Optimization of Machining Parameters to Minimize Surface Roughness using Integrated ANN-GA Approach

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Abstract

The surface roughness is a widely used index of product quality in terms of precision fit of mating surfaces, fatigue life improvement, corrosion resistance, aesthetics, etc. Surface roughness also denotes the amount of energy and other resources consumed during machining. This paper presents an approach for determining the optimum machining parameters leading to minimum surface roughness by integrating Artificial Neural Network (ANN) and Genetic Algorithm (GA). To check the capability of the ANN-GA approach for prediction and optimization of surface roughness, a real machining experiment has been referred in this study. A feed forward neural network is developed by collecting the data obtained during the turning of Ti-6Al-4V titanium alloy. The MATLAB toolbox has been used for training and testing of neural network model. The predicted results using ANN indicate good agreement between the predicted values and experimental values. Further, GA is integrated with neural network model to determine the optimal machining parameters leading to minimum surface roughness. The analysis of this study proves that the ANN-GA approach is capable of predicting the optimum machining parameters.

Keywords: Surface roughness; Artificial neural network; Genetic algorithm; Optimization; Machining

1. Introduction

Recently, titanium alloys have received renewed attention due to their electrochemical and biochemical compatibility. The application of titanium alloys in aerospace and biomedical industry is increasing because of its compatibility with composite materials. The other typical aerospace material, aluminum, is electrochemically incompatible with the composite materials forming a galvanic couple, therefore, titanium is replacing aluminum in many applications [1]. Composite materials are finding increasing application in aerospace industry to reduce aircraft weight, thus, improving efficiency and emissions. Titanium usage in aerospace has increased from less than 5% by weight in the 1980s for Boeing 737 and Airbus 320, 8% in the early 1990s for Boeing 777 and 12%–15% in the new Airbus 380 and the Boeing 787[2]. It is anticipated that new programs at Airbus (A350 and A400M) will boost the titanium industry [3]. However, titanium alloys are one of the most difficult materials to machine because of their low thermal conductivity, which leads to high cutting temperatures, and low elastic modulus, which leads to tool vibrations and poor surface finish [4]. Khanna and Sangwan [5] compared the machinability of various heat treated titanium alloys and commented that more studies on the machinability of titanium alloys are required to exploit the full capabilities of titanium alloys.

The process parameters, energy flow in production machines and supporting processes in the process chain have been studied by Herrman et al. [6]. Li et al. [7] presented an eco-efficiency approach to evaluate energy as well as resource efficiency of manufacturing processes through a case study of grinding process. They demonstrated that coolant and dressing have an impact on quality performance and the environment. Sustainability performance of machining processes can be achieved by reducing the power consumption [8]. If the energy consumption is reduced, the environmental impact generated from power production is diminished [9]. But, sustainability performance may be reduced artificially by increasing the surface roughness as lower surface finish requires lesser power and resources to finish the machining [10]. However, this may lead to more rejects, rework and time. Therefore, surface finish is one of
the important factors desired for sustainability performance of the machining processes [10]. Surface roughness is a widely used index of product quality as well as environmental impact. Quality features include parameters such as aesthetics, corrosion resistance, subsequent processing advantages, tribological considerations, fatigue life improvement, precision fit of critical mating surfaces, etc [10]. Surface roughness also denotes the amount of energy and other resources consumed during machining. Good surface finish can also help reduce the life cycle environmental impacts of spur gears in automotive drivetrain components. Improved surface finish of one spur gear has been found to decrease life cycle primary energy consumption by 1 MMBtu, which represents approximately 17% of the energy usually required to manufacture an automobile [11]. Since, there are variety of gears in the drivetrain and the other automotive components where surface quality plays an important role in overall working efficiency, so, the potential impact of this strategy could be significantly larger. Therefore, its optimum value is always desired. Feed rate, cutting speed, depth of cut, tool angle, and cutting fluids are important machining parameters affecting surface roughness particularly in the turning process at low speeds. Even small changes in any of these parameters may have a significant effect on the surface roughness. But the experimental investigations on titanium are very costly because of material cost. It is expected that the predictive modeling and optimization will provide a cheaper and time efficient yet effective alternative to costly and time consuming experimental research. This paper proposes an integrated artificial neural network – genetic algorithm (ANN-GA) approach for predictive modeling and optimization of machining parameters during turning to minimize surface roughness. Rest of the paper is as: next section provides the experimental dataset from literature. The development and adequacy of the proposed ANN is presented in section 3. The proposed GA and its characteristics are given in section 4. Section 5 provides the results and discussion of the paper followed by the conclusions in section 6.

