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OPTIMIZATION OF MACHINING AND SIC COMPOSITION PARAMETERS FOR AL1050/SICP USING ANOVA, ANN AND GA TECHNIQUES

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ABSTRACT

Surface roughness imposes one of the most critical constraints for the selection of machine and cutting parameters in process planning. Therefore, the present research is focused on optimization of machining conditions of Al 1050/SiCp MMCs. The cutting conditions used in this research are; cutting speed, depth of cut, feed rate as well as volume fraction and particle size of the reinforcement. The experimental results collected are tested with analyses of variance (ANOVA), artificial neural network (ANN) and genetic algorithm (GA) techniques. Multilayer perception model has been constructed with back- propagation algorithm using the input parameters. Output parameter is surface roughness of the machined part. On completion of the experimental test, the three techniques are used to validate the obtained results and also to optimize the behavior of the system under cutting conditions within the machining range. From the analysis of the results, it can be seen that, this approach is more flexible when compared with other models developed based on the experimental results that constrain their applicability of selecting the process parameters from limited range. From the output data obtained through ANOVA, ANN and GA approaches, the optimum conditions are; cutting speed (112 and 140 rpm), depth of cut (1.0 and1.5 mm), feed rate(0.8 and 1.25 mm/rev), volume fraction(10 and 25 %) and particle size(10 and 25μm). There is a close matching between the models outputs and the experimental results of surface roughness (Ra). ANOVA technique is more accurate than the two others techniques ANN and GA. In ANOVA outputs the deviation between model outputs and the experimental results of (Ra) is between 0.0 and 0.1.

تعتبر خشونة أسطح المؤتلفات المعدنية من أهم العناصر المؤثرة في اختيار كلا من الماكينة وعناصر القطع وذلك عند التخطيط للإنتاج. وعلي هذا وللأهمية القصوى لهذا العنصر ومع التوسع الكبير في استخدام المؤتلفات المعدنية في العديد من مناحى الحياة تم إجراء هذا البحث لتحديد كيفية التشغيل للمؤتلف Al 1050/SiCp علي ماكينة التفريز (milling machine) في ظروف قطع مثالية تضمن الحصول علي أقل درجة خشونة للسطح الناتج- وعناصر القطع هي- سرعة القطع وعمق القطع والتغذية بالإضافة إلي عنصرين هامين آخرين من المحتمل أنهما لم يدرسا بما فيه الكفاية مع العناصر السابقة وهما نسبة إضافة كربيد السيلكون(SiC) وحجم حبيباته.

ولقد تم تجميع نتائج قياسات خشونة السطح عند تأثير العناصر المذكورة وتم إختبارها وتحليلها باستخدام ثلاث طرق هي ANOVA, ANN وأيضاً GA وتم تطبيق أساسيات وبرامج الطرق الثلاث للحصول علي القيم المثالية لعناصر القطع الخمس المستخدمة والتي من خلال التحليل تم الحصول علي أقل خشونة للسطح الناتج. ومن تحليل نتائج استخدام الطرق الثلاث يتضح أنها أكثر مرونة لتغطية جميع عناصر القطع مقارنة بالطرق الأخرى والتي تستخدم النتائج العملية لتغطية مدي محدد لعناصر القطع، ومن نتائج استخدام هذه الطرق في تحديد عناصر القطع المثالية للسطح المشغل – وجد أن قيم عناصر القطع المثالية هي : سرعة قطع (١١٢، ١٤٠ لفة/ دقيقة) عمق القطع(١، ١,٥مم)، التغذية(.٨ ، ١,٢٥مم/لفة) ونسبة الإضافة لكريبد السيلكون(١٠، ٢٥%) وأخيراً حجم الحبيبات (١٠، ٢٥ ميكرون) وأيضاً اتضح أن الفرق بين النتائج العملية والنتائج المستخلصة باستخدام هذه الطرق تتراوح بين+.٣، -.٦ ميكرون

وبمقارنة نتائج الطرق الثلاث وجد أن ANOVA Technique هو الأكثر تطابقا فى نتائجه مع النتائج العملية ووجد أن الفرق بين نتائج ANOVA والنتائج العملية يتراوح بين صفر، ١ , ميكرون.

Keywords: Surface roughness, metal matrix, composites, ANN, ANOVA, GA , Taguchi Technique

1. INTRODUCTION

The wide scale introduction of MMCs will increase simultaneously with the development in technologies. Accordingly, the need for accurate machining of MMCs has increased enormously. As a consequence of the widening range of application of MMCs, the machining of these materials has become a very important subject for research. Surface roughness evaluation of MMCs is very important for many fundamental problems, such as friction, contact deformation, heat and electric current conduction, tightness of contact joints and positional accuracy. For these reasons, surface roughness has been also the subject of experimental and theoretical investigations for many decades. Also, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in process planning. Although many factors affect the surface condition of machined part, such as cutting speed, feed rate, depth of cut and workpiece conditions.

These conditions of workpiece have more influences on the surface roughness for a given machine and workpiece set up. Several of researches in this field are focused to evaluate and analyze the surface roughness of particulate composite material (PMMCs).

