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Research Article

Prediction of Cutting Conditions in Turning AZ61 and Parameters Optimization Using Regression Analysis and Artificial Neural Network

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All manufacturing engineers are faced with a lot of difficulties and high expenses associated with grinding processes of AZ61. For that reason, manufacturing engineers waste a lot of time and effort trying to reach the required surface roughness values according to the design drawing during the turning process. In this paper, an artificial neural network (ANN) modeling is used to estimate and optimize the surface roughness (R_a) value in cutting conditions of AZ61 magnesium alloy. A number of ANN models were developed and evaluated to obtain the most successful one. In addition to ANN models, traditional regression analysis was also used to build a mathematical model representing the equation required to obtain the surface roughness. Predictions from the model were examined against experimental data and then compared to the ANN model predictions using different performance criteria such as the mean absolute error, mean square error, and coefficient of determination.

1. Introduction

Magnesium alloys are often used in many industrial applications such as the manufacturing of several components used in the aerospace and modern automobiles industry. Also, magnesium block engines have been widely used in some high-performance vehicles. In those applications, the final surface roughness of machined components is playing a major factor in the acceptance of those parts.

Many researchers have investigated the optimization of cutting parameters for the prediction of surface roughness as a key performance measure. Asiltürk used ANN (artificial neural network) and MRM (multiregression models) to predict the surface roughness of steel AISI 1040. They developed their own models and used ANN to optimize the cutting parameters formulating the surface roughness as objective function. They used cutting speed, feed rate, depth of cut, and nose radius as optimized parameters. Surface roughness is characterized by the mean (R_a) and total (R_t) values of the recorded roughness at different locations on the produced surface. They conducted many experiments, each with a different set of the cutting parameters, and the corresponding R_a and R_t values were reported. Obtained results were then used to train an ANN model. Mean squared error of approximately 0.003% was achieved which outperforms error rates reported in the early literature and are claimed to be suitable for robust prediction of the surface roughness in industrial settings [1].

Another approach can be found in the work of Mokhtariet Homami et al. [2], and they employed a design of experiment

(DOE) technique based on a full factorial design to determine the number of experiment and the corresponding parameters. They represented their results in a statistical analysis, and they used ANN to model the system. Optimization was done using genetic algorithm (GA). The conclusion of their work was that the main factors affecting the flank wear and the produced surface roughness are the feed rate, nose radius, and approach angle, while the cutting speed had the major effect on flank wear. Optimized values of the cutting conditions were attained and showed a significant reduction in the surface roughness values.

Jafarian et al. [3] used GA and particle swarm optimization (PSO) techniques to determine optimal cutting parameters in turning operations with a multiobjective optimization aiming to minimize surface roughness and cutting forces and maximize tool life. They discussed their results claiming that training ANN using GA gave superior results than those reported in the literature with high accuracy and gives the flexibility of analyzing the effect of each parameter separately on the output.

The PSO technique was also utilized in the work of Karpat and Özel [4], and they used the Pareto optimal frontier to select optimized parameters to maximize material removal rate (MRR) without affecting the induced stresses or the final surface finish of the produced components. They obtained good results making use of dynamic-neighborhood PSO approach in solving complex turning optimization problems.

A different approach was utilized in the work of Natarajan et al. [5] to test the reliability of ANN in the prediction of surface roughness values when machining Brass C26000 material in dry cutting condition on a CNC turning machine. Surface roughness has been measured and compared to the experimental data and concluded that ANN can be implemented reliably and accurately to predict surface roughness in turning operations of Brass C26000 material.

The applicability of radial base function (RBF) neural networks was investigated in the work of Pontes et al. [6] to predict surface roughness in turning processes of SAE 52100 hardened steel. Networks were trained using different sets. They considered several design variables and found that ANN models were capable of providing accurate estimates of surface roughness values in an affordable way.

The turning of Ti-6Al-4V titanium alloy was investigated in the work of Sangwan et al. [7] to minimize surface roughness using ANN-GA approach. A feed forward neural network was proposed for training and testing of the neural network model. The predicted results were found to be in good agreement with the obtained experimental results.

A comparison between linear regression models and ANN approach has been studied in the work of Acayaba and Escalona [8]. A target of saving cost, effort, and machining time leads to the necessity of predicting surface roughness prior to performing machining operations. They used experimental data to validate their claim and found that using ANN outperforms linear modeling. Instead of using GA like other researchers previously listed, this research employed a simulated annealing (SA) optimization algorithm to optimize cutting parameters for minimizing surface roughness. Results show similar findings as reported previously with no major significant improvement.

A more concise investigation focusing only on the three major cutting parameters influencing the surface roughness was presented in the work of Bajić et al. [9]. Cutting speed, feed rate, and depth of cut are optimized using regression analysis and ANN. Results obtained show no superiority of one approach over the other, and both gave a good prediction of the surface roughness.

