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Comparison between ANN, Regression and Genetic in Turning Process

A. S. El-Akkad [a*], Omar M. Koura [b]

[a] *Design and production eng. Dept., Ain shams university Cairo, Egypt*

[b] *Mechanical Department, Faculty of Engineering, Modern University for Technology & Information, Egypt*

[a] *Email: Elakkad_ahmed@yahoo.com*

[b] *Email: koura_Omar@yahoo.com*

Abstract

In literature predicting surface roughness has gained greater interest. Several approaches has been adopted. One is using regression analysis, other uses the Genetic Algorithm and third used Artificial Neural Networks. Different results were usually obtained. This paper aims at comparing the three models to come out with the most reasonable model describing surface roughness (Ra).

Keywords: Surface roughness; artificial neural network; regression; Genetic Algorithm; turning operations.

1. Introduction

Estimation and prediction of surface roughness in turning operation is one of the main research subjects. Authors are handling this problem by different ways. Several techniques and methodologies are used. Authors in reference [1] present a study to discuss the influence of turning parameters (feed, cutting speed, and depth of cut) on surface finish of hardened AISI 1055 steel using Taguchi technique, using multi-layer coated cemented carbide tool. They found that feed rate is most significant on surface roughness, while cutting speed is less significant than feed, and depth of cut is in significant on surface roughness. It is also found that in order to achieve the best surface finish, the highest cutting speed, the lowest depth of cut, and lowest feed rate should be selected.

Authors in reference [2] developed a study using Taguchi techniques to study the effect of cutting parameters (cutting speed, feed ate, and depth of cut) on surface roughness during turning of hardened AISI 4140 steel using mixed ceramic tool.

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* Corresponding author.

It is found that in order to minimize the surface roughness, the highest level of the cutting speed, the lowest level of depth of cut, and the medium level of feed rate should be selected.

Authors in reference [3] develop a model based on Artificial Neural Network to simulate hard turning of AISI H13 steel with minimal cutting fluid application. This model is expected to predict the surface roughness in terms of cutting parameters. Networks with different architecture were trained using a set of training data for a fixed number of cycles and were tested using a set of input / output data reserved for this purpose. It is observed that with ANN model that the predictions accuracy (error percentage of < 7%) is possible even with smaller number of training data.

Authors in reference [4] proposed a neural-network-based methodology for predicting the surface roughness in a turning process by taking the acceleration of the radial vibration of the tool holder and cutting parameters as network inputs. It was observed that in most cases, the experimental value is close to the most likely estimate and within the upper and lower estimates.

Authors in reference [5] conducted an experimental investigation determine the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the bearing steel (AISI 52100). The investigations of this study indicated that the parameters cutting velocity, feed, effective rake angle and nose radius are the primary influencing factors, which affect the surface finish. The results also indicate that feed is the dominant factor affecting the surface roughness, followed by the nose radius, cutting velocity and effective rake angle. First order surface roughness prediction model has been found to represent the hard turning process very well.

Authors in reference [6] designed an artificial neural network (ANN) model through feed forward back-propagation network for the data obtained. Comparison of the experimental data and ANN results show that there is no significant difference and ANN has been used confidently.

All the above and many others such as Vikas Upadhyay [7] who used the regression technique have used either the graphical results or regression or the artificial neural networks to reach their conclusions. As there are other techniques available such as optimization from genetic algorithm it was decided to compare between the three approaches to determine the best methods that can be used to optimized or predict the surface roughness.

So the aim of this paper is not a correlation between the cutting condition and the surface roughness, but to compare between the three techniques; namely regression, Genetic and ANN.

2. Results

27 tests were carried out on a center lathe using carbide insert without any lubrication (dry process). The turned material is mild steel bar. The results obtained are summarized in table1.

Table 1: Test results

No	a (mm)	v (m/min)	f (mm/rev)	R_a (µm)	No	a (mm)	v (m/min)	f (mm/rev)	R_a µm
1	٠,٥	٢٥,٣	٠,٢	7.11	١٥	١	٤٢,١	٠,٦	13.05
2	٠,٥	٢٥,٣	٠,٤	16.29	١٦	١,٥	٤٢,١	٠,٢	7.31
3	٠,٥	٢٥,٣	٠,٦	16.79	١٧	١,٥	٤٢,١	٠,٤	11.47
4	١	٢٥,٣	٠,٢	9.59	١٨	١,٥	٤٢,١	٠,٦	13.65
5	١	٢٥,٣	٠,٤	16.99	١٩	٠,٥	٥٢,٥	٠,٢	6.41
٦	١	٢٥,٣	٠,٦	21.33	٢٠	٠,٥	٥٢,٥	٠,٤	18.27
٧	١,٥	٢٥,٣	٠,٢	12.43	٢١	٠,٥	٥٢,٥	٠,٦	32.77
٨	١,٥	٢٥,٣	٠,٤	17.73	٢٢	١	٥٢,٥	٠,٢	7.37
٩	١,٥	٢٥,٣	٠,٦	20.89	٢٣	١	٥٢,٥	٠,٤	9.73
١٠	٠,٥	٤٢,١	٠,٢	7.43	٢٤	١	٥٢,٥	٠,٦	10.61
١١	٠,٥	٤٢,١	٠,٤	14.15	٢٥	١,٥	٥٢,٥	٠,٢	7.29
١٢	٠,٥	٤٢,١	٠,٦	25.01	٢٦	١,٥	٥٢,٥	٠,٤	8.11
١٣	١	٤٢,١	٠,٢	9.65	٢٧	١,٥	٥٢,٥	٠,٦	13.39
١٤	١	٤٢,١	٠,٤	10.31					

