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Predicting tool life in turning operations using neural networks and image processing

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ABSTRACT

A two-step method is presented for the automatic prediction of tool life in turning operations. First, experimental data are collected for three cutting edges under the same constant processing conditions. In these experiments, the parameter of tool wear, V_B, is measured with conventional methods and the same parameter is estimated using *Neural Wear*, a customized software package that combines flank wear image recognition and Artificial Neural Networks (ANNs). Second, an ANN model of tool life is trained with the data collected from the first two cutting edges and the subsequent model is evaluated on two different subsets for the third cutting edge: the first subset is obtained from the direct measurement of tool wear and the second is obtained from the *Neural Wear* software that estimates tool wear using edge images. Although the complete-automated solution, *Neural Wear* software for tool wear recognition plus the ANN model of tool life prediction, presented a slightly higher error than the direct measurements, it was within the same range and can meet all industrial requirements. These results confirm that the combination of image recognition software and ANN modelling could potentially be developed into a useful industrial tool for low-cost estimation of tool life in turning operations.

1. Introduction

Increasing the scope of automated turning processes will at all times have to respond to the highest requirements in terms of reliable predictions of tool life. Tool-life assessment usually requires significant time and material resources and is therefore a relatively expensive procedure. Hence, the importance of accurately predicting tool life and the cutting- edge replacement schedule, before defects or catastrophic wear stop the process, even more so as accurate tool life is crucial for optimizing cutting productivity and the cost of turning processes. Tool life depends directly on the level of tool cutting edge wear. If we are to control the surface conditions of the cutting edge and the prediction of machining time, then the level of cutting-edge wear must be very carefully established. There is a considerable body of research on cutting-edge wear that report prediction methods for tool-life and cutting-condition with the aim of preventing catastrophic wear.

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Recent publications on the subject include reports on studies of wear resistance and turning tool wear [1–5]. Soliman et al. [1] studied the parameters of cutting-edge wear for work-pieces with and without TiN with respect to the cutting time coating in various modes of dry turning. The cutting edge durability of coated tools has been found to be 4.5–5 times greater than that of uncoated tools. Jawaid et al. [2] studied the parameters of cutting-edge wear in the turning of Ti-6246 titanium alloy at various cutting speeds and feed rates. An optical microscope was used to measure tool wear and to determine tool life, both of which varied significantly at different feed rates and cutting speeds. Mrkvica et al. [3] discussed the tool life of Pramet Tools Ltd., studying varied intensities of tool wear at various feed rates and cutting speeds in the turning of an Inconel 718 alloy. Sadílek et al. [4] performed real-time monitoring of cutting tool wear on an XCSRNR2525M-1207SEN turning tool, by measuring impedance layers applied to Silicon Nitride Ceramic KS6000 inserts. Kupczyk and Komolka [5] studied the high durability of cutting insert edges made of WC-5 nanocrystalline cemented carbides in the turning of EN-ISO 42CrMo4 toughening steel. However, no real-time monitoring of these parameters may be found in the studies of tool wear and cutting edge durability described in [1–3,5]. The real-time electrical resistance measurement used in [4] requires the use of special tools, which significantly limits its use.

There are various papers that have described the monitoring of tool wear and the life of turning tools [6–12]. Rehorn et al. [6] offered a review of sensors and signal processing methodologies used for tool condition monitoring in turning, drilling and milling. Cakir and Isik [7] used the tool life and condition monitoring system to study variations in the cutting forces when turning AISI 1050 steel with coated and uncoated tungsten carbide ISO P25 tools. Sahin [8] compared the tool life of ceramic and cubic boron nitride (CBN) cutting tools when machining hardened bearing steels using the Taguchi method. Gadelmawla et al. [9] determined the correlation between the texture of machined surfaces and machining time. Krolczyk et al. [10] carried out a study to determine the life of carbide-coated tools and the tool point surface topography. Antonialli et al. [11] monitored tool life and tool wear of Inconel 625, and the resulting surface roughness following taper turning in comparison with straight turning was evaluated. Kundrák et al. [12] offered a mathematical model for tool life and its experimental assessment in the turning of 100Cr6 bearing steel with CBN tools at various cutting speeds.