A new approach that integrates artificial intelligence (AI) with ANN and GA has been introduced by Gupta et al. [10], and the paper illustrates the impact of using AI on the quality and type of results obtained for the surface roughness prediction. They analyzed the experimental data using support vector regression (SVR) defining the tool wear and power required as output parameters.

Grade-H high-strength steel had its share in the investigation for better surface quality studied by Abbas et al. [11] in their work. They emphasized that the key factors for the manufacturing of parts produced using Grade-H high-strength steel are parts accuracy and surface roughness MRR. Identifying the final surface roughness of produced parts prior to machining is crucial to ensure that those parts will not be rejected. The rejection of these parts at any processing stage will represent huge problems to any factory because the processing and raw material of these parts are very expensive. ANN was used in this work to determine the optimized cutting parameters to ensure minimum surface roughness during the turning operations.

As a continuation of their work, Abbas et al. [12] investigated the turning of high-strength steel focusing on three main cutting parameters: cutting speed, feed rate, and depth of cut. Their results included a Pareto frontier between surface roughness and machining time of finished components made from high-strength steel using the ANN model that was later used to determine the optimum cutting conditions. This study showed the feasibility of integrating optimization algorithms with computer-aided manufacturing CAM systems using Matlab.

A quantitative approach to evaluate the cutting process and its stability was demonstrated in the work of Yamane et al. [13], and they used the turning operation as a base for their study aiming at identifying the machining system deviation from a perfect process. Such a deviation can be identified by monitoring the machined surface and comparing it with the cutter profile. Adhesion and builtup edge produced during machining operation can then be easily noticed and monitored. Excessive vibration and the accuracy of spindle rotation can also be recorded and is a good indication of system instability and related directly to the quality of parts produced. Their conclusion was that the proposed method can be successfully implemented to evaluate turning operations.

The influence of the type of inserts used in the machining process on the quality of the surface produced was investigated in the work of D'Addona and Raykar [14]. They compared wiper inserts to conventional ones in the turning operation of oil hardened nonshrinking steel used in the manufacture of strain gauges and measuring instruments. Surface roughness was a major factor in this study as it is a very important aspect in the performance of those devices.

They used analysis of variance (ANOVA) and analysis of means (AOM) plots to evaluate their results.

Pu et al. [15] reported that magnesium alloys are gaining a lot of intension from researchers in the literature due to their advanced properties over conventional materials used in the automotive industry as well as medical applications such as biodegradable implants. One of the major factors looked at in machining of this alloy is the surface integrity. Pu et al. [15] investigated the effect of machining AZ31B Mg alloy under dry conditions as well as using liquid nitrogen as a lubricant. They concluded that using cryogenic machining with large nose radii improved several material performance criteria such as surface finish and grain size refinement.

Increasing productivity and maximizing material removal rate (MMR) have been also investigated for the machining of magnesium alloys. Using very high cutting speeds has its drawbacks and has been analyzed by Tomac et al. [16] in their work. They concluded that using speeds in excess of 600 m/min will result in buildup edge on the flank face of the cutting tool. They supported their argument with microstructure pictures of tool inserts as well as the machined surface of three different Mg-Al-Zn alloys.

Different coating materials have been used in industry to reduce the builtup edge effect appearing on the tool flank face during turning operations of magnesium alloys at high speeds. Tönshoff and Winkler [17] reported the different interactions happening between the cutting tool inserts, the coating, and the workpiece materials in turning of AZ91 HP at very high speeds ranging between 900 and 2400 m/min. They concluded that cutting tools with polycrystalline diamond (PCD) inserts can significantly reduce the cutting forces and hence the frictions at the tool-workpiece interface.

The optimization of cutting parameters is another venue pursued by researchers to improve surface quality of machined magnesium alloys. Wojtowicz et al. [18] studied the effect of changing cutting parameters on the turning of AZ91 HP. Parameters explored include cutting speed, feed rate, depth of cut, and tool nose radius. Surface integrity and increasing fatigue life were the major optimized parameters of the machined components, and other reported parameters include microstructure, grain size and residual stresses improve fatigue life. They also supported the argument provided by Tönshoff and Winkler [17] regarding the superior performance of PCD coating tool inserts at high cutting speeds and feed rates.

In this paper, an ANN model has been employed to estimate and optimize the produced surface roughness of AZ61 material during turning operations. This method proves to be more efficient and provided the manufacturing engineers with a good tool to be utilized to effectively predict the quality of the surface produced in an economical and time saving manner. Thus this eliminates the possibility of part rejection due to manufacturing process errors that costs the factory time and money and wasted raw material.

