Hindawi Publishing Corporation
Advances in Materials Science and Engineering
Volume 2014, Article ID 138168, 8 pages
http://dx.doi.org/10.1155/2014/138168

Research Article

A New Mathematical Model for Flank Wear Prediction Using Functional Data Analysis Methodology

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Received 17 September 2014; Revised 1 December 2014; Accepted 4 December 2014; Published 24 December 2014

Academic Editor: Luigi Nicolais

This paper presents a new approach improving the reliability of flank wear prediction during the end milling process. In the present work, prediction of flank wear has been achieved by using cutting parameters and force signals as the sensitive carriers of information about the machining process. A series of experiments were conducted to establish the relationship between flank wear and cutting force components as well as the cutting parameters such as cutting speed, feed per tooth, and radial depth of cut. In order to be able to predict flank wear a new linear regression mathematical model has been developed by utilizing functional data analysis methodology. Regression coefficients of the model are in the form of time dependent functions that have been determined through the use of functional data analysis methodology. The mathematical model has been developed by means of applied cutting parameters and measured cutting forces components during the end milling of workpiece made of 42CrMo4 steel. The efficiency and flexibility of the developed model have been verified by comparing it with the separate experimental data set.

1. Introduction

The final shapes of most machine elements are obtained by machining operations. The selection of the applicable machining method depends on the required geometry, dimensional accuracy, and surface quality of the part. Thanks to the development of the computer numerical control (CNC) machine tools, technology of computer aided design and computer aided manufacturing (CAD/CAM), as well as modern tools, and technology of high-speed machining, milling becomes indispensable and the most propulsive machining operation. The cutting tools in any machining process are subjected to changes of its geometry and changes of respective material properties. Tribological processes leading to tool wear occur at rake and flank face, as it is shown in Figure 1, [1]. Flank wear, VB [mm], is caused by friction between the flank face of the tool and the machined workpiece surface and leads to loss of the cutting edge. Hence, flank wear affects the dimensional accuracy and surface finish quality. In practice, flank wear is generally used as the tool wear criterion.

In conventional machining, the process of tool wear consists of three stages. These are rapid initial wear, gradual intermediate wear, and finally very rapid wear or catastrophic wear. When the critical value of the tool wear criterion has been reached, the tool fails due to excessive stresses and thermal alterations caused by large friction forces. To avoid this, the cutting tool must be replaced before reaching its critical limit. However, this approach has two typical shortcomings. The first one is that a worn tool will produce out-of-specification parts or even cause catastrophic tool breakage. The second one is the fact that if the tool is dismissed prematurely, the direct consequence will be a significant waste of manufacturing resources. During milling process, the cutting edges periodically enter and exit the workpiece. Hence, it experiences stress and temperature cycling during cutting. This periodic coupled mechanical-thermal cycle produces alternating compression and tensile stresses on the tool that may exceed its strength. Even if the thermal stress amplitudes are not large enough to break the tool instantly, the thermal stress cycling causes gradual fatigue failure and wear of the tool. As the flank wear increases, the tool-workpiece contact area increases as well [2]. Tool wear hence becomes the key factor in the machining processes. If a worn tool is not identified beforehand, significant degradation of the

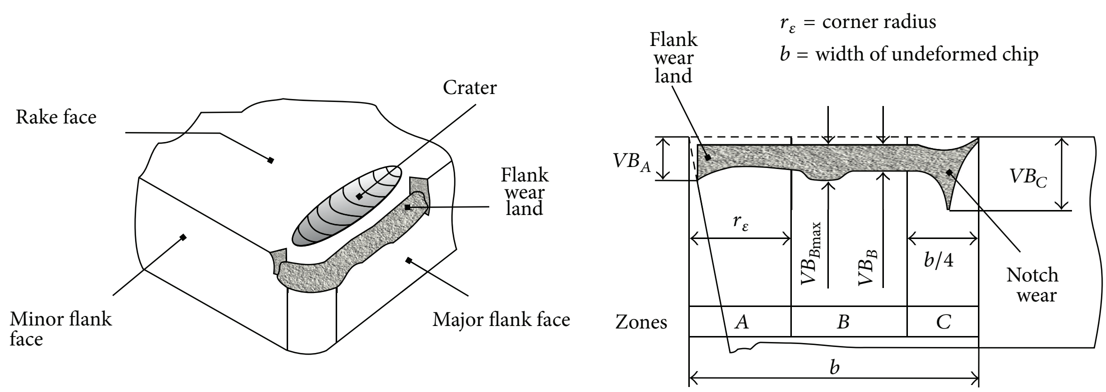

Figure 1: Form of tool wear.

