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Prediction of surface roughness for milling of GFRP composites using R.S.M. and ANN

Abeer S. Eisa
Lecture, Production Engineering & Mech. Design Dept., Faculty of Engineering,
Menoufiya University, Egypt. Drabeer78@yahoo.com

Abstract— Surface roughness prediction for the end-milling process, is a very important economical consideration in order to decrease the production cost in manufacturing environments. In this research, prediction of surface roughness (Ra) for GFRP composite material based on cutting parameters; cutting speed, feed rate, volume fraction ratio and cutter diameter are studied. Response Surface Methodology (RSM) and Artificial Neural Network (ANN) are used to present the application of predict surface roughness for end milling process. The results revealed that; the deviation between experimental results and predicted values using (ANOVA) is between (-0.2 and 0.3) and for (ANN) is between (-0.3 and 0.1). The cutting speed and feed rate are the most significant factors followed by volume fraction ratio and cutter diameter respectively. The used techniques, (RSM) and (ANN) can be used for direct evaluation of (Ra) under various combinations of machining parameters during end milling of the GFRP composite materials

Index Terms— Minimum 7 keywords are mandatory, Keywords should closely reflect the topic and should optimally characterize the paper. Use about four key words or phrases in alphabetical order, separated by commas.

1. INTRODUCTION

The applications of the end milling process can be found in almost every industry ranging from large aerospace industry to small tool and a lot of the parts. The major problem which may result from the end milling process is the generation of a finished part surface which does not satisfy product design specifications. A finished part surface might be too rough or poor dimension accuracy specially at machining of composite materials and lead to lower productivity and increasing the cost of the production. For produce parts which conform to design specifications, proper machining conditions (spindle speed, feed rate, depth of cut, cutter diameter, etc.) must be selected. In this research, the parameters which influence the resultant surface roughness are selected and predicted and analyzed using modern techniques. In addition to, a lot of the previous work are deeply studied and analyzed.

