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Dimensionality Reduction of Sensorial Features by Principal Component Analysis for ANN Machine Learning in Tool Condition Monitoring of CFRP Drilling

Alessandra Caggiano[a,b,*], Roberta Angelone[b,c], Francesco Napolitano[b,c], Luigi Nele[c], Roberto Teti[b,c]

[a]*Department of Industrial Engineering, University of Naples Federico II, Naples, Italy*
[b]*Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT UniNaples), Naples, Italy*
[c] *Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, Naples, Italy*

* Corresponding author. Tel.: +39-0817682371; fax: +39-0817682362. *E-mail address:* alessandra.caggiano@unina.it

Abstract

With the aim to perform sensor monitoring of tool conditions in drilling of stacks made of two carbon fiber reinforced plastic (CFRP) laminates, a machine learning procedure based on the acquisition and processing of thrust force, torque, acoustic emission and vibration sensor signals during drilling is developed. From the acquired sensor signals, multiple sensorial features are extracted to feed artificial neural network-based machine learning paradigms, and an advanced feature extraction methodology based on Principal Component Analysis (PCA) is implemented to decrease the dimensionality of sensorial features via linear projection of the original features into a new space. By feeding artificial neural networks with the PCA features, the diagnosis of tool flank wear is accurately carried out.

Keywords: CFRP drilling; Tool condition monitoring; Machine learning; Principal Component Analysis

1. Introduction

Drilling of carbon fibre reinforced plastic (CFRP) materials is an increasingly common process in manufacturing industry, particularly in the aeronautical sector [1–3].

The main challenges of this process are related to the rapid tool wear due to the abrasiveness of the carbon fibres and the high risk of producing severe material damages such as delamination, especially when the tool gets worn out [3–5].

In this context, tool condition monitoring plays an essential role for a timely tool replacement strategy based on the actual tool wear state, allowing to optimally exploit the tool life [6–9].

With the aim to perform sensor monitoring of tool conditions during drilling of stacks made of two CFRP laminates, a machine learning procedure based on the acquisition and processing of thrust force, torque, acoustic emission and vibration sensor signals is developed in this research work.

From the acquired sensor signals, multiple sensorial features are extracted to feed artificial neural network-based machine learning paradigms, and an advanced feature extraction methodology based on Principal Component Analysis (PCA) is implemented to perform sensorial features dimensionality reduction. In this way, a smaller number of q features, the principal component scores, able to describe the variance of the sensorial data, are obtained via linear projection of the original d features into a new space with reduced dimensionality q. By feeding artificial neural networks with the PCA features, an accurate diagnosis of tool flank wear is carried out.

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2. Experimental tests

Experimental tests of CFRP/CFRP stack drilling were carried out with the objective to reproduce the industrial setup employed during the aeronautical drilling process. The setup including CNC machine tool, multiple sensor monitoring system, workpiece, tool and parameters is described hereafter.

2.1. CNC machine tool and multiple sensor monitoring system

The machine tool selected to carry out the drilling tests is a vertical CNC drill press equipped with a multiple sensor monitoring system which is composed of:

- Kistler 9257A piezoelectric dynamometer to acquire the thrust force along the vertical direction, F_z.
- Kistler 9277A25 piezoelectric dynamometer to acquire the cutting torque along the vertical axis, T.
- Montronix BV100 sensor to acquire the acoustic emission, AE_{RMS}, and the vibration acceleration, V.

The analog signals were amplified and sent to a NI USB-6361 DAQ board for digitalization at 10 kS/s sampling rate.

2.2. Workpiece details

The workpiece employed is represented by CFRP/CFRP stacks commonly used in the aircraft fuselage assembly. In order to reproduce the industrial operating conditions, each stack is composed of two superimposed laminates to be drilled together. Each laminate has a thickness of 5 mm and is made up of 26 prepreg unidirectional plies arranged according the following stacking sequence $[\pm45_2/0/90_4/0/90/0_2]_s$, with a lightweight 0°/90° fiberglass/epoxy fabric on the laminate top and bottom. The prepreg plies are made of Toray T300 carbon fibres and CYCOM 977-2 epoxy matrix. The laminates display two differently finished surfaces because they were produced using vacuum bag moulding and autoclave curing, so the surface on the bag side is very irregular. The two CFRP laminates of a stack were placed with their bag sides in contact.