3. Regression analysis

Regression analysis generates an equation to describe the statistical relationship between one or more predictors and the response variable and to predict new observations. Regression generally uses the ordinary least squares method which derives the equation by minimizing the sum of the squared residuals. Regression results indicate the direction, size, and statistical significance of the relationship between a predictor and response. Minitab16 is used to develop the regression equations in this paper. The output results are summarized in table 2.

$$\text{Roughness} = -76.2 + 84.8\,a + 1.92\,v + 212\,f - 1.71\,av - 93.7\,af - 2.21\,vf - 12.8\,a^2 - 0.0091\,v^2 - 120\,f^2 + 0.00797(av)^2 + 41.5\,(af)^2 + 0.0384\,(vf)^2$$

S = 3.02622   R2 = 87.6%   R2(adj) = 76.9%

Where the t statistics is the coefficient divided by its standard error, and the P- value for each term tests the null hypothesis.

Table 2: Regression results

Predictor	Coef	SE Coef	t	P
Constant	-76.16	33.25	-2.29	0.038
A	84.84	35.92	2.36	0.033
V	1.919	1.190	1.61	0.129
F	212.27	89.81	2.36	0.033
Av	-1.7101	0.7458	-2.29	0.038
Af	-93.71	43.46	-2.16	0.049
Vf	-2.209	1.864	-1.18	0.256
a^2	-12.77	10.82	-1.18	0.258
v^2	-0.00912	0.01064	-0.86	0.406
f^2	-120.16	67.61	-1.78	0.097
av^2	0.007972	0.004783	1.67	0.118
af^2	41.53	26.61	1.56	0.141
vf^2	0.03838	0.02990	1.28	0.220

4. Genetic algorithm

Many regression models of different orders are developed and the one which gives the best result is presented and used to develop the optimum cutting condition using genetic algorithm

In order to optimize the value of the surface roughness of turning operation, a genetic algorithm (GA) is used. The GA is used to estimate the combination of the values of depth of cut, speed, and feed that minimize the value of surface roughness. For handling solutions using genetic operators, they have to be encoded in form of chromosomes. In this paper binary code representation is used.

As the crossover depends on the idea that good parents should give good child, one or more child is generated from combinations of two parents. In this paper one point cross over is used, in which a random point is selected randomly on the two parents. These random points split parents into two part, head and tail. Child is formed by exchange the tail of the two parents.In this paper scramble mutation is used, in which a random point on one parent is chosen. After this point the arrangement of the genes in the chromosome is changed.

Fitness function is used to assess the performance of the individual. Based on their fitness, parents are selected to reproduce offspring for a new generation. In this paper the fitness function deduced using regression is used. This is subjected to:

$0.5 \leq A \leq 1.5$, $25.3 \leq V \leq 52.5$ and $0.2 \leq f \leq 0.6$

The condition used for stopping criteria is when the algorithm reaches a specified number of generations as shown in Table 3

Table 3: parameters used in the developed GA

Parameter	Values
Population size (Ps)	30
Crossover rate (Rc)	0.8
Mutation rate (Rm)	0.2
Elite (e)	2
Number of generation (Ng)	300

The minimum surface roughness obtained by GA is equal to: Ra=3.94 μm , at V=25.6 m/min, f=0.2 mm/rev, and a = 0.5 mm.