2. Materials and Methods

Table 1 presents the chemical composition of magnesium alloy AZ61 which contains zinc and aluminum with 1 and 6 percent content, respectively. The microstructure of the composition is analyzed at the previously mentioned aluminum concentration, and the phase diagram shows a magnesium-rich phase interacting with an $Al_{12}Mg_{17}$ composite. Zinc along with other traces is found to have no effect on the alloy microstructure.

The machining of test specimens is done using Emco mill concept 45 CNC turning machine equipped with Sinumeric 840-D. The diameter of the workpiece is equal to 40 mm with a length of 100 mm. Tool holder specification is SVJCL2020K16, while the insert is VCGT160404 FN-ALU. The cutting edge angle, nose radius, and clearance angle are set at 35°, 0.4 mm, and 5°, respectively. All experiments were conducted in wet conditions while the cutting parameters are controlled via CNC part program. The surface roughness tester TESA Rugosurf 90-G is used to evaluate the produced surface roughness. A sketch of the test specimen is shown in Figure 1. The test plan was implemented through 64 turning runs. These runs were divided into 16 groups. Each of four groups was subjected to one common cutting speed (125, 150, 175, and 200 m/min). Each group was machined using four levels of cutting depth (0.30, 0.60, 0.90, and 1.12 mm). Each depth was processed using feed rate having four levels (0.05, 0.010, 0.15, and 0.20 mm/rev). Full listing of all samples and the resulting measured surface roughness are provided in Appendix A.

Multivariable regression analysis was used to build a mathematical model relating the process outcome (surface roughness R_a) with the three studied input parameters (cutting speed (V), depth of cut (d), and feed rate (fr)). 56 experiments were conducted that cover the input parameter range described previously. Eight extra experimental runs were carried out to be used in testing both the regression and ANN models.

Regression was conducted using Minitab 17 software with stepwise technique to eliminate the insignificant terms from the model. The model was fitted in the form given by the following equation [19]:

$$R_a = \beta_o + \sum_{i=1}^{k}\beta_i X_i + \sum_{i=1}^{k}\beta_{ii} X_i^2 + \sum\sum_{i<j}\beta_{ij} X_i X_j + \sum\sum_{i<j<k}\beta_{ijk} X_i X_j X_k + \sum\sum_{i\neq j}\beta_{iij} X_i^2 X_j + \varepsilon_i, \quad (1)$$

where β_o is the constant term, β_i represents the linear effects, β_{ii} represents the pure quadratic effects, β_{ij} represents the second level interaction effects, β_{ijk} the third level interaction effects, β_{iij} represents the effect of interaction between linear and quadratic terms, and ε_i represents the error in predicting experimental surface roughness. The material removal rate (MRR) was calculated using (2) for each run. Desirability function approach was used to maximize MRR maintaining R_a below 0.4 as a maximum limit for the surface roughness value:

$$\mathrm{MRR} = 1000\, V * \mathrm{fr} * d, \quad (2)$$

where MRR is the volume removed per unit time (mm^3/min.), V is the cutting speed (m/min.), fr is the feed

Table 1: AZ61 magnesium alloy chemical composition.

Element	Aluminium	Zinc	Copper	Silicon	Iron	Nickel	Magnesium
% by mass	5.95	0.95	<0.03	<0.01	<0.01	<0.005	Balance

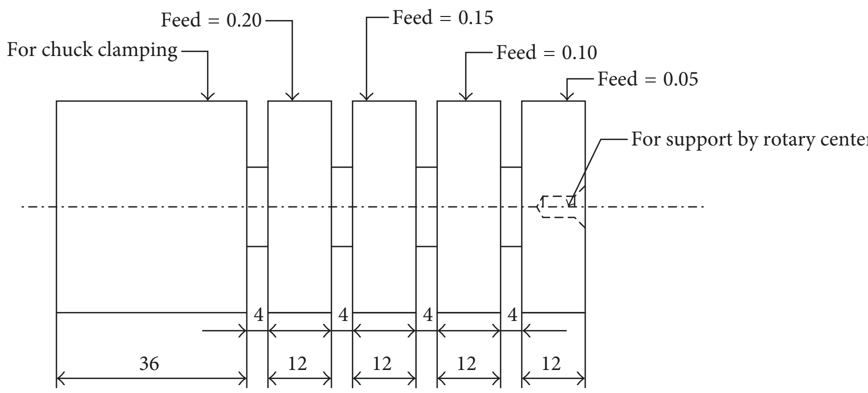

Figure 1: Working drawing of the test workpiece.

rate (mm/rev), and d is the depth of cut (mm). Multivariable regression analysis was used to build a mathematical model relating the process outcome (surface roughness R_a) with the three studied input parameters (cutting speed (V), depth of cut (d), and feed rate (fr)). 56 experiments were conducted that cover the input parameters range described previously. Eight extra experimental runs were carried out to be used in testing both the regression and ANN models.

