MODELING OF SURFACE ROUGHNESS USING MRA AND ANN METHOD

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Abstract: Surface roughness is one of the most specified customer requirements in machining of parts. The predictive modeling of surface roughness is an important aspect in machining. This paper focuses on developing empirical models for surface roughness in turning X210Cr12 steel. Two competing modeling approaches, multiple regression analysis (MRA) and artificial neural networks (AN) are applied and compared.

1 INTRODUCTION

Increasing the productivity and the quality of the machined parts are the main challenges of metal-based industry. Machining is one of the most important and widely used manufacturing processes. Surface roughness is an important parameter in machining. It is a characteristic that could influence the performance of mechanical parts and the production costs. The surface roughness is mainly affected by tool geometry (nose radius, edge geometry, rake angle), machining parameters (cutting speed, feed rate, depth of cut), and workpiece properties. Predictive modeling of surface roughness is of high importance. Since machining is complex, non-linear and stochastic process, analytical models are often insufficient. In recent years, multiple regression analysis (MRA) and artificial neural networks (ANN) have become preferred trend in development of surface roughness prediction models.

The aim of this study is to develop and compare MRA and ANN surface roughness prediction models in turning operation of X210Cr12 steel (DIN). Three process parameters were considered, which are cutting speed, feed rate and tool nose radius. The selection of both MRA and ANN model has been carried considering bias-variance trade off. Two statistical methods were used in order to compare the prediction accuracy of the MRA and ANN models with experimental results.

2 DESIGN OF EXPERIMENT

There are conducted 36 turning experiments on X210Cr12 steel [2]. The experiments have been done on NC lathe machine ″MORY-SEIKI″ type SL-3 using cutting insert ″SINTAL″ TPMR of TNC S+ quality. Three machining parameters were considered as input variables, which are: cutting speed – v, feed rate – f, and tool nose radius – r. The considered output was surface roughness – R_a (μm). The machining parameters were considered at three levels (-1, 0 and 1), shown in table 1.

Table 1. Parameters and levels for turning experiments

Level	Machining parameters		
	v [m/min]	f [mm/rev]	r [mm]
Low (-1)	92	0.107	0.2
Center (0)	113	0.214	0.4
High (+1)	138	0.428	0.8

The surface roughness R_a (μm) was measured by using a profilometer ″Talysurf-5M″. The experimental matrix and responses are given in table 2.

Table 2. Design of experiment matrix and data for model development

Exp. no	Exp. run	Machining parameters			R_a [μm]			$\overline{R}_a$ [μm]
		v [m/min]	f [mm/rev]	r [mm]	1	2	3	
1	4	92	0.107	0.8	1.86	1.74	1.8	1.8
2	11	113	0.214	0.4	3.12	3.2	2.68	3
3	3	138	0.107	0.8	1.8	1.76	1.63	1.73
4	7	138	0.107	0.2	2	1.8	2.16	1.99
5	9	113	0.214	0.4	3.1	3.14	2.91	3.05
6	2	92	0.428	0.8	7.8	7.9	9.14	8.28
7	1	138	0.428	0.8	8.1	8.3	8.95	8.45
8	5	138	0.428	0.2	7.5	6.8	6.97	7.09
9	12	113	0.214	0.4	3.15	3.25	2.45	2.95
10	6	92	0.428	0.2	8.4	11.96	10.41	10.26
11	8	92	0.107	0.2	1.8	1.71	2.01	1.84
12	10	113	0.214	0.4	2.92	3.28	3.1	3.1

3 MODEL DEVELOPMENT: BIAS-VARIANCE TRADE-OFF

In any data-driven empirical modeling, model development comprises of selection of functional form of the model and determining the adjustable parameters using the available data. These two issues are closely related but result in different types of errors. Decreasing one type of error is likely to increase the other type and vice versa. This is the so-called bias-variance trade-off. In MRA one need to determine the right functional and order form of the polynomial and to determine coefficients of the polynomial equation. A low degree polynomial will not have the needed flexibility and will make large errors on test sample because of a large bias. A high degree polynomial is too much sensitive to the sample and will make large errors on test sample because of a large variance. In ANN modeling, bias-variance trade-of is less well defined since they have many more free parameters. It is closely related to ANN architecture (number of hidden neurons in hidden layers, transfer functions) and training (number of training epochs). A complex ANN model having large number of hidden neurons or trained with excessively large number of epochs has low bias but high variance. On the other hand, a simple ANN model has high bias but low variance. In both modeling techniques, the goal is to find simplest model that has both bias and variance (the total error) considerably low [1].