Today, a whole range of neural network and Artificial Intelligence (AI)-based methodologies [13–38] have been developed that model the correlation between the input (process data) and the output (tool life or tool wear) parameters of the turning process. Ezugwu et al. [13] predicted tool life and failure modes in turning grey cast iron (grade G-14) with a mixed-oxide ceramic cutting tool (type K090). Tool life and failure mode for each experiment and the corresponding data were used to train an Artificial Neural Network (ANN), in this case a Multi-Layer Perceptron (MLP), using the back-propagation algorithm. Sick [14] assessed on-line and indirect tool-wear monitoring in turning with ANNs, comparing the methods applied in the publications and the methodologies used to select certain methods for the performance of simulation experiments, to evaluate the results and for their presentation. Abu-Zahra and Yu [15] used discrete wavelet transformations of ultrasound waves to measure the gradual wear of carbide inserts during turning. A three-layer MLP architecture was developed that yielded the best correlation (95.9%) of the ultrasound measurements with the level of tool wear. Scheffer et al. [16] conducted a comparative evaluation using ANNs and hidden Markov models (HMMs) for modeling complex correlations between the input set of sensor signal functions and tool life during turning. Ojha and Dixit [17] assessed tool wear by fitting a best-fit line on the data in the steady wear zone and establishing the time until tool failure by extrapolation. ANNs are often used to predict lower, upper, and most likely estimates of tool life. Silva et al. [18] used an artificial intelligence system for condition monitoring that is able to detect when a tool wears out. Natarajan et al. [19] expanded the use of the back-propagation feed from ANN to predict tool life in turning. Özel et al. [20] developed a multiple linear regression model and ANN models for predicting surface roughness and tool flank wear when finishing the turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts. Sarma and Dixit [21] compared the performance of a mixed oxide ceramic tool in dry and air-cooled turning of grey cast iron, taking into account tool wear, surface roughness of the machined piece, forces and cutting vibration. Pal et al. [22] offered an ANN-based sensor fusion model for a tool-wear monitoring system in turning processes. A wavelet packet tree approach was used for the analysis of the acquired signals, namely cutting strains in tool holder and motor current, and the extraction of wear-sensitive features. D'Addona et al. [23] used cognitive modelling of tool-wear progress based on ANN supervised training derived from investigational tool-wear measurements during industrial turning of Inconel 718 aircraft engines. They obtained a dependable trend of tool-wear curves for optimal utilization of tool life and stepped increases in productivity, while preserving the surface integrity of the machined parts. Attanasio et al. [24,25] compared Response Surface Methodology (RSM) with ANN fitting techniques for tool-wear prediction in longitudinal turning of AISI 1045 steel rods. These papers have all shown that the ANN models provide better approximations than RSM in the prediction of the amount of the tool-wear parameters. Finally, although ANN is the most common AI technique used for tool-wear prediction in turning [26], other AI techniques have been tested for this industrial task: Gajate et al. [27] presented a two model-based approach for tool-wear monitoring on the basis of neuro-fuzzy techniques. A four-input (i.e., time, cutting forces, vibrations and acoustic emissions signals) single-output (tool wear rate) model was designed and implemented on the basis of three neuro-fuzzy approaches (inductive, transductive and evolving neuro-fuzzy systems). Yiqiu et al. [28] tested Support Vector Machines (SVM) to predict tool wear, considering texture features of the surface as inputs with better generalization capabilities compared with ANN models.

Tool images as a source of data for assessing tool wear or tool life are usually used in the direct approach [29–38]. Jammu et al. [29] covered the use of unsupervised neural networks for tool breakage detection in turning assisted by a number of sensors. Pfeifer and Wiegers [30] discussed the advantages of machine vision as a direct measurement technique. Kerr et al. [31] described the use of digital image-processing techniques in the analysis of worn cutting-tool images for assessing their degree of wear and their remaining useful life. Castejón et al. [32] used 1383 images obtained using a CNC parallel lathe and a computer vision system for statistical system learning and estimation of the wear level in cutting inserts, in order to predict their useful working time before replacement. Barreiro et al. [33] studied the use of different moments to describe tool-wear images and to classify the tool condition in wear classes. The novelty of the study by Alegre et al. [34] is found in its use of contour signatures of the wear region as the input to two classification techniques, k-nearest neighbor and a neural network. D'Addona and Teti [35] implemented the procedure for the processing of cutting-tool images obtained during tests. D'Addona et al. [36] developed an Artificial Neural Network (NN) for automatic tool-wear recognition. Karam et al. [37] developed an ANN-based online cognitive system to predict tool life in turning operations. Mikołajczyk et al. [38] described ANN-based automatic image analysis for assessing tool wear. Their results promised a good correlation between the new methods and the commonly used optically measured V_B index, with an absolute mean relative error of 6.7% for the entire life range of the tools.

The purpose of this study is to build a bridge between both research lines: the development of AI-based models for image processing and the development of reliable AI-based models for wear prediction. The objective of this study is therefore the validation of a 2-step model for predicting the life of a turning tool that uses cutting-edge wear parameters obtained by image processing as inputs for an AI-based model. Artificial neural networks will be used to create such models, because of their extensive and reliable use in similar tasks.

The industrial advantage of such a proposal is clear: an automated tool will mean that manual and expensive tool-wear measurements will be unnecessary and, once the real-time cutting-edge wear parameter of the tool is known, the machine operator will be able to adjust the programmed cutting path, to avoid distortion of the machined dimensions due to tool wear. Besides, this 2-step system will mean significant automation and simplification of the procedure for determining the cutting-edge life.

2. Methods and materials

2.1. Research problem

The research problem can be described in terms of how to predict tool life based on measurements of the tool-wear parameter, V_B, in turning. Three trial tests were conducted on another edge. The in-process wear of two edges yielded results that were the data inputs to train the ANN edge-wear models based on the V_B parameter value. The results of observing the third edge were used to analyze tool-life predictions based on partial results of edge wear. Conventional measurements were taken by an operator using a standard method and an automated analysis of edge wear was performed with the *Neural Wear* software [38].