2. Experimental dataset

The dataset for our analysis is taken from the experimental work done by Ramesh et al. [12] to analyze the surface finish during turning of a solid cylindrical work of Ti-6Al-4V (grade-5) alloy. Authors conducted the experiments using Taguchi’s L27 orthogonal array with 3 levels, as shown in Table 1. The machining parameters considered were cutting speed (v), feed (f) and depth of cut (d) and the response considered was surface roughness (Ra). Table 1 is taken as the dataset for this study for training and testing the proposed ANN model. 23 values were used for training and 4 were used for validation as shown in Table 1. All the responses of the training dataset were set as targets while training of the network was ongoing. The neural network toolbox of Matlab software was used for modeling. After proper training, the networks were simulated with validation dataset that had not been used for the network training. The experiments were conducted on commercial Ti-6Al-4V (grade-5) solid cylindrical work of 90 mm diameter and 160 mm length. The cutting tool used was TaeguTec RCMT 10T300 – MT TT3500 round insert. TaeguTec SRGCR/L 12-10C tool holder was used to hold the insert properly. The surface roughness was measured parallel and perpendicular to the tool grooves by a Talysurf surface roughness measuring instrument (Form Talysurf 50). A surface roughness cut off value of 2.54 mm was used. The values reported in table 1.

Table 1: Experimental dataset [12]

| S. No | v(m/min) | f(mn/rev) | d (mm) | Ra (μm) |
|-------|---------|-----------|--------|---------|
| 1*    | 80      | 0.06      | 0.50   | 0.3390  |
| 2     | 80      | 0.06      | 0.75   | 0.3114  |
| 3     | 80      | 0.06      | 1.00   | 0.2975  |
| 4     | 80      | 0.13      | 0.50   | 0.7532  |
| 5     | 80      | 0.13      | 0.75   | 0.7318  |
| 6     | 80      | 0.13      | 1.00   | 0.7213  |
| 7     | 80      | 0.21      | 0.50   | 1.5103  |
| 8     | 80      | 0.21      | 0.75   | 1.4932  |
| 9     | 80      | 0.21      | 1.00   | 1.4764  |
| 10    | 180     | 0.06      | 0.50   | 0.4302  |
| 11    | 180     | 0.06      | 0.75   | 0.4105  |
| 12    | 180     | 0.06      | 1.00   | 0.4074  |
| 13*   | 180     | 0.13      | 0.50   | 0.7611  |
| 14    | 180     | 0.13      | 0.75   | 0.7542  |
| 15    | 180     | 0.13      | 1.00   | 0.7435  |
| 16    | 180     | 0.21      | 0.50   | 1.5076  |
| 17*   | 180     | 0.21      | 0.75   | 1.4956  |
| 18    | 180     | 0.21      | 1.00   | 1.4892  |
| 19    | 280     | 0.06      | 0.50   | 0.5037  |
| 20    | 280     | 0.06      | 0.75   | 0.4965  |
| 21    | 280     | 0.06      | 1.00   | 0.4852  |
| 22*   | 280     | 0.13      | 0.50   | 0.8967  |
| 23    | 280     | 0.13      | 0.75   | 0.8873  |
| 24    | 280     | 0.13      | 1.00   | 0.8017  |
| 25    | 280     | 0.21      | 0.50   | 1.6846  |
| 26    | 280     | 0.21      | 0.75   | 1.6754  |
| 27    | 280     | 0.21      | 1.00   | 1.6687  |

Note: *- used for validation of ANN model and not included in training

3. Artificial neural network

Predictive models have proved their worth as beneficial tools in the machining processes where the effect of input parameters is required to be investigated on output(s) of the process [13]. ANNs are one of the most well-known predictive models that are able to estimate output(s) of the machining processes in the range of investigated input parameters. ANNs have been successfully used for modeling of turning process by several researchers [14-18].

In present study, Matlab with the neural networks toolbox is used for the formulation of artificial neural network. Several models were designed and tested to determine the optimal architecture, the most suitable activation function and the best training algorithm. The main selection criteria used were mean absolute percentage error (MAPE) in prediction and the regression coefficient (R) values of the trained models.

