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Analytical Models for Tool Wear Prediction during AISI 1045 Turning Operations

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Abstract

Tool wear is one of the most important topic in cutting field. Its interest is due to the influence of tool wear on surface integrity of the final parts and on tool life, and, consequently, on the substitution policies and production costs. Analytical models, able to forecast the tool wear with a satisfactory accuracy, can give to the companies working in the material removal field a valid instrument to optimize the cutting processes. In the present work a comparison between response surface methodology (RSM) and artificial neural networks (ANNs) fitting techniques for tool wear forecasting was performed. For developing these predictive models, tool life tests, consisting of longitudinal turning operations of AISI 1045 steel bars using uncoated tungsten carbide inserts and variable cutting parameters, were conducted. Both flank (VB) and crater wears (KT) of the tool were monitored. The models were validated comparing the calculated tool wear values with the experimental ones, showing that ANNs model provides better approximation than RSM in the prediction of the amount of the tool wear parameters. So, from an industrial point of view, this model should be implemented into a production management software in order to correctly define the tool substitution policy during batch production.

Keywords: tool wear; analytical model; Response Surface Methods; Artificial Neural Networks.

1. Introduction

In manufacturing field, turning operation is a very common material removal technique. Researches on this topic take into account several aspects, such as: geometrical and metallurgical characteristics of the cutting tool, workpiece material influence on the process and process parameters (cutting speed, feed rate, depth of cut). The interaction of all these factors during a cutting operation causes a series of physical, chemical and thermo-mechanical phenomena that influence the wear of the tool. In cutting operations it is difficult to establish a dominant cause [1] of tool wear. In fact, a simultaneous combination of several and different wear mechanisms like abrasion, adhesion, diffusion or oxidation, can be observed. The ISO 3685 standard describes how tool wear can be measured providing a description of the parameters to control during tool life tests.

Typically, flank wear (VB) and K ratio (ratio between depth of the crater wear – KT – and the position of the maximum depth of crater – KM), are the most used ones because of their influence on tool life, substitution policy, manufacturing costs and surface integrity of the final part in terms of surface roughness [2], residual stress distribution [3-5] and strain hardening [6].

For these reasons, a good way to optimize a turning process is the possibility of predicting the tool wear. Since the on-line evaluation of the tool wear parameters during a turning process is a very expensive and time consuming effort for industries, it is very important to provide models able to predict these parameters with a good accuracy. For this purpose response surface methodology (RSM) [7,8] or artificial neural networks (ANNs) [9] can be utilized. The RSM technique fits data

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coming from experimental tests with a suitable analytical function applying statistical rules and regression modeling techniques. While ANNs are global optimization algorithms employed in solving difficult problems.

The aim of the present research is to apply RSM and ANNs techniques in order to obtain models able to predict flank wear (VB) and crater depth (KT) when turning AISI 1045 steel bars with uncoated tungsten carbide (WC) tools. Experimental tests provided the tool wear data, needed for developing the models. Longitudinal turning operations were carried out and the development of flank wear (VB) and depth of crater wear (KT) was measured. The considered variables are the cutting time and the main process parameter (i.e., cutting speed and feed rate). Design of experiments (DOE) technique was utilized for planning the experimental campaign.

For evaluating the influence of the selected variables on the tool wear, a preliminary ANOVA analysis was performed on the data collected during the experimental campaign. After that, the RSM analysis was carried out, defining a second order analytical model for VB and KT prediction.

ANN's, based on backpropagation and feed-forward algorithm, were tested too. The wear models validation was performed using tool wear data collected performing additional experimental tests using cutting conditions different from those used during the training and the validating phases.

The models are able to forecast VB and KT with a good accuracy. The best performances were obtained when using ANNs technique.