2.2. Experimental setup and measurement protocol

Machining experiments were performed on specimens of C45 carbon steel in the normalized state. The chemical compositions of the selected materials are specified in Table 1.

The workpiece was a cylinder with a diameter of 120 mm. All cutting parameters employed for the turning processes and the characteristics of the tool edges in use are specified in Table 2. For the turning process experiment, a modified universal lathe SNB400 (Romania) was used, equipped with a variable spindle speed control utilizing the TPC 60 inverter.

Turning was carried out for 1–2 min depending on the total tool operating time. The first five minutes of operating time were used as one-minute turning series. Two-minute turning sessions were applied throughout 4–12 min of the tool life. Finally, after 12 min of tool life, one-minute operating sequences were used.

After each work cycle, the cutting insert was removed from the holder and moved to the imaging station, where the flank and rake sides of the insert were digitalized. The resulting image files were then saved to the computer hard drive. At the same time, the V_B wear indicator value was read.

Measurements were carried out until the cutting edge-life indicator, V_B, reached a value of 0.4 mm. Three cutting inserts were tested in succession with this method.

The cutting edge image was recorded using a camera type CCD-FS-5612p at 684 × 512 resolution (S-VHS PAL, without overscan), digitized using the Aver card, using the Aver compression module for image compression (Fig. 1). An optical camera zoom of 100× was used. Finally, the image was converted to 256 grayscale windows bitmap file (BMP) format. Edge view was used for the measurement of V_B by an operator using special *MultiScan* software.

Table 1
Chemical compositions of material of the machined workpiece.

Material	Microstructure	Chemical composition %					
		C	Mn	Si	Cr	Ni	S
C45	Perlite + Ferrite	0.45	0.65	0.25	0.20	0.20	0.04

Table 2
Specifications of machining conditions.

Workpiece material	Machining operation	Cutting parameters								
		Rake angle, γ, deg	Back angle, α, deg	Angle of the main cutting edge, λ, deg	Major cutting edge angle, k_r, deg	Tool included angle, ε_r, deg	Corner radius, r_ε, mm	Cutting speed for turning, V, m/min	Feed rate, f, mm/rev	Depth of cut, a_p, mm
C45	Longitudinal turning with S20 uncoated carbide	−6	6	−6	45	90	0.4	220	0.067	0.6

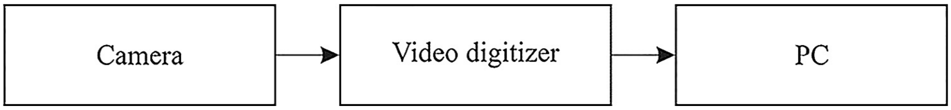

Fig. 1. Diagram of measurement and image capture system.

This approach obtained highly accurate measurements, although the measurements were taken by one person and therefore had an element of subjectivity. By doing so, it was possible to maintain a constantly updated image for the interpretation of tool wear.

The image analysis was performed on a PC. Customized software was used to simulate the operation of the SCBC neural network.

The cutting edge image, acquired before the turning process, was digitized because an initial sample is needed so that the network can distinguish between the background image and the cutting edge image.

The tool-wear research technique has previously been presented in a previous paper [38]. Edge wear was measured in two ways: directly in view of the edge and indirectly through computer analysis using a trained neural network. For this task, a specially developed *Neural Wear* software program (Fig. 2) [38] was used. In this software, the Single Category-Based neural network Classifier was used to process the tool image data; basically, a Kohonen network with a threshold activation function that analyzes the individual lines of the image to accelerate the recognition cycle of the wear field rather than