3. Results and Discussions

The regression-fitted mathematical model is given by (3). Box-Cox transformation was used to normalize the residuals with $\lambda = 0$ (natural log) for R_a. Anderson–Darling test was conducted to check the normality of residuals with a result of p value $= 0.885 > 0.05$. The null hypothesis of such a test is that the data are normal, and a p value < 0.05 proves nonnormality.

Determination coefficient (R^2), mean square error (MSE), and mean absolute error (MAE) were calculated to be 0.975, 0.02, and 0.12, respectively. Figure 2 shows a scatter plot for the predicted R_a versus measured R_a. It is clear from the figure that the relation between them is very close to linear with calculated R^2 equals 0.97.

$$\ln(R_a) = -2.6420 + 0.1874\ d + 16.516\ \text{fr}. \tag{3}$$

Desirability function approach was used to estimate the values of studied process parameters that maximize the MRR keeping R_a at levels not exceeding a practical value of 0.4 μm. The optimization plot, illustrated in Figure 3, shows that an optimum MRR of 13,928 mm^3/min with $R_a = 0.4\,\mu$m is obtained at cutting speed 200 m/min., depth of cut 1.12 mm, and feed rate 0.09 mm/rev.

ANN modeling was used to predict the surface roughness of AZ61 magnesium alloy. The three input parameters cutting speed (V), depth of cut (d), and feed rate (fr) were taken into account to predict the surface roughness as an output parameter. The data were taken from the experimental result. The transfer function was selected as a TanhAxon. The data were divided in two parts as training and test data. 80% of data were used for training stage while the left 20% of data were used for test stage to understand the performance of the developed ANN model. The best ANN model predicting the R_a value between developed trial models was obtained according to the values of R^2 and MSE. Figure 4 gives the experimental and ANN-predicted results. It can be seen from the figure that a good agreement was obtained between experimental and ANN-predicted results. It is also seen from Figure 5 that the value of R^2 is 0.9629 for experimental surface R_a and ANN-predicted surface R_a, while R^2 is 0.9931 for experimental MRR and ANN-predicted MRR in Figure 6.

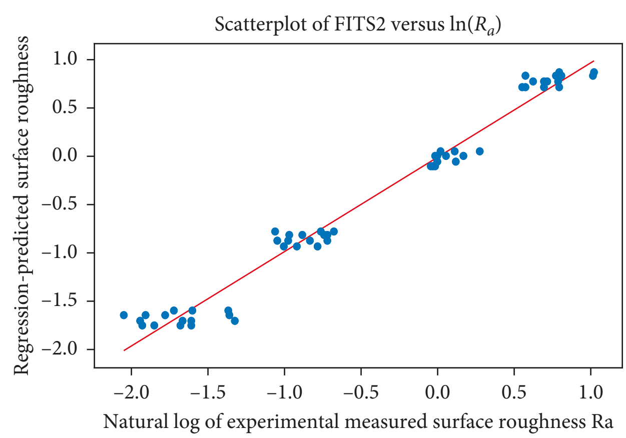

Figure 2: Experimental readings versus regression model predictions.