In the study of, V.S.Kausika and M. Subramanian [1], the effects of the process parameters; cutting speed, feed rate, axial depth of cut, radial angle, tool helix angle, and cutting condition on arithmetic average roughness (Ra) by the design of experiments during CNC end milling of Al 7068 Aluminum are presented. These experiments are carried out under dry cutting conditions and the tests are deliberated as per the requisites of response surface methodology. The effect of process parameters on the (Ra) is determined by ANOVA analysis. In addition, mathematical models for surface roughness (Ra) are formulated with the assistance of response second order surface methodology. From the results, the percentage of deviation between the predicted results and the experimental results is in between 3% and 5% and it is found that the predicted values and the experimental values lie very close to each other. Also, the helix angle plays a vital role and it is the most significant parameter for reducing the surface roughness. The fewer values of surface roughness are between 30° and 40° helix angles and the surface roughness is decreased with the increase of cutting speed and the radial rake angle. In addition, the surface roughness is increased with the increase of axial depth of cut and the feed rate. From this study, response surface methodology can better predict the effect of cutting parameters on the results and is a better method for optimization. It clear that when used desirability function in the RSM method for the optimization of multi-response problems is a very useful tool for predicting surface roughness. An efficient method based on Taguchi's design of experiment coupled with the grey relational analysis is investigated to optimize the process parameters over surface roughness in the research of, Subramanian Shankar, et al. [2]. The studied cutting parameters are cutting force and tool wear rate in the milling of mild steel. The used steps are experimental work, single response optimization using Taguchi's S/N value and multi-response optimization using grey relational analysis. The effects of process parameters (spindle speed, feed rate and depth of cut) on surface roughness, cutting force and tool wear rate are investigated using analysis of variance. Taguchi's signal-to-noise ratio is used to optimize the responses and finally, multi-response optimization is carried out using grey relational analysis. In addition, the analysis of variance (ANOVA) is applied to determine the most significant factor for the optimal response for milling. From the results, the most significant factor is the cutting speed. The proposed method of this work can be an effective approach to enhance the multi-response optimization for the milling process. In the work of, Rishi Raj Singh, et al. [3], by using Design of experiments, three independent factors (cutting speed, feed rate and depth of cut) and one category factor nose radius, five-level central composite rotatable designs has been used to develop relationships for predicting surface roughness in CNC end milling. The used model is conducted using ANOVA table and the effects of different parameters are investigated and presented in the form of contour plots and 3D surface graphs. In addition, the numerical optimization is carried out to minimize the surface roughness considering all the input parameters. From the results, cutting speed is the most significant followed by feed rate. The nose radius has the least effect on the surface roughness and depth of cut has a weak influence on the surface roughness. The model for surface roughness shows excellent fit and provide predicted values of surface roughness that are close to the experimental values, with a 95 percent confidence level. The deviation between the predicted and experimental values of the response factor during the confirmation experiments are within 5 percent. Therefore, the model can be used for direct evaluation of (Ra) under various combinations of machining parameters during end milling of the material used in this work. The influence of machining process, feed rate, cutting speed and axial depth of cut on the output parameters such as surface roughness and amplitude of tool vibration levels in Al-6061 workpiece has been studied in the work of, Jakeer Hussain Shaik and Srinivas J. [4]. By using Box-Behnken design (BBD), the experiments are planned with response surface methodology (RSM). A multi-objective optimization approach based on genetic algorithms using experimental data to simultaneously minimize the tool vibration amplitudes and work-piece surface roughness. But the optimum combination of the process variable is further verified by the radial basis neural network model. Finally, based on the multi-objective optimization approach and neural network models an interactive platform is developed to obtain the correct combination of process parameters. Shadab Anwar and Saleem Uz Zaman Khan [5] presented a study to investigate the effect of the end milling machining parameters (cutting speed, feed rate and depth of cut) on the surface roughness of the EN 31 steel. Taguchi method is used and nine of experiments runs based on an orthogonal array and it is subsequently applied to determine an optimal end milling parameter combination. This study shows that the high cutting speed with small feed rate produces fewer values of surface roughness and the effect of depth of cut is found to be negligible. From the analysis of the results, feed rate contributes maximum (59.84%) followed by cutting speed (29.58%) and depth of cut (9.162%) must be used in this case to minimize the surface roughness. M. Vamsi Krishna and M. Anthony Xavior [6] presented research to optimize the cutting forces, surface roughness and material removal rate of end milling for Aluminum composite using Response Surface Methodology (RSM) and Genetic Algorithm (GA). Empirical model (RSM L31) is conducted with various compositions of Al/SiC composites. For predicting responses, the second order mathematical models in terms of machining parameters are developed. From the results, the optimal configuration of end milling is 5 wt. % of reinforcement, 0.3 mm depth of cut, the