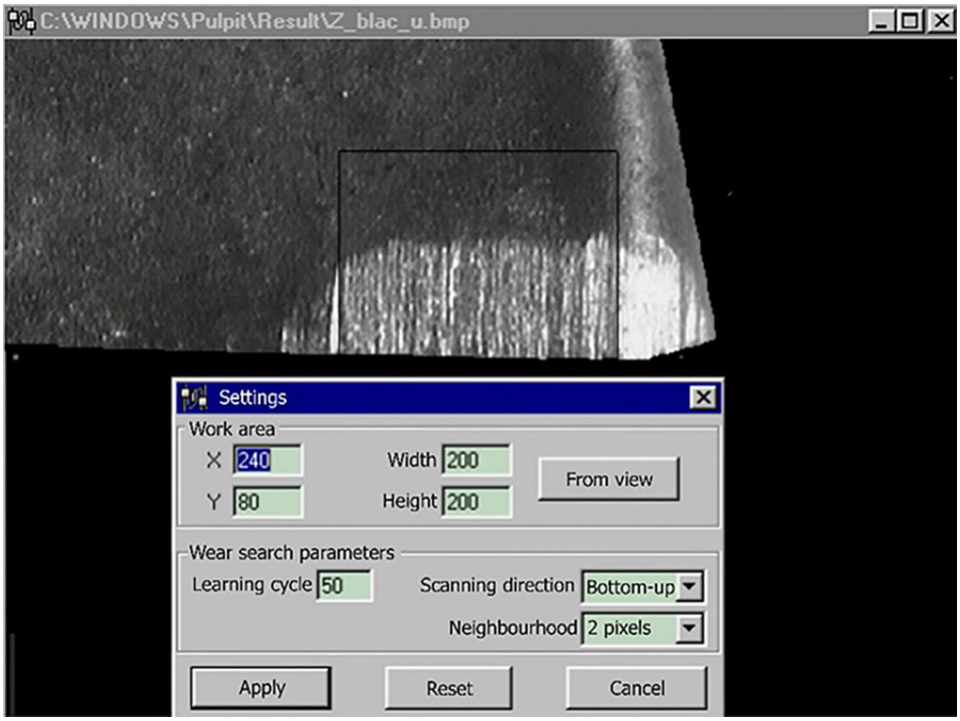

Fig. 2. *Neural Wear* software used to analyze images of third edge wear.

the whole image. For example, images of the worn edge were analyzed to show the best parameters to search for the worn areas using *Neural Wear*. The output of this analysis was the number of pixels that belonged to a worn area. An image analysis of edge wear for different working times was prepared with these settings. A calculated parameter of correlation between the number of pixels and the V_B index was used for comparative purposes (Fig. 3).

Based on an analysis of neighborhood size influence presented in [38], an eight-pixel neighborhood was used to analyze the worn edge images. As an example, the analysis of tool wear using the optimized settings of *Neural Wear* software is presented in Fig. 3.

2.3. Artificial neural networks modeling procedure

Edge-wear measurements were used to predict the lifetime of the cutting edge using ANNs. As described in the Introduction, ANNs were chosen because they are the most common AI technique for tool-wear prediction in turning operations [26]. The WEKA data-mining tool [39] was used in this research to build all the AI models. ANNs are built from many interconnected processing units that are called neurons, because of their functional analogies with human neurons. Different typologies exist in artificial neural networks, the most common of which is the Multilayer Perceptron [40]. A multilayer perceptron organizes the neurons in layers: in the input layer each neuron receives only one input: usually the value provided by a sensor. In the second layer, called the hidden layer, each neuron receives as many inputs as there are neurons in the input layer; in this research, only two inputs are considered for each experiment: the edge number (x_1) and the V_B (x_2), as will be explained later on; then the neuron will calculate its output using an activation function and a different weight for each input [41], finally it will transfer this value to the output layer where there is one neuron for each output or state to be predicted, dependent on whether the output is either a continuous or a discrete variable. Fig. 4 shows an example of a real neural network of the dataset presented in this research. The weight of each input for a neuron (expressed as W_{ij} in Fig. 4) is calculated by a back–propagation algorithm with two main parameters: momentum and learning rate [41]. This architecture has demonstrated its capability to model non-linearly-separable datasets [42].

The activation function, $\Phi(x)$, of the neurons in the input and hidden layer of the MLPs used in this work is shown in Eq. (1). This activation function is a hyperbolic tangent that belongs to the family of sigmoid functions. In Eq. (1), x represents a neuronal input. Only MLPs with one hidden layer are considered in this study, due to the reduced number of inputs.

$$\Phi(x) = \tanh(x) \tag{1}$$

The output of the neuron, $y(x_1,x_2)$, in the output layer is a linear combination of the outputs of n neurons in the hidden layer (n = 2 in this case), as shown in Eq. (2). The values of w'_{ij} are the weights of each connection of the network, as indicated in Fig. 4, and are calculated by the model during the training phase.

$$y(x_1, x_2) = \sum_{i=1}^{2} w'_{1i}\Phi(x_i) \tag{2}$$

In the MLPs used in WEKA software the weights of each neuron are learned from the training set in an iterative process. This process minimizes the error using the steepest descent, while the gradient is determined using the backpropagation algorithm: the change in weight, ΔW_i, in the i^{th} iteration is computed by multiplying the gradient by one parameter of the MLP, the learning rate *lr*, and adding the previous weight change multiplied by another parameter called the momentum *m*, as shown in Eqs. (3) and (4).

$$W_i = W_{i-1} + \Delta W_i \tag{3}$$

$$\Delta W_i = -lr \times gradient + m \times \Delta W_{i-1} \tag{4}$$

The dataset generated from the turning experiments has one output (tool lifetime) and one input (the V_B index). However, one of the main disadvantages of reducing the number of changing conditions in a cutting process to be modeled with AI techniques, which in turn is a requirement to maintain experimental costs, is the loss of accuracy of these techniques.