workpiece quality can occur. Therefore, research in this area is of great significance. Several methods have been proposed to monitor tool wear. There are two main categories: direct and indirect methods. With direct methods it is possible to measure tool wear directly using some optical instrument such as video camera, which requires cutting operations to be interrupted periodically. Various indirect methods for tool condition monitoring (TCM) are used by modeling the correlation between tool wear and sensory signals, namely, the cutting force, torque, current, power, vibration, and acoustic emission acquired in machining processes [3–7]. A large number of research articles have been published on the subject of indirect TCM over the past decade, describing numerous methods of collecting process signals, the analysis and extraction of wear-sensitive features. Researchers have attempted to model those features together with applied cutting parameters, machining time, workpiece, and tool materials bringing them in correlation with tool wear.

Kwon and Fischer [8] have developed the tool wear index (TWI) and the tool life model, analysing the wear surface areas and the tool material loss by means of microoptics, image processing, and an analysis algorithm. With relation to surface roughness, the TWI measures the minimum risk for in-process tool failure, and it is integrated in an optimal control strategy according to criteria of productivity improvement and reduction of manufacturing cost. Özel et al. [9] have investigated the influence of cutting parameters on the tool flank wear and surface roughness in finish turning of hard steel. Crater and flank wear of ceramic tool are observed with scanning electron microscopy (SEM) after corresponding runs. Linear regression and neural network models are developed for the prediction of tool flank wear and surface roughness. Lajis et al. [10] have performed similar modeling methodology and measuring techniques in end milling of hardened steel. Nouari and Molinari [11] have investigated uncoated tool wear during machining of low-alloyed steel (DIN 42CrMo4, AISI 4140). The main influencing parameter on the diffusion wear is the contact temperature. The temperature field is simulated by means of the finite element method. As main parameters, the authors have used the contact length between the chip and rake interface, shear angle, and width of removed material. Iqbal et al. [6] have used fuzzy rules based strategies for estimation of tool's flank wear in hard milling process. Two approaches are explained, namely, off-line strategy which uses length of cut as input parameter, besides workpiece hardness and inserts geometry, and on-line strategy which uses the force Fxy—resultant of peak values of two components of cutting force acting in X and Y directions. The second strategy gives better and more robust estimation of tool wear.

The successful detection of the tool deviation, such as tool wear or tool runout during cutting process, can ensure high-quality part and safeguard the machining system. Arizmendi et al. [12] developed a model for the prediction of the surface roughness machined by peripheral milling. They take into account that the tool vibrates during the cutting process. This research concluded that tool runout and spindle tilting have a strong influence on the integrity of the milled surface. Since the acoustic emission (AE) signals obtained in processing include not only the information closely related to the change of the tool condition, but also that generated from other sources or noise, Yen et al. [13] have presented self-organizing mapping algorithms to the feature processing step to reduce the system noise or system variation effect. Cutting forces are widely known as the most reliable indicators for on-line tool condition monitoring and a lot of researchers use this method to determine the relevant parameters which best characterize the cutting tool wear [14–17]. Wang et al. [18] proposed Gaussian mixture regression to realise robust prediction of the tool wear. Choudhury and Rath [19] have shown that tool wear can be well correlated with cutting parameters and cutting force coefficient with maximum deviation between experimental and calculated results in amount of 8%. Kious et al. [20] have performed cutting force signals analysis based on both time and frequency signal processing techniques in order to extract the relevant indicators of cutting tool state. They have shown that the variation of the variance and the first harmonic amplitudes are linked to the flank wear evolution.

This work deals with tool wear in milling process and the prediction of its behaviour by utilizing functional data analysis (FDA) methodology. The mathematical model has been developed by means of applied cutting parameters and measured cutting forces components during the end milling. Cutting force increases with tool wear, which among other things depends on the cutting parameters and insert

Table 1: Insert and end mill geometry.

