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Prediction of the Surface Roughness for Milling of GFRP Composites Using R.S.M. and ANN

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Abstract:
The prediction of the surface roughness for the end-milling process is a very important economic consideration to decrease the production cost in manufacturing environments. In this research, the prediction of the surface roughness (Ra) for GFRP composite material based on the cutting parameters; the cutting speed, the feed rate, the volume fraction ratio and the cutter diameter are studied. Response Surface Methodology (RSM) and Artificial Neural Network (ANN) are used to present the application to predicting the surface roughness for end milling process. The results revealed that; the deviation between the experimental results and the 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 the feed rate are the most significant factors followed by the volume fraction ratio and the 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.

الملخص:

التنبؤ بخشونة السطح لتفريز المؤتلف البلومري (GFRP) باستخدام الطريقتين (RSM) و(ANN)

يعتبر التنبؤ بخشونة السطح الناتج عند استخدام سكينة (End Mill) من الأهمية بمكان من الناحية الاقتصادية وذلك لخفض تكلفة الإنتاج في البيئات الصناعية. وفي هذا البحث تم التنبؤ بخشونة السطح للمؤتلف البلومري (GFRP) استنادا الي عناصر القطع (سرعة القطع، ومعدل التغذية ونسبة التقوية وأيضا قطر السكينة). وتم استخدام كلا من (RSM) و (ANN)للتنبؤ بخشونة السطح عند استخدام سكينة (End Mill) في عملية التشغيل. ولقد كشفت النتائج أن الانحراف بين النتائج العملية والنتائج المتنبأ بها باستخدام (ANOVA) تتراوح بين (-0.2 و0.3) أما مع (ANN) فتتراوح بين (-0.3 و0.1). وأظهرت النتائج أيضا أن سرعة القطع ومعدل التغذية هما أهم عنصرين في التأثير على نتائج خشونة السطح تليهما نسبة التقوية وقطر السكينة على التوالي. ومن النتائج الهامة أن الطرق (RSM) و (ANN) مناسبة للتنبؤ بخشونة السطح للمؤتلف البلومري عند استخدام (End Mill) وعناصر القطع المذكورة.

Keywords: ANN , ANOVA, Composite Materials, GFRP, Delamination, Surface Quality, Machining processes.

1-INTRODUCTION

The applications of the end milling process can be found in almost every industry ranging from the large aerospace industry to the small tool and many 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 bad or poor dimension accuracy especially 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 (the spindle speed, the feed rate, the depth of cut, the cutter diameter, etc.) must be selected.

In this research, the parameters that influence the resultant surface roughness selected, predicted, and analyzed using modern techniques. In addition, a great deal of the previous work is deeply studied and analyzed.