Several networks were designed with trial and error procedure and tested with validation dataset. The Levenberg-Marquadt (LM) algorithm was used for training the algorithm. LM algorithms are fast and consume less memory [19]. Hyperbolic tangent sigmoid transfer function (tansig) has been used for the activation function in the hidden layer as well as in the output layer. The learning algorithm used was
the back propagation algorithm. It minimizes the total mean square error of the output computed by the network using gradient-descent method. The best network was found to be a feed forward neural network with single hidden layer consisting of 4 neurons as shown in Fig. 1. Therefore, a network of structure 3-4-1 is found to be most suitable for the present research as it had the lowest mean absolute prediction error of 4.13. The regression coefficient (R) for validation data set was found to be 0.99821 which is close to 1, thus, indicating a strong correlation between the experimental outputs and network outputs. The network has been tested for the randomly selected four experimental values and it was found that the MAPE for the three values is very low (less than 0.4) as shown in Table 2. Validation is an important aspect used to confirm that the training of the network is sufficient. Less training makes the ANNs inefficient and may leads to inaccurate predictions. Fig. 3 shows that the model and training are capable of accurately predicting the experimental results. The developed model is shown schematically in Fig. 2.

![Fig. 1: Variation of mean absolute percentage error in prediction with number of neurons](image1)

![Fig. 2: Neural network architecture selected](image2)

![Fig. 3: Comparison of experimental and ANN predicted surface roughness values](image3)

### Table 2: Verification of the developed model with experimental data

| S. No. | Cutting speed (m/min) | Feed rate (mm/rev) | Depth of cut (mm) | Experimental roughness (μm) | ANN predicted roughness (μm) | Absolute prediction error (%) |
|--------|-----------------------|--------------------|-------------------|----------------------------|------------------------------|-----------------------------|
| 1      | 80                    | 0.06               | 0.50              | 0.3390                     | 0.3403                       | 0.38                        |
| 2      | 180                   | 0.13               | 0.50              | 0.7611                     | 0.7634                       | 0.31                        |
| 3      | 180                   | 0.21               | 0.75              | 1.4956                     | 1.4961                       | 0.03                        |
| 4      | 280                   | 0.13               | 0.50              | 0.8967                     | 1.0383                       | 15.8                        |

4. Optimization using genetic algorithm

Optimization algorithms are the branch of intelligent methods used to find optimal machining conditions [20]. Genetic algorithm (GA) is one of the most popular evolutionary optimization algorithms. Artificial neural network and genetic algorithm as evolutionary procedures have been successfully used in the past for typical multi objective optimization problem by researchers [21-24]. The optimization problem in the present study is the minimization of surface roughness and the constraints are: cutting speed from 80 to 280(m/min), feed rate from 0.06 to 0.21(mm/rev) and depth of cut from 0.5 to 1.0(m/min). It is solved to obtain solutions by using genetic algorithm in optimization tool of Matlab on an Intel® Pentium®2.00 GHz with 2 GB ram. The ANN model developed earlier was used as the fitness function. The GA terminated after 60 iterations as shown in Fig. 4.
5. Results and Discussion

The results of present study are summarized as follows:

5.1. ANN modeling

- It has been found that the feed-forward back propagation ANN of type 3-4-1 is giving best results for the prediction of surface roughness.
- The mean absolute percentage error (MAPE) in the prediction of developed predictive model is 4.13%.
- The prediction capability of ANN model was found to be better than the RSM model developed by Ramesh et al. for the same problem.

5.1.1 Comparative results from the proposed model and literature model

Table 3 shows the experimental surface roughness, predictive surface roughness from literature using response surface methodology (RSM) and the proposed ANN model. It shows that the proposed model predicts results which are closer to the experimental values as compared with the literature model. The closeness of the proposed model results to the experimental results is also high as the mean absolute percentage error between the proposed model results and experimental results is only 1.79. This value for the literature model is 4.3 as shown in Table 4.

5.1.2 Effect of machining parameters on surface roughness

Fig. 5 shows the 3D surface roughness model by varying cutting speed and feed and keeping the depth of cut constant. The figure indicates that the surface roughness increases with increase in feed and cutting speed. However, the increase in surface roughness with increase in cutting speed is quite less as compared with the increase observed with increase in feed suggesting that feed is the main contributing factor for variation in surface roughness. It has also been proven by analytical methods that feed is the main factor influencing surface roughness. Fig. 6 illustrates the influence of feed rate and depth of cut on surface roughness by keeping the cutting speed constant at the middle level. It shows that the increase in feed increases the surface roughness whereas increase in depth of cut decreases the surface roughness slightly. Fig. 7 shows the effect of cutting speed and depth of cut on surface roughness at constant feed. It can be seen that that the increase in cutting speed increases the surface roughness, whereas increase in depth of cut decreases the surface roughness. It seems that the increase in depth of cut increases the temperature of chip leading to its softening and lowering frictional forces thereby improving the surface finish. It is pertinent to mention here that a generalized relationship between the cutting parameters and process performance is hard to model accurately mainly due to the nature of the complicated stochastic process mechanism in machining [6]. The development of predictive models is more important for machining of titanium alloys where not much experimental trends are available from literature.

