

Surface Roughness Prediction Using Circular Interpolation Based on Artificial Neural Network in Milling Operation

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ABSTRACT

This paper presents a method to generate tool path and get G-codes for complex shapes depending on mathematical equations without using the package programs that use linear interpolation. Circular interpolation (G02, and G03) were used to generate tool path. This needs to define the tool radius and radius of curvature in addition to the cutting direction whether clockwise or counter clockwise. In addition many other factors had been considered in the machining process of the proposed surface to find the best tool path and G-code. Side step, feed rate and cutting speed had been studied as machining factors affecting tool path generation process. Artificial Neural Network technique had also been considered to find the best tool path depending on the cutting parameters proposed while surface roughness was the characteristic that the tool path process and G-code generation depend on. The impact of the machining parameters on the surface roughness was determined by the use of analysis of variance (ANOVA) that detects more influence for side step (85%, 53%, and 67%). From this study, it has been learned that less side step (0.2) mm and feed speed (1000) mm/min and high value for cutting speed (94.2) m/min give better tool path to be used in machining operations. This study would help engineers and machinists to select the best tool path for their products.

Keywords: Tool path generation, Surface roughness, radius of curvature, Artificial Neural Network.

INTRODUCTION

The demand of low tolerances and better quality products has forced manufacturing industry to continuously progress in quality control and machining technologies. One of the fundamental metal cutting processes is end milling which is one of the most popular and efficient operations for removing metal from the material surfaces highly used in automotive parts, moulds/dies, electronic devices, medical components, and other engineering applications [1]. An end milling operation is associated with surface roughness due to some requirements such as machining efficiency, high quality surfaces, dimensional accuracy, and the process reliability [2]. Quality of a product is directly evaluated with its surface roughness attribute since functional attributes of a product such as contact, wearing, heat transmission and coating could be affected by surface roughness [3].

A lot of research has been conducted for determining optimal cutting parameters in machining processes. However, Different cutter paths in face milling operations can be used with end mills.

Gershon E, et al. (1994)[4] presented an algorithm to adaptively extract ISO curves. It is adapted and enhanced to generate milling tool paths for models consisting of trimmed surfaces. They used 3 axis milling. The tool paths generation does not find gouge locally and combine the advantages of both prior approaches. The researchers found that algorithm has been used to compute gouge avoiding tool paths for automatically milling free form surfaces without requiring the introduction of auxiliary check and drive surfaces

Akeel S, (2006)[5] presented an algorithm to make an efficient and accurate three dimensions surface interior data depending on primary initial data based on approximation and interpolation techniques. The researcher used mathematical algorithm to generate three dimensions surface design using three approximation different methods (Hermite technique, Bezier technique, and B-Spline technique) presented. A new method of surface generation which extends the conventional Lagrange interpolation (1D) to generate (3D) surface design is presented in his work. Comparison is made between the two proposed techniques of surface generation approximation and interpolation depending on several standard functions; sin-cosine, exponential, parabola, fractional functions and polygon.

Tahseen F. Abbas (2008)[6] presented an algorithm that generates NC tool path for parametric surfaces depending on the accuracy of a desired surface. A designed surface was represented by sufficient control points, by using these control points, the surface was represented depending on Bezier technique to generate reliable surface. The proposed algorithm includes two functions, forward step function that computes the maximum distance between cutter contact points and the given surface tolerance and side step function which calculates the maximum distance between two adjacent tool paths with a given scallop height.

The aim of this study is to generate tool path and G-codes for complex shapes depending on mathematical equations and investigate optimum cutting characteristics of AL-Alloy 7024. The cutting parameters to be utilized are side step, feed speed, and cutting speed. The aim will be addressed by means of using ANN. The effects of cutting parameters on surface roughness performance indexes are analyzed.

Tool path generation

Free form surfaces are relatively difficult to machine due to their complex geometry. Free form surfaces machining primarily has two phases, the first phase roughing and the other finishing. The present work focuses on generating tool paths for the finishing operation. Given any arbitrary free form surfaces and G-code machine have been generated to machine that surface using ball-end milling cutters on a 3-axis CNC machine. Tool path planning has been done on the offset surface.

Circular Interpolation for Forward Step

Circular arc interpolation is essential in manufacturing of curve contours. Thus, the problems of how to determine the parameters of the circular arcs and how to minimize the number of arcs according to desired interpolation accuracy are solved.

Radius of Curvature and Normal Vector Calculations

Calculations have been made, which include the radius of the curvature and normal vector for each point of the surface through mathematical equation that adopted in the present work and using the ready-made surfnorm in MATLAB program and function as later.

$$T=\dot{P}(u) \text{ Tangent} \quad \dots(1)$$

$$N=\ddot{P}(u) \text{ Normal} \quad \dots (2)$$

$$k = \frac{|TxN|}{|T|^3} \quad \dots (3)$$

$$R = \frac{1}{k} \quad \text{radius of the curvature} \quad \dots (4)$$

Where:

Tool-path generation methods are classified as either the cutter contact based method or the cutter location based method depending on the type of tool path generation surface.

Cutter Contact and Cutter Location detection

The cutter contact point can be defined as the points that are located on the tool path, where there is instantaneous contact between the tool and the manufactured part. While the cutter location points are a fixed point on the tool which is taken as tool reference in moving along the tool path as shown in figure (1).