2. Experimental campaign

The experimental campaign was performed on a CNC lathe. Longitudinal turning operations on cylindrical bars made of AISI 1045 steel, with an initial diameter of 98 mm and a length of 275 mm, were realized. Tungsten carbide ISO P40 inserts (ISO specification SPUN 120308) with a nose radius of 0.8 mm and a flank angle (α) equal to 11° was utilized during the tests. Even if the ISO P40 inserts quality is not the best choice for cutting AISI 1045 steel, this insert material quality was chosen for obtaining high wear rate. The selected toolholder (ISO specification CSBPR 2020K12) is characterized by:

- rake angle (γ) equal to +1°;
- inclination angle (λ) equal to +7°;
- entering angle (χ) equal to 75°

Figure 1 shows the experimental set-up, while Table 1 summarizes the chemical composition and the mechanical characteristics of tool and workpiece materials.

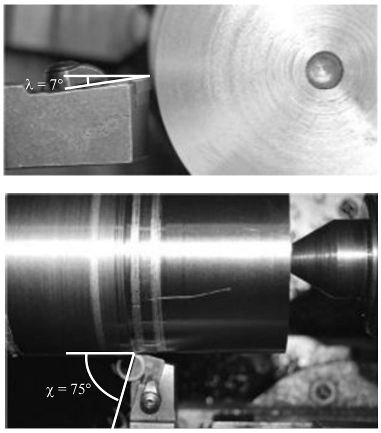


Fig. 1. Cutting operation set-up.

Table 1. AISI 1045 and ISO P40 chemical and mechanical specifications.

AISI 1045 chemical (% weight) and mechanical specifications	
%C	0.42÷0.50
%Mn	0.60÷0.90
%P	<0.040
%S	<0.050
Hardness Brinell [HB]	170
Ultimate Tensile Strength [MPa]	515
Yield Tensile Strength [MPa]	485
Elongation at break [%]	10.0
Reduction of area [%]	25.0
Modulus of elasticity [GPa]	200.0
Poisson ratio	0.290
Shear modulus [GPa]	80.0
ISO P40 chemical (% weight) mechanical specifications	
%W	82.8
%C	5.2
%Co	12.0
Hardness Rockwell A [HRA]	90
Ultimate Tensile Strength [MPa]	344
Modulus of elasticity [GPa]	670
Compressive Strength [MPa]	2683

DOE technique was applied for planning the experimental campaign. In this manner the influence of cutting speed (V_C), feed rate (f) and cutting time (t) on tool wear parameters was investigated.

Figure 2 shows the conduced experimental tests and the corresponding process parameters. Three levels were set for cutting velocity and feed rate (squares in Figure 2). As far as the cutting time is concerned, each test was carried out for 7 minutes and stopped at regular intervals of 30 seconds for measuring the extension of flank wear (VB) and the depth of crater wear (KT) for a total of fourteen intervals.

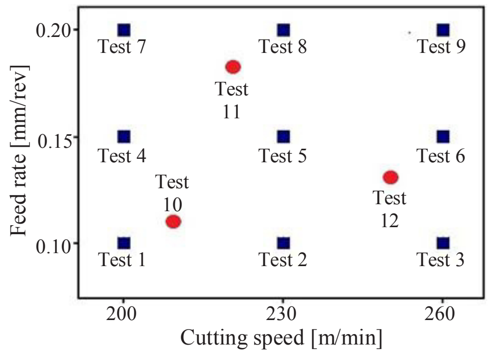


Fig. 2. Experimental test.

For validating the models three additional tests (dots in Figure 2) were performed. In these tests the time intervals for tool wear measurement were set as follow: steps of 45 seconds till reaching 6 minutes of cutting time followed by two steps of 30 seconds.

Depth of cut was kept constant to 1.5 mm; no lubrication was used, in order to accelerate the tool wear, according to the ISO standard 3685 suggestions. Every test was repeated three times for testing the process repeatability.

Flank wear (VB) was measured using an optical CMM (Mitutoyo QS200Z). This machine guarantee a measurement accuracy of 0.5 μm. Figure 3 shows the flank wear measuring technique.