In the study of, V.S. Kausika and M. Subramanian [1], the effects of the process parameters; the cutting speed, the feed rate, the axial depth of cut, the radial angle, the tool helix angle, and the cutting condition on arithmetic average roughness (Ra) by the design of experiments during CNC end milling of Al 7068 Aluminum are presented. The experiments carried out under dry cutting conditions and the tests deliberated as per the requisites of response surface methodology. The effect of the process parameters on the (Ra) determined by ANOVA analysis. In addition, mathematical models for the surface roughness (Ra) 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 found that the predicted values and the experimental values lie very close to each other. In addition, the helix angle plays a vital role and it is the most significant parameter for reducing the surface roughness. The fewer values of the surface roughness are between 30°, 40° helix angles, and the surface roughness decreased with the increase of cutting speed and the radial rake angle. Furthermore, the surface roughness 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 the surface roughness. An efficient method based on Taguchi's design of experiment coupled with the grey relational analysis investigated to optimize the process parameters over surface roughness in the research of, Subramanian Shankar, et al. [2]. The studied cutting parameters is the cutting the force and the 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 the process parameters (spindle speed, feed rate and depth of cut) on surface roughness, cutting force and tool wear rate investigated using analysis of variance. Taguchi's signal-to-noise ratio used to optimize the responses and finally, multi-response optimization carried out using grey relational analysis. In addition, the analysis of variance (ANOVA) applied to determine the most significant factor for the optimal response for milling operation. From the analysis, the most significant factor is the cutting speed. The proposed method in this work can be an effective approach to enhance the multi-response optimization for the milling process. In the research 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 the surface roughness in CNC end milling. The used model conducted using ANOVA table and the effects of different parameters investigated and presented in the form of contour plots and 3D surface graphs. In addition, the numerical optimization carried out to minimize the surface roughness considering all the input parameters. From the results, the cutting speed is the most significant followed by feed rate. The nose radius has the least effect on the surface roughness and the depth of cut has a weak influence on the surface roughness. The model for the 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 the experimental values of the response factor during the confirmation experiments are within 5 percent. So, 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, the feed rate, the cutting speed and the axial depth of cut on the output parameters such as the 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 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 the work-piece surface roughness. However, the radial basis neural network model further verifies the optimum combination of the process variable. Finally, based on the multi-objective optimization approach and neural network models an interactive platform developed to obtain the correct combination of process parameters. Shadab Anwar and Saleem Uz Zaman Khan [5] presented a work 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 subsequently applied to determine an optimal end milling parameter combination. This study shows that the high cutting speed with a small feed rate produces fewer values of the surface roughness and the effect of depth of cut found to be negligible. From the results, the feed rate contributes the 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 work 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) conducted with various compositions of Al/SiC composites. For predicting responses, the second order mathematical models in terms of the machining parameters are developed. 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 the 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 results of 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 study for modeling and optimization of milling parameters on Al-6061 alloy using Multi-Objective Genetic Algorithm. In this study, 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 used in this investigation. Thirty experiments in face milling of Al-6061 alloy have been conducted based on RSM. ANOVA used to find the most influential parameters on both material removal rate (MRR) and surface roughness (Ra). The results indicated that, this study introduced a solution to the multi-objective problem of milling operation for the devolvement of quality and productivity. It found that when MRR 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 the milling process and achieved minimum surface roughness. On the process environment, the quality of the structures is highly correlated and must be expected to influence directly or indirectly by the direct effect of process parameters. Due to these reasons, the optimization of surface roughness is a multi-factor, multi-objective optimization difficulty and to solve these problems, it sensed necessary to classify optimal parametric combination, following which all purposes could be optimized instantaneously. From the results, as cutting speed increases, the surface roughness decreases and when feed increases surface roughness increases. Also, for achieving the better surface finish on the material used in this research, the higher cutting speed, the lower feed and the 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) used CNC milling machine with (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 results. The feed rate is the most influencing parameter for minimum surface finish, which 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 important role in today's manufacturing market and surface finish and dimensional accuracy becomes very important. For this, K. Prasadraju, et al. [10] presented work to optimize the surface roughness and economic performance at macro levels. By using Taguchi's experimental design technique, the experiments planned. To analyze the effect of each parameter on the machining characteristics and to predict the optimal choice for each milling parameter such as (the spindle speed, the feed rate and the depth of cut) in the cutting process, A L9 orthogonal array, and analysis of variance (ANOVA) are used. The results 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 the surface roughness and removal rate parameters such as the spindle speed, the feed rate and the depth of cut against variations in milling. From the analysis, 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 work of L.S. Shirsat, et al. [11] aims to present an overview of the non-conventional approaches that used for the prediction of surface roughness at end-milling operations of Aluminum. Taguchi parameter design 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. To set the cutting parameters (the depth of cut, the cutting speed and the 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 work of, Chaoyang Zhang, et al. [12], a systemic optimization approach presented to identify the Pareto-optimal values of some parameters at milling of low-carbon Aluminum operation. The regression models established to characterize the relationship between milling parameters and material removal rate, carbon emission, and surface roughness. Multi – techniques 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. In addition, 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 develop 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. Likewise, 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; the cutting speed at level 2 (75 m/min), feed at level 1 (0.15 mm/rev) and the depth of cut at level 3 (1.5 mm) i.e. v2-f1-d3. In addition, 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 optimiz 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 the surface roughness, the material removal rate and the resultant cutting force studied and optimized. The used process parameters are (the spindle speed, the feed per tooth, and the axial depth of cut and radial depth of cut) 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 greatly enhanced by using this method. Suha K. Shihab and Arindam Kumar Chanda [15] demonstrates an application of a simple multi-objective optimization based on ratio analysis (MOORA) method to optimize the parameters in different milling processes such as face milling, end milling, micro-end milling, and the 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 found to be simple, logical and robust applied to solve several multi objective optimization problems pertaining to a wide range of manufacturing environment. However, in case of problems involving many qualitative attributes, (MOORA) method 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) 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). In addition, the cutting speed is the most important parameter influencing the tool life with 95 %. The lowest surface roughness and the highest tool life 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 recognize the optimal combination of influential factors in the milling process of Al 6061 material. The studied process parameters are the cutting speed, the feed rate and the depth of cut. By using Taguchi S/N ratios, the resulted surface roughness (Ra) analyzed and the optimum controllable parameter combination 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. In addition, 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 implemented for the better and nearest result. The number of experiments has been done by using Hy-tech CNC milling machine. The results from the Taguchi method indicated that, surface roughness most influenced by feed rate followed by spindle speed and lastly depends on the depth of cut. Predicted surface roughness obtained and the average percentage error calculated by ANN method. The mathematical model 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 implement in the manufacturing industry to reduce the time and cost in surface roughness prediction. Jignesh G. Parmar1, 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 measured using Mitutoyo Surface Roughness Tester. Neural Network Fitting Tool Graphical User Interface 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 implement in the industry to reduce the time and cost in surface roughness prediction. In addition, this model 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. In addition, Artificial Neural Network (ANN) is state of the art and it is the best method for predicting the surface roughness. Therefore, the two techniques 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 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 the different volume fraction 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). Standard end mill of HSS (four fluted) and with different diameters (10, 12, 14, 16 and 18mm) used for the machining operations. To prevent the effect of the wear on the results of experiments, the cutter used for making five grooves only. A tapered shank mounted into the spindle of CNC milling machine. The used parameters and their levels presented in Table (2).