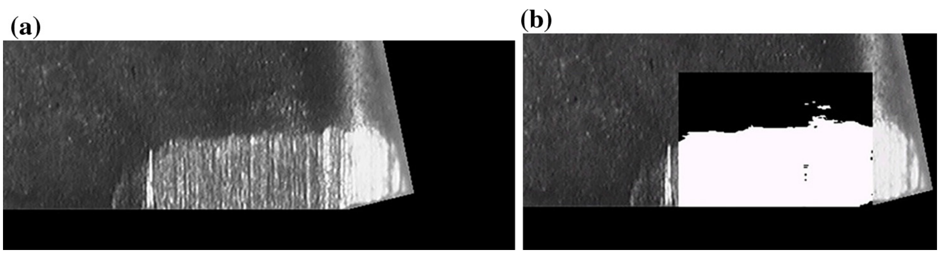

Fig. 3. Example of edge images before and after analysis using *Neural Wear* software (neighborhood 8 pix, width = 200 px), (a) before analysis, Time – 14 min, V_B = 0.378 mm, (b) after *Neural Wear*, Time – 14 min, wear area – 16318 px, V_{BNW} = 0.416 mm.

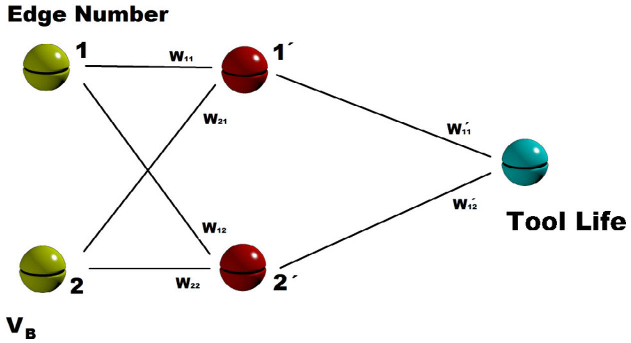

Fig. 4. Example of an MLP for the experimental dataset presented in this research.

One reason is that the predictive capabilities of any AI technique improve when many inputs are considered, because all of them are designed for noisy and multivariable environments as often happens in real life. In this research, the main objective is to reduce the number of inputs to be measured or monitored, in satisfaction of industrial requirements. By doing so, however, many variables that play an important role in the turning process are not taken into account. The number of the edge has also been considered as a second input for the ANNs, as at least one partial solution to this lack of direct information on the process. This strategy is at no-extra cost, because the process engineer should only label each new datum with the number of the cutting edge that has been used and the AI technique will, at the very least, have to differentiate the behavior of each edge (due to quality inhomogenities, differences in coatings, etc.). The use of small datasets for training artificial intelligence models is an open research topic that has merged many recent publications for different manufacturing problems [43,44]. These proposals attempt to solve the problem of insufficient instances using two approaches: cross-validation schemes and ensembles. Ensembles are combinations of more than one prediction model at the same time that achieve more stable and accurate predictions that are reliable solutions to many manufacturing problems. Unfortunately, most of the existing ensemble techniques are only suitable, if the dataset has many different inputs, while in our case the wear problem is defined with only two inputs to avoid the extra-cost of additional sensors, so only a cross-validation scheme can assure the accuracy of the ANN models, even though the number of instances is limited.

The dataset is split into two groups to calculate the weights of each connection in an ANN: the training set -that includes the instances that will be used to train the model- and the validation set -that includes the rest of the dataset instances, which are used to measure the accuracy of the model. The instances used at the validation-stage have not been used during the training-stage, to avoid over fitting: the prediction model will exactly calculate the weights for the training instances assuring a very high accuracy for the training dataset, but producing poor predictions for new instances with different conditions. Splitting the dataset into two subsets permits the two capabilities of the prediction model to be evaluated: the capability to adapt to known situations (training subset accuracy) and the generalization capability to deal with new situations (validation subset accuracy). In this research, the two first edges generated 30 training instances, while the third edge produced 15 instances that were used for validation purposes.

3. Results and discusion

In this Section, ANN capability to predict tool life is discussed; firstly, the ANNs are trained using the direct edge-wear measurements of two tools; secondly, the ANN model is validated using the direct edge-wear measurements of a third tool; finally, the same ANN model is validated using the estimated edge wear for the third tool, using the software tool developed in a previous paper [38]; the results are then sequentially presented in graphs and tables.

3.1. ANN training using direct measurement of edge wear

Once the experimental test was finished, the actual tool life was calculated, based on the result of the tool life of the full worn edge. The value of the V_B parameter was calculated from the conventional method presented in Section 2.2. Table 3 shows the actual values of tool life and the measured V_B parameter, while Fig. 5 shows the same results in the form of graphs.

Subsequently, the MLPs were trained using the data extracted from the experiments with edge number 1 and edge number 2 to predict the tool life; a process explained in Section 2.3. As previously explained, MLPs have three parameters that should be tuned to find their optimal values: number of neurons in the hidden layer, momentum, and learning rate. A grid search was then performed on the main parameters of each prediction model, to find the right combination. The most accurate configuration was found for 2 neurons in the hidden layer, with a learning rate of 0.01 and a momentum of 0.5. Table 3 also collects the predicted value of this MLP for each training condition and the difference between the actual and the predicted value; the differences are in the range of −0.9 to 1.6 min with a Root Mean Squared Error (RMSE) of 0.85 min. These errors can be visualized in Fig. 6, where both actual and predicted tool life are presented. It is interesting to point out that the

Table 3
Measurements of V_B index values of edges number 1 and 2 used for training the neural network for the prediction of tool life.