The tool crater wear was measured using a profilometer with an accuracy of 0.01 μm. Crater profiles were acquired along sections orthogonal to the cutting edge and to the rake face, spaced by 0.1 mm for a total length of 2.1 mm. Typically, the profiles are characterized by peaks and valleys due to the workpiece material adhesion (Figure 4a). For this reason, each profile was filtered by a band-pass filter, with the band-centre around the medium trend of the profile, obtaining a cleaner profile. The so elaborated profiles were utilized for generating a three dimensional model of the tool crater (Figure 4b). From this three dimensional representation it is possible to measure the depth of the crater wear (KT) as distance between the rake surface and the deepest point of the crater as shown in Figure 4b.

The evolution of flank (VB) and crater (KT) wear parameters for each test is reported in Figure 5.

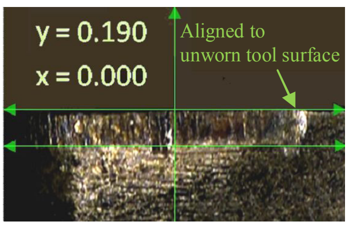


Fig. 3. VB measuring technique (v_c=230m/min; f=0.20mm/rev; t=120 s).

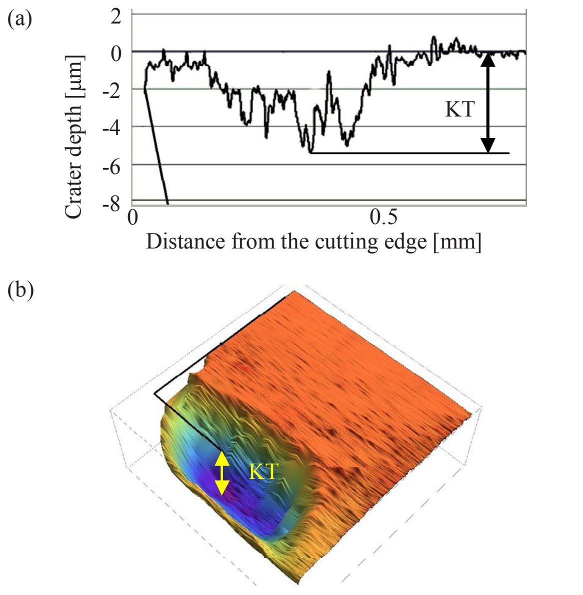


Fig. 4. (a) unfiltered crater profile; (b) 3D representation of the crater of the insert.

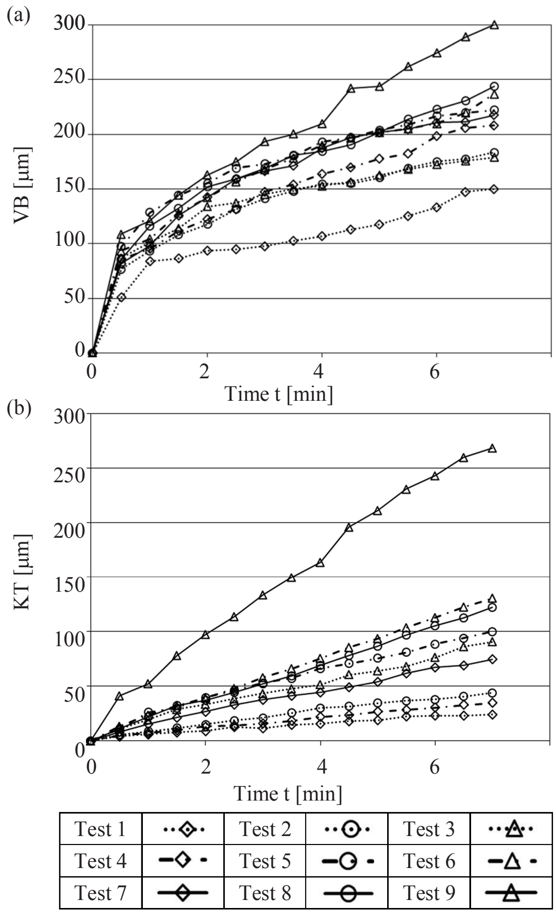


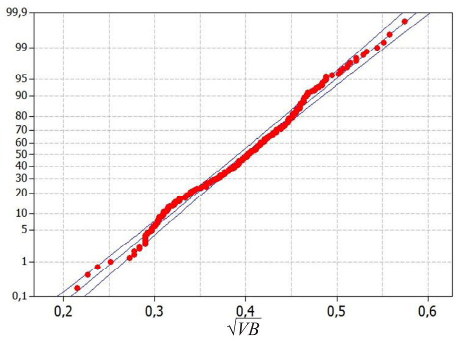
Fig. 5. Evolution of VB (a) and KT (b) wear parameters.