feed rate of 49.3 mm/min and cutting speed of 474.3 rpm to acquire minimum cutting force, surface roughness with maximum material removal rate is done by Genetic Algorithm (GA). From the estimated model, the responses are with the experimental deviation of 11% material removal rate, 13% surface roughness and 17% cutting force for the desirability of 98.7%. Rishi Kumar, et al. [7] presented a work for modeling and optimization of milling parameters on Al-6061 alloy using Multi-Objective Genetic Algorithm. In this work, an approach to determine the best cutting parameters which lead to a minimum (Ra) and maximum MRR simultaneously by integrating Response Surface Methodology (RSM) with Multi-Objective Genetic Algorithm (MOGA). Four parameters, cutting speed, feed rate, and depth of cut and coolant speed and three levels of each are used in this investigation. Thirty experiments in face milling of Al-6061 alloy have been conducted based on RSM. ANOVA is used to find the most influential parameters on both material removal rate (MRR) and surface roughness (Ra). From the results, this study introduced a solution to the multi-objective problem of milling operation for the devolvement of quality and productivity. It is found that when MRR is compared on nearly same (Ra) obtained from optimal setting and experimental result, there is an increase of 41.88% in MRR and similarly for Ra on same MRR, there is a decrease of 93% in the value of (Ra). The research of Dimple Rani and Dinesh Kumar [8], aims to predict surface roughness by using artificial neural systems. Using the neural network model to find the best cutting parameters in milling operation and achieved minimum surface roughness. On the process environment, the quality of structures is highly correlated and must be expected to be influenced directly or indirectly by the direct effect of process parameters. Due to these reasons, optimization of surface roughness is a multi-factor, multi-objective optimization difficulty and to solve these problems, it is sensed necessary to classify optimal parametric combination, following which all purposes could be optimized instantaneously. From the results, as cutting speed increases surface roughness decreases and when feed increases surface roughness increases. Also, for achieving better surface finish on the material used in this research, higher cutting speed, lower feed and lower depth of cut are preferred and the used approach can be recommended for continuous quality improvement and off-line quality of any production process. In research of, S. Sakthivelu, et al. [9], an experimental investigation of the machining characteristics of Aluminum Alloy (7075 T6) in CNC milling machine using (HSS) cutting tool has been carried out. Based on L16 standard orthogonal array design with three process parameters (cutting Speed, feed rate, depth of cut), the experiment has been carried out. The results obtained from the Taguchi method exactly matches with ANOVA. From the results, the feed rate is the most influencing parameter for minimum surface finish, which is followed by the depth of cut and cutting speed. Also, the optimal parameters for minimum surface roughness (Ra, 0.76 µm) are (feed rate, 30 mm/rev), (cutting speed, 2000 rpm) and (depth of cut, 0.6 mm). For maximum MRR (MRR, 538.899 mm3/min) are (feed rate, 60 mm/rev), (cutting speed, 1000 rpm) and (depth of cut, 0.8 mm) are obtained, which produced very close to the results during the confirmation experiments. Quality and productivity play a vital role in today's manufacturing market and surface finish and dimensional accuracy becomes very important. For these reasons, K.Prasadraju, et al. [10] presented a work to optimize surface roughness and economic performance at macro levels. By using Taguchi's experimental design technique, the experiments have been planned. To analyze the effect of each parameter on the machining characteristics and to predict the optimal choice for each milling parameter such as (spindle speed, feed rate and depth of cut) in the cutting process, A L9 orthogonal array, and analysis of variance (ANOVA) are used. The values obtaining after applying the Taguchi technique is more effective than the experimental values. By using ANOVA techniques, the influence of each milling parameter is studied, and the prediction of the surface roughness and material removals rate is done. Analysis of surface roughness and material removal rate parameters such as spindle speed, feed rate and depth of cut against variations in milling. From the analysis of the results, the optimum value for surface roughness and material removal rate is not available in the nine numbers of experiments. The surface finish quality characteristic is smaller the better, but the experimental value is 3.00 mm (at parameters S3, F1, D2) and for material removal rate quality characteristic is bigger the better, but the experimental value is 0.98 (at S1, F1, D1). The paper of L.S.Shirsat, et al. [11] aims to present an overview on the non-conventional approaches that have been used for the prediction of surface roughness at end-milling operations of Aluminum. Taguchi parameter design is used because it can provide a systematic procedure that can effectively and efficiently identify the optimum surface roughness in the process control of individual end milling machines. In order to set the cutting parameters (depth of cut, cutting speed and feed rate), four confirmation runs are conducted and the average value of surface roughness and S/N ratio are calculated and are found to be within the 95% confidence interval. In the study of, Chaoyang Zhang, et al. [12], a systemic optimization approach is presented to identify the Pareto-optimal values of some parameters at milling of low-carbon Aluminum operation. The regression models are established to characterize the relationship between milling parameters and material removal rate, carbon emission, and surface roughness. Multi – techniques are used such as multi-objective optimization model and Genetic Algorithm-II based on the Taguchi design method. From this study, the results show that a higher feed rate and spindle speed are more advantageous for achieving the performance