Number of edge	Cutting time [min]	V_B [mm]	Actual tool life [min]	Predicted tool life [min]	Differenceof time [min]	Relative error [%]	NN Process use
1	0	0.000	17	18.544	1.544	8.3	Training
1	1	0.182	16	14.587	−1.413	9.7	Training
1	2	0.196	15	13.889	−1.111	8.0	Training
1	3	0.210	14	13.101	−0.899	6.9	Training
1	4	0.224	13	12.223	−0.777	6.4	Training
1	6	0.252	11	10.214	−0.786	7.7	Training
1	8	0.266	9	9.105	0.105	1.2	Training
1	10	0.280	7	7.949	0.949	11.9	Training
1	12	0.308	5	5.589	0.589	10.5	Training
1	13	0.322	4	4.435	0.435	9.8	Training
1	14	0.336	3	3.328	0.328	9.9	Training
1	15	0.350	2	2.287	0.287	12.5	Training
1	16	0.357	1	1.796	0.796	44.3	Training
1	17	0.378	0	0.453	0.453	–	Training
2	0	0.000	17	18.635	1.635	8.8	Training
2	1	0.168	16	15.743	−0.257	1.6	Training
2	2	0.196	15	14.609	−0.391	2.7	Training
2	3	0.210	14	13.919	−0.081	0.6	Training
2	4	0.224	13	13.140	0.140	1.1	Training
2	6	0.266	11	10.277	−0.723	7.0	Training
2	8	0.280	9	9.173	0.173	1.9	Training
2	10	0.294	7	8.021	1.021	12.7	Training
2	12	0.308	5	6.842	1.842	26.9	Training
2	13	0.350	4	3.391	−0.609	18.0	Training
2	14	0.364	3	2.344	−0.656	28.0	Training
2	15	0.378	2	1.375	−0.625	45.5	Training
2	16	0.385	1	0.922	−0.078	8.5	Training
2	17	0.420	0	−1.001	−1.001	–	Training

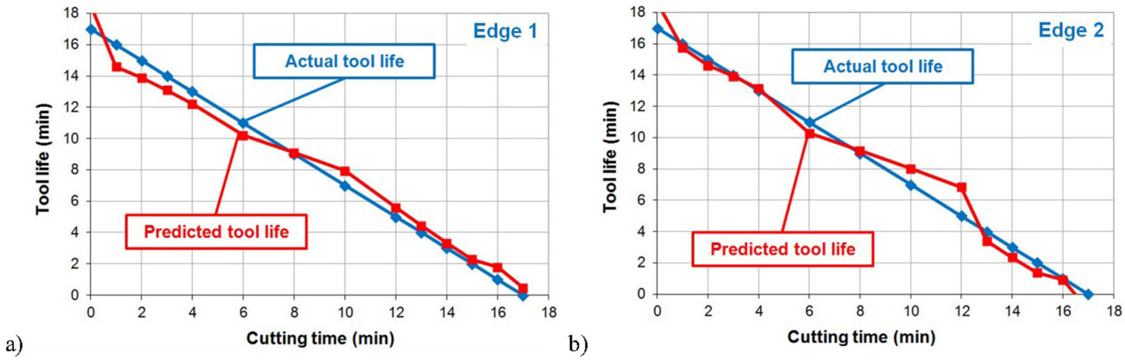

Fig. 5. Predicted and actual tool life for both cutting edges: (a) for Edge 1, (b) for Edge 2.

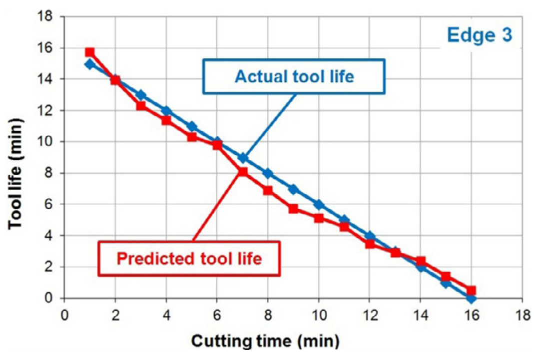

Fig. 6. Comparison of actual and predicted values of tool life for optical measurements of V_B for Edge 3.

correlation between wear and cutting time is not linear during the first minute of the turning process. At the same time, it achieves greater linearity in the rest of the cutting process; this dual behavior will determine the way the MLPs adapt themselves to the wear process, providing a higher error at the beginning of the cutting process (0–2 min).

3.2. ANN validation using direct measurement of edge wear

The MLP, trained with data extracted from Edge 1 and 2, was validated with data measured with Edge 3; the prediction results are shown in Table 4. The actual tool-life values and the predicted tool life are presented graphically in Fig. 6. The RMSE for these predictions is 0.678 min; an error margin that is in the same range as the RMSE for the validation data presented in Section 3.1 (0.85 min). This difference is due to a wear process of greater irregularity in the training dataset than in the validation dataset, a real possibility when working with small datasets. It is important to outline that the ANN model is very accurate for the three cutting edges under evaluation in the final range of the cutting time; or, the higher values of this cutting time. That range would be the most important in any industrial application of this model, because the machine operator would have to change the tool within that range, before tool breakage damaged the workpiece, or before the wear level could no longer assure the specified geometry of the final workpiece.