3. Tool wear models

3.1. Response surface model (RSM)

Minitab® software was used for the statistical analyses. First of all, the ANOVA analysis was applied on the experimental data to evaluate the influence of V_C, f and t on VB and KT. This analysis allows to verify the normal distribution of residuals and to test the normality of experimental data. If necessary, it is also possible to optimize the representation of the experimental data using a tool of Minitab® called "Box-Cox transformation" [10] that minimizes the standard deviation of a standardized transformed variable. After "Box-Cox transformation", the experimental values of VB were substituted by the square root of their values while the values of KT by the natural logarithm of experimental data. The so transformed data passed the normality test as shown in Figure 6a and Figure 6b.

(a)



(b)

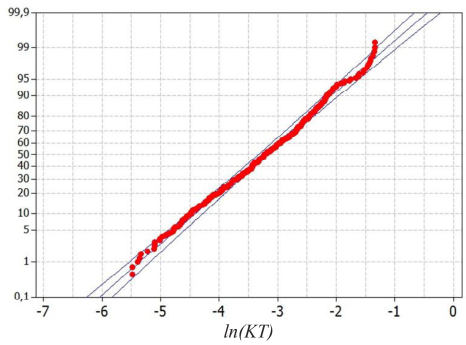


Fig. 6. Probability plots for $\sqrt{VB}$ (a) and ln(KT) (b).

The ANOVA F-test was performed on the "Box-Cox" transformed data for analyzing the significant effects of input variables. The analysis was carried out for a level of significance of 5%, so for a level of confidence of 95%. Table 2 shows the ANOVA results for the transformed data of VB and KT. By observing the P-value of Table 2, it is possible to state that all the factors and their interactions affect the amount of VB and KT. Only the interaction between feed rate and cutting time showed a light influence on VB.

Table 2. ANOVA results for $\sqrt{VB}$ and ln(KT).

ANOVA results				
	$\sqrt{VB}$		ln(KT)	
Factor	F-test	P-value	F-test	P-value
V_C	1262.8	<0.001	9735.7	<0.001
F	483.8	<0.001	14673.4	<0.001
T	600.7	<0.001	3085.7	<0.001
V_C x f	64.5	<0.001	439.4	<0.001
V_C x t	7.6	<0.001	6.3	<0.001
f x t	1.4	0.117	5.5	<0.001
V_C x f x t	2.8	<0.001	5.4	<0.001

Through the RSM analysis analytical full second order models of each wear parameter was determined. The models are reported in Equations (1) and (2).

$$
\begin{aligned}
VB(V_c, f, t) &= (-0.70199 + 0.00836V_c + \\
&+ 1.88679f + 0.00723t - 0.00002V_c^2 - \\
&- 3.89975f^2 - 0.00288t^2 - 0.001697V_c f \\
&+ 0.00015V_c t + 0.02176ft)^2
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
KT(V_c, f, t) &= \exp(-3.2648 - 0.0367V_c + \\
&+ 5.6378f + 0.4999t + 0.0001V_c^2 + \\
&+ 11.0695f^2 - 0.0483t^2 + 0.01257V_c f \\
&+ 0.0005V_c t + 0.1929ft)^2
\end{aligned} \tag{2}
$$

3.2. Artificial Neural Network (ANN)

Tool wear models were defined utilizing feed forward neural networks based on backpropagation algorithm.

The cutting test data were provided to the designed neural networks in order to train, validate and test them. Several configurations of networks, characterized by different number of hidden layers and number of neurons in the hidden layers, were trained for carrying out the best arrangement for the wear parameters prediction, in terms of resulting errors as reported in Table 3. The input neurons are the investigated cutting parameters (V_C, f and t), while the output layer corresponds to the wear parameters KT and VB.