Insert length, l_a	11 mm
Insert width, iW	6.8 mm
Insert thickness, s	3.59 mm
Edge radius, r_ε	0.8 mm
Clearance angle	21°
Number of inserts	3
Nominal cutter diameter	20 mm

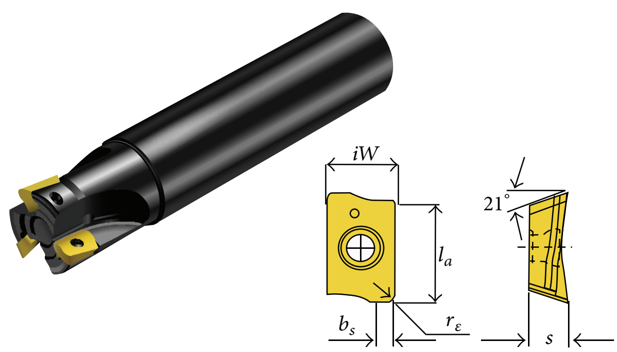

Figure 2: End mill and insert used in the cutting tests.

engagement time. As far as the authors know, FDA methodology has never been used in investigation of machining processes.

2. Experimental Setup

The end milling experiments were carried out on CNC vertical machining center, Spinner VC560, equipped with a 12000 rpm electrospindle and the SK 40 tool holder. Workpiece material was steel 42CrMo4 and was prepared for milling operations in the form 250 mm × 110 mm × 110 mm blocks and adapted to the experiment needs.

The cutting tool was end mill CoroMill R390-02A20-11M produced by Sandvik. The insert was hard metal coated with highly resistant TiN coating, Grade Coromant GC1025. Insert geometry varies depending on the depth of cut in order to obtain a better condition of the chips flow. The closest point for the clearance angle is 21° and before that angle there is one facet ~0.2 mm with the angle of 0°. The end mill and insert are shown in Figure 2. Tool specification is given in Table 1.

2.1. Measurement and Analysis of Tool Wear and Cutting Force. Flank wear measurements were performed in accordance with the International Standard ISO 8688-1 by means of toolmaker's microscope with 100x magnification and USB camera. The system for measuring the components of cutting force consists of dynamometer Kistler 9257A mounted between the workpiece and the machining table and multichannel charge amplifier Kistler 5007 that forwards the signals to the A/D interface board (BMC USB-AD16f). Analogue signal is transformed into a digital signal so that software Next View 4.3 is able to read and to process the data. The measured voltages are then converted into the forces in X, Y, and Z directions.

Recommendations for the criterion of the flank wear VB_c are numerous but because of the large number of impact factors, they are not unambiguous. Therefore, the experimental determination of the tool wear criterion was performed. Measurements of cutting force components, surface roughness, and flank wear are performed so that all of the measured values correspond to the same point of insert engagement time. After the measurement and analysis of the results, flank wear criterion $VB_c = 0.15$ mm has been adopted. When the flank wear reaches the value of 0.15 mm, the process becomes unstable. The instability is reflected in the increasing of cutting force components as well as surface roughness.

In this study, cutting speed v_c, feed per tooth f_t, and radial depth of cut $a_e$were employed as controlling variables. Axial depth of cut a_p was constant, 5 mm. The adopted values of cutting parameters correspond to the operational limits recommended by the toolmaker together with the machine tool capabilities. Those cutting parameters varied as follows: 100 m/min $\leq v_c \leq$ 150 m/min, 0.02 mm/tooth $\leq f_t \leq$ 0.15 mm/tooth, and 0.5 mm $\leq a_e \leq$ 2.5 mm. Overall 20 experiments were carried out using various combinations of cutting speed, feed per tooth, and radial depth of cut. These combinations can be seen in Table 2. All experiments were conducted without cutting fluid and every experiment was performed with nontest inserts.

Tool wear increases progressively with cutting time, that is, with insert engagement time. In order to achieve high data resolution, time intervals between two flank wear measurements were one minute of insert engagement time. This time is a function of mill diameter, radial depth of cut, and spindle speed. The data obtained in the first ten minutes were not used because of the small value of flank wear. The inserts were removed from the tool holder after a given interval, and the flank wear of the all three inserts was measured wherein the average flank wear value has been used. After that, the inserts were clamped into the tool holder to continue the one run. Total observation insert engagement time was 22 minutes.