3.3. ANN validation using neural wear software for estimation of edge wear

Images of the wear zone of edge number 3 were analyzed using *Neural Wear* software that automatically calculated the V_B parameter based on image recognition. The results of the flank wear values of the V_B index for the third edge are presented in Table 5. These results were compared with the results of the automation analysis of tool wear, $V_{B\mathrm{nn}}$, using the sum of the pixels qualified, as in the wear area, by *Neural Wear* software. The wear coefficients, V_B and $V_{B\mathrm{nn}}$, are compiled in Table 5 and graphically shown in Fig. 7. The average and maximum absolute differences between the measured and computed data are 0.016 mm and 0.046 mm, respectively.

The maximum relative error was 20.6% for the case of 2 min (Table 5), while the average relative error was 6.7%. Although the average value of the relative error was relatively low, it presented a relatively high dispersion, a fact that will affect the ANN model described below.

The values of V_{BNW}, presented in Table 6, were used to predict tool life using neural networks trained on conventional measurements carried out for cutting-edge numbers 1 and 2. A comparison of the results of tool-life assessment obtained by experimentation and analysis of the neural network V_{BNW} ratio predictions are shown in Table 6. The results of the analysis are presented in Fig. 8.

A maximum error was specified in relation to the predicted tool life of 2.1 min with an average error of 1.10 min.

Figs. 7 and 8 show that the ANN prediction model is very sensitive to V_B errors, but, again, the ANN model is able to predict the most important wear condition: the last one (16 mm) for industrial use.

A comparison of neural network output error during processing of the V_B index and tool wear from *Neural Wear* – V_{BNW} is presented in Fig. 9. Some conclusions can be extracted from Fig. 9: first, the software tool presents a higher error in the calculation of tool wear than manual measurement of the wear, the ANN model shows higher errors in all cases (RMSE, mean error and maximal error) than in the training and validation subsets that include only tool wear values obtained from direct measurement. But, although the use of the software tool increases the error, it is still within the same range as the manual measurements (no more than 0.7 min in RMSE, 0.4 min in mean error and 0.3 min in maximal error). These results suggest that the combination of image recognition software and ANN modelling can be a useful industrial tool for low-cost estima-

Table 4
Measurements of V_B index values of edge number 3 used for validation based on the trained ANN.

Number of edge	Cutting time	V_B [mm]	Actual tool life [min]	Predicted tool life [min]	Difference of time [min]	Relative error [%]	ANN Process use
3	1	0.182	15	15.749	0.749	4.8	Validation
3	2	0.224	14	13.948	−0.052	0.4	Validation
3	3	0.252	13	12.317	−0.683	5.5	Validation
3	4	0.266	12	11.368	−0.632	5.6	Validation
3	5	0.280	11	10.338	−0.662	6.4	Validation
3	6	0.287	10	9.797	−0.203	2.1	Validation
3	7	0.308	9	8.092	−0.908	11.2	Validation
3	8	0.322	8	6.915	−1.085	15.7	Validation
3	9	0.336	7	5.733	−1.267	22.1	Validation
3	10	0.343	6	5.149	−0.851	16.5	Validation
3	11	0.350	5	4.572	−0.428	9.4	Validation
3	12	0.364	4	3.455	−0.545	15.8	Validation
3	13	0.371	3	2.919	−0.081	2.8	Validation
3	14	0.378	2	2.401	0.401	16.7	Validation
3	15	0.392	1	1.424	0.424	29.8	Validation
3	16	0.406	0	0.533	0.533	–	Validation

Table 5
Wear indicators for tool-cutting edge number 3 resulting from optical measurements and wear image analysis using *Neural Wear* software [38].

Number of edge	Cutting time T, min	Flank wear, V_B, mm	Wear area, number of pixels	Flank wear, V_{Bnn}, mm	Abs. diff. dV_B, mm	Relative error %
3	2.00	0.224	6963	0.178	−0.046	20.6
3	4.00	0.266	10096	0.258	−0.008	3.1
3	6.00	0.287	10945	0.279	−0.008	2.6
3	8.00	0.322	13000	0.332	0.010	3.1
3	10.00	0.343	12070	0.308	−0.035	10.2
3	12.00	0.364	14152	0.361	−0.003	0.7
3	14.00	0.378	16318	0.416	0.038	10.2
3	16.00	0.406	16346	0.417	0.011	2.8