For developing ANNs the Neural Network Toolbox of Matlab® was used and the Levenberg-Marquardt backpropagation algorithm was chosen for its low computational time and good reliability. For training and validating the network the input pattern had to be divided in two sets, one for each phase. The Matlab® toolbox was programmed to divide the input pattern as: the 80% for training the network and the 20% for validating it. After these two first phases, the ANNs giving the lowest MSE were chosen as the right predictive instruments. In particular, tool wear data of experiments from 1 to 9 were utilized for these two phases As shown in Table 3, the 3-14-1 (3 neurons for the input layer, 14 neurons for the hidden layer and 1 neuron for the output layer) ANN architecture provided the best results for VB prediction; while the best network for KT prediction is the 3-7-1 network.

A final testing phase was realized using the wear data coming from tests 10, 11 and 12.

Table 3. Performances of trained and validated ANNs for tool wear parameters prediction.

Performances of trained and validated ANNs for VB prediction			
Config.	Epochs	E_{med} [μm]	E_{MAX} [μm]
3-10-3-1	79	7.38	41.45
3-20-3-1	124	9.31	233.20
3-8-1	5000	8.54	26.90
3-10-1	1733	8.48	119.66
3-12-1	65	9.50	84.76
3-14-1	**5000**	**5.19**	**20.73**
3-16-1	5000	6.08	39.31
3-20-1	283	10.03	128.90
Performances of trained and validated ANNs for KT prediction			
Config.	Epochs	E_{med} [μm]	E_{MAX} [μm]
3-5-1	5000	6.67	46.54
3-7-1	**5000**	**1.55**	**10.19**
3-8-1	2407	16.13	239.37
3-9-1	5000	5.54	29.29
3-10-1	5000	2.15	13.47
3-11-1	154	34.67	903.35
3-12-1	541	3.40	30.12
3-13-1	61	5.72	42.22
3-15-1	83	6.10	238.32
3-20-1	69	3.86	16.75

4. Result discussion

Once obtained the models of flank and crater wear by using RMS and ANNs technique, the absolute errors with respect to the mean value of the experimental data were estimated. Figure 7 shows the absolute errors after a cutting time of 7 minutes, when the highest error values were observed. The light grey bars refer to the errors of DOE tests (form 1 to 9 in Figure 2), while the dark grey bars refer to the additional tests (from 10 to 12 in Figure 2) errors.