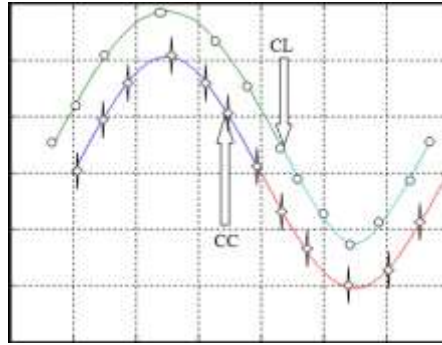


Figure (1): Cutter contact and cutter location points

To reduce machining errors, cutter contact points can be converted to cutter location points in order to compensate. The cutter location point is always placed along the normal direction of the point on the surface in 3-axis CNC milling machine using ball cutter. Thus, a cutter location point can be obtained from a cutter contact point and the surface normal of the point [7].

$$Pcl = Pcc + r.n \quad \dots (5)$$

where:

Pcc = cutter contact point

Pcl = cutter location point

r = radius of cutter

n = normal vector that can be calculated as follows:

$$t = \frac{T}{|T|} \quad \text{unit vector for tangent} \quad \dots (6)$$

$$b = \frac{TxN}{|TxN|} \quad \dots (7)$$

$$n = t \times b \quad \dots (8)$$

Side Step Estimation

The distance between two adjacent tool-paths is called the side-step. The side-step varies along the machined surface and the un-machined region between two adjacent tool paths is the scallop

height. Typically, the desired value of the scallop height is given, from which the side-step is calculated.

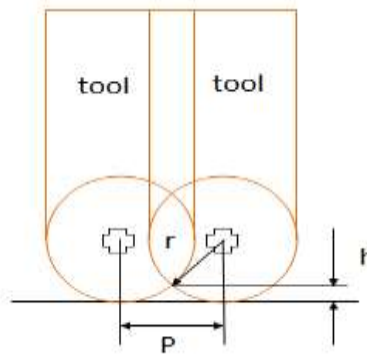


Figure (2): The workpiece machined showing the side steps

From figure (2):

$$h = r - \sqrt{r^2 - \left(\frac{P}{2}\right)^2}$$

$$P = 2 \sqrt{r^2 - (r - h)^2} \quad \dots\dots (9)$$

Where:

P= side-step length in physical domain,

r = cutter nose radius, h = scallop height [7].

Nine tool paths types had been generated and MATLAB program had been used to facilitate the calculations according to flow chart figure (4). Then the text file created by MATLAB file will be opened in program CIMCO edit V5 as shown in figure (3). Which includes the G02 and G03 (circular interpolation) to simulate the tool path generated from the equations and program built in the present work.