Yue Tiao et al [1] investigated a new approach to control the complexity of the machine tool structure and cutting process, these complex phenomenon combined with learning ability are needed. The combined neural fuzzy approach appears to be ideally suited for this purpose. This research was organized as follows; introduces the basic aspects of fazzy neural approach (FNA), and then the network is formed and is used to model the relationships between surface roughnesses and cutting parameters, predicts the influence of the individual process parameters on the surface roughness based on the obtained FAN network. In the last part of this research, discussion of the pilot experiments to verify the inferred model and compares the predicted results with those obtained by statistical analysis. From this work it is clear that; the FAN network is suited for modeling with a large amount of data. Further more, the data can be in any irregular or random form such as the daily operating data of the machining process as long as the resulting data cover the desired range of operation. Another advantage of the proposed network is its learning ability. Thus, a rough model can be obtained first and the model can be continuously improved based on the daily operating. This approach summarizes past data and there is non-need to repeat the calculations of post data whenever new data become available, which is the case in the regression approach. This approach also has the learning ability of the neural network with the newly available daily operation data. Finally the FAN network can estimate many parameters and even tune the network structure and thus is much more powerful than the usual multiple variables regression analysis. The disadvantage is that the resulting model is implicit and is presented. However, this implicit model can be obtained or represented explicitly in equation forms by further manipulations or optimization. ***Yusu fsahin, A Riza Motorcu [2]*** presented a study of surface roughness model for turning of mild steel with coated carbide tools. The model was developed in terms of cutting speed, feed rate and depth of cut, using response surface methodology. Machining tests are carried out with tin coated carbide cutting tools under various cutting conditions. The experimental data is utilized to build mathematical model for first and second order model by regression method. The established equations showed that, the feed rate is the main influencing factor on the surface roughness. The surface roughness increased with the increase in the feed rate but decreased with the increasing of cutting speed and depth of cut. ***Shibendu S. Roy [3]*** presented an attempt to design an expert system using two soft computing tools, namely fuzzy logic and genetic algorithm. In this work, the surface finish of ultra-precision diamond turning of MMC is modeled forest of given cutting parameters (spindle speed, feed rate and depth of cut). An optimized knowledge based on the fuzzy expert system is obtained using a binary coded genetic algorithm. The genetic algorithm (GA) based training is done off – line. Once trained the GA trained fuzzy expert system (GAFES) will be able to predict surface finish in ultra-precision diamond turning of AL6061/SiCp MMC before conducting at experiment. It is clear that, the ability of predicting outputs of a machining process without carrying out actual experiment will help us to develop automatic manufacturing system. Simulation results showed that in most of the cases, GAFES is found to perform better than FES technique. It may be happen because author defined FES may not be optimal in any sense. It is interesting to note that the error of author defined FES in predicting surface finish may be reduced by proper design of knowledge base of the FES. For example, there might be more number of divisions for each of the variables resulting into a large number of rules in the knowledge base. The nature of membership function distribution of the inputs and output variables can designed automatically using an optimization tools like GA, artificial neural networks to reduce error in prediction. ***Öguz Colak, Cahit kurbanoğlu [4]*** used a new approach method called gene expression programming (GEP) to predict the surface roughness of metal matrix composite (MMC). Three milling parameters have been selected; spindle speed, feed rate and depth of cut. Based on these three milling parameters and another important parameters affected on surface roughness are investigating how to use GEP for surface roughness prediction. GEP algorithm is a solution method which makes a global function search for the problem. Characteristic of GA algorithms is linear array of constant length chromosomes. GEP algorithms try to find a suitable solution-using parse three, which create to define relations between different size and shape non-linear variables. GEP is coming from its ability to generate mathematical equation that can be easily programmed even into programming for use in monitoring of surface roughness. ***H. Öktem et al [5]*** developed Taguchi optimization methods for low surface roughness in terms of process parameters when milling the mold surfaces of 7075-T6 aluminum material considering the process parameters of feed rate, cutting speed axial - radial depth of cut, and machining tolerance.

Regression analysis is performed to identify whether the experimental measurements represent a fitness characteristic for the optimization process. A taguchi orthogonal arrays signal to noise, the S/N ratio and (ANOVA) are used to find the optimal levels and the effect of the process parameters on surface roughness. In the multiple regression analysis R^2 is found to be 0.906 of the value that is less than 0.8. ANOVA results show the machining tolerance, radial depth of cut, and axial depth of cut. Feed and cutting speed affects the surface roughness by 96.035%, 2.53%, 0.17% and 0.098% for the surface of mold cavity. ***C.C. Tsao, H. Hocheng [6]*** presented the prediction and evaluation of thrust force and surface roughness in drilling of composite material using candle stick dill. The approach is based on tagchi methods and the artificial neural network. The experimental results indicated that, the feed rate and drill diameter are the most significant factors affecting the thrust force, while the feed rate and spindle speed contribute the most to the surface roughness. The correlations are obtained by multi-variable regression analysis and radial basis function network (RBFN) and compared with the experimental results.