4 REGRESSION-BASED MODELING

Regression analysis is a conceptually simple method for investigating functional relationships between variables. As multiple input variables are used multiple regression analysis (MRA) is applied. MRA can be generally expressed by the following equation:

$$y = f\left(x_1, x_2, \ldots x_n; b_0, b_1, \ldots, b_p\right) + \varepsilon \tag{1}$$

Where y is a output variable, $x_1, \ldots, x_n$ are input variables, $b_0, \ldots, b_p$ are regression parameters and ε is a random error. The MRA model is used to develop functional relationship between the surface roughness and cutting parameters (cutting speed - v, feed rate - f and tool radius - r). The response function representing the surface roughness - R_a can be expressed as R_a = f(v, f, r) and the relationship selected second order with interactions polynomial response. The MRA was carried out with MINITAB 15 software package, using the least squares method (LSM) for 95% confidence interval. The results of MRA with all the variables and the interaction terms in second-degree response and the corresponding coefficients are shown in table 3.

Table 3. MRA for for surface roughness

Predictor	Coefficient	SE coefficient	T	P	
Constant	30.398	8.752	3.47	0.002	
v	-0.5351	0.1478	-3.62	0.002	
f	30.012	6.004	5.00	0.000	
r	-6.162	3.515	-1.75	0.095	
v f	-0.07610	0.04986	-1.53	0.143	
v r	0.04952	0.02710	1.83	0.083	
f r	-0.631	3.913	-0.16	0.873	
v v	0.0022533	0.0006280	3.59	0.002	
S=0.770517	R^2 = 0.954	R^2_{adj} = 0.938			
Analysis of variance (ANOVA)					
Source	DF	SS	MS	F	P
Regression	7	246.447	35.207	59.30	0.000
Residual Error	20	11.874	0.594		
Total	27	258.321			

The insignificant model terms f·f and r·r were automatically eliminated by the software since it is highly correlated with other variables. The mathematical model for surface roughness can be expressed by the following equation:

$$R_a = 30.4 - 0.535 \cdot v + 30 \cdot f - 6.16 \cdot r - 0.0761 \cdot v \cdot f + 0.0495 \cdot v \cdot r - 0.63 \cdot f \cdot r + 0.00225 \cdot v^2 \qquad (2)$$

The validity of the equation developed is evident from the high coefficient of correlation of R^2 = 0.954.

5 ANN-BASED MODELING

Artificial neural networks (ANNs) are massive parallel systems made up of numerous simple processing units called neurons that are linked with weighted connections. By tuning a set of weights and biases in the training process ANN learns the relationship between given inputs and related outputs. The ANN-based modeling is not a straight-forward process and numerous decisions have to be made. In order to develop efficient and reliable ANN model of high performance, issues related to ANN architecture and training have to be considered carefully. The ANN used for modeling is a feed-forward multilayer network trained with back-propagation (BP) algorithm. This type of ANN is most widely used for modeling of machining processes. The ANN model has three inputs which corresponds to cutting speed – v, feed rate – f, and tool nose radius – r, and one output which stands for surface roughness - R_a. Configuring ANN usually comprise the decisions about ANN architecture (number of hidden layers, number of hidden neurons in each layer, transfer function) and ANN training algorithm.