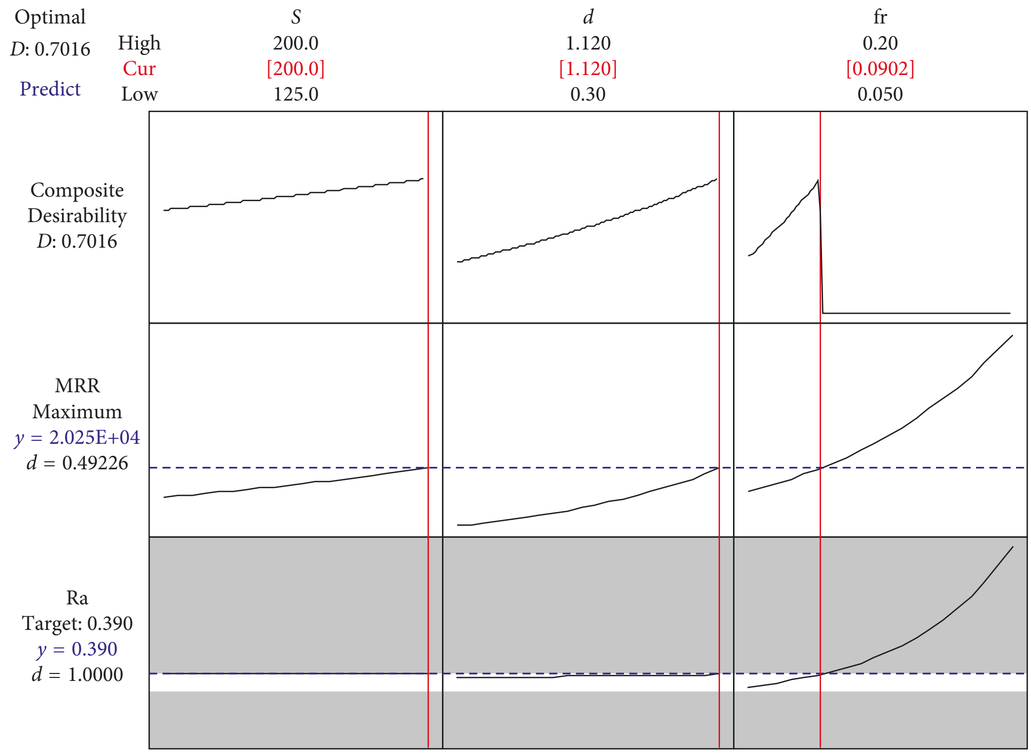

FIGURE 3: Optimization plot for R_a and MRR.

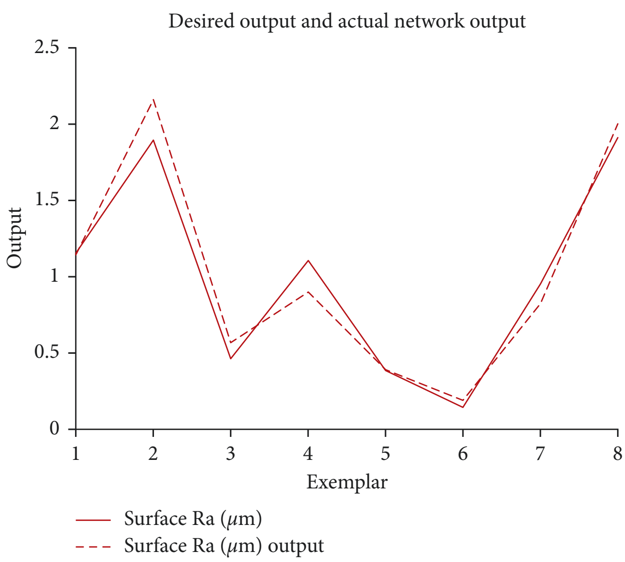

FIGURE 4: Desired output and actual network output.

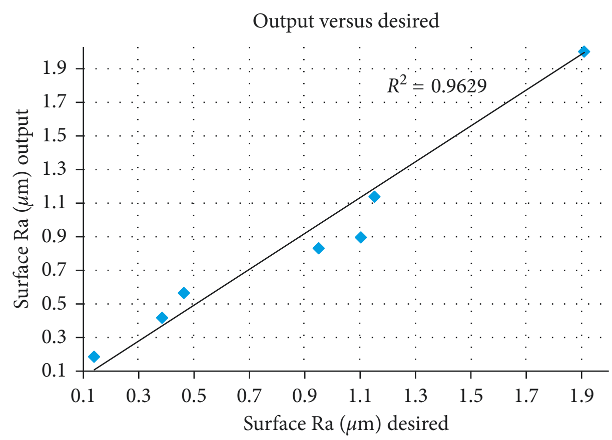

FIGURE 5: Comparison between ANN predicted and desired output for R_a.

Predictability of both regression and ANN models were compared using eight extra experimental cases that were not included in the modeling phase. Table 2 illustrates the results of this comparison. Figures 4–6 and Table 2 clearly show the good agreement between the results. From the table, both ANN and regression-predicted R_a and MRR values can be acceptable when they are compared with experimental results.

Feed rate has a direct impact on product surface finish. Although increasing feed rate can result in a significant increase in the material removal rate (MMR) and increase productivity, it will also increase cutting forces resulting in higher tool-workpiece friction associated with poor surface finish. Horizontal markings as well as vertical ones in surface roughness profile can be detected when examining the surface profile produced using high feed rates. MRR and surface roughness are two contradicting objectives in determining an optimized value for the feed rate. Optimization algorithms are often used to come up with optimized cutting parameters for different machining processes. Figure 7 represents an optical microscopy view of machined surface, while Figure 8 shows the surface roughness profile produced by

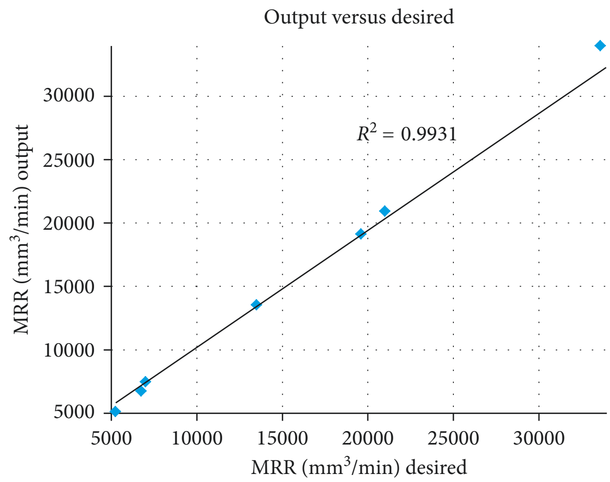

FIGURE 6: Comparison between ANN predicted and desired output for MRR.