2.3. Tool details

The tool selected for the experimental tests is commonly employed in the aircraft industry for CFRP drilling. It is a 2-flute twist drill bit with 4.85 mm diameter, 120° point angle and 30° helix angle made of tungsten carbide (WC). Based on the tool geometry and according to the literature, tool flank wear is expected due to the effect of the fiber cutting and the cobalt loss which is softer than the base material and suffers the abrasive effect of the carbon fibers [10].

2.4. Cutting parameters

During the experimental tests different cutting parameters were adopted with the aim to study the drilling process behavior under diverse cutting conditions. Two parameter combinations were proposed by the industrial partner, 2700 rpm - 0.11 mm/rev and 6000 rpm - 0.20 mm/rev. The other combinations were proposed considering that on the one hand, increasing the spindle speed helps increase the productivity, on the other hand, decreasing the feed reduces the thrust force exerted on the laminate and the related delamination damage.

2.5. Tool wear measurement

The mechanisms of tool wear can occur on different parts of a drill bit, but the most widely employed parameter used for tool wear monitoring with these tool geometries is flank wear, expressed in terms of VB and VBmax values in mm [11–13].

To measure flank wear of the drill bits during the experimental drilling tests, a Tesa Visio V-200 optical measuring machine was employed. The drill bits were notched to identify the left and right side and clamped in a fixture to make the measuring process repeatable.

In order to evaluate the tool wear, after every 10 consecutive drilled holes the flank wear (VB) was measured. The VB (mm) was evaluated according to the reference proposed by [14,15] and calculated for both left and right cutting edges as in Fig. 1.

For each drilling condition, 6 VB values were obtained both on the left and the right tool side, then the average was calculated, and a third order interpolation curve was built to describe the entire tool wear development (Fig. 2).

Table 1. Experimental testing conditions.

Test no.	T1	T2	T3	T4
Spindle speed (rpm)	2700	6000	6000	7500
Feed (mm/rev)	0.11	0.15	0.20	0.20

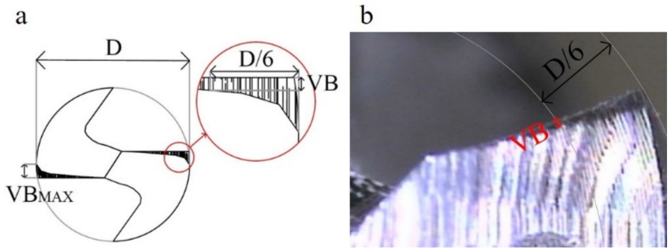

Fig. 1. a) Operational definition of VB and VBmax b) Experimental procedure for VB measurement.

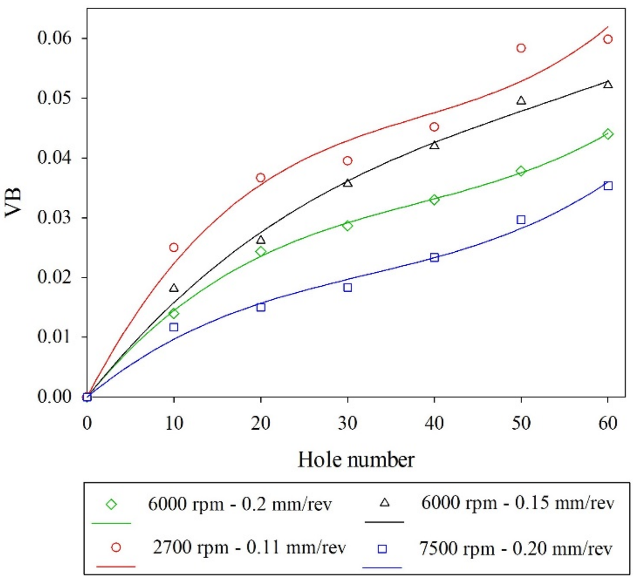

Fig. 2. Measured flank wear values and interpolated flank wear curves.