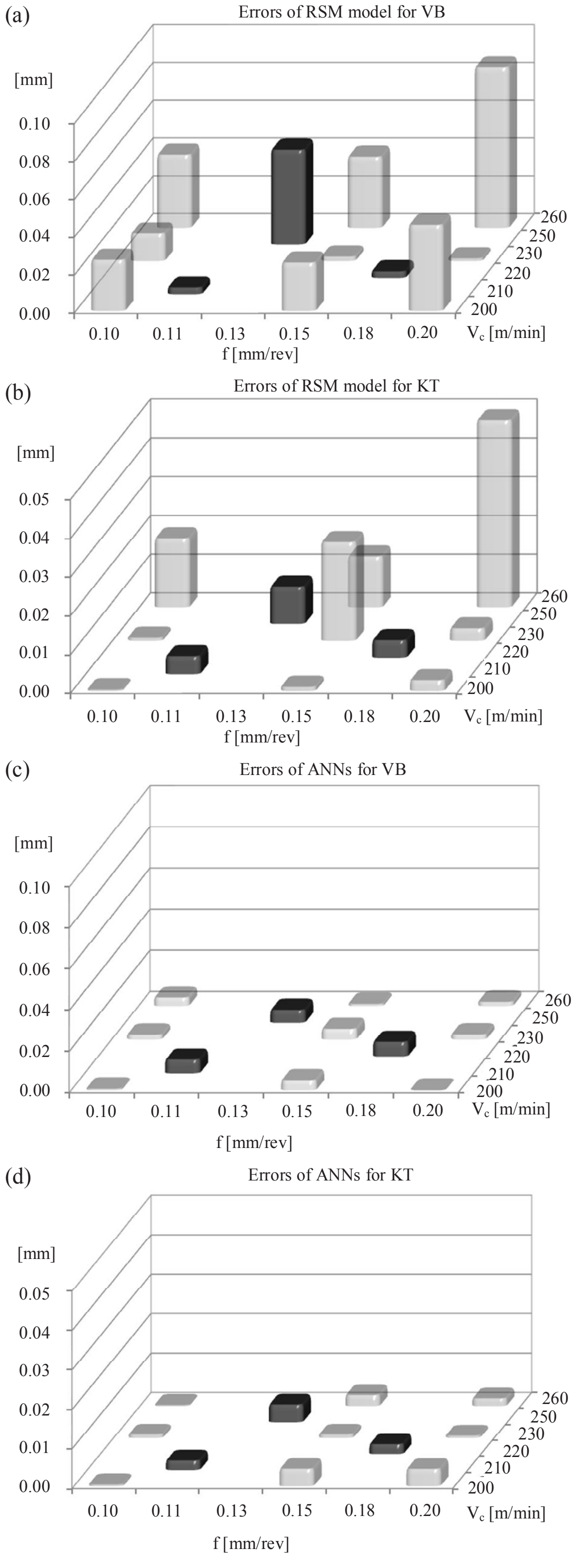


Fig. 7. VB and KT absolute errors after 7 minutes of cut for RSM (a and b) and ANNs (c and d) models.

Observing Figure 7, it is evident that ANNs technique gives the smallest errors for both *VB* and *KT* parameters. This is due to the fact that RSM approximates the experimental data by means of a second order polynomial function. This approximation shows limits when the fitting surface of the experimental data (Figure 8) is characterized by inflection points as in this case.

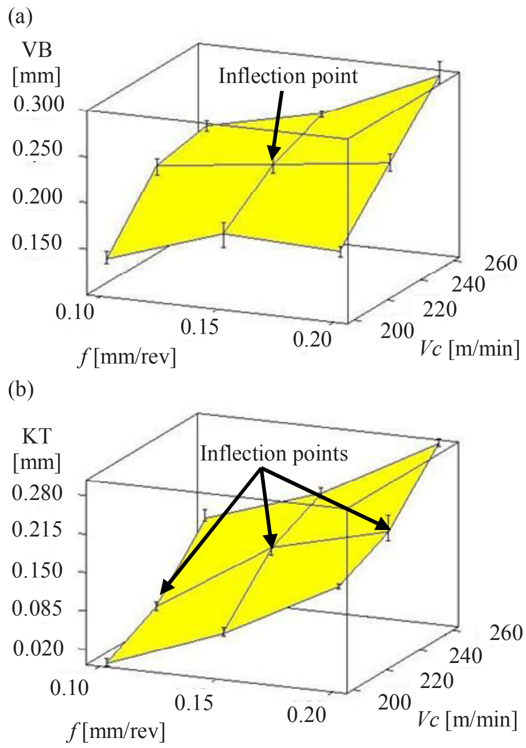


Fig. 8. Fitting surface of experimental data: (a) VB; (b) KT.

5. Conclusions

In this study a comparison between two different techniques for modeling the behavior of wear parameters in turning operations is presented. These methodologies are the RSM, that uses the multidimensional regression technique, and the artificial neural networks approximations. For collecting the experimental data, necessary for developing the predictive models, a series of longitudinal turning operations, varying the process parameters, was performed.

Several regression models and ANNs configurations were built up and verified for selecting the best wear parameters representation. By the fitting analysis, it was observed that the ANNs technique gives lower errors with respect to the RMS method This because ANNs technique is able to represent curvature and inflection points of the fitting surface with high accuracy. Thus, ANNs techniques are the best choice amongst the analyzed methodologies, for forecasting the amount of the wear parameters. Further studies will be focused on improving these models considering other important aspects of cutting operations such as the lubrication, the tool geometry or the tool coatings.

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