TABLE 2: Comparison between the regression model and ANN predictions.

Machining parameters			Measured R_a (μm)	Regression model		ANN	
Speed	Depth	Feed		Predicted R_a	Residual	Predicted R_a	Residual
125	1.12	0.15	1.154	1.05	0.11	1.14	0.01
200	1.12	0.2	1.896	2.39	−0.49	2.16	−0.26
175	1.12	0.1	0.464	0.46	0.01	0.57	−0.11
150	0.6	0.15	1.1058	0.95	0.16	0.90	0.21
175	0.3	0.1	0.386	0.39	−0.01	0.39	−0.01
125	1.12	0.05	0.144	0.20	−0.06	0.19	−0.05
150	0.3	0.15	0.954	0.90	0.06	0.83	0.12
150	1.12	0.2	1.911	2.39	−0.48	2.00	−0.09

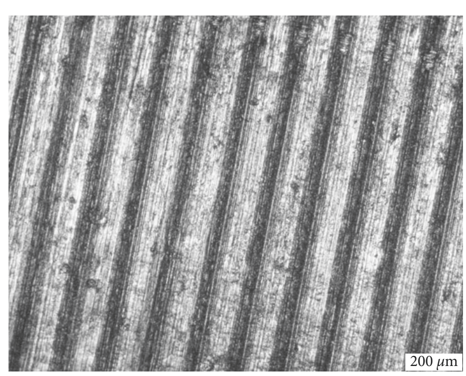

FIGURE 7: Optical microscopy for machined surface with $V = 125$ m/min, $d = 0.30$ mm, and fr = 0.20 mm/rev.

the surface roughness tester under the following cutting conditions: a speed of 125 m/min, a depth of cut of 0.3 mm, and a feed rate of 0.20 mm/rev. Another set of views and graph is also provided in Figures 9 and 10 for different cutting conditions summarized as follows: a cutting speed of 125 m/min, a depth of cut of 0.3 mm, and a feed rate of 0.05 mm/rev. From those results, we can conclude that reducing feed rate will produce thinner surface roughness markings, and increasing the feed rate is associated with the presence of distant thick surface roughness markings.

4. Conclusions

Optimization and estimation of R_a and MRR in cutting conditions of AZ61 magnesium alloy were realized by ANN modeling and regression analysis. The results of the developed ANN-predicted model and regression model were

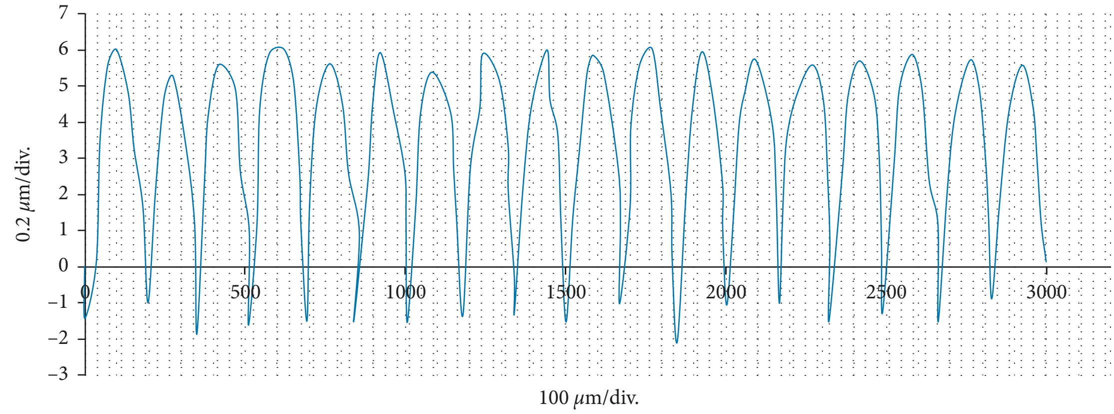

Figure 8: Profile of surface roughness graph by the surface roughness tester for machined surface with $V = 125$ m/min, $d = 0.30$ mm, and fr = 0.20 mm/rev.

Figure 9: Optical microscopy for machined surface with $V = 125$ m/min, $d = 0.30$ mm, and fr = 0.05 mm/rev.