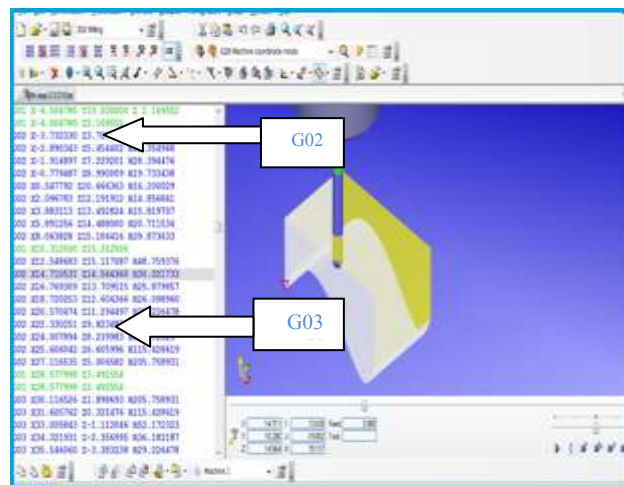


Figure (3): Windows of CIMCO edit V5

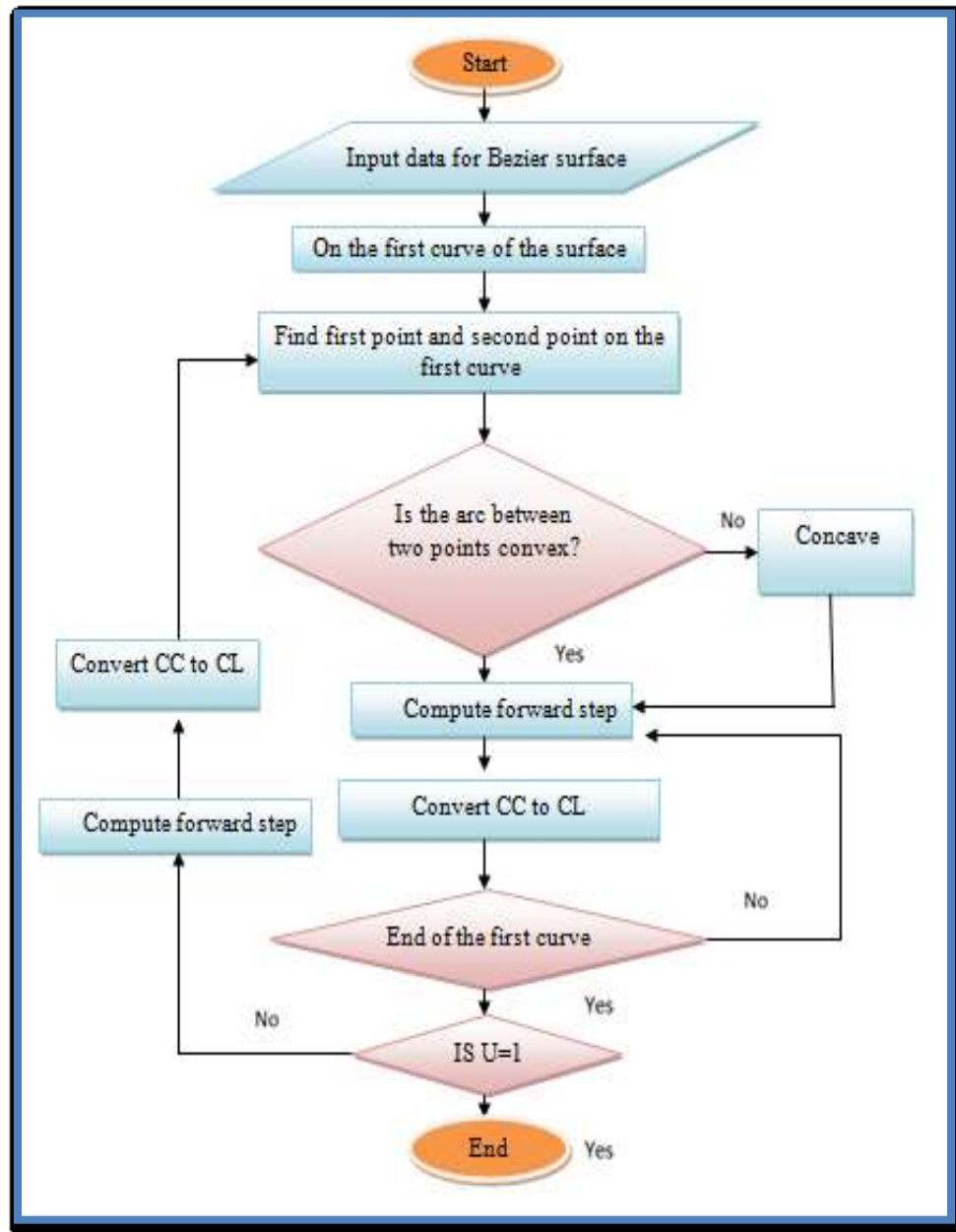


Figure (4): Flow chart of tool path in MATLAB.

Experimental set-up and procedure

Design of experiments

The design of experimentation has a significant role on the number of experiments needed. Therefore, cutting experiments should be well-designed. In the present study, a number of cutting experiments (a total of 27 experiments) based on a three-level full factorial design were performed to obtain surface roughness values measured for (AL-alloy 7024) specimens. Cutting parameters such as cutting speed (v_c), feed speed (f), side step (a) were selected for 27 experiments in end

milling of (AL-alloy 7024) specimens. The experiment is performed by using C-TEK CNC milling machine as shown in figure (5). The levels of cutting parameters are listed in Table (1).

Table (1): The levels of cutting parameters.

Levels	Side step a (mm)	Feed speed f (mm/min)	Cutting speed v_c (m/min)
1	0.2	1000	62.8
2	0.4	1500	78.5
3	0.6	2000	94.2

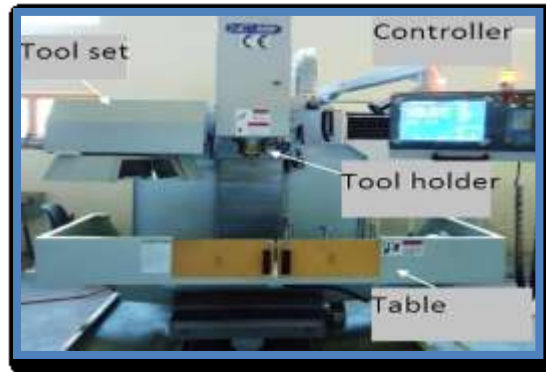


Figure (5): CNC C-TEK milling machine.

Cutting tool and material:-

The cutting tool used was ball -end mill tool with diameter (8, 10 and 12) mm and flout length 20 mm made from HSS with four flutes. The material of the specimens is aluminum (AL-alloy7024). A block of AL-alloy with a dimension of 30 mm ×60 mm×40 mm has been used to prepare the specimens in experimental work. Surface roughness testing is conducted for all 27 specimens after machining them with a different tool path and different cutting parameters. The chemical composition is listed in Tables (2) which is checked in the central organization for standardization and quality control.

Table(2):Chemical composition of Aluminum 7024.

Si%	Fe%	Cu%	Mn%	Mg%	Cr%	Ni%
0.163	0.422	2.14	0.216	1.55	0.090	0.012
Zn%	Ti%	Ga%	V%	Pb%	Other%	AL%
4.93	0.038	0.010	0.007	0.071	0.132	90.219

Measurement of surface roughness:-

All the machined surfaces are measured for surface roughness by using a portable surface roughness tester (Pocket Surf tester) available in the measurement laboratory at the University of Technology, department of production engineering and metallurgy. In the present study, 27 Ra values were measured from workpiece surfaces at three equally divided regions and then, the average of these values was recorded. During the roughness measurements, the tracing velocity and the sampling length were fixed at 1mm/s and 2.5mm. Surface roughness measurements recorded in the perpendicular to cutting direction are shown in figure (6).



Figure (6): Measuring surface roughness by Pocket Surf tester

Artificial Neural Network Modeling:-

In minimizing surface roughness, a mathematical model that expresses surface roughness in terms of cutting parameters is needed. The mathematical model in this study is established utilizing ANN. ANN is a multilayered architecture made up of one or more hidden layers placed between the input and output layers. Layers include several processing units known as neurons. They are connected with variable weights to be determined. In the network, each neuron receives total input from all of the neuron in the previous layer as [8]:

$$net_j = \sum_{i=0}^N w_{ij} x_i \quad \dots \dots (10)$$

Where: net_j is the total or net input and N is the number of inputs to the j th neuron in the hidden layer. w_{ij} is the weight of the connection from the i th neuron in the forward layer to the j th neuron in the hidden layer and x_i is the input from the i th neuron in the preceding layer. A neuron in the network produces its output (out_j) by processing the net input through an activation (transfer) function f , such as tangent hyperbolic function chosen in this study as below [9]:

$$out_j = f(net_j) = \frac{1 - e^{-net_j}}{1 + e^{-net_j}} \quad \dots \dots (11)$$

In this study, the Bayesian regularization back-propagation based on Levenberg –Marquardt algorithm was selected for training of the NN. It minimizes a combination of squared errors and then determines the correct combination to produce a well-generalized network. Optimal neural network architecture was designed by MATLAB Neural Network Toolbox. One hidden layer with three inputs and one output were used to model the process, as shown in figure (7). The three most important input parameters are side step, feed speed, cutting speed and the output parameter is average surface roughness. The distribution of experimental data consists of 27 groups was done so that the training subset includes 21 groups or 75% of the data and the testing subset includes 6 groups or 25% of the data. The sequential mode of training was used for the training of the network. In order to find the suitable architecture of the network, different architectures have been studied. The model with 3-5-1 architecture was found to be the most suitable for the task.