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

Material	Properties	Sym	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]

Table (2) Used parameters and their Levels.

Process parameters	Unit	-2	-1	0	1	2
speed	rpm	500	100	150	200	250
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. Measurement of the surface roughness

The measurements of surface roughness are performing using SJ-201P surface test and the measurements 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) measured at three points of the wall of the two sides of the groove and the average value of surface roughness considered for the investigation. The results of measurements 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 designed by using Response Surface Methodology (RSM), [Design Expert Software (DOE),] as a tool for the 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 the 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) The defects at groove walls surfaces.

Table (2) Experimental design matrix.

Exp.	Coded values				Surface roughness
	A	B	C	D	Ra µm
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 the surface roughness (Ra) using analysis of variance (ANOVA).

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

Source	Sum of squares	Df	Mean square	- value	P- value prob > F
Model	16.35	14	16.35	3.15	<0.0134 significant
A	0.11	1	0.11	0.14	<0.0001
B	0.058	1	0.058	0.075	<0.0001
C	0.26	1	0.26	0.34	<0.0001
D	3.12	1	3.12	4.03	<0.0001
AB	3.91	1	3.91	5.04	<0.0001
AC	1.02	1	1.02	1.31	<0.0001
AD	0.74	1	0.74	0.96	<0.000
BC	8.556E-3	1	.556E-3	0.11	<0.0001
BD	3.249 E-3	1	.249 E-3	.189 E-3	<0.0001
CD	3.052 E-3	1	.052 E-3	.014 E3	<0.0001
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	.245 E-3	.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	.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 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 shown in Fig. (1) and indicates that residuals are falling on a straight line, indicating that errors are normally distributed.

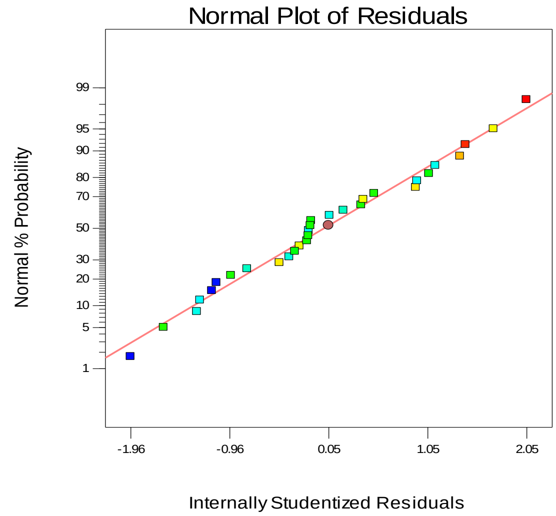

Fig. (1) Normal probability plot of residuals for surface roughness, (Ra).

2.3.2. Measured and prediction of Surface Roughness.

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

Table (4), Measured and prediction surface roughness.

Reading number	Surface roughness of ex-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 presented.