Determining the number of hidden layers and the number of neurons in each hidden layer can be a considerable task. It has been shown that a multilayer ANN with one hidden layer and sigmoid transfer functions can approximate any function with arbitrary accuracy and this therefore reduces the problem of defining the ANN architecture to one of choosing the number of hidden neurons. The number of neurons in the hidden layer is data dependent. The number of hidden neurons is set as i and 2i, where i is the number of ANN inputs. The available data was randomly divided in two sets: training (28 data) and testing (8 data). The training set was used for model development, while the testing set was used to evaluate the model’s accuracy. Given the available training set with 28 data, three ANN architectures were developed, which are: 3-3-1, 3-6-1 and 3-3-3-1. In such a way it was taken into account that the sum of product between number of neurons in layers is less than the number of data available for training. For all developed ANN models linear transfer function and tangent sigmoid transfer function were used in the output and hidden layer, respectively. In order to stabilize and enhance ANN training the data was normalized to a range of (-1 to +1) using the following equation:

$$x_{norm} = 2 \cdot \frac{(x - x_{min})}{(x_{max} - x_{min})} - 1 \qquad (3)$$

Where x is the data to be normalized, i.e. cutting speed - v, feed rate - f, tool nose radius - r, and x_{min} and x_{max} are minimum and maximum values of the raw data. Prior to ANN training, the initial values of weights were set according to Nguyen-Widrow method. The MATLAB's Neural Network Toolbox software package is used for training and testing the ANN models [3]. BP algorithm with momentum was used for ANN training ("traingdm" procedure in MATLAB). After some preliminary investigations, learning rate 0.01 and momentum constant of 0.9 were chosen for ANN training. The ANN's performance during training was measured according to the mean of squared errors (MSE). Training was terminated after a maximum number of epochs (10000) or when no further improvement in the MSE was achieved.

After ANN models analysis during training and testing it was turned out that 3-3-3-1 is the optimal ANN model giving the smallest MSE on both training and testing data. Figure 1 shows architecture of this model, according to the notation system of the software package MATLAB.

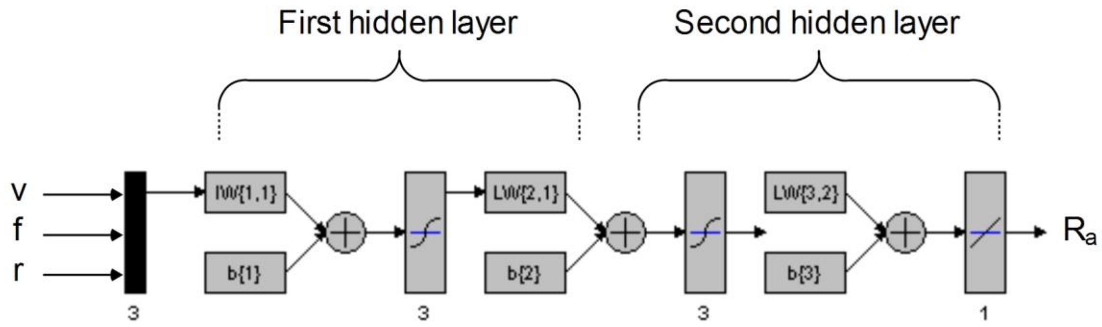

Figure 1. Two-hidden layer 3-3-3-1 ANN architecture. IW and LW denotes the weights of the first and second hidden layer respectively, and b{1,2,3} layer biases

6 STATISTICAL EVALUATION OF MRA AND ANN MODELS

The MRA and ANN models are evaluated and compared to determine the best prediction model that provides high accuracy and better results. There are a number of statistical measures for evaluating the accuracy of prediction models and each has advantages and limitations. The statistical methods of mean absolute percent error (MAPE), correlation coefficient (R) have been used for estimating the prediction errors. These values are mathematically defined by the following equations:

$$R = \frac{\sum_{i=1}^{N} (m_i - \overline{m}) \cdot (p_i - \overline{p})}{\sqrt{\sum_{i=1}^{N} (m_i - \overline{m})^2} \cdot \sqrt{\sum_{i=1}^{N} (p_i - \overline{p})^2}} \qquad (4)$$

$$\mathrm{MAPE} = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| \frac{m_i - p_i}{m_i} \right| \tag{5}$$

Where: m and p are measured and predicted values respectively (¯ denotes mean), and N is the sample size. MAPE is a useful measure because it presents errors as a percentage, which is often easier to understand. Also it is useful for comparing relative accuracy of the methods. The correlation coefficient is a statistical measure of the strength of correlation between actual versus predicted values. The calculated values for the training and testing data using MRA and ANN model are compared with experimental values and are given in table 4.