Milling force components F_x, F_y, and F_z, are the sum of projections of the tangential, radial, and axial forces acting on the cutting edges during milling. Milling force components present the mean value of the maximum cutting force on each insert.

Table 2 also shows values of the flank wear measured during the run of the experiments. Values for milling force components, which also have been measured in the experiments, have not been presented in tables, but in the form of pictures in the sequel, because of the data extensiveness.

3. Functional Data Analysis

Nowadays, sophisticated measuring devices used in production processes make it easy to obtain the large amounts of high resolution data. That enables utilizing functional data analysis (FDA) for prediction of the behaviour of some of the process parameters. FDA is a term coined by Ramsay and

Table 2: Values of control variables used in the experiments and appropriate measured flank wear.

v_c	100	150	105	120	150	135	125	130	145	100	110	140	150	110	100	125	115	115	125	125
f_t	0.05	0.05	0.07	0.09	0.11	0.15	0.02	0.11	0.06	0.11	0.1	0.13	0.05	0.08	0.14	0.08	0.09	0.1	0.08	0.14
a_e	1	1	0.8	1.2	2	1.7	1.5	2.1	1.8	2	2.4	1.2	2	0.5	2.5	2.5	2	1	1.5	1.5
t [min]	VB [mm]																			
10	0.037	0.069	0.045	0.055	0.091	0.097	0.037	0.082	0.062	0.077	0.095	0.096	0.065	0.059	0.116	0.092	0.069	0.058	0.055	0.082
11	0.045	0.077	0.052	0.062	0.096	0.101	0.045	0.087	0.068	0.082	0.100	0.101	0.071	0.067	0.120	0.097	0.075	0.065	0.061	0.087
12	0.052	0.084	0.059	0.068	0.101	0.105	0.053	0.092	0.074	0.088	0.105	0.106	0.077	0.074	0.124	0.103	0.080	0.071	0.067	0.091
13	0.060	0.091	0.066	0.074	0.106	0.110	0.060	0.096	0.081	0.093	0.110	0.111	0.084	0.081	0.128	0.108	0.086	0.077	0.074	0.096
14	0.067	0.098	0.074	0.081	0.111	0.114	0.068	0.101	0.087	0.098	0.115	0.116	0.090	0.088	0.132	0.113	0.091	0.084	0.080	0.101
15	0.074	0.105	0.081	0.087	0.115	0.118	0.075	0.106	0.093	0.103	0.120	0.121	0.096	0.095	0.136	0.118	0.097	0.090	0.086	0.105
16	0.082	0.112	0.087	0.093	0.120	0.122	0.082	0.110	0.099	0.108	0.124	0.126	0.102	0.102	0.139	0.123	0.102	0.096	0.091	0.110
17	0.089	0.118	0.094	0.098	0.124	0.126	0.089	0.115	0.104	0.113	0.129	0.131	0.107	0.109	0.143	0.128	0.107	0.101	0.097	0.114
18	0.096	0.125	0.101	0.104	0.128	0.129	0.097	0.119	0.110	0.117	0.133	0.136	0.113	0.116	0.146	0.133	0.112	0.107	0.103	0.118
19	0.103	0.131	0.108	0.110	0.133	0.133	0.103	0.123	0.116	0.122	0.138	0.140	0.119	0.122	0.150	0.137	0.117	0.113	0.108	0.123
20	0.109	0.138	0.114	0.115	0.137	0.137	0.110	0.127	0.121	0.126	0.142	0.145	0.124	0.129	0.153	0.142	0.122	0.118	0.114	0.127
21	0.116	0.144	0.120	0.121	0.141	0.140	0.117	0.131	0.126	0.131	0.146	0.149	0.129	0.135	0.156	0.146	0.126	0.124	0.119	0.131
22	0.123	0.150	0.127	0.126	0.145	0.143	0.124	0.135	0.132	0.135	0.150	0.153	0.135	0.141	0.159	0.150	0.131	0.129	0.124	0.134