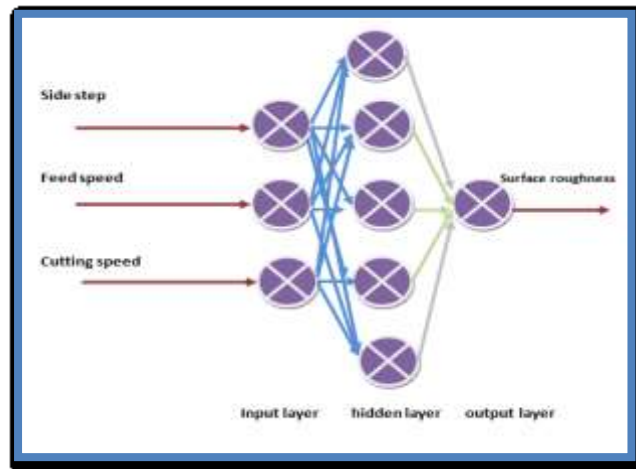


Figure (7): Neural network architecture designed.

In order to measure the accuracy of the prediction model, percentage error ϕ_i and average percentage error $\bar{\phi}$ were used and defined as [10]:

$$\phi_i = \frac{|R_{aie} - R_{aip}|}{R_{aie}} \times 100\% \quad \dots\dots (12)$$

Where

ϕ_i = Percentage error for each experiment.

R_{aie} = Experimental surface roughness.

R_{aip} = Predicted surface roughness.

$$\bar{\phi} = \frac{\sum_{i=1}^m \phi_i}{m} \quad \dots\dots (13)$$

Where

$\bar{\phi}$ = average percentage error.

m = number of experiments.

Analysis of Variance:-

The experimental results are analyzed by using analysis of variance (ANOVA) to determine the effect of cutting parameters on the surface roughness, surface finish as the dependent variables and side step (a), feed speed (f) and cutting speed (V_c) as independent variables. The results of the ANOVA with surface roughness are shown in tables (3, 4 and 5) for three cutter path regions. This analysis was carried out for significance level of $\alpha = 0.05$, i.e. for a confidence level of 95%.

The F ratio value of 430 for the side step of first region is greater among the parameters (see Table 3). Therefore, the most influential parameter is the side step (85%) is almost larger of the cutting velocity and feed speed.

The F ratio value of 52 for the side step of second region is the most influential control factor (Table 4). Since, it contributes a greater percentage than all the other control factors. Percentage contribution of the side step (53%) is the highest influence and then the cutting velocity and feed speed.

The F ratio value of 32.5 for the side step of third region is the most significant control factor (Table 5). Therefore, the most influential parameter in third region is the side step (67%) followed by cutting velocity and feed speed.

The percentage distributions calculated are given in figure (8). The most influential effects within the range of specified cutting conditions are side step (a) for first, second and third region because it considers the measuring of the scallop height that is un machined region.

Results and Discussion:-

Effect of Cutting Speed and side step on the Surface Roughness:-

Figures (9 to 11) show the effect of cutting speed and depth of cut on the value of surface roughness at constant feed speed. These figures also demonstrate the effect of three regions on R_a . It can be noted that the increase in cutting speed will decrease the R_a ; this means that increasing the cutting speed improves machine ability. This may be due to the continuous reduction in the buildup edge formation as the cutting speed increases. The R_a decreases with the increase in cutting speed (62.8-94.2 m/min) and the R_a increases with the increase in depth of cut (0.2-0.6 mm). From these previous figures the experimental result show that the change of cutting speed at different depth of cut gives the same relationship.

The first case, when the feed speed $f=1000$ mm/min, the results give the best roughness near the cutting speed 94.2 (m/min) for the three side steps. Then decreasing the cutting speed leads to deteriorate the surface roughness.

In the second case, feed speed $f=1500$ mm/min (large than the first case), the results show that when the cutting speed increases to 62.8 (m/min) the surface roughness increases, increasing the cutting speed to 94.2 (m/min) and more gives better roughness for three side step.

In the third case, when the feed speed $f=2000$ mm/min, the results give the large surface roughness for the three side steps. Decreasing depth of cut leads to better surface roughness while the increase in depth of cut leads to increase the R_a , where scallop height of workpiece increases as depth of cut increases causing an increase in the value of surface roughness.

Effect of Cutting Speed and Feed Speed on the Surface Roughness:-

Figures (12 to 14) show the change of surface roughness for different cutting conditions (cutting speed, feed speed and depth of cut) and the effect of three regions on it. Increasing the cutting speed improves the surface finish. From these figures the experimental result show that the change of cutting speed at different feed speed gives the same relationship.

The first case, when the side step $a=0.2$ mm, the results give the best roughness near the cutting speed 94.2 (m/min) for the three feed speeds. Then decreasing the cutting speed leads to deteriorate the surface roughness.

In the second case, when the side step $a=0.4$ mm (large than the first case), the results show that when the cutting speed increases to 62.8 (m/min) the surface roughness increases, increasing the cutting speed to 94.2 (m/min) and more gives better roughness for three feed speed.

In the third case, when the side step $a=0.6$ mm, the results give the large surface roughness for the three feed speeds. Decreasing feed speed leads to better surface roughness while increasing side step deteriorates the surface finish, this is due to the increase in distance between the successive grooves made by the tool during the cutting action, as feed speed increases.

Comparison of the Results:-

The measured and predicted results were compared in order to validate the ANN model. Figures (15 to 20) show the variation of 27 value of R_a with the number of experiments. The 21 values of R_a were utilized to train the ANN model, while the remaining data (six R_a values) were employed to test the trained ANN in 'MATLAB' Toolbox. The relationship between the 21 values

of Ra measured from experiments and those of predicted the ANN model is plotted in figures (15, 17, and 19) for first, second, and third respectively. It is seen from these figures that the measured Ra values match very close to the predicted Ra values.

The relationship between the 6 values of Ra measured from experiments and those of predicted ANN model is plotted in figures (16, 18, and 20) for first, second, and third respectively. It is seen from these figures that a good agreement is observed between the measured and the predicted of Ra values.

