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Predictive Modelling and Optimization of Machining Parameters to Minimize Surface Roughness using Artificial Neural Network Coupled with Genetic Algorithm

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Abstract

This paper develops a predictive and optimization model by coupling the two artificial intelligence approaches – artificial neural network and genetic algorithm – as an alternative to conventional approaches in predicting the optimal value of machining parameters leading to minimum surface roughness. A real machining experiment has been referred in this study to check the capability of the proposed model for prediction and optimization of surface roughness. The results predicted by the proposed model indicate good agreement between the predicted values and experimental values. The analysis of this study proves that the proposed approach is capable of determining the optimum machining parameters.

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Keywords: Roughness; Artificial neural network; Genetic Algorithm; Optimization; Predictive modelling;

1. Introduction

Designers constantly strive to design products and machinery that can run faster, last longer and operate more precisely. Modern development of high speed machines has resulted in higher loading and increased speeds of moving parts which requires that bearings, seals, shafts, machine ways, gears, etc. must be dimensionally and geometrically accurate or the surface texture of the produced parts must be precise. Unfortunately, manufacturing processes produce parts with surfaces that are either unsatisfactory from the standpoint of geometrical perfection or quality of surface texture. Therefore, surface texture of produced parts demands significant attention at the design as well as manufacturing stage. Process models have often targeted the prediction of fundamental variables such as stresses, strains, strain rate, temperature, etc but to be useful for industry these variables must be correlated to performance measures and product quality [1].

There is a close interdependence among productivity, quality and power consumption of a machine tool and the surface roughness is a widely used index of product quality in terms of various parameters such as aesthetics, corrosion resistance, subsequent processing advantages, tribological considerations, fatigue life improvement, precision fit of critical mating surfaces, *etc*. [2]. In practice, the machining parameters are generally chosen primarily on the basis of human judgment and experience and to some extent on the basis of handbooks, which are highly conservative and does not lead to achievement of optimum machining parameters and hence loss of productivity and accuracy. The loss of productivity and accuracy is more significant for the costly computerized numerical control machine tools. The capability of a manufacturing process to produce a desired surface roughness depends on machining parameters, cutting phenomenon, work piece properties, and cutting tool properties [3]. Feed, cutting speed, depth of cut, tool wear, and cutting fluids are important machining parameters affecting surface roughness. Even small changes in any of these parameters may have a significant effect on the surface

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roughness. Therefore, it is important for the researchers to model and quantify the relationship between surface roughness and the parameters affecting its value.

As a result analytical, experimental, empirical and artificial intelligence models have been developed to predict the surface roughness [3]. Experimental and analytical models are generally based on machining theory. Empirical models are developed using conventional approaches such as factorial design, statistical regression, response surface methodology etc. Artificial intelligence based models are developed using nonconventional approaches such as the artificial neural network (ANN), Fuzzy logic(FL), Support Vector Regression (SVR), and Genetic Algorithm (GA). The machining process is very complex and does not permit pure analytical physical modeling [4]. Empirical models developed using conventional approaches may not describe the nonlinear complex relationship between machining parameters and machining performance [5–7]. Recently there has been a lot of interest to develop predictive and optimization models for investigating the influence of machining parameters on machining performance using artificial intelligence techniques as an alternative to conventional approaches [8–19].

This paper presents the following contributions. First, the experimental data of surface roughness as a performance characteristic is used to develop predictive model using ANN during milling of AISI 1060 steel. The machining parameters are cutting speed (v), feed per tooth (f), depth of cut (a) and flank wear (VB). Second, the ANN results are compared with the experimental data, regression model and fuzzy logic models from literature using relative error analysis. Third, the developed model is validated using representative hypothesis testing. Finally, the optimization of machining parameters is done to minimize the surface roughness using GA.

This paper is organized as follows. The experimental set up and design of experiment is presented in section 2. ANN methodology is presented in the section 3. The experimental data of section 2 is used to develop ANN model in section 4. The comparison of ANN results with experimental data and the optimization of machining parameters using GA is also discussed in the section 4. Finally, conclusions are highlighted and presented in section 5.