indicators. Also, the depth of cut is the most critical process parameter because of the increase of the depth of cut results in the decrease of the specific carbon emission but the increase of the material removal rate and surface roughness. The empirical process models, which users need to be developed for other cutting tools, workpiece materials, cutting fluids, and machine tools. The study of, Abhishek Kumbhar, et al. [13], investigates the optimization of CNC end milling operation parameters for stainless steel 304 using Taguchi methodology and Grey Relational Analysis approach. Also, different techniques are used such as, grey relational analysis, Response table and graphs based on Taguchi L9 orthogonal array by selecting cutting speed (mm/min), feed rate (mm/rev) and depth of cut (mm) at three levels to validate the optimal results of surface roughness (Ra), material removal rate (MRR). From this study, based on Grey Relational Grade analysis, the optimal process parameters for multi-objective optimization are ;cutting speed at level 2 (75 m/min), feed at level 1 (0.15 mm/rev) and depth of cut at level 3 (1.5 mm) i.e. v2-f1-d3. Also, it has been established that, Taguchi based Grey Relational Analysis is an effective multi-objective optimization tool. Milenko Sekuli, et al [14] presented a paper to optimizing the machining parameters with multi-response outputs using the design of experiment in ball-end milling of hardened steel. The effect of process parameters on surface roughness, material removal rate and resultant cutting force is studied and optimized. The used process parameters are (spindle speed, feed per tooth, and axial depth of cut and radial depth of cut) are optimized by the Taguchi-based Grey relational analysis. The optimum levels have been identified by the response table and response graph. The significant contributions of controlling parameters are estimated using analysis of variances (ANOVA). From the results, the cutting force, the surface roughness and the material removal rate are greatly enhanced by using this method. Suha K. Shihab and Arindam Kumar Chanda [15] demonstrates an application of a simple multi-objective optimization on the basis of ratio analysis (MOORA) method to optimize the parameters in different milling processes such as face milling, end milling, micro-end milling, and micro-ball end milling . The used method provides not only a better result but also an accurate evaluation of the alternatives. The used method as compared to many other MODM methods is found to be simple, logical and robust and can be applied to solve several multi objective optimization problems pertaining to a wide range of manufacturing environment. But, in case of problems involving a large number of qualitative attributes, (MOORA) method is not found to be as efficient as other MODM methods. Murat Sarýkaya, et al. [16] presented a study on optimization of the process parameters in face milling of AISI D3 steel for surface roughness and tool life using Taguchi Analysis. Orthogonal array, a signal-to-noise (S/N) ratio, and analysis of variance (ANOVA) are also employed to investigate the tool life and the surface-roughness characteristics. From the results, it has been observed that, the optimum levels of the control factors providing a less surface roughness and tool life when; the cutting speed, 80 m/min-(A1), the feed rate, 0.08 mm/r-(B1), and the number of cutting inserts, 1 insert-(C1). Also, the cutting speed is the most important parameter influencing the tool life with 95 %. The lowest surface roughness and the highest tool life are estimated to be 0.436 µm and 434.1 sec, respectively. In the paper of M. S. Sukumar, et al. [17], Taguchi method has been used to identify the optimal combination of influential factors in the milling process of Al 6061 material. The studied process parameters are, cutting speed, feed rate and depth of cut. By using Taguchi S/N ratios, the resulted surface roughness (Ra) is analyzed and the optimum controllable parameter combination is identified. Also, ANN model has been developed and trained with full factorial design experimental data and a combination of control parameters has been found. The results have shown that the Taguchi method and ANN found different sets of optimal combinations, but the confirmation test revealed that both got almost the same Ra values. Also, cutting speed has the most influence on the resulted surface roughness. Ravikumar D Patel1, Nigam V Oza1 and Sanket N Bhavsar [18], presented a workshop on the prediction of surface roughness in CNC milling machine by controlling machining parameters using ANN. In this work, Artificial Neural Network has been implemented for better and nearest result. Number of experiments have been done by using Hy-tech CNC milling machine. The result from the Taguchi method indicated that, surface roughness is most influenced by feed rate followed by spindle speed and lastly depends on the depth of cut. Predicted surface roughness has been obtained and the average percentage error is calculated by ANN method. The mathematical model is developed by using Artificial Neural Network (ANN) technique shows the higher accuracy is achieved which is feasible and more efficient in the prediction of surface roughness in CNC milling. The result from this work is useful to be implemented in the manufacturing industry to reduce the time and cost in surface roughness prediction. Jignesh G. Parmar1, Prof. Alpesh Makwana [19], presented an investigation to predict surface roughness by using artificial neural networks (ANN). An experimental investigation of the end milling on M.S material up to 30 HRC with carbide tool by varying feed, speed and depth of cut and the surface roughness is measured using Mitutoyo Surface Roughness Tester. Neural Network Fitting Tool Graphical User Interface is used to establish the relationship between the surface roughness and the cutting input parameters (spindle speed, feed and depth of cut). The result from this research is useful to be implemented in the industry to reduce the time and cost in surface roughness prediction. In addition, this model can be used to predict surface roughness in end milling process.