Tables (6, 7, and 8) indicate the results obtained from the testing of the trained ANN model compared with experimental measurements results. The data set consisting of six Ra values which were randomly selected from 27 Ra experiments, and they were not used for training of ANN. it is seen from these tables that ANN prediction presents a good agreement with the experimental measurements.

Table (6) presents the test data for first region .It can be observed from this table that the average prediction error for data set is found to be 1.44%, i.e., the accuracy is 98.56% and the MSE is 0.001746415consecutively.

Table (7) presents the test data for second region. It can be observed from this table that the average prediction error for data set is found to be 2.6870%, i.e., the accuracy is 97.313% and the MSE is 0.006838672 consecutively.

Table (8) presents the test data for third region .It can be observed from this table that the average prediction error for data set is found to be 4.8221%, i.e., the accuracy is 95.17% and the MSE is 0.031372 consecutively.

From tables (6, 7, and 8) it can be noted that more identical model for the experimental work is first region followed by second and third region because of movement for spindle clockwise and lift down to up on region during the machining .Where the average error and MSE less than the other types while the accuracy is high.

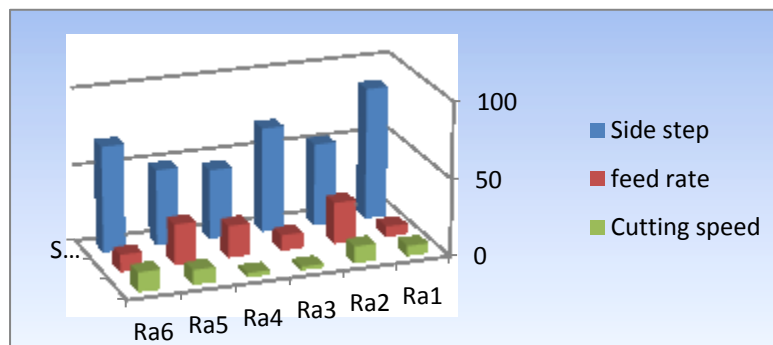


Figure (8): Influential effects based on percentage distribution

Table (3): ANOVA for first region.

Source of variance	Degree of freedom,v	Sum of squares ,ss	Variance, V	F ratio	P (%)
Side step,p (mm)	2	10.595	5.297	430.6	85.49
Cutting velocity, VC (mm/min)	2	0.793	0.396	32.06	6.39
Feed speed , f (mm/min)	2	0.757	0.378	30.6	6.1
Error ,e	20	0.247	0.01235		1.99
Total	26	12.392			100

Table (4): ANOVA for second region.

Source of variance	Degree of freedom, ν	Sum of squares, ss	Variance, V	F ratio	P (%)
Side step, p (mm)	2	4.182	2.091	52.0	53
Cutting velocity, VC (mm/min)	2	2.087	1.0435	26.35	26.46
Feed speed, f (mm/min)	2	0.825	0.4125	10.41	10.46
Error, e	20	0.792	0.0396		10.04
Total	26	7.886			100

Table (5): ANOVA for third region.

Source of variance	Degree of freedom, ν	Sum of squares, ss	Variance, V	F ratio	P (%)
Side step, p (mm)	2	6.930	3.465	32.596	67.62
Cutting velocity, VC (mm/min)	2	0.997	0.498	4.684	9.72
Feed speed, f (mm/min)	2	0.194	0.097	0.9125	1.89
Error, e	20	2.126	0.1063		20.74
Total	26	10.247			100

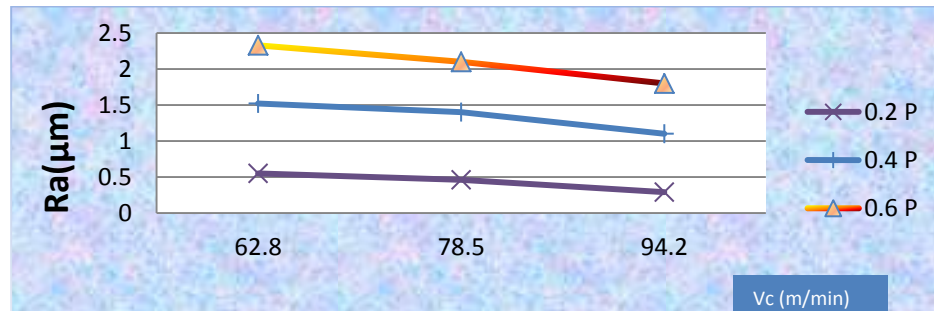


Figure (9): Effect of cutting speed on experimental Surface roughness at constant feed speed of (1000) (mm/min) for first region.

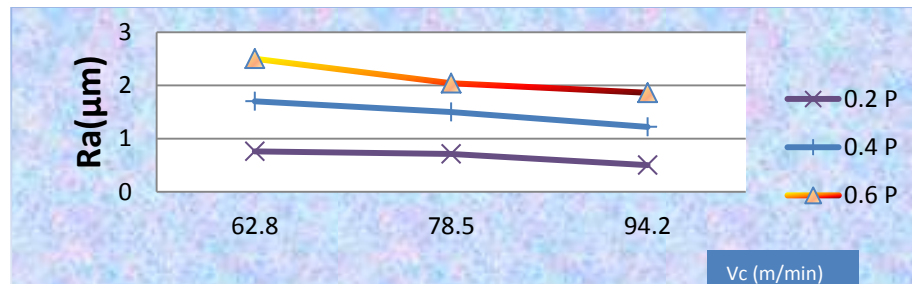


Figure (10): Effect of cutting speed on experimental Surface roughness at constant feed speed of (1500) (mm/min) for first region.