2. Experimental Procedure

To investigate the potential of ANN coupled with GA to optimize the machining parameters leading to minimum surface roughness, the work of Kovac et al. [20] is undertaken as a case study. This work developed predictive models using regression and fuzzy logic to predict the surface roughness. It conducted cutting tests on the AISI 1060 steel workpiece with 125 mm diameter, single tooth carbide tool in dry cutting environment on 14kW vertical milling machine. A tool microscope was used to measure the width of flank wear land. The four factorial 2^k central composite standard orthogonal array was used to design the experimental. The measurements were carried out by varying four machining parameters: cutting speed (v), feed rate (f), depth of cut (a), and flank wear (VB). The combination of machining parameters and surface roughness (R_a) values are shown in Table 1.

Table 1. Central composite experimental design and surface roughness[20].

Experiment No.	v (m/s)	f (mm/tooth)	a (mm)	VB (mm)	R_a (µm)
1	2.32	0.178	1	0.12	2
2	3.67	0.178	1	0.12	1.45
3	2.32	0.28	1	0.12	2
4	3.67	0.28	1	0.12	1.3
5	2.32	0.178	2.25	0.12	2.1
6	3.67	0.178	2.25	0.12	1.4
7	2.32	0.28	2.25	0.12	2
8	3.67	0.28	2.25	0.28	1.45
9	2.32	0.178	1	0.28	3.05
10	3.67	0.178	1	0.28	2.2
11	2.32	0.28	1	0.28	3.1
12	3.67	0.28	1	0.28	2.7
13	2.32	0.178	2.25	0.28	3.5
14	3.67	0.178	2.25	0.28	2.45
15	2.32	0.28	2.25	0.28	2.4
16	3.67	0.28	2.25	0.28	1.75
17	2.95	0.223	1.5	0.18	1.6
18	2.95	0.223	1.5	0.18	1.6
19	2.95	0.223	1.5	0.18	2.2
20	2.95	0.223	1.5	0.18	1.85
21	2.95	0.223	1.5	0.18	2.3
22	2.95	0.223	1.5	0.18	2.7
23	1.83	0.223	1.5	0.18	3.3
24	4.65	0.223	1.5	0.18	1.05
25	2.95	0.142	1.5	0.18	2.1
26	2.95	0.351	1.5	0.18	2.5
27	2.95	0.223	0.67	0.18	2
28	2.95	0.223	3.37	0.18	2.2
29	2.95	0.223	1.5	0.08	1.45
30	2.95	0.223	1.5	0.4	2.6

3. Artificial Neural Network

3.1. Overview of ANN

Artificial neural networks (ANNs) are inspired by the biological nervous system, the brain, which consists of a large number of highly connected elements called neurons. The brain stores and processes the information by adjusting the linking patterns of the neurons [21]. In an ANN these neurons are connected together to form a network which mimics a biological nervous system. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between neurons. Neural networks are trained so that a particular input leads to a specific output target. In the artificial intelligence learning, many input and target pairs are used to train a network. The network is adjusted based on a comparison of the output and the target until the network output matches the target.

3.2. Methodology

ANN as a computational model consists of three layers containing different neurons in each layer. The three layers are input layer, hidden layers and output layer. These layers are further interconnected to each other in such a way so that each neuron in one layer is connected to all neurons in the next layer. The diagram for a network with a single neuron is shown in Fig. 1.

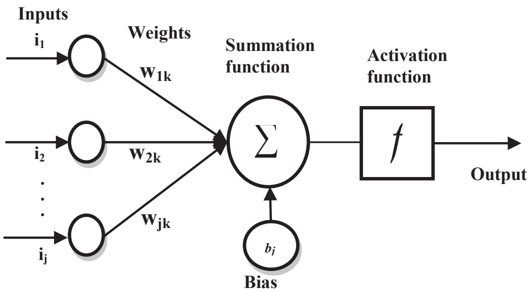

Fig. 1. Mathematical principal of a neuron.

The input layer does not perform any information processing. Each of its neuron takes the input from the actual environment. The input vector (multiple neurons) (i_j) is transmitted using a connection that multiplies its strength by a weight (w) to make the product (w_i). This neuron has a bias (b_j). The corresponding output can be given into other interconnected neurons or directly into the environment. The output is produced by a summation function and an activation function. Summation function calculates the net input from the processing neurons. The activation function converts the neuron's weighted input to its output activation. An activation function consists of linear and non linear algebraic equations which make a neural network capable of storing nonlinear relationships between the input and the output. After being weighted and transformed by an activation function, neurons are then passed to other neurons. Output accepts the results of the activation function and presents them either to the relevant processing neuron or to the outside of the network. As each input is applied to the network, the network output is compared to the target. The difference between the target output and the network output is known as error. Further, different network algorithms are applied to reduce the error.