3. Signal processing and analysis

3.1. Signal segmentation

The acquired sensor signals comprise a transient portion, located at the beginning and at the end of the signals, related to the movement of the tool before and after the actual machining.

In order to perform sensor signal features extraction, the first step consists in the isolation of the relevant machining portion of the signal. The segmentation procedure is based on the identification of the start and end machining points by analyzing the thrust force signals. The acquired sensor signals have high frequency oscillations which make the identification of the significant points hard (Fig. 3) so the thrust force signal was filtered using a moving average based on 150 points (Fig. 4). Based on the start and end points of the filtered thrust force signal, the original acquired thrust force, torque, acoustic emission and vibration signals were segmented (Fig. 5).

3.2. Sensor signal features extraction

With the aim to find correlations between the sensor signals and the tool wear, a conventional statistical analysis in the time domain was performed to extract, from each sensor signal, these 5 features: average, variance, skewness, kurtosis, energy.

Accordingly, a total number of 5 × 4 = 20 features were extracted for each drilled hole, making up a feature set of n = 60 feature vectors (where n = 60 is the number of holes) in a *20*-dimensional space (d = 20 features for each hole) for each experimental test of Table 1.

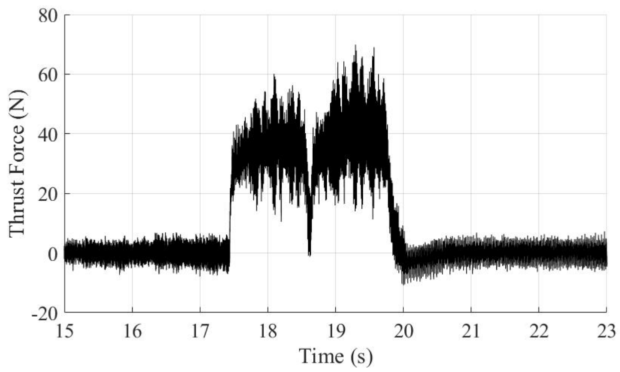

Fig. 3. Acquired thrust force signal. 2700 rpm - 0.11 rev/min, hole no. 1.

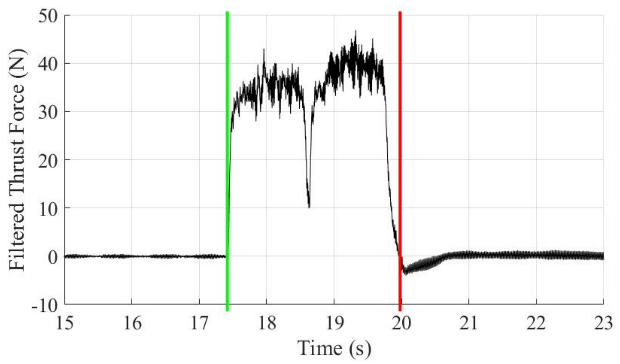

Fig. 4. Filtered thrust force signal. 2700 rpm - 0.11 rev/min, hole no. 1.

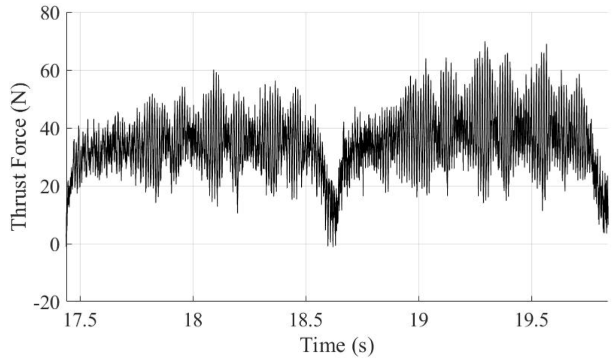

Fig. 5. Segmented thrust force signal. 2700 rpm - 0.11 rev/min, hole no. 1.