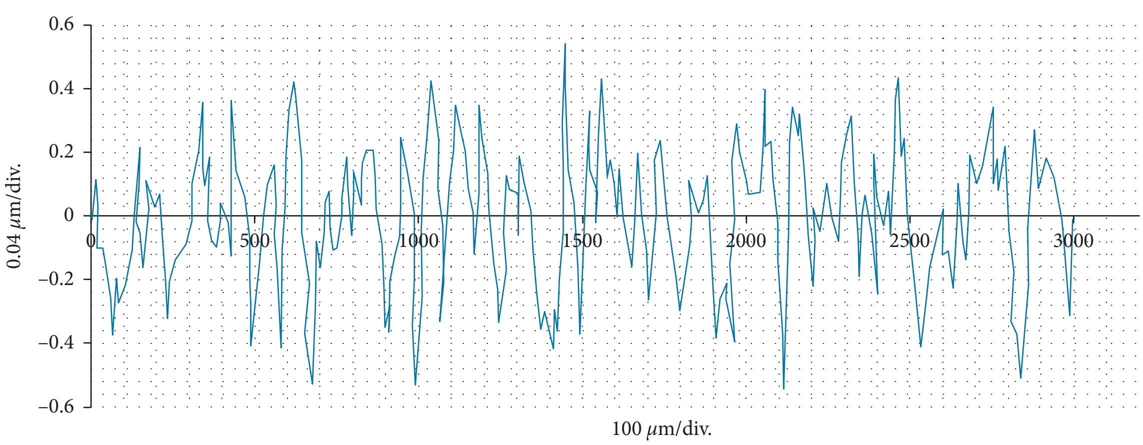

Figure 10: Profile of surface roughness graph by the surface roughness tester for machined surface with $V = 125$ m/min, $d = 0.30$ mm, and fr = 0.05 mm/rev.

compared with experimental results. The results showed that a good agreement was obtained for both developed ANN-predicted and regression analysis results. In addition, the compatibility between the developed ANN model and experimental results showed that ANN approach is an accurate method to estimate surface R_a and MRR. Optical microscopy views and the corresponding surface roughness profile for different sets of cutting parameters were utilized on two machined surfaces to showcase the direct effect of increasing the feed rate on surface finish. A hypothetical analysis relating the higher surface roughness values associated with the increase in feed rate is reported.

Appendix

The listing of all samples and the resulting measured surface roughness are provided in Table 3.

Table 3: Listing of four-level full factorial samples.

Sample ID	Group	Cutting speed (m/min)	Depth of cut (mm)	Feed (mm/rev)	Surface R_a (μm)	MRR (mm^3/min)
1	1	125	0.30	0.05	0.185	1875
2		125	0.30	0.10	0.457	3750
3		125	0.30	0.15	0.972	5625
4		125	0.30	0.20	1.779	7500
5	2	125	0.60	0.05	0.188	3750
6		125	0.60	0.10	0.375	7500
7		125	0.60	0.15	0.998	11250
8		125	0.60	0.20	2.205	15000
9	3	125	0.90	0.05	0.168	5625
10		125	0.90	0.10	0.378	11250
11		125	0.90	0.15	1.059	16875
12		125	0.90	0.20	2.254	22500
13	4	125	1.12	0.05	0.144	7000
14		125	1.12	0.10	0.466	14000
15		125	1.12	0.15	1.154	21000
16		125	1.12	0.20	2.786	28000
17	5	150	0.30	0.05	0.156	2250
18		150	0.30	0.10	0.365	4500
19		150	0.30	0.15	0.954	6750
20		150	0.30	0.20	1.737	9000
21	6	150	0.60	0.05	0.143	4500
22		150	0.60	0.10	0.349	9000
23		150	0.60	0.15	1.1058	13500
24		150	0.60	0.20	1.866	18000
25	7	150	0.90	0.05	0.128	6750
26		150	0.90	0.10	0.413	13500
27		150	0.90	0.15	0.999	20250
28		150	0.90	0.20	1.782	27000
29	8	150	1.12	0.05	0.201	8400
30		150	1.12	0.10	0.508	16800
31		150	1.12	0.15	1.020	25200
32		150	1.12	0.20	1.911	33600
33	9	175	0.30	0.05	0.199	2625
34		175	0.30	0.10	0.386	5250
35		175	0.30	0.15	0.982	7875
36		175	0.30	0.20	2.005	10500
37	10	175	0.60	0.05	0.199	5250
38		175	0.60	0.10	0.432	10500
39		175	0.60	0.15	1.128	15750
40		175	0.60	0.20	2.054	21000
41	11	175	0.90	0.05	0.256	7875
42		175	0.90	0.10	0.486	15750
43		175	0.90	0.15	1.187	23625
44		175	0.90	0.20	2.759	31500
45	12	175	1.12	0.05	0.178	9800
46		175	1.12	0.10	0.464	19600
47		175	1.12	0.15	1.316	29400
48		175	1.12	0.20	2.214	39200

Table 3: Continued.