Dalzell [21] and implies statistical methods for analysing the observed data in the form of curves and images. Observed curves and images are examples of functions, which are, in the FDA method, called functional data (FD). In the FDA the basic unit of information is the entire observed function rather than a vector. This way of proceedings has numerous advantages over a classical multivariate analysis. For example, it allows dealing with irregularly sampled data and with missing data too. An advantage of dealing directly with functions is the possibility of using functional pre- or postprocessing such as derivation and integration [22]. Popularization of FDA was started with the publication of book by Ramsay and Silverman [22] whose first edition was in 1997. Afterwards several books, for example, Ferraty and Vieu [23] and Bosq and Blanke [24], as well as numerous papers have been published on the topic of FDA. So far FDA has been applied to various fields of science and technology, for example, in biomechanics, biomedicine, geophysics, demography, psychology, environment, finance, and chemical and electrical engineering. Survey and overview papers regarding all these applications along with the outcome of interest and features used in specific application of FDA can be found in Ullah and Finch [25] and Manteiga and Vieu [26].

The first step in FDA is conversion of discretely measured data into FD. In this work FD was obtained using the monomial basis function system approximation. Basis function procedure represents a function x by a linear expansion

$$x(t) = \sum_{i=1}^{K} w_i h_i(t) = \mathbf{w}^T \mathbf{h} \tag{1}$$

in terms of K known basis functions h_i. In this work three monomial basis functions were used to describe a polynomial. Weight factors w_i in (1) were determined using a regularization smoothing method by putting roughness penalty to sum of squared errors fitting criterion

$$P = [\mathbf{y} - x(\mathbf{t})]^T [\mathbf{y} - x(\mathbf{t})] + \lambda \cdot \int \left[\frac{d^2}{dt^2} x(t) \right]^2 dt, \tag{2}$$

where $\mathbf{y}$ is a vector of measured data, $x(\mathbf{t})$ is linear basis function expansion containing weight factors that have to be determined, and λ is called smoothing parameter and measures the rate of exchange between fitting to the data and variability of the function x. In this research, parameter $\lambda = 1.6 \cdot 10^{-3}$ was the same for all curves and was determined by cross validation. Functional data was determined out of data that were recorded in the end milling operations, as described in the previous chapter. Examples of FD obtained from end milling experiments are shown in Figures 3, 4, and 5.

Figure 3 shows 20 pieces of FD obtained from measured cutting force component in X direction during end milling experiments. It can be seen that F_x force varies within the interval of ~200 N to 950 N.

Force component F_y varies within the interval of ~500 N to 1600 N, which is shown in Figure 4. Comparing Figure 4 with Figures 3 and 5 one can notice that during the down end milling the greatest force on tool inserts appears in Y direction.

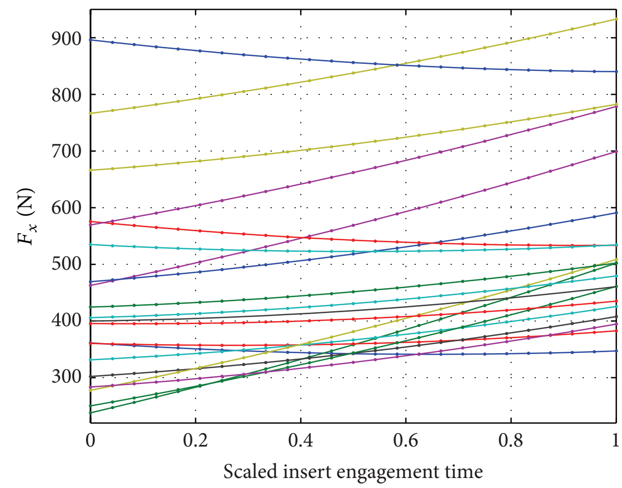

Figure 3: Functional data made out of recorded data for cutting force component in X direction during end milling experiments.

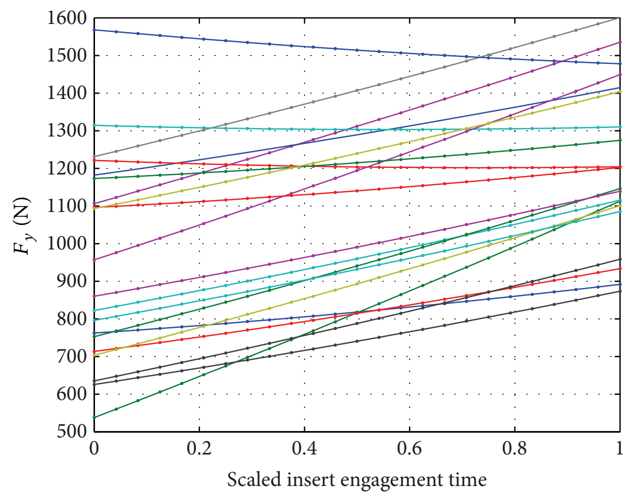

Figure 4: Functional data made out of recorded data for cutting force component in Y direction during end milling experiments.