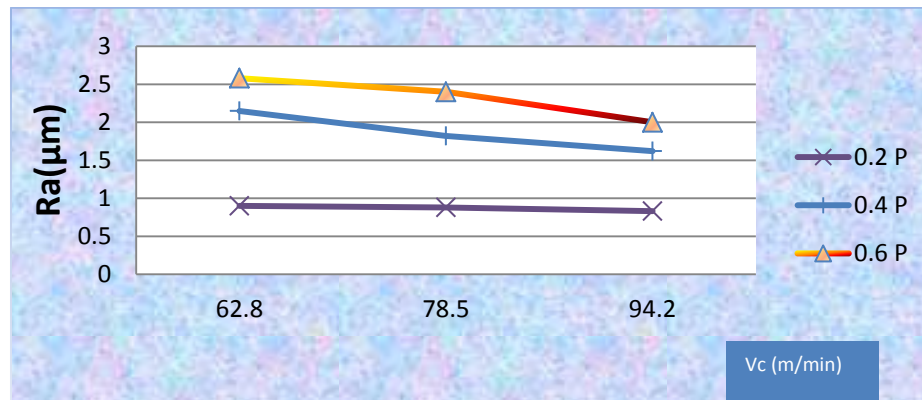


Figure (11): Effect of cutting speed on experimental Surface roughness at constant feed speed (2000) (mm/min) for first region.

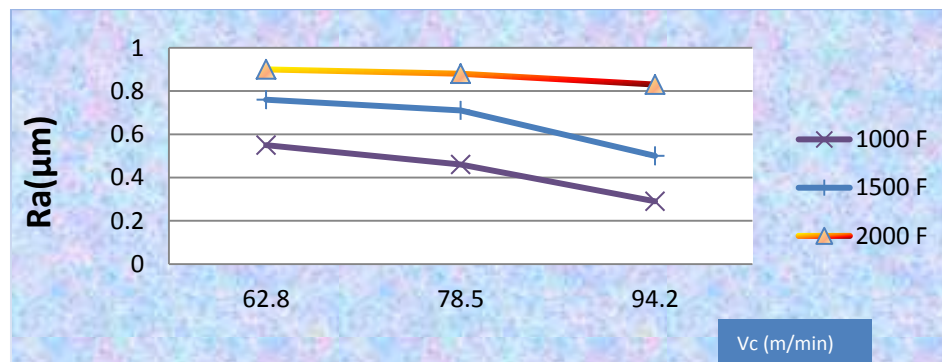


Figure (12): Effect of cutting speed on experimental Surface at constant depth of cut of (0.2 mm) for first region.

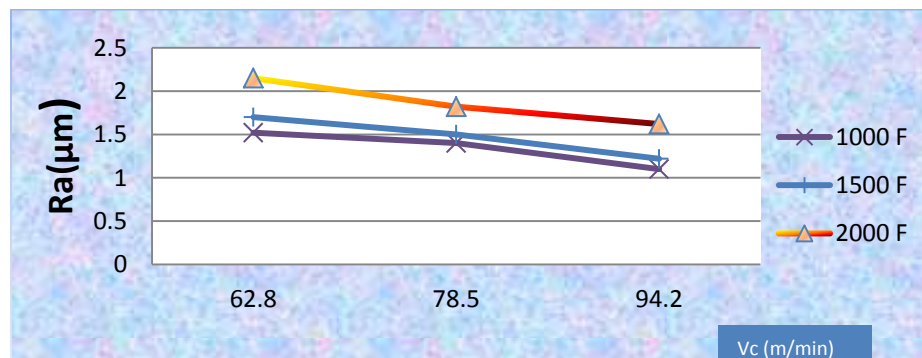


Figure (13): Effect of cutting speed on experimental Surface at constant depth of cut of (0.4 mm) for first region.

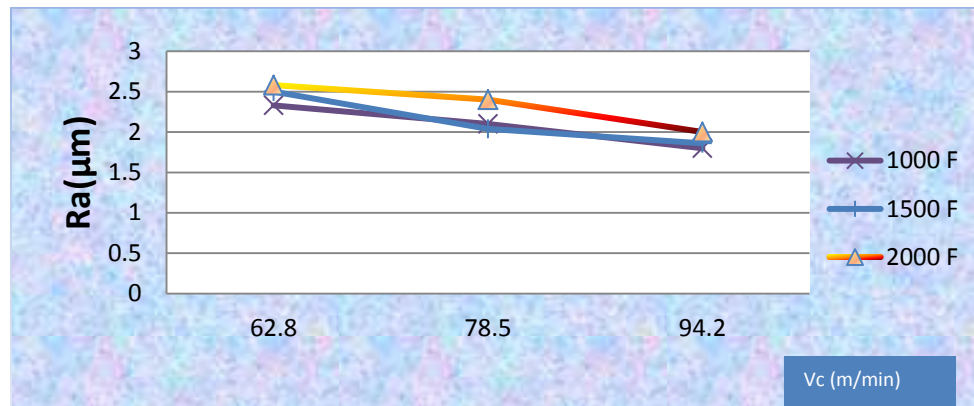


Figure (14): Effect of cutting speed on experimental Surface at constant depth of cut of (0.6 mm) for first region.

Table (6): Comparison of neural network predictions with experimental measurement for test set of first region.

No	Side step (mm)	Cutting velocity (m/min)	Feed speed (mm/min)	Surface roughness		Error	ANN result		
				Measured	predicted		$\bar{\phi}$	MSE	accuracy
1	0.2	94.2	1000	0.29	0.29	1.8E-05	1.448	0.0017	98.56%
2	0.2	62.8	1500	0.76	0.778	2.3			
3	0.4	78.5	1500	1.5	1.512372	0.82			
4	0.4	78.5	2000	1.82	1.82	1.7E-05			
5	0.6	94.2	1000	1.8	1.9	5.55			
6	0.6	78.5	2000	2.4	2.39881	0.049603012			

Table (7): Comparison of neural network predictions with experimental measurement for test set of second region.

No	Side step (mm)	Cutting velocity (m/min)	Feed speed (mm/min)	Surface roughness		Error	ANN result		
				Measured	predicted		$\bar{\phi}$	MSE	accuracy
1	0.2	94.2	1000	0.68	0.68	2.E-07	2.68	0.006838672	97.313%
2	0.2	62.8	1500	2.22	2.33	4.95			
3	0.4	78.5	1500	1.5	1.67	11.33			
4	0.4	78.5	2000	1.82	1.814989	0.275			
5	0.6	94.2	1000	1.81	1.81	6.42E-07			
6	0.6	78.5	2000	2.4	2.402631	0.10			

Table (8): Comparison of neural network predictions with experimental measurement for test set of third region.