Yonming Liu, Chaojun Wang [7] presented an adaptive controller with optimization for the milling process. This was designed based on two kinds of neural network. A modified BP neural network is proposed adjusting its learning rate and adding a dynamic factor in the learning process and is used for the on-line modeling of the milling system. The milling process can usually be optimized by adjusting the feed rate or spindle speed. In this work, the feed rate is selected as the optimized variable, and the milling state is estimated by the hidden layer having 10 neurons and the out put layer having only one neuron. The input of he modified BPNN is the milling feed rate and the output is the milling force. They also modified neural network and proposed adjusting its iteration steps, and is used for the real time optimal control of the milling process. The simulation and experiments showed that the adaptive milling system with the modified BPNN and ALMNN has a high robustness and global stability and that the adaptive milling force achieves the maximum constrained value and maximum efficiency.

Abeech C. Basheer et al [8] presented an experimental work on the analysis of machined surface quality of AL/SiC composites using artificial neural network (ANN) model to predict the surface roughness. From this work, the size of reinforcements in the composite material influences roughness of the machined surfaces significantly when its magnitude is comparable to that of the feed rate and tool nose radius employed during machining of the composite materials. The best surface quality is obtained at the lowest value of feed rate, the smaller particle size and the largest tool nose radius. ANN based model is developed to predict roughness of machined surfaces uses a feed forward network and an algorithm involving Bayesian regularization combined with the leveberg-Marquardt modification to train the neural network. The predicted response of the ANN model is in very good agreement correlation coefficient of 0.977 and the mean absolute error of 10.4% with experimental data. *Tuğrul özel, Yiğit Karpat [9]* presented neural network modeling to predict surface roughness and tool flank wear over the machining time for a variety of cutting conditions in finish hard turning. A set of sparse experimental data for finish turning of hardened steel obtained from literature and experimental data obtained from performed experiments in finish turning of hardened HISIH-13 steel have been utilized. The neural network is also compared to the regression models. Neural network models with cutting force inputs and a single output yielded better results than neural network with two outputs, which predict surface roughness and tool wear together. The experimental data of measured surface train the neural network models. Trained neural network models are used in predicting surface roughness and flank wear for various different cutting conditions. *P.G. Benardos, G.C. Vosniakos [10]* developed a neural network model using elements from the theory of face milling. Surface roughness formation mechanism based on DoE methodology is used in this work. Face milling finish of AL alloy in vertical axis and CNC milling machine are also used. The goal is to train an artificial neural network to include the most important factors affecting surface roughness in order to make accurate and consistent predictions for any new combination of value for these factors. Taguchi's DoE method is thought appropriate for that purpose and is analyzed. The connection of these factors to the surface roughness values is made through feed forward neural network whose principles are presented. Each factor influences surface roughness to a different extent, the best network should be chosen. The results of all models which are used in this work can be summarized as follow; ANNs are a powerful tool easy to use in complex problems where not all the parameters are straight forwardly engaged. ANN can be used reliably, successfully and very formation mechanism and the prediction of its value in face milling. Given the accuracy that was achieved, it is safe to conclude that, all the significant factors are included in the DoE process. The most influential are found to be the feed rate per tooth, the Fx component of the cutting force, the depth of cut, the engagement of the cutting tool and the use of cutting fluid.

The present research is focused on optimization of machining (dry milling) conditions of AL 1050/SiCp MMCs. The cutting conditions are, cutting speed, depth of cut, feed rate, volume fraction and particle size. An artificial neural network (ANN) is used to train and simulate the experimental data. Multiplayer perceptron model has been constructed with back-propagation algorithm using the input parameters. Output parameters are surface roughness of the machined part. On completion of the experimental test, ANOVA, ANN and genetic algorithm (GA) are used to validate the results obtained and also to predict the behavior of the system under any conditions within the machining rang.

2. EXPERIMENTAL PROCEDURE

2.1. Design of Experiment

For conducting experiments, design of experiment in statics has been used. This reduces considerable number of experiments and time compared to one factor at a time type experiment. Also, the design of experiments (DoE) dictates a series of steps to follow for the experiment to yield an improved understanding of product or process performance.

The selection of the appropriate orthogonal array OA is based on the following criteria; the number of factors and interactions of interest, the number of levels of the factors of interest and the desired experimental resolution or cost limitations. In order to assign the various factors to an OAs column, some mathematical property should be taken into account [5].

The identified factors are based on the previous work in this filed [8 and 10].The independently controllable machining parameters which are having greater influences on surface roughness while machining of Al /SiCp -MMC specimen are as follows, 1) cutting speed, 2) feed , 3) depth of cut, 4) fraction ratio % of SiC and 5) sizes of particles. These parameters and their levels are presented in Table (1) and the upper and lower limits of these factors are shown in Table (2).

Table 1, Parameters used and their levels

Parameters	***Unit***	***Level 0***	***Level 1***	***Level 2***	***Level 3***	***Level 4***
Cutting speed	rpm	28	45	90	112	140
Depth of cut	mm	0.25	0.50	1.00	1.25	1.5
Feed	mm/rev	0.40	0.60	0.80	1.0	1.25
Volume fraction	%	5.00	10.0	15.0	20.0	25
Particle size	µm	7.0	10.0	14.0	20.0	25

Table 2, Upper and lower levels

Par. No	Parameter	Unit		Level	
				Low	High
1	Cutting speed	rpm	A	28	140
2	Depth of cut	mm	B	0.25	1.50
2	Feed	mm/rev	C	0.40	1.25
4	Volume fraction	%	D	5.0	25
5	Particle size	µm	E	7.0	25

3. MATERIALS

3.1. Matrix Material

Aluminum alloy 1050 is used in this work. This alloy is popular grade of aluminum for general applications where moderate strength is required. Alloy 1050 is known for excelled corrosion resistance, high ductility and highly reflective finish. The fabrication of Al 1050 has a lot of advantages as shown in Table (3) .Table (4) presents the physical and mechanical properties of AL1050. In Table (5) Chemical composition of AL1050 is listed.