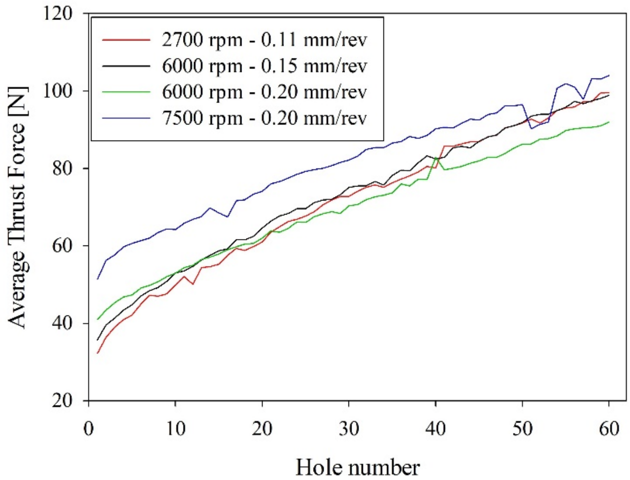

Fig. 6. Thrust force average values ($F_{z,avg}$) vs. hole number for all the experimental testing conditions.

4. Feature dimensionality reduction

In machine learning, it is essential to reduce the feature set dimensionality to simplify modelling, decrease the problem complexity and shorten the training time. Simpler models are also more robust on small datasets and are less affected by variance due to noise or outliers [16,17].

However, to avoid loss of information, suitable techniques of feature selection (to select a subset of significant features) and feature extraction (to generate a lower number of new features from the initial ones) are required [16,17].

In this work, feature set dimensionality reduction was performed on the sensor signal features by using an initial supervised feature selection method to cut off irrelevant features followed by an unsupervised feature extraction method based on linear projection via Principal Components Analysis (PCA) to combine the relevant features into fewer new features.

4.1. Features selection based on Spearman's correlation

A filter method for feature selection based on the Spearman's correlation coefficient, r_s, was employed to isolate the relevant features by evaluating the correlation between the features and the output tool wear values. For each feature x, the correlation with the measured tool wear y was evaluated by calculating r_s, able to identify three correlation classes: if $0 < r_s$

< 0.3, correlation between variables is weak, if 0.3 < r_s < 0.7, correlation is moderate, if 0.7 < r_s < 1, correlation is strong.

Based on this coefficient, the features showing the highest correlation with tool wear were selected: thrust force average, $F_{z,avg}$, torque average, T_{avg}, thrust force variance, $F_{z,var}$, torque variance, T_{var}, acoustic emission variance, $AE_{RMS,var}$, torque skewness, T_{ske}, acoustic emission skewness, $AE_{RMS,sk}$, acoustic emission kurtosis, $AE_{RMS,kur}$.

The identified correlations are also confirmed by graphical analysis: as an example, the thrust force average shows a rising trend with increasing hole number (Fig. 6) confirming good agreement with tool wear progression (Fig. 2).

Using the filter method for feature selection, the number of features was initially cut from 20 to 8 features by removing those which did not exhibit a robust correlation with tool wear.

4.2. Features extraction via Principal Component Analysis

With the aim to further decrease the number of features and hence reduce the feature set dimensionality without going through any loss of information, a feature extraction method based on linear projection via Principal Components Analysis (PCA) was adopted [16–18]. PCA consists in an unsupervised linear projection allowing to perform a mapping from the input vectors $\boldsymbol{x}$ in the original d-dimensional space to new vectors $\boldsymbol{z}$ in the q-dimensional space (with $q < d$), with minimum loss of information. In practice, PCA identifies new variables along new directions, namely the principal components, that are linear combinations of the original variables. PCA is an unsupervised technique since it does not utilize the output data.

