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Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method

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ABSTRACT

Machine parts during their useful life are significantly influenced by surface roughness quality. The machining process is more complex, and therefore, it is very hard to develop a comprehensive model involving all cutting parameters. In this study, the surface roughness is measured during turning at different cutting parameters such as speed, feed, and depth of cut. Full factorial experimental design is implemented to increase the confidence limit and reliability of the experimental data. Artificial neural networks (ANN) and multiple regression approaches are used to model the surface roughness of AISI 1040 steel. Multiple regression and neural network-based models are compared using statistical methods. It is clearly seen that the proposed models are capable of prediction of the surface roughness. The ANN model estimates the surface roughness with high accuracy compared to the multiple regression model.

1. Introduction

Machined surface characteristics greatly affect the fatigue strength, corrosion resistance and tribological properties of machined components. The surface finish obtained after machining determines the quality of material. High surface roughness values reduce the fatigue life. Therefore, control of the machined surface is essential to safe turning operations (Sharma, Suresh, Rakesh, & Sharma, 2008). Machine parts that are in contact with other elements or materials during their useful life are influenced by surface quality and dimensional precision. Therefore, the most important aspects in manufacturing processes are measuring and characterizing of surface properties. The surface roughness is one of the important properties of workpiece quality in the turning process. A good surface roughness and hence poor surface roughness improve the tribological properties, fatigue strength, corrosion resistance, and esthetic appeal of the product. The various models for the optimum surface roughness have been reported in several research works. These models can be arranged as follows: the multiple regression technique, mathematical modeling based on the physics of the process, the fuzzy-set-based technique, and neural network modeling (Arbizu & Pérez, 2003; Kohli & Dixit, 2005; Risbood, Dixit, & Sahasrabudhe, 2003). The studies of some researchers on turning and milling are given below.

Thiele and Melkote (1999) carried out an experimental investigation of effects of workpiece hardness and tool edge geometry on surface roughness in finish hard turning using CBN tools. They applied an analysis of variance (ANOVA) to the experimental results in order to distinguish whether differences in surface quality for various runs were statistically important. Feng and Wang (2002) focus on developing an empirical model for the prediction of surface roughness using non linear regression analysis with logarithmic data transformation in finish turning. Also, they investigated the impact of workpiece hardness, feed, tool point angle, depth of cut, spindle speed, and cutting time on the surface roughness. Chou, Evans, and Barash (2002) studied the performance and wear behavior of different cubic boron nitride (CBN) tools in finish turning of hardened AISI 52100 steel. Tool performance was evaluated by taking into the part surface finish and the tool flank wear. Zuperl and Cus (2003) proposed a neural network-based approach to ensure simple, fast, and efficient optimization of all important turning parameters. They used the multi-objective optimization technique for cutting conditions taking into consideration the technological, economic, and organizational limitations. Özel and Karpat (2005) presented a neural network modeling to predict surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish hard turning. They also developed the regression models in order to capture process-specific parameters by using the experimental data obtained from hardened AISI H-13 and AISI 52100 steels. Sharma et al. (2008) proposed a neural network modeling to estimate surface roughness in turning operations. Machining variables (i.e. cutting forces

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and surface roughness) are measured during turning at different cutting parameters such as approaching angle, speed, feed, and depth of cut. Ho, Tsai, Lin, and Chou (2009) used an adaptive network-based fuzzy inference system (ANFIS) with the genetic learning algorithm to predict the workpiece surface roughness in the end milling process. They applied the hybrid Taguchi-genetic learning algorithm (HTGLA) in the ANFIS to determine the most suitable membership functions. Zain, Haron, & Sharif, 2010 presented the ANN model for predicting the surface roughness in the end milling machining process. They recommended that the best combination of cutting conditions for achieving the best surface roughness value could be obtained at high speed with a low feed rate and radial rake angle.

The aim of present study is to develop an effective approach based on artificial neural networks and multiple regression to predict the surface roughness in AISI 1040 steel. For this purpose, full factorial experimental design is implemented to investigate the effect of the cutting parameters (i.e. cutting speed, feed rate, and depth of cut) on the surface roughness. The multiple regression models are tested by aiding the analysis of variance (ANOVA). Multilayer perception (MLP) architecture with back-propagation algorithm having two different variants is used in neural network. The performances of multiple regression and neural network-based models are compared by means of statistical methods. The proposed models can be used effectively to predict the surface roughness in turning process. The results obtained show that ANN produces the better results compared to multiple regression.