Table 3, General properties of Al 1050

Process	**Rating**
Workability-cold	Excellent
Machinability	Poor
Weldability -Gas	Excellent
Weldability -Arc	Excellent
Weldability - Resistance	Excellent
Brazability	Excellent
Solderability	Excellent

Table 4, Physical and mechanical properties of Al 1050

Property	Value
Proof stress 2%	35 MPa
Tensile strength	80 MPa
Shear strength	50 MPa
Elongation, A5	42 %
H. Vickers	20 HV
Density	2.71 kg/am3
Melting point	650 oC
Modulus of elasticity	71 GPa
Electrical resistively	0.0282 x 10-6Ωm
Thermal conductivity	222 W/m.k
Thermal expansion	$24x10^{-6}$ /k

Table 5, Chemical composition of Al 1050

Element	% Present
Cu	0.05%
Mg	0.05%
Si	0.25%
Fe	0.4%
Mn	0.05%
Zn	0.07%
Ti	0.05%
Al	Balance

3.2. Reinforcement Material

Silicon carbide (SiC) is used as reinforcement material in this work. The physical and mechanical properties of SiC are listed in Table (6). Also SiC chemical composition is listed in Table (7).

Table 6, Physical and mechanical properties of SiC

Property	***Value***
Density	3.1 gm/cc
Porosity	0.0 %
Flexural strength	550 Mpa
Elastic modulus	410 Gpa
Poisons ratio	0.14
Compressive strength	3900 MPa
Hardness	2800 kg/mm^2
Fracture toughness	4.6 Mpa. m
Max use temperature (no-load)	1650 ^{o}C
Thermal conductivity	120 w/m.k

Table 7, Chemical composition of SiC

Normal abrasive particle size range (μn)	***1180~1000 to 180~150***	***150~125 to 90~63***	***75~ 53***	***63 ~50 to 20~14***	***14~10 to 10~7***	***7 ~ 5 to 5 ~ 3.5***
Chemical composition %(by weight)	**≥ 99.0 %**	**≥ 98.5%**	**≥ 97.5 %**	**≥ 97.0%**	**≥ 95.5%**	**≥ 94.0%**

3.3. Casting and Machining of Specimens

The reo-cast method is used for fabricating the specimens which are used in this research. At the machining; Ten-millimeter diameter HSS end mill-cutting tool is used. A new end mill is used after each experiment. The cutting tool is used for only five pieces of workpieces to eliminate tool wear effect Therefore; five new tools are used at dry cutting conditions of this work.

3.4. Surface Roughness Measurement

The instrument which used in this work is SJ-201P.The surface test SJ-201P is a shop –floor type surface roughness measuring instrument, which traces the surface of various machined parts, calculate their surface roughness based on roughness standards and displays the results. After calibration of the instrument the machined parts are prepared for measurements and the results are tabulated for every specimen and classified all results are classified into groups related to the following; fraction (Vf) ratios, particle sizes and machining cutting parameters (cutting speed, depth of and feed rate).

4. OPTIMIZATION OF MACHINING CONDITIONS OF Al /SiCp (MMCs)

4.1. Optimization of Machining Conditions using ANOVA

4.2. Experimental Data S /N Ratio

The experimental work consists of three replications:

1) the term “signal” represents the desirable value,

2) noise (represents the undesirable value),

3) the formulae for signal – to- noise ratio.

This formula is designed such that the experimental list can always select the larger factor level setting to optimize the quality characteristics of the experiment. Therefore, the method of calculating the signal to noise ratio depends on whether the quality characteristics has smaller the best, larger the better. When normal the better formulation is chosen the equations for calculating S/N ratio are as follow;

$$\zeta = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^{-2}\right] \text{..... for larger the better} \qquad (1)$$

$$\zeta = -10\log\left[\frac{1}{n}\right]\sum_{i=1}^{n} y_i^2 \;..... \textit{for smaller the better} \qquad (2)$$

Where; Y_i is the observed data and n is the number of observations.

However, the cutting parameters for surface roughness will be discussed using the analysis of variance. In Table (8) the cutting conditions are presented. Also, the orthogonal array L_{25} is presented in Table (9).