The criterion to be maximized is the variance. The principal components are computed as the normalized eigenvectors of the covariance matrix of the original variables and ranked according to how much of the variation existing in the data they comprehend. The first principal component, PC1, is the eigenvector of the covariance matrix of the input sample with the largest eigenvalue, that is the direction along which the samples show the largest variation. The second principal component, PC2, is the direction, uncorrelated to the first component, with the largest eigenvalue, and so on. The positions of each observation in this new coordinate system of principal components are called scores and are linear combinations of the original variables and the relative weights.

Given a set of data vectors in a d-dimensional space, if the first q eigenvalues have significantly larger values than the remaining d-q eigenvalues, it means that the data can be represented to a relatively high accuracy by projection onto the first q eigenvectors. If the dimensions are highly correlated, there will be few eigenvectors with large eigenvalues, hence q will be much smaller than d and a notable dimensionality reduction may be achieved. If the dimensions are not correlated, q will be as large as d and PCA is not helpful.

In this work, PCA was applied via Singular Value Decomposition (SVD), which is a computationally efficient method for determining principal components. Through linear projection from the d = 8 original statistical features, d = 8 principal components were generated (named PC_1, …, PC_8).

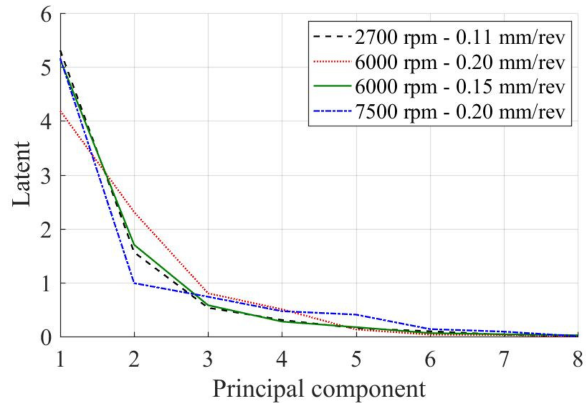

Figure 7. Scree plot reporting the variance explained as a function of the principal components for all the drilling tests.

To decide the suitable size of q ($q < d$) allowing for feature reduction without loss of important information, visual analysis through the scree graph technique was employed. The scree graph is the plot of variance explained (i.e. the eigenvalues of the covariance matrix of $\boldsymbol{x}$) as a function of the number of eigenvectors (i.e. the principal components). When the plot takes a bend displaying an "elbow", it indicates that adding another eigenvector does not considerably increase the variance explained.

Figure 7 shows the scree plot reporting the variance explained as a function of the principal components for all the drilling tests. The plot elbows suggest that a number of q = 2 components is sufficient to describe the variance of the data. Hence, for all the drilling tests, the first 2 principal components were selected to be used for machine learning.

Specifically, the scores, i.e. the representations of the original data in the principal component space, corresponding to the first 2 principal components were used as input for machine learning. The principal components scores are sensor fusion features, as they are linear combinations of the original features extracted from the multiple sensor signals of different nature (in this case force, torque and acoustic emission).

In this way, a significant dimensionality reduction by one order of magnitude was achieved, decreasing the number of required features from the initial 20 statistical features to 8 features via statistical correlation and finally to 2 features via PCA. Irrelevant features were cut off and the significant ones were combined to retain important information.

In practice, each of the 4 experimental tests in Table 1 was initially represented by a set of n = 60 data vectors (where n = 60 is the number of holes) in a *20*-dimensional space (d = 20 features for each hole). After the implementation of the PCA method, the data set for each experimental test was drastically reduced to a set of n = 60 vectors in a smaller *2*-dimensional space (q = 2 principal components for each hole n_i).

Graphical analysis of the first principal component scores plotted together with the corresponding tool wear value, VB, shows that the behaviour with increasing hole number is in agreement with tool wear development. Fig. 8 illustrates the PC1 scores and the tool wear values for the drilling test carried out at v = 6000 rpm and f = 0.15 mm/rev.