Based on the previous literature review, Response Surface Methodology (RSM) is suitable to find the best combination of independent variables, to achieve desired surface roughness. Also, Artificial Neural Network (ANN) is state of the art and it is the best method for predicting the surface roughness. Therefore, the two techniques are used in this research to present the application to predict surface roughness for the end milling process.

2. Experimental Setup

2.1. Materials, Process Parameters and Tools

Glass fiber is used as reinforcement in the form of bidirectional fabric (Standard E-Glass Fiberglass) and polyester with catalyst addition as a matrix for the used composite material. The material used is a typical composite plate of dimensions (100×20×20 mm) with different volume fraction ratios of, 5,10,15,20 and 25%. The plates fabricated by hand lay-up process followed by a curing process under constant pressure. The material properties presented in Table (1).

Table (1)
Material properties due to (International System – SI)

Material	Properties	Symbol	Value	units
Glass Fiber	Elasticity Modulus Density Poisson´s coefficient	Ef ρf υf	76.00x109 2.56x103 0.22	[N/m2] [Kg/m3]
Polyester	Elasticity Modulus Density Poisson´s coefficient	Em ρm υ m	4.00x109 1.30x103 0.40	[N/m2] [Kg/m3]
Composite material	Elasticity Modulus of Fiber direction Normal to fiber Density Shear Modulus Poisson´s coefficient Fiber volume fraction	E11 E22 ρc G12 υ 12 Vf	44.8x109 11.27x109 1780 4.86x109 0.28 60%	[N/m2] [N/m2] [Kg/m3] [N/m2]

Standard end mill of HSS (four fluted) and with different diameters (10, 12, 14, 16 and 18mm) are used for the machining operations. To prevent the effect of the wear on the results of experiments, the cutter is used for making five grooves only. A tapered shank is mounted into the spindle of CNC milling machine. The used parameters and their levels are presented in Table (2).

Table (2) Used parameters and their Levels.

Process parameters	Unit	-2	-1	0	1	2
speed	rpm	500	1000	1500	2000	2500
Feed rate	mm/min	10	20	30	40	50
Volume fraction ratio	%	5	10	15	20	25
Cutter diameter	mm	10	12	14	16	18

2.2. Surface roughness measurement

The measurements of surface roughness are performing using SJ-201P surface test and the measurements are made after the calibration of the instrument and with the cut-off length of (0.8mm). The machined groove is prepared for the measurements. The surface roughness (Ra) is measured at three points of the wall of the two sides of the groove and the average value of surface roughness is considered for the investigation. The results of measurements are tabulated for every groove and classified all results into groups related to the following; cutting speed, feed rate, cutter diameter and volume fraction ratios.

2.3. Planning for experiments

The experiments are designed by using Response Surface Methodology (RSM), [Design Expert Software (DOE),] as a tool for development of a prediction surface roughness (Ra). Response surface methodology is an empirical modelization technique devoted to the evaluation of relations existing between a group of controlled experimental factors and the observed results of one or more selected criteria. In the present research, four of the experimental factors are selected which can influence the studied process yield. In the following table (2), the coded of selected parameters and the resultant surface roughness (Ra) using Response Surface Methodology (RSM) and in Fig. (1) Defects at groove walls surfaces are shown.

Table (2) Experimental design matrix.

Exp. No.	Coded values				Surface roughness Ra μm
	A	B	C	D	
1	-1	-1	-1	-1	2.124
2	1	-1	-1	-1	1.156
3	-1	1	-1	-1	3.211
4	1	1	-1	-1	2.222
5	-1	-1	1	-1	1.211
6	1	-1	1	-1	4.205
7	-1	1	1	-1	3.312
8	1	1	1	-1	2.418
9	-1	-1	-1	1	2.405
10	1	-1	-1	1	4.207
11	-1	1	-1	1	3.312
12	1	1	-1	1	3.315
13	-1	-1	1	1	2.312
14	1	-1	1	1	4.302
15	-1	1	1	1	4.523
16	1	1	1	1	4.315
17	-2	0	0	0	2.189
18	2	0	0	0	1.125
19	0	-2	0	0	5.102
20	0	2	0	0	3.341
21	0	0	-2	0	3.225
22	0	0	2	0	2.154
23	0	0	0	-2	3.245
24	0	0	0	2	3.158
25	0	0	0	0	3.245
26	0	0	0	0	3.287
27	0	0	0	0	3.256
28	0	0	0	0	3.271
29	0	0	0	0	3.268
30	0	0	0	0	3.145

Fig. (1) Defects at groove walls surfaces.

3. Estimation of Surface roughness using analysis of variance (ANOVA).

In the following table, the estimation of surface roughness (Ra) using analysis of variance (ANOVA).

Table (3) Analysis of Variance (ANOVA) for Ra.

Source	Sum of squares	Df	Mean square	F - value	P- value prob > F
Model	16.35	14	16.35	3.15	<0.0134 significant
A	0.11	1	0.11	0.14	< 0.0147
B	0.058	1	0.058	0.075	< 0.0245
C	0.26	1	0.26	0.34	< 0.0007
D	3.12	1	3.12	4.03	< 0.0244
AB	3.91	1	3.91	5.04	< 0.0681
AC	1.02	1	1.02	1.31	< 0.0924
AD	0.74	1	0.74	0.96	< 0.0147
BC	8.556 E-3	1	8.556 E-3	0.11	<0.0526
BD	3.249 E-3	1	3.249 E-3	4.189 E-3	< 0.0012
CD	3.052 E-3	1	3.052 E-3	3.014 E3	< 0.0004
A2	4.000	1	4.000	5.15	< 0.0194
B2	1.801	1	1.801	2.38	< 0.0001
C2	0.425	1	0.425	0.54	< 0.0245
D2	5.245 E-3	1	5.245 E-3	6.768 E-3	< 0.0861
Residual	0.442	15	0.78		
Lack of Fit	0.436	10	1.16	446	< 0.0001 significant
Pure Error	6.809 E-3	5	2.624 E-3		
Cor Total	0.34534	29			

The model F-value of 3.15 implies that the model is significant as shown in Table (3). Values of "Prob > F" (< 0.0500) indicate model terms are significant. The "lack of fit- F- value" of 0.436 implies the lack of fit is significant.