Table 8, Cutting Conditions

Code No.	Cutting speed, rpm (V)	Depth of cut, mm (d)	Feed, mm/rev (f)	Volume fraction, %	Particle size, µm (ps)	Ra, µm
1	28	0.25	0.40	5.0	7.0	2.1
2	45	0.25	0.40	5.0	7.0	1.9
3	90	0.25	0.40	5.0	7.0	1.3
4	112	0.25	0.40	5.0	7.0	1.15
5	140	0.25	0.40	5.0	7.0	0.6
1	28	0.50	0.60	10	10	2.5
2	45	0.50	0.60	10	10	2.2
3	90	0.50	0.60	10	10	1.5
4	112	0.50	0.60	10	10	1.2
5	114	0.50	0.60	10	10	0.8
1	28	1.0	0.8	15	14	4.0
2	45	1.0	0.8	15	14	3.0
3	90	1.0	0.8	15	14	2.5
4	112	1.0	0.8	15	14	2.0
5	140	1.0	0.8	15	14	1.5
1	28	1.25	1.0	20	20	4.5
2	45	1.25	1.0	20	20	3.9
3	90	1.25	1.0	20	20	3.0
4	112	1.25	1.0	20	20	2.6
5	140	1.25	1.0	20	20	2.2
1	28	1.5	1.25	25	25	5.2
2	45	1.5	1.25	25	25	4.0
3	90	1.5	1.25	25	25	3.5
4	112	1.5	1.25	25	25	3.0
5	140	1.5	1.25	25	25	2.6

Table 9, orthogonal array L25.

A	B	C	D	E
1	1	1	1	1
1	2	2	2	2
1	3	3	3	3
1	4	4	4	4
1	5	5	5	5
2	4	3	2	1
2	5	4	3	2
2	1	5	4	3
2	2	1	5	4
2	3	2	1	5
3	2	5	3	1
3	3	1	4	2
3	4	2	5	3
3	5	3	1	4
3	1	4	2	5
4	5	2	4	1
4	1	3	5	2
4	2	4	1	3
4	3	5	2	4
4	4	2	5	3
5	4	5	1	2
5	5	1	2	3
5	1	2	3	4
5	2	3	4	5
5	3	2	4	5

4.3. Analysis of Variance

Analysis of variance is a method of portioning variability into identifiable source of variation and the associated degree of freedom in an experiment. The frequency test (F-test) is utilized in statistics to analyze the significant effects of the parameters, which form the quality characteristics. Table (10) shows the results of ANOVA analysis of S/N ratio for surface roughness. This analysis is carried out for a level of significance of (5%), i. e., for (95%) a level of confidence. The last column of the table shows the "percent "contribution (P) of each factor as the total variation, indicating its influence on the result. Form Table (10) it is apparent that, the F – values of cutting speed, feed rate, depth of cut, volume fraction and practical size have statistical, physical significance on the surface roughness.

Table 10, Analysis of variance for surface roughness

Source	DF	Seq SS	MS	F-Test	P
Cutting speed rpm	4	64.876	16.595	12.30	7.7
Depth of Cut mm	4	129.667	26.012	19.27	30
Feed , mm/rev	6	23.099	3.099	2.30	50
Volume fraction,%	4	4.825	1.081	0.80	4.1
Practical Size µm	4	2.773	0.693	0.51	8.2
Error	2	2.699	1.350		7
Total	24	227.967			100

Where ; DF: degree of freedom, SS: sum square , MS: mean square and P: percentage of contribution.

4.4. Determination of Optimum Factor Level Combination

Figure (1) shows five graphs, each represents the mean response and the mean S/N ratio for cutting speed, depth of cut, feed rate, volume fraction and practical size. The values of the graphs have been tabulated in Tables (11), and (12) based on the S/N ratio and ANOVA analysis .The optimum cutting conditions for surface roughness shown in Table (11) are; A_2, B_5, C_3, D_1 and E_3.

Table 11, Response table for signal to noise ratio of surface roughness :(Smaller is better).(*Optimum level)

Level	Cutting speed rpm (A)	Depth of Cut mm (B)	Feed mm/rev (C)	Fraction ratio % (D)	Practical Size µm (E)
1	-14.822	-7.731	-12.952	-14.690*	-10.873
2	-15.237*	-3.629	-11.931	-10.518	10.978
3	-11.566	-11.651	-13.157*	-10.100	-12.075*
4	-6.244	-14.395	-10.911	-9.178	-12.002
5	-7.872	-18.336*	-8.407	-11.828	-9.814
Delta	8.993	14.707	8.929	5.513	2.261
Rank	2	1	3	4	5

Table 12, Response table for means surface roughness

Level	Cutting speed rpm	Depth of Cut mm	Feed mm/rev	Fraction ratio %	Practical Size µm
1	6.168	3.559	5.631	5.824	4.965
2	6.935	1.867	4.373	4.568	4.144
3	4.368	4.017	5.175	4.509	5.284
4	3.023	5.389	4.227	3.736	4.644
5	2.996	8.658	4.806	4.999	4.453
6			1.627		
7			3.363		
Delta	3.939	6.791	4.004	2.088	1.139
Rank	3	1	2	4	5

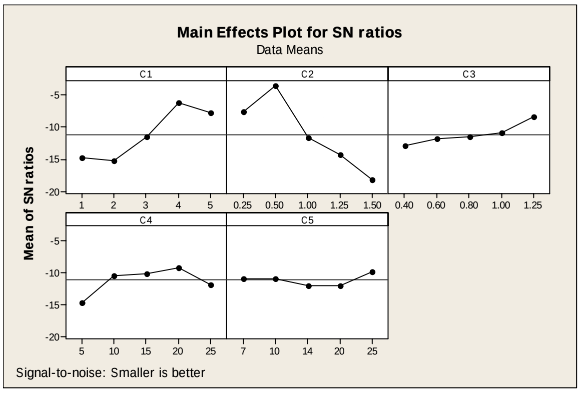

Fig. 1 Determination of optimum factor using ANOVA

4.5. Optimum Performance Prediction

After the optimum level has been selected, one could predict the optimum surface roughness using the following equation [16]:

$$\mu_{Predicted} = \mu_m + \sum_{i=1}^{n} (\mu_0 + \mu_m)$$

Where μ_m is the mean response or mean S/N ratio, μ_0 is the mean response or mean S/N ratio at optimal level, and n is the number of main design parameters that affect the quality characteristics. It is very essential to perform a confirmation experiment for the parameter design, particularly when less numbers of data utilized for optimization. The purpose of this confirmation experiment is to verify the improvement in the quality characteristics.