Figure 5 shows 20 pieces of FD obtained from data measured and recorded for cutting force component in Z direction during the end milling experiments. It appears that this force component varies form ~20 N to 160 N exhibiting the lowest force on tool inserts.

Having determined functional data of the linear equation for the flank wear, prediction can be developed in a form

$$\begin{aligned} VB(t) = {} & \beta_1(t) + \beta_2(t) \cdot v_c(t) + \beta_3(t) \cdot f_t(t) \\ & + \beta_4(t) \cdot a_e(t) + \beta_5(t) \cdot F_x(t) \\ & + \beta_6(t) \cdot F_y(t) + \beta_7(t) \cdot F_z(t), \end{aligned} \tag{3}$$

where VB [mm] is flank wear; v_c [m/min] is cutting speed; f_t [mm/tooth] is feed per tooth; a_e [mm] is radial depth of cut; F_x, F_y, and F_z [N] are cutting force components; β_i ($i = 1, \ldots, 7$) are coefficient functions that are to be determined.

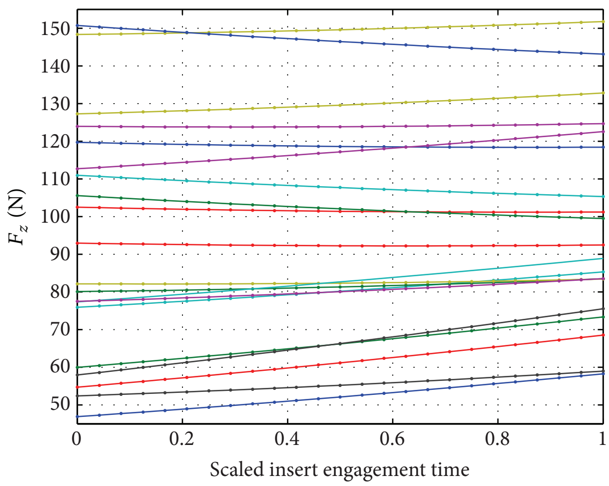

Figure 5: Functional data made out of recorded data for cutting force component in Z direction during end milling experiments.

All functions in (3) are functions of insert engagement time t. The main difference between linear regression equation obtained by FDA methodology (3) and that obtained using classical statistics is in the form of regression coefficients. In the FDA methodology, the regression coefficients as well as the dependent and independent variables are functions. All data in functional form are represented by linear expansion in terms of monomial basis functions. The main goal is to determine coefficient functions β_i, that is, their weight factors in linear basis expansion. That can be carried out by fitting penalized least squares criterion extended for functional data in the form

$$\mathrm{PL} = \int \left[\mathbf{y}(t) - \mathbf{Z}(t) \cdot \boldsymbol{\beta}(t)\right]^{\mathrm{T}} \left[\mathbf{y}(t) - \mathbf{Z}(t) \cdot \boldsymbol{\beta}(t)\right] dt + \sum_j \lambda_j \int \left[\frac{d^2}{dt^2} \beta_j(t)\right]^2 dt, \quad (4)$$

where $\mathbf{Z}$ is functional matrix that contains covariate functions and $\boldsymbol{\beta}$ is a vector of regression coefficient functions. Other symbols have been described in the text above. Computer code for solving (4) was written in MATLAB.

4. Flank Wear Prediction

After completion of the above-mentioned experiments FD, that is, $VB(t)$, $v_c(t)$, $f_t(t)$, $a_e(t)$, $F_x(t)$, $F_y(t)$, and $F_z(t)$, were created by using (2) for each experiment. That means 20 FD sets were created. One FD set consists of seven above-mentioned functions. Functions $v_c(t)$, $f_t(t)$, and $a_e(t)$ are constant for a particular experiment. Six FD sets of overall twenty were randomly chosen and set aside for the sake of testing of the proposed mathematical model. So fourteen FD sets were utilized for determination of regression coefficient functions β. These coefficients were determined by solving (4) and their appearance can be seen in Figure 6. Computing time for the calculation of the regression coefficients was 2.3 seconds on Intel Core (TM)2 Duo 1.97 GHz processor.