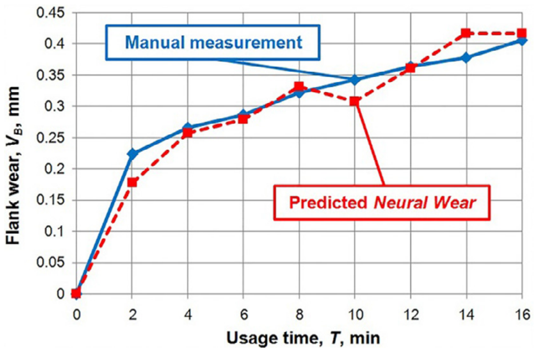

Fig. 7. Comparison of tool wear measured as V_B and as normalized image pixel count using *Neural Wear* [38].

tion of tool life in turning operations. The results that are presented are only valid for those specific cutting conditions, because the cutting parameters remained unchanged in the experiment. Edge-wear gradients during cutting time depend on the cutting parameters although other data would require new learning processes. However, the procedures presented here permit tool-life prediction, if the current settings are maintained for the cutting parameters.

4. Conclusions

The overall picture from the literature review would suggest that AI-based models are suitable for two main tasks related to the automation of wear prediction in turning operations: image processing to evaluate existing tool wear and wear prediction considering the previous behavior of similar tools. By merging these two research lines, a two-step method has been presented in this paper for the automatic prediction of tool wear in turning operations. First, the V_B parameter of tool wear was measured by conventional means for three cutting edges under the same constant turning conditions. Second, an ANN model was trained with the data collected from the first two cutting edges and the generated model was evaluated on the third cutting edge. The comparison of predicted values and real wear values showed a high level of accuracy, especially in the range of high wear levels; the most important under industrial conditions. Third, the ANN model was trained to predict tool life considering an automatically estimated V_B, using an image-processing tool that included an ANN model. Although this complete-automated solution presents a higher error, it is within the same range as direct measurement and meets indus-

Table 6
Results of V_{BNW} tool wear data calculated using the Neural *Wear* software for the validation of the neural network.

Number of edge	Cutting time [min]	V_{BNW} [mm]	Actual tool life [min]	Predicted tool life [min]	Difference of time [min]	Relative error %	NN process use
3	2	0.178	14	15.89	1.89	11.9	Validation
3	4	0.258	12	11.93	−0.073	0.6	Validation
3	6	0.279	10	10.42	0.42	4.1	Validation
3	8	0.332	8	6.08	−1.92	31.6	Validation
3	10	0.308	6	8.10	2.10	25.9	Validation
3	12	0.361	4	3.70	−0.30	8.1	Validation
3	14	0.416	2	−0.038	−2.04	[a]5363.2	Validation
3	16	0.417	0	−0.094	−0.094	–	Validation

[a] The relative error might not be taken into account for a cutting time of 14 min, because the predicted value (divisor in the division sum) is very close to zero.

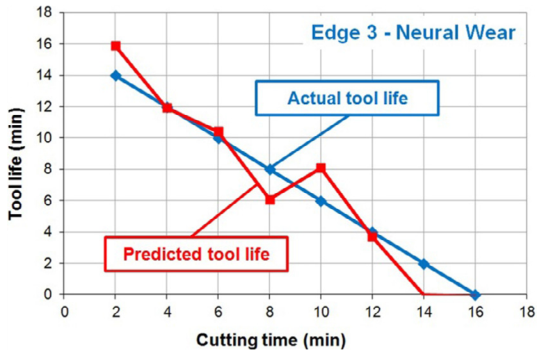

Fig. 8. Comparison of experimental and neural network results of a tool life estimation (edge No. 3, V_{BNW} index).

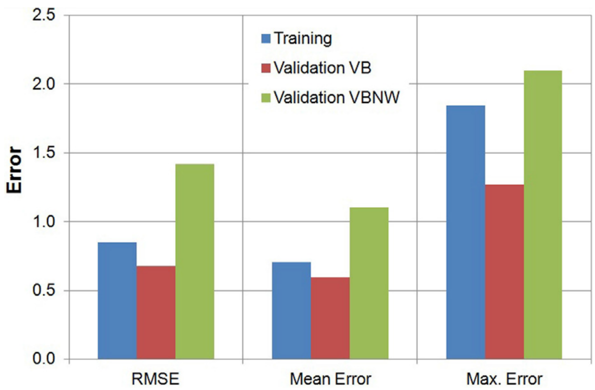

Fig. 9. Comparison of neural network output error during processing V_B index and tool wear from *Neural Wear* - V_{BNW}.

trial requirements, especially because of its highly accurate predictions for the highest tool-wear values. The database should for practical use be supplemented with other edge-wear cases for neural learning to predict tool life, because the edge-wear gradient depends on the cutting conditions (mainly speed, feed rate, and workpiece material). The edge-wear recognition software -*Neural Wear*- recognizes the image of the edge as an input and will if possible classify the level of edge wear with no further research. The results are then fed into the ANN based tool-life prediction system.

Future research lines will be focused on improving the accuracy level of this 2-step approach. Two strategies will be followed: first improvements to the accuracy of the image-processing tool will be done by enlarging the ANN model training dataset with new instances collected under different turning conditions, new cutting edges etc.; second, the accuracy of the tool-life prediction model will be increased by testing other AI-based models such as regressor ensembles.

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