4.6. Verification of Optimum Performance through Confirmation Test

To verify the improvement in the matching characteristics of MMCs , implying that the factors and levels chosen for the experiment provide the desired result. Table (13) shows that the increase in S/N ratio form the initial cutting parameters is (-6.47) for surface roughness, which implies that the surface roughness qualities have improved. It is obvious that, the experimental results are closed to the predicted values, and they are falling within the confidence limits.

Form the analysis of Table (13), it can be observed that, the effect of cutting parameters are as follow; the feed rate mm/rev (P=50%), depth of cut mm (p=30%), particle size µm(P=8.2%), cutting speed m/min(P=7.7%)and volume fraction %(P=4.1%).

Table 13, Results of confirmation experiment for surface roughness using ANOVA

Initial Cutting parameters		Optimal Cutting parameters: Predicted	Optimal Cutting parameters: Experimental
Setting level	A_1, B_5, C_3. D_2, E4	A_2, B_5, C_3. D_1, E3	A_2, B_5, C_3. D_1, E3
Surface roughness	3.5	3.75	3.82
S/N ratio	-6.47	-8.27	-8.41

In Table (14) the experimental results and predicted values of surface roughness (Ra) are presented. The deviation between experimental results and predicted value is between (0.0 and 0.1 µm).

5. OPTIMIZATION OF MACHINING CONDITIONS USING ANN

5.1. Introduction to Artificial Neural Network Modeling (ANN)

Artificial neural network plays an important role in predicting the linear and non – linear problems in different fields of engineering [8]. A three layered back propagation network is shown in Fig(3).The general architecture of of a 3 –layered multilayer perceptron (MLP) using back propagation artificial (BPA) is a steepest decent method , where weight values are adjusted in an iterative fasion while moving along the error surface to arrive at minimal range of error , when input patterns are presented to the network for learning the netwok . The learning processess consists of two passes through different layers of the network , a forward pass and a bcakward pass .In the forward pass , the input pattern is applied to the nodes of the input layers and its effect propagates through the network , layer by layer. During the forward pass, synaptic weights are all fixed. The error, which is the difference between the actual output of the network and the desired output, is propagated as backward pass to updated synaptic weights. The weights are continuously updated every time, the input patterns are presented to the network and the process continues till the actual output of the network comes closer to desired output. If all the input patterns are propagated once through the network, it is called as cycle or epoch. The modern second order algorithms such as conjugate gradient descent and Levenberg – Marquardt are substantially faster for many problems, but back propagation still has advantages in some circumstances, and it is the easiest algorithm to understand. The (BPN) back propagation network consists of five input neurons corresponding to feed, cutting speed, depth of cut, volume fraction and practical size and one output neuron corresponding to surface roughness. The number of hidden is one to 25 neurons.

Table 14, Measured and prediction surface roughness Of (ANOVA) technique

Reading number	Surface roughness of experimental (Ra)	Predicted by ANOVA	Deviation
1	2.1	2.35	- 0.25
2	1.9	1.89	0.01
3	1.3	1.4	- 0.1
4	1.15	1.14	0.01
5	0.6	0. 69	- 0.09
6	2.5	2.05	0.45
7	2.2	2.83	- 0.6
8	1.5	1.53	- 0.03
9	1.2	1.31	- 0.11
10	0.8	0.79	0.01
11	4	3. 8	0.2
12	3	3.1	- 0.1
13	2.5	2.05	0.45
14	2	2	0
15	1.5	1.41	0.09
16	4.5	4.64	- 0.1
17	3.9	3.81	0.09
18	3	2.98	0.1
9	2.6	2.62	- 0.02
20	2.2	2.20	0
21	5.2	5.32	- 0.1
22	4	3.92	0.1
23	3.5	3.41	0.1
24	3	3.01	- 0.01
25	2.6	2.65	- 0.05