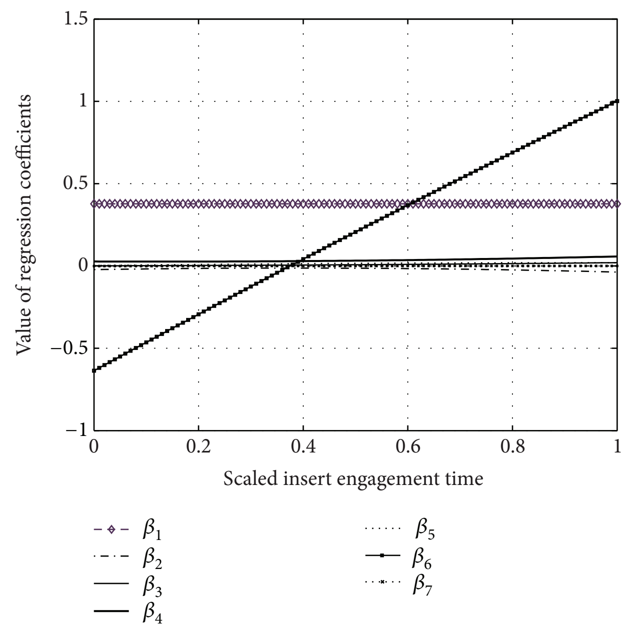

Figure 6: Regression coefficient functions β_1 to β_7.

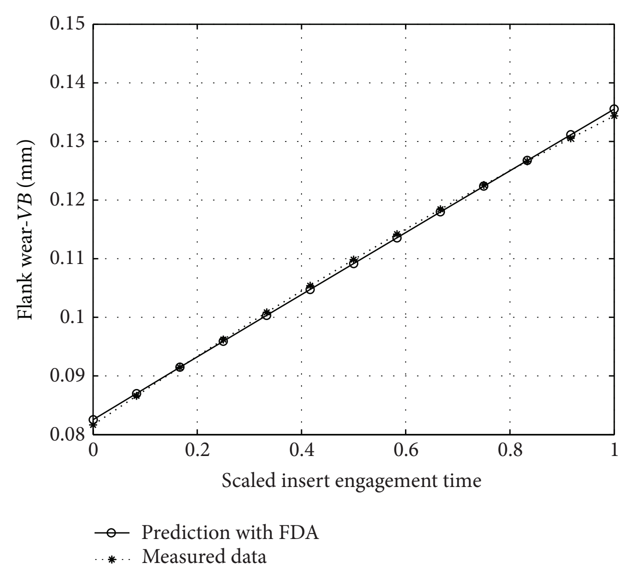

Figure 7: Comparison of the flank wear values predicted with the proposed model and experimentally measured ones for one randomly chosen functional datum out of the testing data set.

It can be noticed from Figure 6 that the greatest variability exhibits coefficients β_6 while other coefficients show only slight variations during insert engagement time interval.

Having determined regression coefficients functions proposed mathematical model has been completed and can be used for the flank wear prediction in various end milling conditions. In order to test the prediction power of the model one functional datum out of the testing data set was randomly chosen and put into the model. Results of that procedure are shown in Figure 7. This figure exhibits comparison between

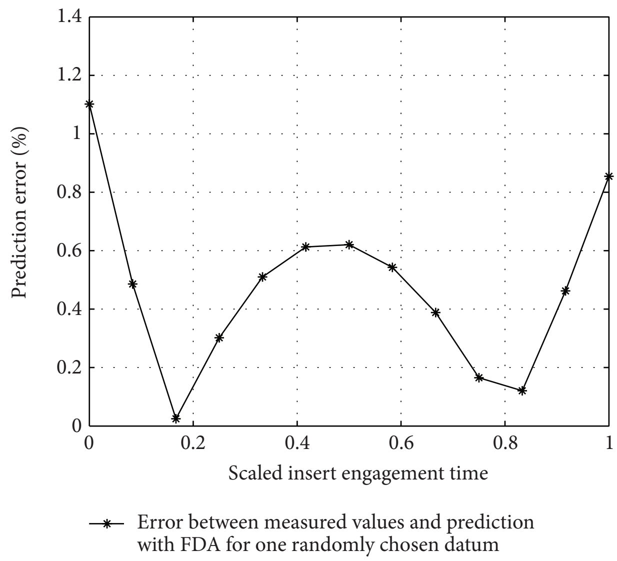

Figure 8: Prediction errors of the model for above-mentioned randomly chosen datum.