Df: Degree of freedom,

SS: Sum of squares and MS: Mean of squares

The residuals are examined using the normal probability plots of the residuals and the plot of the residuals versus the predicted response. The normal probability plots of the residuals and the plots of the residuals versus the predicted responses for the Ra values are shown in Fig. (1) And indicates that residuals are falling on a straight line, indicating that errors are normally distributed.

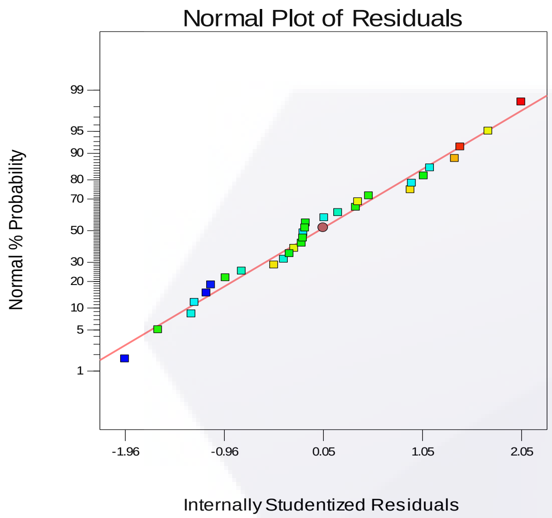

Fig. (1) Normal probability plot of residuals for surface roughness, Ra.

2.3.2. Measured and prediction of Surface Roughness.

In the following table, measured and prediction surface roughness. The deviation between experimental results and predicted values is between (-0.2 and 0.3).

Table (4), Measured and prediction surface roughness.

Reading number	Surface roughness of experimental (Ra)	Predicted By (RSM)	Deviation Error
1	2.124	2.315	- 0.19
2	1.156	1.119	0.03
3	3.211	3.411	- 0.2
4	2.222	2.132	0.09
5	1.211	1. 312	- 0.01
6	4.205	4.051	0.1
7	3.312	3.312	0
8	2.418	2.513	-0.09
9	2.405	2.312	0.09
10	4.207	4.191	0.01
11	3.312	3. 124	0.1
12	3.315	3.132	0.1
13	2.312	2.054	0.2
14	4.302	4.301	0
15	4.523	4.158	0.3
16	4.315	4.641	- 0.1
17	2.189	2.147	0.04
18	1.125	1.245	-0.1
9	5.102	5.102	0
20	3.341	3.124	0.2
21	3.225	3.225	0
22	2.154	2.147	0.007
23	3.245	3.415	-0.1
24	3.158	3.011	0.1
25	3.245	3.125	0.1
26	3.287	3.286	0.001
27	3.256	3.284	-0.02
28	3.271	3.281	-0.01
29	3.268	3.264	0.004
30	3.145	3.153	-0.008

In Fig. (2) The relationship between the experimental and predicted results by RSM is presented.

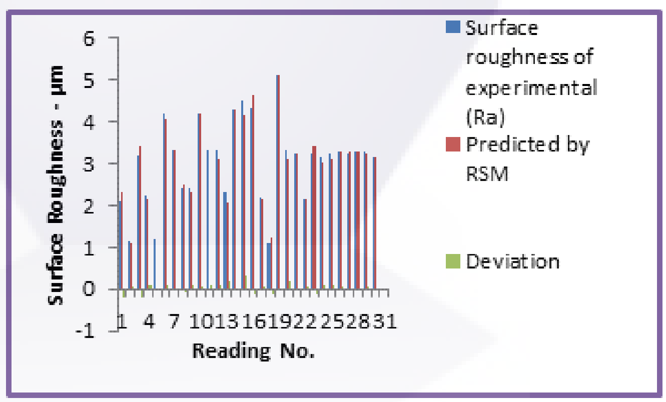

Fig (2) Relationship between the experimental and predicted results by RSM.