Fig. 2 Relationship between the experimental and predicted results by ANOVA

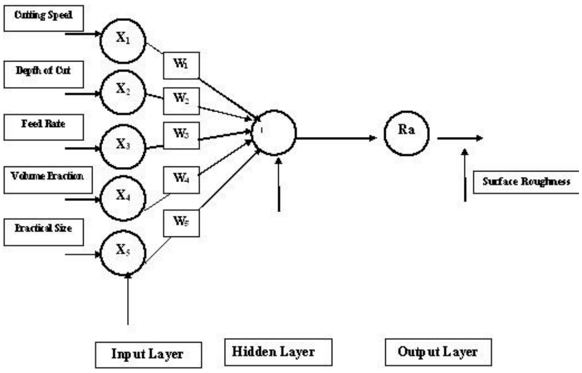

Fig. 3 Configuration of neural networks

5.2 Back Propagation Network – Algorithm

The algorithm for the back propagation network program is described as follows; 1) deterimine 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 wight 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) detemine the output at the output layer and compare those with the desired output values. Determine the error of the output,error = desiredoutput – actuaoutput and also deteimine 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. Also, back – propagate the errors available at the output neurons to the weight values connected between the neurons of hidden layer and output layer using equations taken from [8]. By using the previous steps (3 and 7), determine the root – mean square error value, mean percentage of the error and worst percentage of error over the complete patterns and check whether its of reasonable error or not, if so, go to the following step, otherwise repeat the same from step 3 to step 7, 9) stop the iteration and note the final weight value attached to the hidden layer neurons and also to the output layer neurons.

The neural network model is tested as follows; 1) determine the output for the testing pattern with the trained weight values, 2) check whether the deviation from the desired value is reasonably less or not, if no try the back propagation with revised network by changing the number of neurons, altering; learning rate parameters and momentum value. In Table (15) the typical observation of network performance is presented.

Table 15, Network performance conditions

Typical observation of network performance	
Network configuration	5-25-1
Number of hidden layer	1
Number of hidden neuron	25
Transfer function used	Activation function
Number of patterns used for training	15
Number of patterns used for testing	10
Sum of squared error	0.002
Learning factor (ξ)	0.5
Momentum factor (α)	1

Table (16) the experimental results and predicted values of surface roughness (Ra) are presented. From the previous Table and Fig (4) it is clear that; the deviation between experimental results and predicted values is between (0.0 and 0.4).

6. OPTIMIZATION OF MACHINING CONDITIONS USING GA

Genetic algorithm (GA) is a guided random search technique and is directed through the search space by means of an objective function [17]. GA is classified into seven steps; are setted as follows; 1) Parameter setting, 2) Initialization process, 3) Evaluation, 4) Selection operation ,5) Cross over operation ,6) Mutation operation and 7) Termination set.

6.1. Input Data

The input data is classified as follows; number generation: 60, population size: 20, 10 and the minimum and maximum range is determined as follows:

1-The range for item 1(cutting speed) (28-140).

2-The range for item 2(depth of cut) (0.25-1.5).

3-The range for item 3 (feed) (0.4-1.25).

4-The range for item 4(volume fraction) (5-25).

5-The range for item 5(pratical size) (7-25).

6.2. The Random Direction for Each Input

1-Random direction for item (1) : 0

2-Random direction for item (1) : 0.01

3-Random direction for item (1) : 1

4-Random direction for item (1) : 0

5-Random direction for item (1) :1

The random number generation for selection of chromosome is 0.217 and the crossover probability is 0.5.

6.3. Output Data

In Table (17) the experimental results and predicted values (from GA) of surface roughness (Ra) are presented. The deviation between experimental results and predicted value is between (0.0 and 0.13).

Table 16, Experimental results and predicted values of surface roughness using ANN technique

Reading number	Surface roughness of experimental	Predicted By ANN	Deviation
1	2.1	2.45	- 0.3
2	1.9	1.91	- 0.01
3	1.3	1.41	- 0.11
4	1.15	1.11	0.04
5	0.6	0.71	- 0.1
6	2.5	2.14	0.3
7	2.2	2.23	- 0.03
8	1.5	1.62	- 0.1
9	1.2	1.2	0
10	0.8	0.80	- 0.001
11	4	4	0
12	3	3.01	-0.01
13	2.5	2.61	0.1
14	2	2.01	- 0.01
15	1.5	1.5	0
16	4.5	4.34	0.2
17	3.9	3.80	0.1
18	3	2.94	0.1
19	2.6	2.61	- 0.01
20	2.2	2.40	- 0.2
21	5.2	5.21	0.4
22	4	3.94	0.1
23	3.5	3.51	0.1
24	3	3	0
25	2.6	2.77	- 0.1

Fig. 4 Validation of ANN model for surface roughness

Table 17, Experimental results and predicted values of surface roughness using GA technique

Reading number	Surface roughness of experimental	Predicted by GA	Devaition
1	2.1	2.11	-0.01
2	1.9	1.91	-0.01
3	1.3	1.47	-0.1
4	1.15	1.16	-0.01
5	0.6	0.84	- 0.2
6	2.5	2.51	-0.01
7	2.2	2.43	-0.2
8	1.5	1.52	- 0.02
9	1.2	1.2	0
10	0.8	0.81	- 0.01
11	4	4	0
12	3	2.90	0.01
13	2.5	2.54	0.04
14	2	2.11	- 0.1
15	1.5	1.54	-0.04
16	4.5	4.49	0.01
17	3.9	3.81	0.09
18	3	3	0
19	2.6	2.60	0
20	2.2	2.21	- 0.1
21	5.2	5.22	- 0.02
22	4	4	0
23	3.5	3.51	-0.1
24	3	3.05	- 0.05
25	2.6	2.61	- 0.1