Table 4. R and MAPE for MRA and ANN models

Model	R			MAPE [%]		
	Training	Testing	Training+Testing	Training	Testing	Training+Testing
ANN	0.983	0.998	0.986	7.616	5.389	7.121
MRA	0.969	0.957	0.966	9.627	14.246	10.654

Graphical comparison of selected MRA and ANN model predictions and experimentally measured values is presented in figure 2.

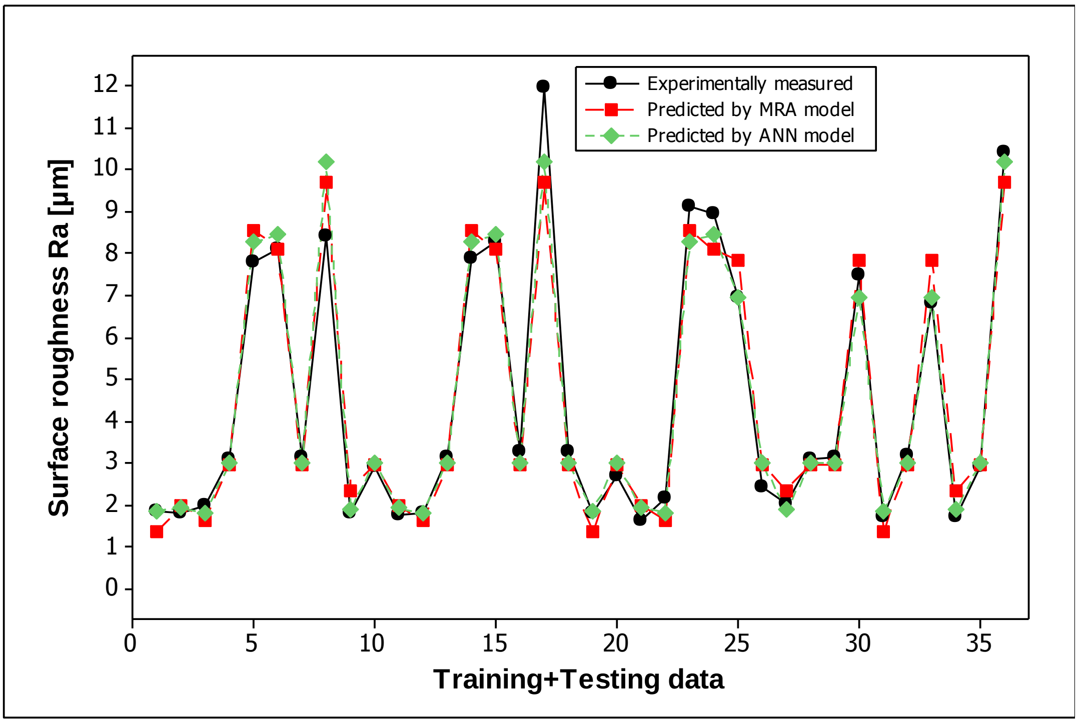

Figure 2. Comparison of MRA and ANN model predictions with corresponding experimental values

Using both the training and testing data, it is found from table 3, that the MRA model yielded correlation coefficient of 0.966 while ANN 0.986. Although the difference between correlation coefficient is not great, the difference in prediction accuracy is much higher taking into account MAPE statistic. The MAPE for MRA and ANN model, using the both training and testing data, are 12.626 % and 7.121 % respectively. From the above comparisons, it can be concluded that the ANN model is better than the MRA model in predicting surface roughness.

7 CONCLUSIONS

The present work is concerned with development of MRA and ANN models for prediction of the surface roughness in turning X210Cr12 steel. The experimental data of measured surface roughness is used for model development considering cutting speed, feed rate and tool nose radius as model's inputs. MRA modeling requires an explicit function to be defined, while the succes of ANN modeling is highly affected by ANN architecture and training parameters. Considering bias-variance tradeoff in both modeling approaches, MRA and ANN model were selected. Although ANN model provided better prediction accuracy than MRA model, both method showed relatively high prediction accuracy and can be used for the same purpose.

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