Sample ID	Group	Cutting speed (m/min)	Depth of cut (mm)	Feed (mm/rev)	Surface R_a (μm)	MRR (mm^3/min)
49	13	200	0.30	0.05	0.145	3000
50		200	0.30	0.10	0.398	6000
51		200	0.30	0.15	0.955	9000
52		200	0.30	0.20	2.211	12000
53	14	200	0.60	0.05	0.265	6000
54		200	0.60	0.10	0.487	12000
55		200	0.60	0.15	0.999	18000
56		200	0.60	0.20	1.999	24000
57	15	200	0.90	0.05	0.148	9000
58		200	0.90	0.10	0.477	18000
59		200	0.90	0.15	0.987	27000
60		200	0.90	0.20	2.165	36000
61	16	200	1.12	0.05	0.254	11200
62		200	1.12	0.10	0.345	22400
63		200	1.12	0.15	1.115	33600
64		200	1.12	0.20	1.896	44800

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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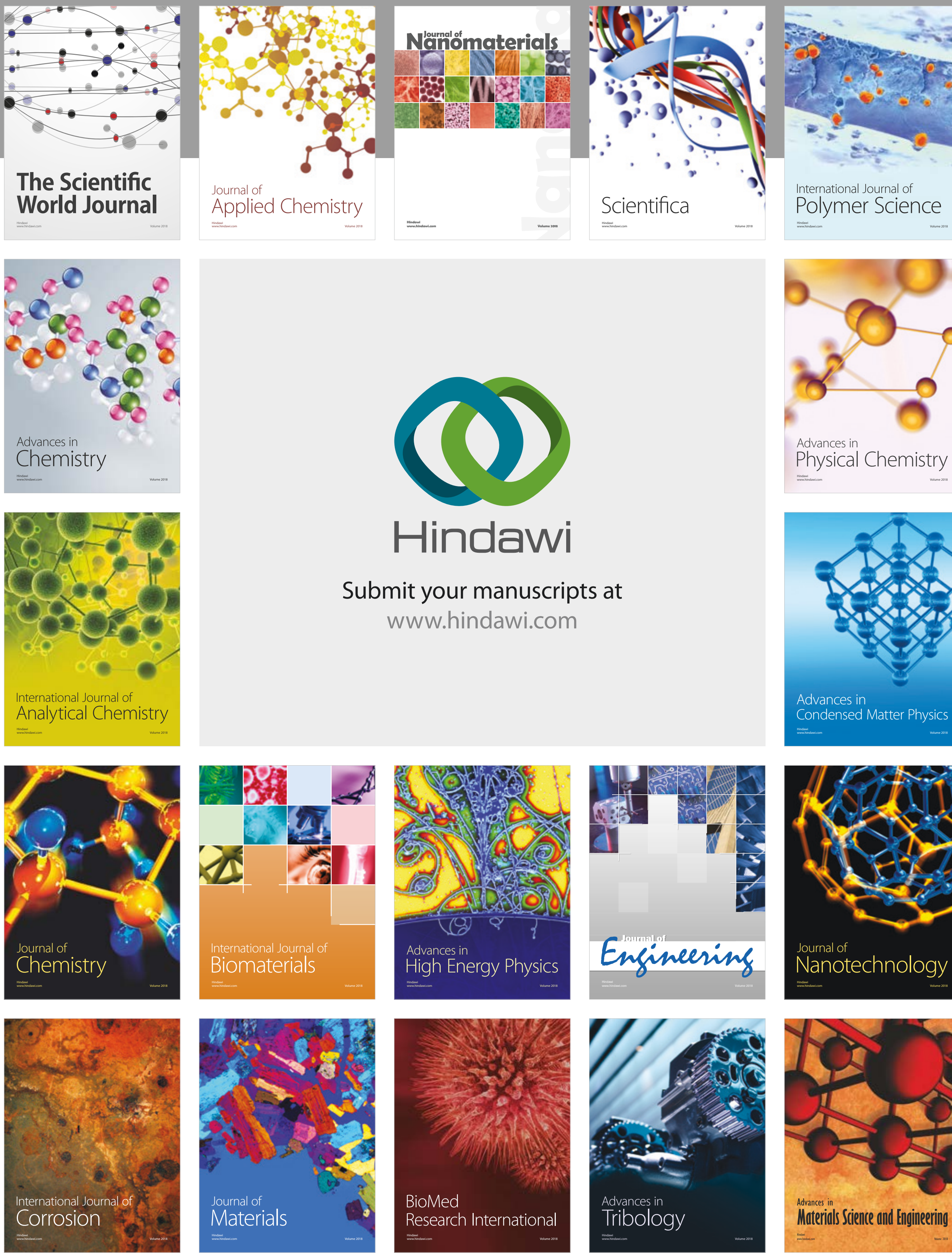
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