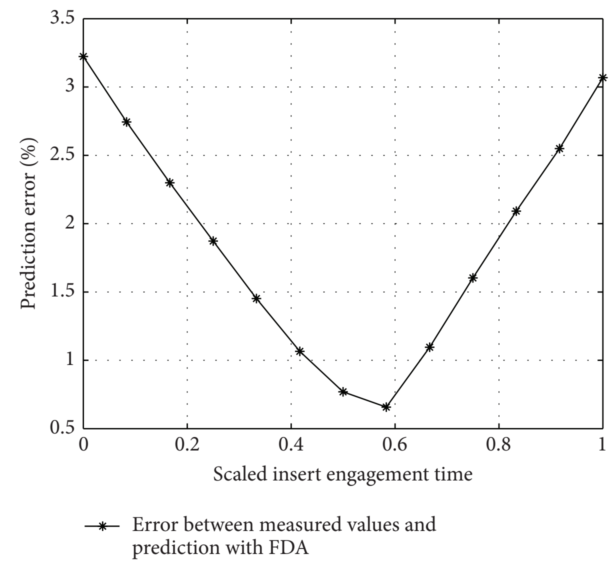

Figure 9: Average prediction errors of the proposed model when all testing FD are used.

values predicted by the proposed model and those measured during experiment for the above-mentioned randomly chosen functional datum. Computing time for the calculation of the predicted flank wear values was 0.15 seconds.

Qualitatively observing it can be noticed from Figure 7 that model has high prediction quality due to excellent matching between two curves. The extent of the prediction errors for this particular case can be calculated and it is shown in Figure 8.

As curve from Figure 8 confirms that there is excellent agreement between predicted and measured values for this particular case, the prediction error, if all insert engagement time is observed, is approximately 0.5% on average.

A better insight into the prediction quality of the proposed model can be obtained if all FD from the testing data set have been put into the model and average prediction error has been calculated. The results of that procedure are shown in Figure 9.

Curve depicted in Figure 9 indicates that prediction power of the proposed mathematical model is rather high. Namely, during the milling process the lowest and highest errors are approximately 0.6% and 3.3%, respectively. The average prediction error over whole milling interval is approximately 1.9% which is quite good result. Another way to present the quality of the model is to calculate correlation coefficients between measured and predicted values. That coefficient was obtained 0.998 which indicates excellent prediction power of the proposed mathematical model.

5. Conclusion

In this study, functional data analysis methodology has been used in order to design a mathematical model for flank wear prediction. Proposed mathematical model is a linear functional regression equation in which there are six independent variables (functions) that affect the flank wear. Three of them, cutting speed, feed per tooth, and radial depth of cut, are adjustable on the machine tool but were kept constant during particular experiment and the other three, milling force components F_x, F_y, and F_z, were measured during the milling process. Twenty pieces of FD were crated out of the performed experiments and fourteen of them were utilized for the assessment of regression coefficient functions.

Results of the mathematical model simulation show satisfactory agreement between values predicted with FDA and those measured during end milling process. As shown in the work, an average prediction error calculated by using overall testing data set over entire milling interval is approximately 1.9% and between measured and predicted values correlation coefficient is 0.998. Therefore, with this result at hand it can be concluded that the prediction power of the proposed model is quite high regardless of the fact that the proposed model is linear.

The main intention of this work was to verify the possibility of using FDA methodology in cutting processes especially in flank wear prediction. In FDA all variables are functions, and in this work all functional data are functions of time, so having determined regression coefficient functions in the proposed mathematical model one enables us to predict flank wear on-line at any moment during the milling process, provided that milling force components are monitored on-line.

FDA has a great deal of potential in machining production area and further research could be aimed at nonlinear models and testing universality of the proposed model under different experimental conditions such as different milling machines, tools, and workpiece materials.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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