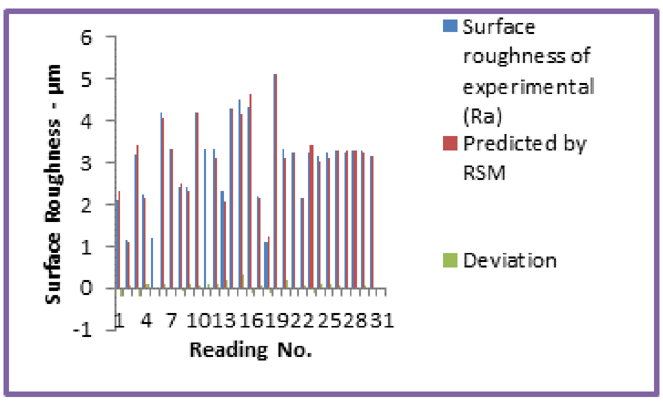

Fig (2) Relationship between the experimental and predicted results by RSM.

3. Optimization of machining conditions using ANN

Artificial Neural Network is an adaptable system that can learn relationships through repeated presentation of data. In addition, it can generalize to new, previously unseen data. For this research, the network given a set of inputs and corresponding desired outputs. Also, 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 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 the 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 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).

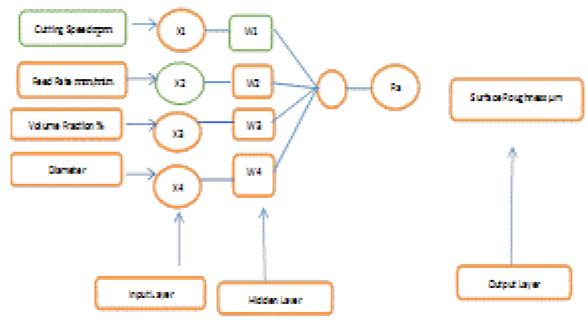

Fig. (3) The configuration of neural networks.

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

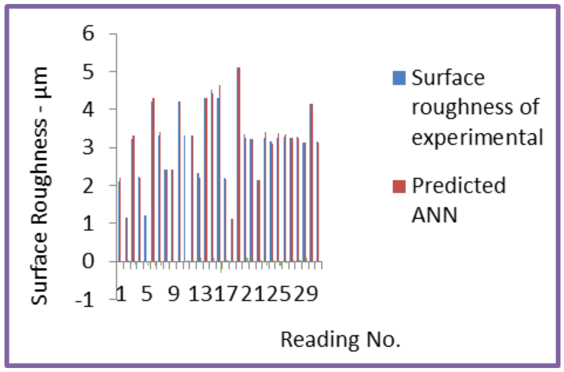

Fig (4) Relationship between the experimental and predicted results by ANN.

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 experi-mental	Predicted By RSM	Predicted By ANN	Deviation (RSM)	Devia-tion (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) comparison for the surface roughness results between the experimental and prediction by using (RSM) and ANN is presented.

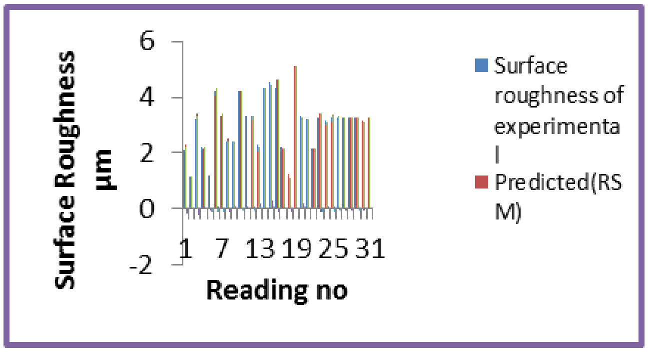

Fig (5) Comparison for the surface roughness results between the experimental and prediction by using (RSM)and ANN.

From the previous table, it found that the predicted values and the experimental values lie very close to each other. The deviation between the predicted and the experimental values of the response factor during the confirmation experiments are (-0.3:0.1). Nevertheless, 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 (the cutting speed, the feed rate, and the volume fraction ratio and the cutter diameter). From the deep analysis of the results, it can conclude 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 the 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). In addition, with Artificial Neural Network (ANN) is between (-0.3 and 0.1). Also, the residuals for the surface roughness are falling on a straight line, indicating that errors are normally distributed.

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

5-The interaction effects of the 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 composite material used in this work.

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

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