No	Side step (mm)	Cutting velocity (m/min)	Feed speed (mm/min)	Surface roughness		Error	ANN result		
				Measured	predicted		$\bar{\phi}$	MSE	accuracy
1	0.2	94.2	1000	1.05	1.05	9.01E-06	4.82	0.0313	95.17%
2	0.2	62.8	1500	1.1	1.15	4.54			
3	0.4	78.5	1500	1.54	1.544926	0.31			
4	0.4	78.5	2000	1.98	2.008438	1.43			
5	0.6	94.2	1000	1.9	2.33	22.631			
6	0.6	78.5	2000	2.5	2.5	1.3E-06			

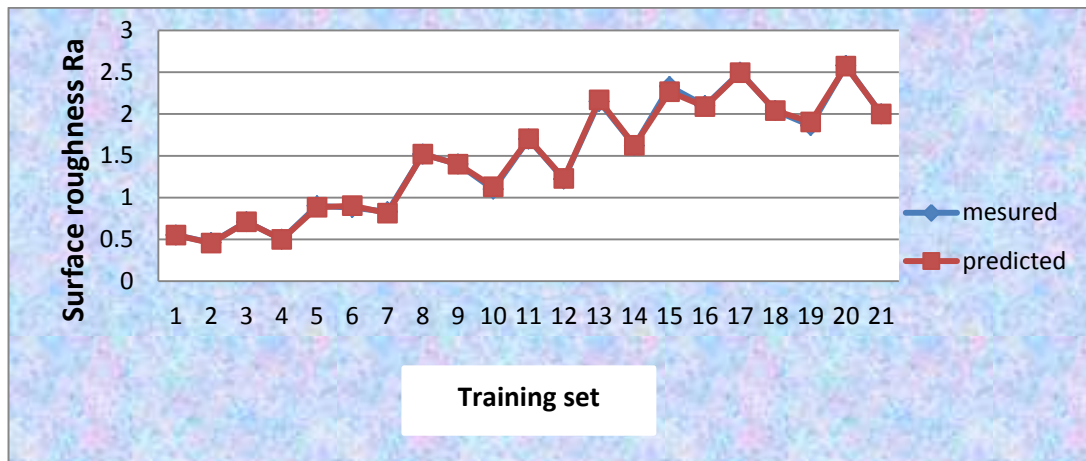


Figure (15): The comparison between the measured with the predicted values of Ra for training set on first region.

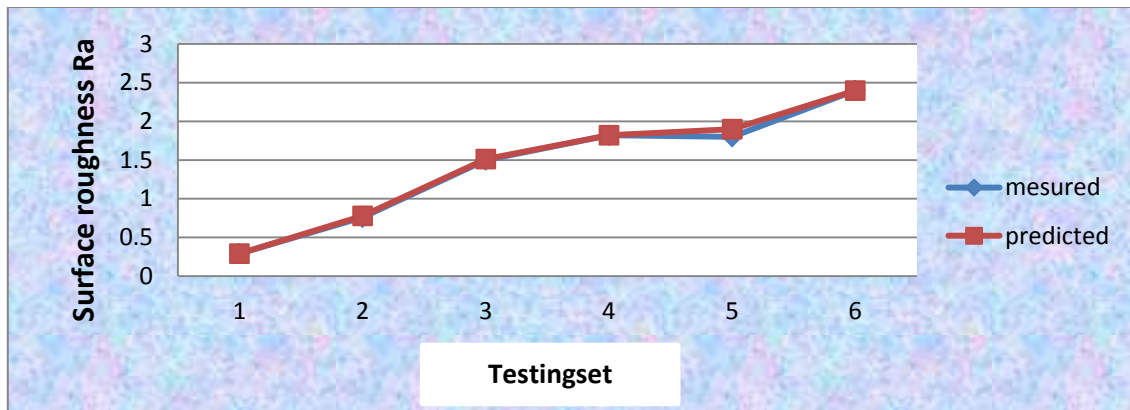


Figure (16): The comparison between the measured and the predicted values of Ra for testing set on first region.

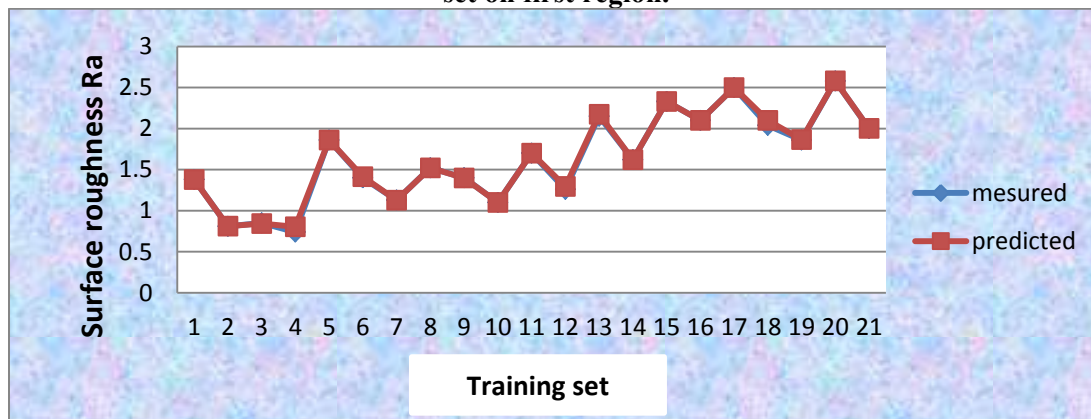


Figure (17): The comparison between the measured and the predicted values of Ra for training set on second region