4. Results and Discussion

The results of ANN coupled with GA used to predict and optimize the surface roughness based on input machining parameters in face milling process are shown and discussed below.

4.1. Prediction of surface roughness by ANN

After a number of trails it was found that the neural network structure 4-9-1 designed using Matlab Neural Network Toolbox leads to the best results. It consists of four input neurons in input layer (corresponding to four machining parameters v, f, a, VB) one hidden layer with nine neurons and one output neuron in output layer (corresponding to R_a). The experimental data shown in Table 1 is utilized as training data. Recommended ratio of training and testing samples could be given as percent, such as 90%:10%, 85%:15% and 80%:20% with a total of 100% for the combined ratio [22]. The preferred ratio is selected as 85%:15% to fit in with the available experimental sample size of 30. The number of training and testing samples are 25and 5 respectively. Data is normalized to a range of 0 and 1 before training and testing. The network is trained by using a random training data set. The training data was never used as the test data. The training is initialized by assigning some random weights and biases to all interconnected neurons. A feed forward back propagation algorithm has been used to train the network. The back propagation algorithm is based on gradient descent method which updates the weights iteratively until convergence to minimize the mean square error between network target values and training values. The final weights after all iterations between the input layer and hidden layer; and between hidden layer and output layer are shown in Table 2 and Table 3. The bias value between hidden layer and output layer was found to be 0.491.

Table 2. The weight values between input and hidden layer.

No. of Neurons	w_{1k}	w_{2k}	w_{3k}	w_{4k}	b_k
1	2.057	-0.814	1.588	-0.831	0.394
2	-0.924	-2.286	1.482	-1.120	-1.234
3	1.860	1.419	0.169	-1.338	-0.377
4	0.059	2.944	-0.372	1.802	-0.727
5	-1.291	0.627	1.549	0.046	0.278
6	1.016	0.041	-0.258	-1.247	-0.826
7	-1.062	0.719	2.451	-1.679	-0.293
8	-2.298	1.867	0.225	0.764	0.233
9	-1.785	1.190	1.035	1.147	-0.449

Table 3. The weight values between hidden and output layer.

No. of Neurons	w_{1z}
1	-3.509
2	1.793
3	-1.375
4	-0.524
5	-0.274
6	0.224
7	-1.398
8	-1.429
9	-2.433

A *logsig* activation function in the hidden layer and a *tansig* activation function in the output layer are used to map the surface roughness values. *traingdx* is used as training function and *learngd* as learning function. The performance of the developed network examined on the basis of correlation coefficient (R value) between the output (predicted) values and the target (experimental) values for the test data (5) and entire data (30) is shown in Fig. 2. and

Fig. 3 respectively. The *R* value is a measure of how closely the variation in output is explained by the targets. It lies in between 0 and 1. If it is 1 then it indicates the perfect correlation between the target values and output. Correlation coefficient of 0.95 was obtained between the entire data set (experimental data) and model predicted values which indicate good correlation.

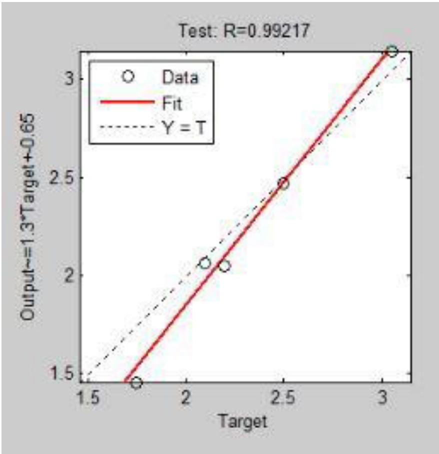

Fig. 2. Correlation between the predicted values and test data.

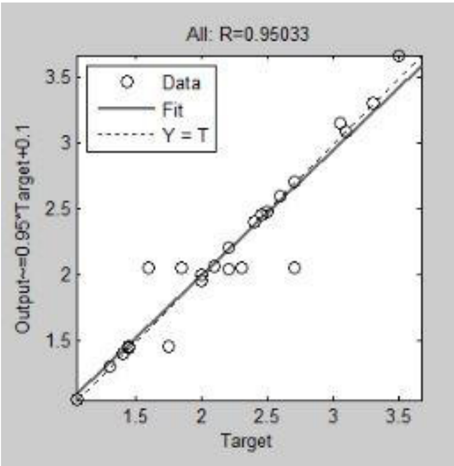

Fig.3. Correlation between the predicted values and entire data.