### Table 3: Comparison of prediction results from RSM and proposed ANN

| S. no. | Experimental Ra (Literature model) | Predictive model | Absolute prediction error (%) |
|--------|----------------------------------|------------------|------------------------------|
|        | Ra (Proposed model)              |                  | RSM                         |
| 1      | 0.3930                           | 0.3573           | 5.40                         |
| 2      | 0.3114                           | 0.3275           | 9.48                         |
| 3      | 0.7532                           | 0.6923           | 8.08                         |
| 4      | 0.7318                           | 0.6796           | 7.13                         |
| 5      | 0.7213                           | 0.6630           | 8.08                         |
| 6      | 1.5103                           | 1.4996           | 0.71                         |
| 7      | 1.4932                           | 1.4882           | 0.34                         |
| 8      | 1.4764                           | 1.4729           | 0.24                         |
| 9      | 0.4302                           | 0.3988           | 7.30                         |
| 10     | 0.4105                           | 0.3831           | 6.68                         |
| 11     | 0.4074                           | 0.3635           | 10.77                        |
| 12     | 0.7611                           | 0.7347           | 3.47                         |
| 13     | 0.7542                           | 0.7201           | 4.52                         |
| 14     | 0.7435                           | 0.7017           | 5.62                         |
| 15     | 1.5076                           | 1.5430           | 2.35                         |
| 16     | 1.4956                           | 1.5297           | 2.28                         |
| 17     | 1.4892                           | 1.5126           | 1.57                         |
| 18     | 0.5037                           | 0.5220           | 3.63                         |
| 19     | 0.4965                           | 0.5044           | 1.59                         |
| 20     | 0.4852                           | 0.4830           | 0.45                         |
| 21     | 0.8967                           | 0.8588           | 4.23                         |
| 22     | 0.8873                           | 0.8423           | 5.07                         |
| 23     | 0.8017                           | 0.8221           | 2.54                         |
| 24     | 1.6846                           | 1.6680           | 0.98                         |
| 25     | 1.6754                           | 1.6529           | 1.34                         |
| 26     | 1.6687                           | 1.6339           | 2.08                         |
| 27     |                                 |                  | 1.53                         |

### Table 4: Mean absolute percentage error (MAPE) comparison

| Predictive model | Mean absolute percentage error |
|------------------|-------------------------------|
| RSM model        | 4.30                          |
| ANN model        | 1.79                          |
Fig. 5: Effect of cutting speed and feed on surface roughness at d=0.75mm

Fig. 6: Effect of depth of cut and feed on surface roughness at v=180m/min

Fig. 7: Effect of depth of cut and cutting speed on surface roughness at f=0.098mm/rev

5.2 Integrated ANN-GA approach

The optimization results obtained for the problem using ANN-GA approach are:
Cutting speed= 80m/min,
Feed rate= 0.06mm/rev,
Depth of cut=1mm and
Optimum surface roughness=0.3083 μm

The optimum (minimum) surface roughness using the developed approach is very close to the experimental value of 0.2975μm. It proves the effectiveness of the proposed ANN-GA approach for predicting the effect of machining parameters on surface roughness.

6. Conclusions

The paper presents an integrated artificial neural network-genetic algorithm approach for predicting the effect of machining parameters on the surface roughness during the machining of Ti-6Al-4V titanium alloy. It has been observed that feed is the main influencing parameter for the minimization of surface roughness. It has also been observed that the increase in depth of cut and cutting speed decrease the surface roughness. However, more studies need to be carried out over the wider range of machining parameters to generalize these findings. The 3D surface and contour plots constructed during the study can be used for choosing the optimal machining parameters to obtain particular values of surface roughness or vice-versa these can be used by the machine tool manufacturers to provide the range of cutting speeds, feed and depth of cut for the particular application. This paper provides machining parameters to optimize surface finish only. Further research can be carried out to analyze the effect of machining parameters on other response variables like energy, cost, productivity/time, etc.

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