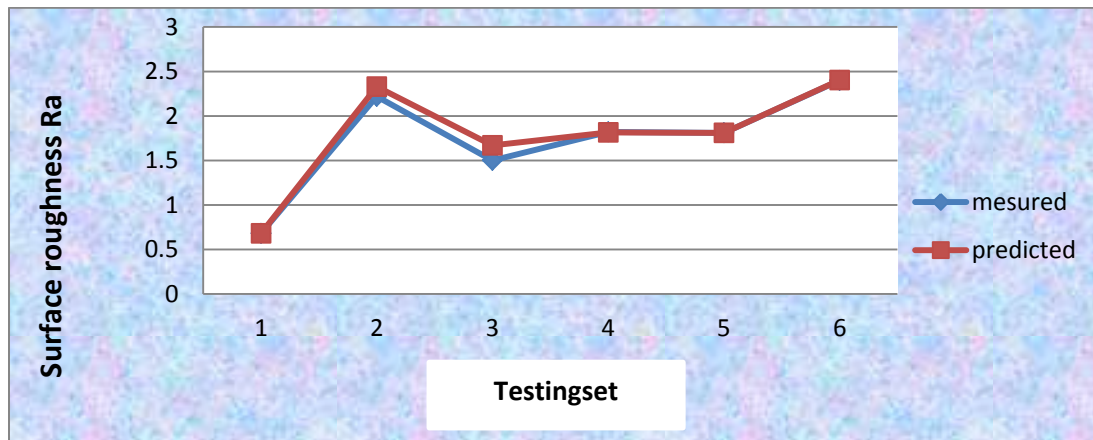


Figure (18): The comparison between the measured and the predicted values of Ra for testing set on second region.

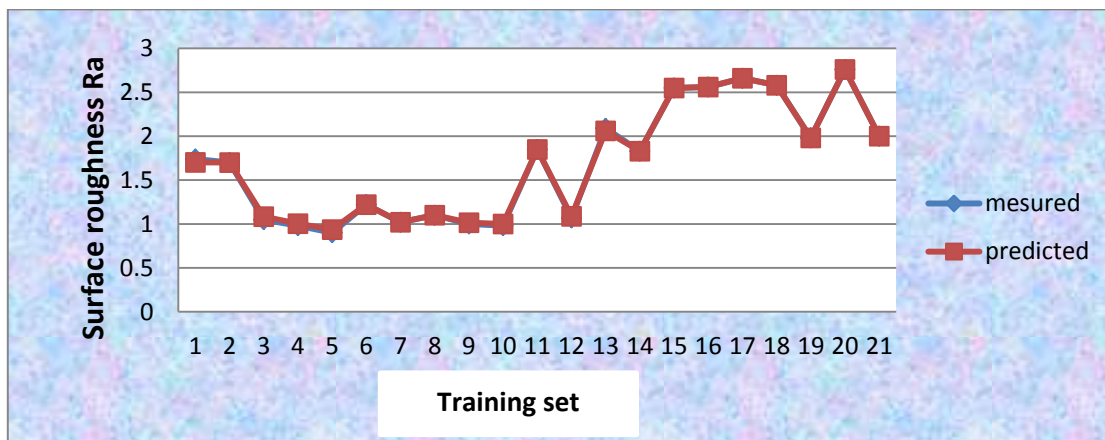


Figure (19): The comparison between the measured and the predicted values of Ra for training set on third region.

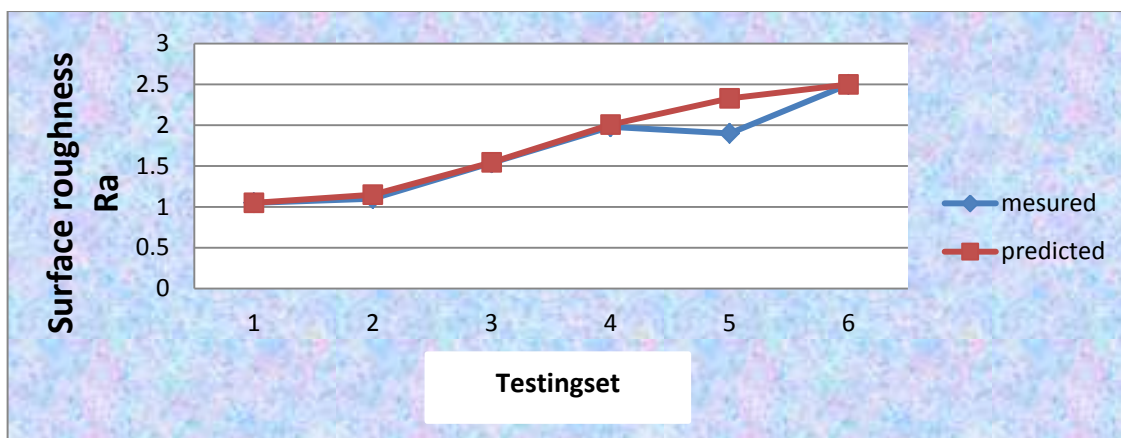


Figure (20): The comparison between the measured and the predicted values of Ra for testing set on third region.

CONCLUSION:-

The surface roughness in end milling process with different regions was measured along with orthogonal array in experiments.

In the present study, the best combinations of cutting parameters have been found to provide the lower surface roughness without any constraint for end milling of AL-alloy 7024 material. ANOVA analysis was conducted to indicate the influence of three cutting parameters on the surface roughness. A multilayered ANN based on BP learning algorithm was trained and tested to construct the prediction model for surface roughness (Ra) measured from experiments.

In light of these results, the following Conclusions can be summarized:

1. The surface roughness increases with increasing feed speed and side step but decreases with increasing cutting speed for all proposed region.
2. The ANNs models of structure 3-5-1 were found to be the best neural networks that can predict the surface roughness with about 98.56%, 97.313%, and 95.17 % accuracies for first, second, and third respectively.
3. The ANOVA results show that the side step (a) is the most important cutting parameters affecting surface roughness by 85%, 53%, and 67% contribution for first, second, and third respectively.
4. Feed forward artificial neural networks can be used reliably, successfully and accurately for the modeling of the surface roughness formation mechanism.
5. The best cutting parameter depends on the minimum value of surface roughness.

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