3. Optimization of machining conditions using ANN

Artificial Neural Network is an adaptable system that can learn relationships through repeated presentation of data. Also, it is capable of generalizing to new, previously unseen data. For this research, the network is given a set of inputs and corresponding desired outputs. In addition, the network tries to learn the input-output relationship by adapting its free parameters.

From the previous literature review [18], the algorithm for the backpropagation network program is calculated using the following steps;
1)determine the number of the hidden layers, 2) decide the number of neurons for the input layer and output layer, 3)get the training input pattern, 4) assign small weight values for the neurons connected in between the input hidden and output layers, 5) calculate the output value for all the neurons in hidden and output layers , 6) determine the output at the output layer and compare those with the desired output values. Determine the error of the output, error = desired output – actual output and also determine the root mean square error value of the output neurons,7) determine the error available at the neurons of the hidden layer and back - propagate those errors to the weight values connected in between the neurons of the hidden layer and input layer as shown in Fig. (3).

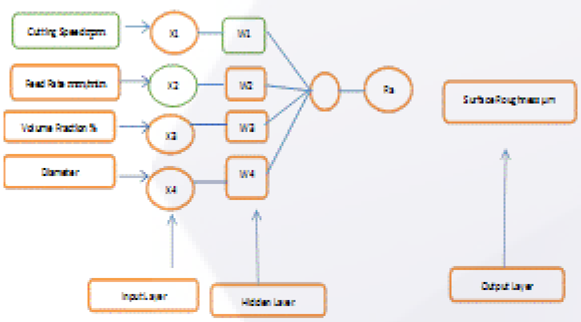

Fig. (3) The configuration of neural networks.

In Table (5), the typical observation of network performance is presented.

Table (5) Network performance conditions.

Typical observation of network performance	
Network configuration	4-30-1
Number of hidden layers	1
Number of hidden neurons	30
Transfer function used	Activation function
Number of patterns used for training	12
Number of patterns used for testing	10
Sum of squared error	0.002
Learning factor (ξ)	0.5
Momentum factor (α)	1

In Table (6), the experimental results and predicted values of surface roughness (Ra) By ANN are presented. From the previous Table, it is clear that; the deviation between experimental results and predicted values is between (-0.3 and 0.1).

Table (6) Experimental results and predicted values of Surface roughness (Ra) By ANN.

Reading number	Surface roughness of experimental	Predicted By ANN	Deviation
1	2.124	2.214	0
2	1.156	1.142	0.01
3	3.211	3.302	- 0.09
4	2.222	2.212	0
5	1.211	1. 325	- 0.1
6	4.205	4.312	-0.1
7	3.312	3.412	- 0.1
8	2.418	2.419	0
9	2.405	2.411	0
10	4.207	4.214	- 0.007
11	3.312	3. 305	0.007
12	3.315	3.324	-0.01
13	2.312	2.214	0.09
14	4.302	4.302	0
15	4.523	4.415	0.1
16	4.315	4.641	-0.3
17	2.189	2.168	0.02
18	1.125	1.125	0
19	5.102	5.102	0
20	3.341	3.248	0.09
21	3.225	3.225	0
22	2.154	2.147	0.007
23	3.245	3.415	-0.1
24	3.158	3.112	0.04
25	3.245	3.369	- 0.1
26	3.287	3.332	-0.04
27	3.256	3.254	0.002
28	3.271	3.245	0.026
29	3.268	3.277	-0.009
30	3.145	3.114	0.03

In Fig. (4) The relationship between the experimental and predicted results by ANN is presented.

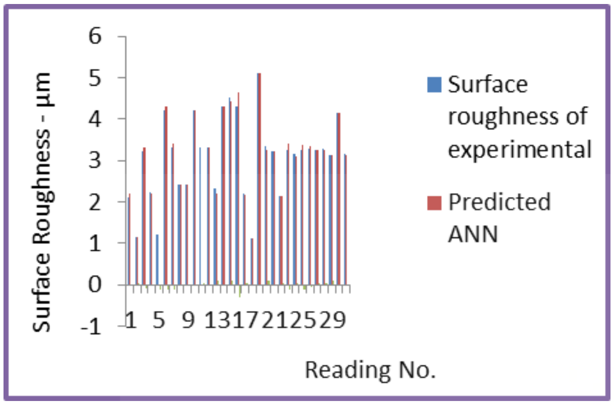

Fig (4) Relationship between the experimental and predicted results by ANN.

4. Discussion

From the previous experimental results and using of, ANOVA and Artificial Neural Network, it can be present the deviation between the experimental results and predicted values of surface roughness for the two used techniques as shown in Table (7).