5. Neural Network Model

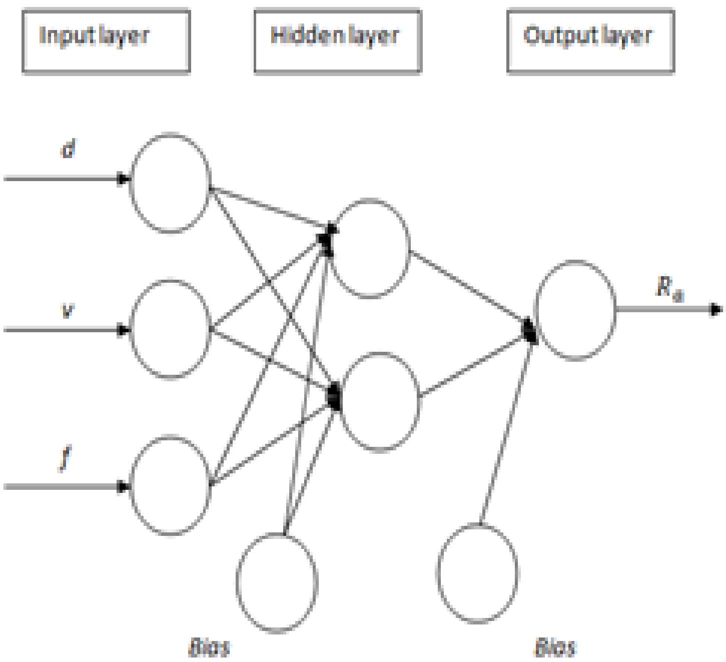

Figure 1: ANN structure

Many neural network structures (at least 20 trials) with different number of neurons in hidden layer and different processing functions are tested and it was found that the best giving results, figure 1 is when the processing function for the hidden layer is logsig, and for the output layer is purelin. Feed-forward back propagation ANN is used, Leven berg-Marquardt back propagation (TRAINLM) algorithm is used for network training and mean square error (MSE) is used as performance function.

The results obtained from the neural model is shown in figure 2 comparing the measured results with the neural output.

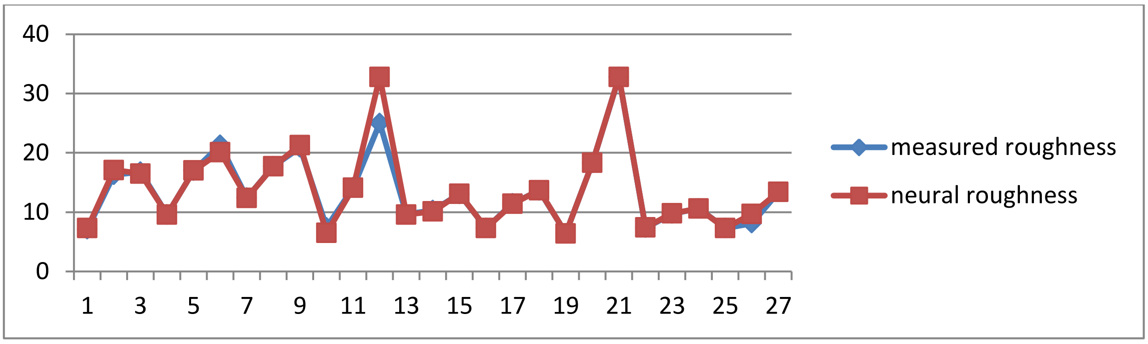

Figure 2: ANN output

Table 4: comparison between ANN and Regression models results

No	Roughness	Neural	Error %	regression	Error %
1	7.11	٧,٣	2.67	3.84	45.98
2	16.29	١٧,١	4.97	15.48	4.96
3	16.79	١٦,٥	1.73	20.32	21.03
4	9.59	٩,٦	0.10	10.71	11.68
5	16.99	١٧	0.06	16.72	1.61
٦	21.33	٢٠,١	5.77	18.41	13.69
٧	12.43	١٢,٤	0.24	14.56	17.14
٨	17.73	١٧,٧	0.17	17.42	1.73
٩	20.89	٢١,٣	1.96	20.12	3.68
١٠	7.43	٦,٥	12.52	8.00	7.65
١١	14.15	١٤,١	0.35	17.43	23.20
١٢	25.01	٣٢,٨	31.15	23.54	5.87
١٣	9.65	٩,٦	0.52	7.27	24.64
١٤	10.31	١٠,١	2.04	11.07	7.39
١٥	13.05	١٣,١	0.38	14.04	7.55
١٦	7.31	٧,٣	0.14	8.04	9.98
١٧	11.47	١١,٤	0.61	8.69	24.21
١٨	13.65	١٣,٧	0.37	12.66	7.23
١٩	6.41	٦,٤	0.16	9.00	40.34
٢٠	18.27	١٨,٣	0.16	18.37	0.53
٢١	32.77	٣٢,٨	0.09	27.43	16.28
٢٢	7.37	٧,٤	0.41	5.26	28.64
٢٣	9.73	٩,٨	0.72	9.00	7.56
٢٤	10.61	١٠,٦	0.09	14.92	40.61
٢٥	7.29	٧,٣	0.14	6.94	4.86
٢٦	8.11	٩,٧	19.61	7.53	7.20
٢٧	13.39	١٣,٤	0.07	14.45	7.95
Average error			3.23		14.56

Table 4 presents the full comparison between the ANN results with the regression results. The average error percentage of neural network is 3.23% against 14.56% for the regression. From the results it can be said that artificial neural network (ANN) model can predict surface roughness more accurate than regression model. The optimal roughness using ANN model is 6.4 μm , while that obtained by Genetic algorithm is 3.94 μm.

6. Conclusion and recommendations

The results obtained concludes that ANN is reliable and accurate for predicting the values. The actual Ra value has been obtained as 1.1999 μm and the corresponding predicted surface roughness value is 1.1859 μm, which implies greater accuracy. for future work we recommend to increase test samples, also making experiments using lubrication (wet process) and compare its results with other experiments (dry process).

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