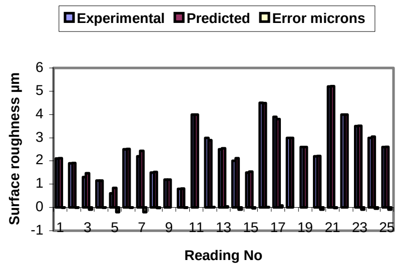

Fig. 5 Validation of GA model for surface roughness

Table 18, Experimental results and predicted values of surface roughness using the three techniques

Reading number	Surface roughness of experimental	Predicted By ANOVA	Predicted By ANN	Predicted By GA	Devaition (ANOVA)	Devaition (ANN)	Devaition (GA)
1	2.1	2.35	2.45	2.11	-0.01	- 0.25	- 0.3
2	1.9	1.89	1.91	1.91	-0.01	0.01	- 0.01
3	1.3	1.4	1.41	1.47	-0.1	- 0.1	- 0.11
4	1.15	1.14	1.11	1.16	-0.01	0.01	0.04
5	0.6	0. 69	0.71	0.84	- 0.2	- 0.09	- 0.1
6	2.5	2.05	2.14	2.51	-0.01	0.45	0.3
7	2.2	2.83	2.23	2.43	-0.2	- 0.6	- 0.03
8	1.5	1.53	1.62	1.52	- 0.02	- 0.03	- 0.1
9	1.2	1.31	1.2	1.2	0	- 0.11	0
10	0.8	0.79	0.80	0.81	- 0.01	0.01	- 0.001
11	4	3. 8	4	4	0	0.2	0
12	3	3.1	3.01	2.90	0.01	- 0.1	-0.01
13	2.5	2.05	2.61	2.54	0.04	0.45	0.1
14	2	2	2.01	2.11	- 0.1	0	- 0.01
15	1.5	1.41	1.5	1.54	-0.04	0.09	0
16	4.5	4.64	4.34	4.49	0.01	- 0.1	0.2
17	3.9	3.81	3.80	3.81	0.09	0.09	0.1
18	3	2.98	2.94	3	0	0.1	0.1
19	2.6	2.62	2.61	2.60	0	- 0.02	- 0.01
20	2.2	2.20	2.40	2.21	- 0.1	0	- 0.2
21	5.2	5.32	5.21	5.22	- 0.02	- 0.1	0.4
22	4	3.92	3.94	4	0	0.1	0.1
23	3.5	3.41	3.51	3.51	-0.1	0.1	0.1
24	3	3.01	3	3.05	- 0.05	- 0.01	0
25	2.6	2.65	2.77	2.61	- 0.1	- 0.05	- 0.1

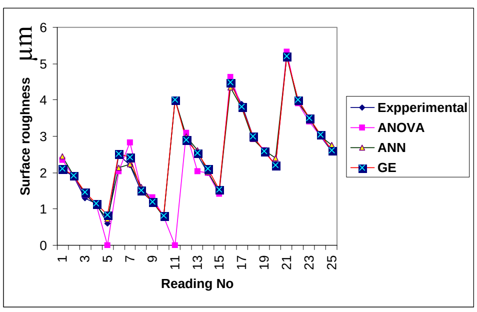

Fig. 6 Comparison for surface roughness between experimental and prediction by using (ANOVA, ANN and GA)

Table 19, Optimum values of different parameters used

Parameters	ANOVA		ANN			GA	
Cutting speed rpm	112	140	112	140	112	112	112
Depth of cut mm	1.0	1.25	0.5	1.0	1.5	0.5	1.25
Feed rate mm/rev	0.8	1.0	0.6	0.8	1.25	0.6	1.0
Volume fraction % age	15.20	20	10	15	25	10	20
Particle size µ m	14,20	20	10	14	25	10	10

From Tables (18 and 19) and also Figs (5 and 6) ,the comparison between these techniques indicated that; these models are suitable to optimize and modeled the machining conditions of AL1050/SiCp at milling Operations .The effect of feed rate is(50%), followed by depth of cut (30%),particle size (8.2 %),cutting speed (7.7 %) and volume fraction (4.1%).

7. DISCUSSION AND CONCLUSIONS

From Tables (18 and 19) and Figures (5 and 6); the use of ANOVA ,ANN and GA methods in modeling and optimization of AL 1050/ SiCp machining conditions is found to be very effective. This approach can be employed to select the machining parameters from a wider range. This approach is more flexible when compared to other models developed based on the experimental results that constrain their applicability of selecting the processes parameters from a limited range .From the previous outputs of the consolidated optimum solution obtained through ANOVA ,ANN and GA approach, it can be seen that ; the optimum cutting conditions are; cutting speed (112 and 140 rpm), depth of cut (1.0 and 1.5 mm) , feed (0.8 and 1.25 mm/rev), volume fraction (10 and 25%) and particle size (10 and 25 µ m respectively. In ANOVA results, the depth of cut has high influence on surface roughness and then feed rate and cutting speed. ANN results indicated that; the cutting speed plays a vital role in the model outputs of surface roughness. Also, there is a close matching between the model outputs and the experimental results of surface roughness. GA results indicated that; the cutting speed has a large effect on the results of surface roughness, then fraction ratio and particle size. ANOVA optimization method is accurately than the other two methods ANN and GA. In this method the deviation between model outputs and the experimental results of surface roughness is less than the two other methods results and nearly is between 0.0 and less than 0.1 µm.

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