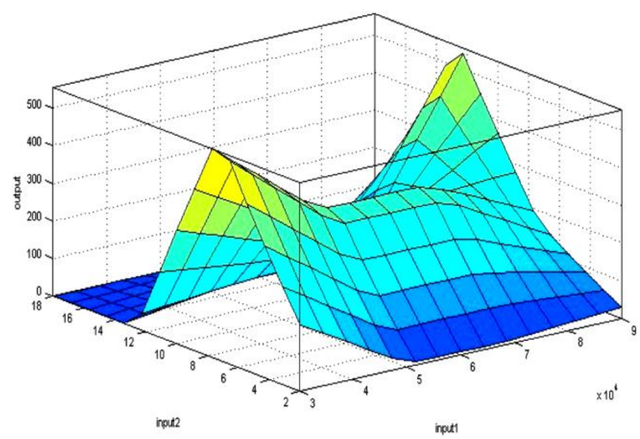

Fig. 20 — 3D view of surface roughness for inputs spindle speed and feed rate

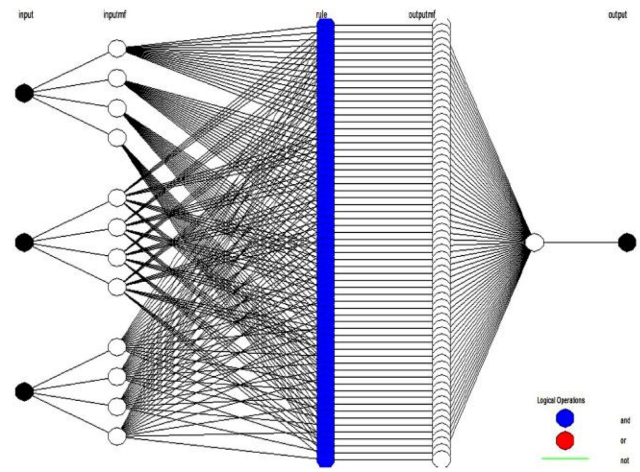

Fig. 21 — ANFIS membership function architecture

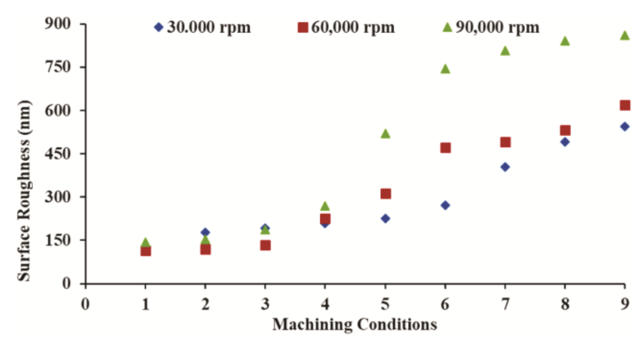

Fig. 22 — Surface roughness versus spindle speed, depth of cut & feed rate

testing data after training by ANFIS for surface roughness at different MF's is shown in Fig. 23. Estimated readings were equivalent to measured readings, i.e. error was very low between five MF's as shown in Fig. 23. ANFIS achieved a good accuracy in the prediction of surface roughness at different type of MF's utilized i.e. in agreement with experimental values. According to the experimental results, the adoption of general bell MF in ANFIS achieved higher prediction accuracy than other MF's of considered cycles of learning for estimating the surface roughness. It was noted from the observations that surface roughness was increased if feed rate and depth of cut was varied for the mentioned spindle speeds. Similar kind of experimental observations were reported by Lo[11], Zuperl[18] and Ho[23].

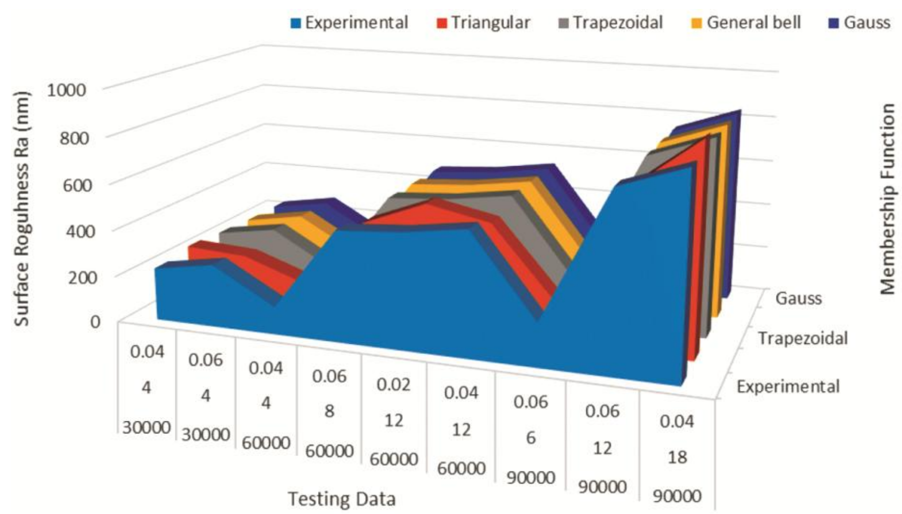

Fig. 23 — 3D Surface roughness surface roughness versus spindle speed, depth of cut & feed rate depth of cut & feed rate at experimental & different membership functions.

5 Conclusions

In this research, ANFIS approach (from the Matlab tool box the four membership functions - triangular, trapezoidal, gbell, gauss) was used to evaluate the prediction accuracy of surface roughness in high speed micro end milling of titanium alloy- Ti-6Al-4V-Grade-5.

(i) Experimental data have shown optimum prediction error for general bell MF as 0.04 % with an accuracy of 99.96%, which surpasses optimum prediction errors of 9.74% with an accuracy of 90.26 % for triangular, 1.46 % with an accuracy of 98.54 % for trapezoidal and 0.37 % with an accuracy of 99.63% for gauss MF's, respectively.

(ii) The optimal experimental condition for surface roughness was obtained at 90,000 rpm, spindle speed, feed rate 6 mm/sec and depth of cut 0.02-0.06 mm machining conditions.

(iii) If the feed rate and depth of cut was maintained constant and only spindle speed was increased then surface roughness achieved a lower value, i.e. excellent milling quality.

(iv) From the input machining process parameters i.e. spindle speed, feed rate and depth of cut, the most influential factor was the feed rate followed by depth of cut & finally by spindle speed on surface roughness.

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