2. Material and methods

2.1. Modeling of surface roughness

In turning, there are many factors affecting the surface roughness such as tool variables, workpiece variables, and cutting conditions. Tool variables consist of tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool point angle, etc., while workpiece variables comprise material, hardness, and other mechanical properties. Furthermore, cutting conditions include speed, feed, and depth of cut. Since the hard turning process contains many parameters, it is complex and difficult to select the appropriate cutting conditions and tool geometry for achieving the required surface quality (Singh & Rao, 2007). Therefore, some scientific approaches are required to represent the process. It is clear that the proper model selection for the surface roughness is essential for the machining of hard materials.

The surface roughness average *Ra* is generally defined on the basis of the ISO 4287 norm, which is the arithmetical mean of the deviations of the roughness profile from the central line *lm* along the measurement. This definition is given in Eq. (1) (Arbizu & Pérez, 2003).

$$R_a = \frac{1}{L}\int_0^L |y(x)|dx \tag{1}$$

where L is the sampling length, and y is coordinate of the profile curve.

The relationship between the surface roughness and independent machining variables can be defined as:

$$R_a = C \cdot V^n \cdot f^m \cdot d^p \cdot r^l \cdot \varepsilon \tag{2}$$

where *Ra* is the surface roughness in μm; *V*, *f*, *d*, and *r* are the cutting speed (m/min), feed rate (mm/rev), depth of cut (mm), and tool nose radius (mm), respectively. *C, n, m, p, and l* are constants and ε is random error. Eq. (1) can be given as shown in Eq. (3) in order to facilitate the presentation of the constants and parameters. The arithmetic average height *Ra* and maximum peak to valley height *Rt* of turned surfaces can be computed as follows:

$$R_a \approx \frac{f^2}{32 \cdot r} \tag{3}$$

$$R_t \approx \frac{f^2}{8 \cdot r} \tag{4}$$

where r = tool nose radius (mm) and f = feed rate (mm/rev). Eqs. (3) and (4) show that while surface roughness proportionally increases with the feed rate, a large tool nose radius reduces the surface roughness of a turned workpiece. The model does not consider any imperfections in the process such as tool vibration or chip adhesion (Sharma et al., 2008).

2.2. Multiple regression modeling for surface roughness

Multiple regression is a statistical technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables. It can be used for a variety of purposes such as analyzing of experimental, ordinal, or categorical data. Thus, it can be considered to be helpful in predicting the surface roughness (Reddy, Padmanabhan, & Reddy, 2008). In order to predict the surface roughness, the second-order regression equation can be expressed as:

$$\begin{aligned} R_a = \beta_0 + \beta_1 \cdot V + \beta_2 \cdot f + \beta_3 \cdot a + \beta_4 \cdot V^2 + \beta_5 \cdot f^2 + \beta_6 \cdot a^2 \\ + \beta_7 \cdot V \cdot f + \beta_8 \cdot V \cdot a + \beta_9 \cdot f \cdot a \end{aligned} \tag{5}$$

Ra is the estimated surface roughness and *V*, *f*, and *a* are the cutting speed, feed rate, and depth of cut, respectively. The coefficients β_0, $\beta_1, \beta_2, \ldots, \beta_9$ are to be estimated using suitable methods. Thereafter, the analysis of variance (ANOVA) is used to seek the relationship between a response variable (output parameter) and two or more continuous or discrete independent variables. The performance criterions given in Eqs. (12) and (13) are applied to compare the developed models.

2.3. Surface roughness prediction strategy using artificial neural network

Artificial neural networks (ANNs) emulating the biological connections between neurons are known as soft computing techniques. ANNs can reproduce some functions of human behavior, which are formed by a finite number of layers with different computing elements called neurons. In order to construct a network, the neurons are interconnected. The organization of connections determines the type and objectives of the ANNs. The processing ability of the network is stored in the interunit connection strengths, or weights, which are tuned in the learning process. The training algorithm (or learning) is defined as a procedure that consists of adjusting the weights and biases of a network that minimize selected function of the error between the actual and desired outputs (Gareta, Romeo, & Gil, 2006; Kalogirou, 2003; Karatas, Sozen, & Dulek, 2009).

ANNs are widely used in many applications such as forecasting, control, data compression, pattern recognition, speech, vision, medicine, and power systems. Neural network models provide an alternative approach to analyze the data, because they can deduce patterns in the data. A simple process element of the ANN is shown in Fig. 1. The network has three layers; the input, hidden, and output layers. The input and output layers are defined as nodes, and the hidden layer provides a relation between the input and output layers. Initially, the weights of the nodes are random and the network has not any knowledge. For a given input pattern, the