Table (7) Experimental results and predicted values of surface roughness.

Reading number	Surface roughness of experimental	Predicted By RSM	Predicted By ANN	Deviation (RSM)	Deviation (ANN)
1	2.124	2.315	2.214	- 0.19	0
2	1.156	1.119	1.142	0.03	0.01
3	3.211	3.411	3.302	- 0.2	- 0.09
4	2.222	2.132	2.212	0.09	0
5	1.211	1. 312	1. 325	- 0.01	- 0.1
6	4.205	4.051	4.312	0.1	-0.1
7	3.312	3.312	3.412	0	- 0.1
8	2.418	2.513	2.419	-0.09	0
9	2.405	2.312	2.411	0.09	0
10	4.207	4.191	4.214	0.01	- 0.007
11	3.312	3. 124	3. 305	0.1	0.007
12	3.315	3.132	3.324	0.1	-0.01
13	2.312	2.054	2.214	0.2	0.09
14	4.302	4.301	4.302	0	0
15	4.523	4.158	4.415	0.3	0.1
16	4.315	4.641	4.641	- 0.1	-0.3
17	2.189	2.147	2.168	0.04	0.02
18	1.125	1.245	1.125	-0.1	0
19	5.102	5.102	5.102	0	0
20	3.341	3.124	3.248	0.2	0.09
21	3.225	3.225	3.225	0	0
22	2.154	2.147	2.147	0.007	0.007
23	3.245	3.415	3.415	-0.1	-0.1
24	3.158	3.011	3.112	0.1	0.04
25	3.245	3.125	3.369	0.1	- 0.1
26	3.287	3.286	3.332	0.001	-0.04
27	3.256	3.284	3.254	-0.02	0.002
28	3.271	3.281	3.245	-0.01	0.026
29	3.268	3.264	3.277	0.004	-0.009
30	3.145	3.153	3.114	-0.008	0.03

In Fig (5) a comparison for the surface roughness results between the experimental and prediction by using (RSM) and ANN is presented.

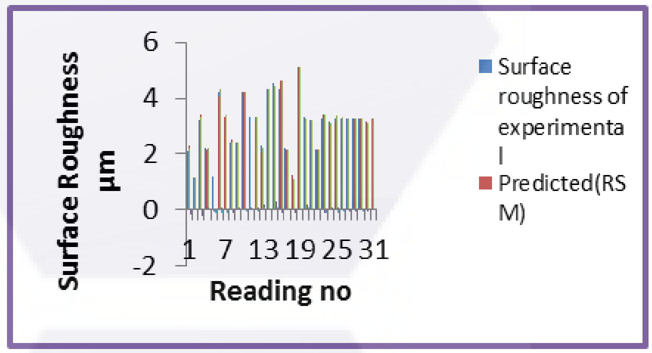

Fig (5) Comparison for the surface roughness results between the experimental and prediction by using (RSM)and ANN.

From the previous table, it is found that the predicted values and the experimental values lie very close to each other. The deviation between the predicted and experimental values of the response factor during the confirmation experiments are (-0.3:0.1). But for the other technique (ANN), the deviation is between (-0.2:0.3). Therefore, the model can be used for direct evaluation of Ra under various combinations of machining parameters during end milling of the material used in this work.

5. Conclusion

The goal of this research is to predict the surface roughness in end milling process on GFRP composite by using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) and roll of main parameters (cutting speed, feed rate, and volume fraction ratio and cutter diameter). From the deep analysis of the results, it can be concluded that:

1-The analysis of experimental results is carried out using Response Surface Methodology (RSM) and analysis of variance. The levels of the cutting parameters on the end milling induced minimum of surface roughness (Ra) are determined by using ANOVA.

2-The deviation between experimental results and predicted values using analysis of variance (ANOVA) is between (-0.2 and 0.3). And with Artificial Neural Network (ANN) is between (-0.3 and 0.1). Also, the residuals for surface roughness are falling on a straight line, indicating that errors are normally distributed.

4-The cutting speed and feed rate are the most significant factors followed by volume fraction ratio and cutter diameter respectively.

5-The interaction effects of cutting speed and feed rate, cutting speed and volume fraction ratio and feed rate and cutter diameters are less significant.

6-The used techniques; Response Surface Methodology (RSM) and analysis of variance can be used for direct evaluation of (Ra) under various combinations of machining parameters during end milling of the material used in this work.

7-A good correlation is observed between the predicted and the experimental measurements.

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