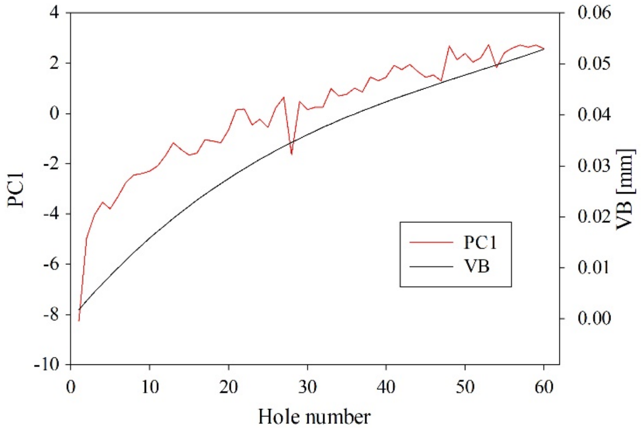

Figure 8. Scores of the first principal component, PC1, and measured tool wear values, VB, vs hole no. for test T3 (v = 6000 rpm, f = 0.15 mm/rev).

5. Machine learning for tool wear diagnosis based on Artificial Neural Network

With the aim to estimate the tool wear through cognitive pattern recognition based on the input PCA features extracted from the sensor signals, a machine learning model based on artificial neural networks (ANN) was developed [17,19,20].

The two selected PCA features, PC1 and PC2, were employed to construct sensor fusion feature pattern vectors (SFPVs) to be fed to the ANN for pattern recognition [21].

For each hole *i*, a 3-feature SFPV was built by combining the first two PCA features with the hole number, n_i.

$$SFPV_i = [PC1_i, PC2_i, n_i] \qquad i = 1, \dots, n \qquad (1)$$

Where *n* is the total number of drilled holes with the same cutting conditions and n_i is the specific hole number.

In this way, for each drilling test of Table 1, a learning set consisting of a number of $n = 60$ SFPVs, equal to the number of holes, was set up.

Supervised machine learning was implemented for each drilling test by associating each 3-feature SFPV to the corresponding flank wear value, VB.

Three-layer cascade-forward backpropagation ANNs were built with a number of input layer nodes equal to 3, that is the number of input features of each SFPV, and varying the numbers of hidden layer nodes between 3, 6, and 9 nodes, i.e. 1x, 2x and 3x the number of input layer nodes, with the objective to find the best ANN configuration providing the highest performance rate. The output layer had a number of nodes equal to 1, corresponding to the tool wear value, VB.

The Levenberg-Marquardt optimization algorithm was chosen for ANN training. ANN cross-validation was performed through the leave-k-out method with $k = 1$ [19]. According to the leave-k-out method, at each step, $k = 1$ SFPV was removed in turn from the original set of *n* SFPVs and used for ANN testing while the remaining *n-k* SFPVs were used for training. This procedure was repeated for all the *n* SFPVs and the overall pattern recognition performance was eventually estimated by aggregating the *n* recognition rates obtained.

6. Results

The tool wear diagnosis performance achieved by the different ANN architectures was estimated in terms of root mean squared error, RMSE, between the VB values predicted by the ANN and the measured VB values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(VB_{ANN} - VB_{meas})^2}{n}} \qquad (2)$$

Table 2 reports the RMSE values obtained by the ANNs for tool wear estimation of all the experimental turning tests. It can be observed that very low RMSE values, between $2.86\text{x}10^{-5}$ and $2.17\text{x}10^{-3}$, were achieved for all the experimental tests. These low values indicate that the ANN output values are very close to the measured flank wear values, therefore the ANN provided an accurate tool wear diagnosis. Table 2 also shows the influence of the varying number of hidden layer nodes: in most cases, the best performance was obtained with a lower number of hidden nodes, namely with the 3-3-1 configuration. In Fig. 9, the ANN predicted VB values are reported vs the measured VB values for the test carried out at v = 6000 rpm, f = 0.15 mm/rev. In the graph, the diagonal line indicates the perfect condition in which the measured VB and the predicted VB coincide: the minimal dispersion of values around this line allows to graphically evaluate the ANN tool wear prediction performance, which shows to be very accurate.