4.2. Comparison of ANN with Literature results

The developed neural network model was trained using the selected parameters. The mean square error decreased with increasing iteration numbers until 250 iterations, but after this point it remained constant. The training of the algorithm was stopped at 250 iterations. After that, the ANN was tested for accuracy using the random test values selected from the experimental values which had not been used for the learning process. The predicted results of the entire data are shown in Table 4.

Table 4. The weight values between hidden and output layer.

Experiment No.	Surface roughness (μm)		Relative Error (%)
	Experimental	ANN model	
1	2	1.994	0.305
2	1.45	1.460	0.690
3	2	2.038	1.915
4	1.3	1.333	2.531
5	2.1	2.064	1.738
6	1.4	1.410	0.729
7	2	2.019	0.955
8	1.45	1.457	0.503
9	3.05	3.147	3.177
10	2.2	2.200	0.009
11	3.1	3.131	1.010
12	2.7	2.728	1.022
13	3.5	3.630	3.709
14	2.45	2.446	0.163
15	2.4	2.383	0.692
16	1.75	1.497	14.440
17	1.6	2.047	27.956
18	1.6	1.985	24.069
19	2.2	2.047	6.941
20	1.85	2.019	9.135
21	2.3	2.121	7.765
22	2.7	2.529	6.333
23	3.3	3.292	0.255
24	1.05	1.070	1.895
25	2.1	2.062	1.833
26	2.5	2.471	1.160
27	2	1.971	1.450
28	2.2	2.198	0.073
29	1.45	1.440	0.703
30	2.6	2.595	0.208

Fig. 4. depicts the comparison of predicted results and the experimental values. It can be seen that the neural network prediction results are very close to the experimental values. The relative percentage error of the model prediction is also calculated as the percentage difference between the experimental and predicted values relative to the experimental values and is shown in Table 4. The average relative error between the experimental and predicted values is 4.11%. It shows that the well trained network has good accuracy in predicting the surface roughness values. Further the relative error of ANN predicted results are compared with the models developed in the case study. Fig. 5. shows the average relative error of ANN, regression model and fuzzy logic models developed [20] in the case study for all the experimental runs. Fig. 5. Clearly shows that ANN outperforms regression and fuzzy logic models. The average relative error found in case study for regression and fuzzy logic model are 10.91% and 7.41%.

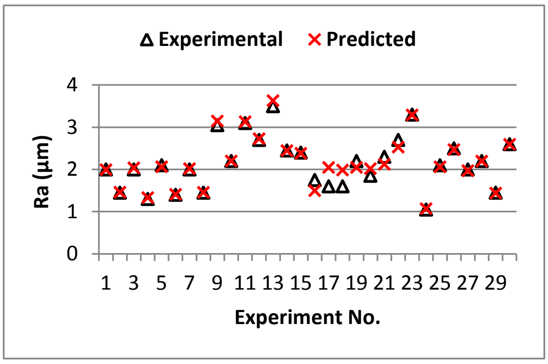

Fig. 4. Comparison of ANN results with experimental values.

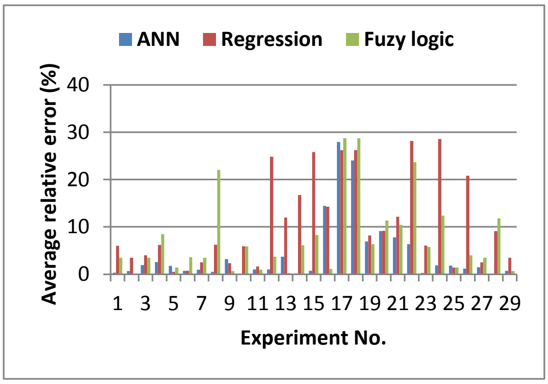

Fig. 5. Comparison of ANN model with Regression and Fuzzy Logic model.

4.3. Statistical validation of ANN model

To compare the goodness of fit of the developed ANN model, representative hypothesis tests – *t*-test to test the means, *f*-test and Levene's test for variance – were conducted and results are shown in Table 5.

Table 5. Hypothesis testing to check the goodness of fit.