Table 2. Overall Root Mean Square Error (RMSE) obtained by ANN tool wear estimation for all the drilling tests.

	RMSE		
	3 nodes	6 nodes	9 nodes
2700 rpm – 0.11 mm/rev	8.95E-05	1.34E-04	1.78E-04
6000 rpm – 0.15 mm/rev	4.09E-04	2.17E-03	9.19E-04
6000 rpm – 0.20 mm/rev	1.18E-04	3.23E-04	4.78E-05
7500 rpm – 0.20 mm/rev	2.86E-05	1.73E-04	7.76E-05

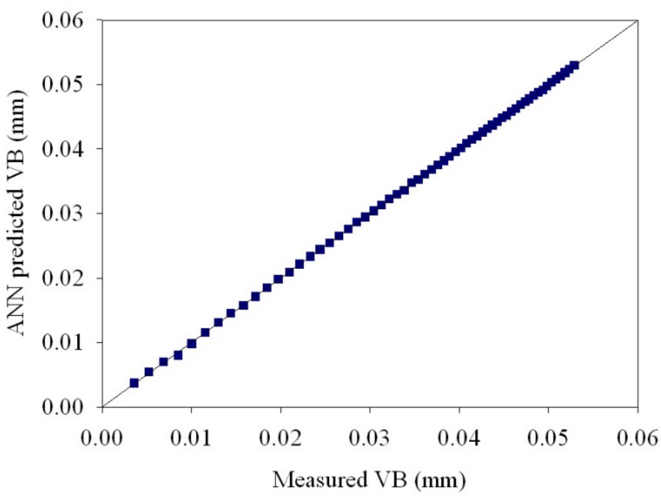

Fig. 9. Regression plot between ANN predicted and measured VB for test v = 6000 rpm, f = 0.15 mm/rev. ANN configuration: 3-3-1. RMSE = 4.09E-04.

7. Conclusions

With the aim to monitor the tool conditions during drilling of carbon fiber reinforced plastic laminates, a machine learning procedure based on the acquisition and processing of thrust force, torque, acoustic emission and vibration sensor signals during drilling was implemented.

The acquired sensor signals were processed to extract multiple sensorial features (d = 20 features) via conventional statistical technique to feed machine learning paradigms based on artificial neural networks for tool wear diagnosis based on pattern recognition. To reduce the large dimensionality of the sensorial features, a methodology based on a supervised feature selection method to cut off irrelevant features followed by an unsupervised feature extraction method based on Principal Components Analysis (PCA) was implemented.

PCA permitted to identify a lower number of features (q = 2 features), namely the principal component scores, obtained via linear projection of the original d features into a new space with reduced dimensionality q = 2, that showed to be adequate for describing the variance of the data. The extracted principal components scores represent sensor fusion features, being linear combinations of the original features extracted from the multiple sensor signals of different nature.

By feeding machine learning algorithms based on artificial neural networks with the PCA features, a very accurate diagnosis of tool wear (flank wear, VB) was achieved, with ANN predicted values very close to the measured tool wear values and root mean squared error always < 2.17E-03.

The accurate diagnosis of tool wear achieved via the machine learning procedure presented in this work can be effectively implemented on-line to monitor the tool conditions during drilling of CFRP stack laminates allowing for the actuation of more efficient tool replacement strategies based on the actual tool conditions.

The features set dimensionality reduction realised using the PCA based methodology allowed to improve the efficiency of the machine learning procedure, by lowering the complexity of the modelling and drastically reducing the number of useful data to be stored by one order of magnitude (from 20 features to 2 features for each drilled hole).

Data volume reduction is a main goal in modern manufacturing industry, where huge amounts of data are increasingly collected and utilised in the Industry 4.0 framework.

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