95 % Confidence Interval	*P*-value
Mean paired *t*-test	0.527
Variance *F*-test	0.985
Levene's test	0.725

These tests are. In all these tests, the *p*-values are greater than 0.05, which means that the null hypothesis cannot be rejected. All the *p*-values in the Table 5 also indicate that there is no significant evidence to conclude that the experimental data and the data predicted from ANN differ to each other. Therefore, ANN as a prediction model has statistically satisfactory goodness of fit from the modeling point of view.

4.4. Optimization using Genetic Algorithm

GA is a method for solving optimization problems based on natural selection that drives from biological evolution. In this study, a set of *v*, *f*, *a*, and *VB* corresponds to a chromosome. In first step, a population comprising of *n* sets of *v*, *f*, *a*, and *VB* is generated randomly. This population is the current generation. The set of *v*, *f*, *a*, and *VB* that gives smaller surface roughness is considered as better or "fitter" than others. Using members of the current population GA generates another population of *n* sets of *v*, *f*, *a*, and *VB* using three operators, viz. selection, cross-over and mutation. This is analogous to next generation being obtained from current generation in biological evolution. Selection operator chooses chromosomes from the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce. Thus, selection is "with replacement", i.e. same chromosome can be selected as a parent more than once. Crossover operator is used to randomly choose a locus from a bit string and exchange the sub-sequences before and after the locus between the parent chromosomes to create offspring. For instance, 01001001 and 11111111 could be crossed over after the fifth locus in each to produce two offspring 01001111 and 11111001. Mutation operator randomly flips some of the bits in a chromosome from current population to generate a new set so that the algorithm does not get trapped in local optima. In addition to cross-over and mutation, a fraction of the current population that is elite, i.e. "fitter" than others is passed on without any change to the next generation. Because all the members of next generation are obtained from the fitter members of current population the overall fitness of population in successive generation improves. After some numbers of iterations, if the improvement in fitness falls below a set tolerance limit then the algorithm is stopped.

In this study, the optimization toolbox of Matab was used for implementing GA. The initial population for the GA was selected randomly covering the full range of parameters. The final GA parameters are: a population size of 200 and initial population range covering the entire range of values for *v*, *f*, *a* and *VB* were used to avoid getting local minimum. The cross over rate used was 0.8 and mutation function was *uniform*. The scaling function and selection function were *rank* and *uniform* respectively.

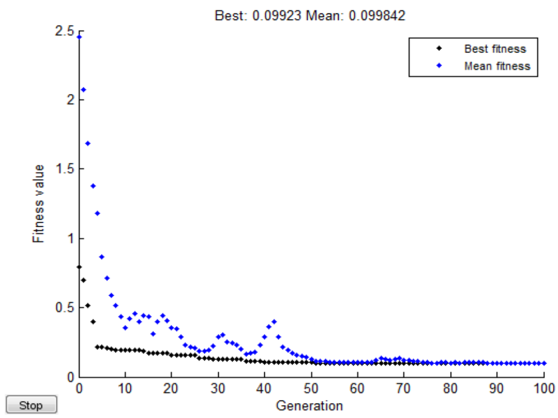

Fig. 6. Variation of best fitness with number of generations.

The values of optimum machining parameters that lead to minimum surface roughness are 4.65 m/sec cutting speed, 0.142 mm/tooth feed, 0.67 mm depth of cut and 0.08 mm flank wear. Fig. 6. indicates that the optimal solution is obtained at the 100^{th} iteration of the algorithm. It is observed that the mean fitness value is 0.099842µm while the best fitness value is 0.09923µm.

5. Conclusions

This paper presents an artificial neural network technique coupled with genetic algorithm for the prediction and optimization of machining parameters leading to minimum surface roughness. The predicted results are found to be close to the experimental values. The mean relative error is 4.11% which shows that the developed model has good accuracy in predicting the surface roughness values. The comparison of the ANN results with the regression and fuzzy logic models developed clearly shows that the developed model outperforms the regression and fuzzy logic models. The hypothesis testing results validates that ANN as a prediction model has statistically satisfactory goodness of fit from the modeling point of view. The ANN model coupled with GA leads to minimum surface roughness value of 0.099µm corresponding to optimum machining parameters 4.65 m/sec of cutting speed, 0.142 mm/tooth of feed, 0.67 mm depth of cut and 0.08 mm of flank wear.

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