Chapter 5

Drilling of Fiber-Reinforced Composite Materials for Aeronautical Assembly Processes

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Additional information is available at the end of the chapter

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Abstract

Composite materials such as fiber-reinforced plastics (FRP) are increasingly employed in the aeronautical industry, where the reduction of aircraft weight is essential to meet environmental and cost requirements related to lower emissions and fuel consumption. Due to structural requirements, aeronautical assembly processes on FRP components are based on the wide use of mechanical joints such as rivets. As the latter require a former hole making process, drilling is extensively applied to FRP composites in the aeronautical industry. The main challenges in FRP composite drilling are related to rapid tool wear and damage generation which affects material integrity and surface quality, with particular reference to delamination damage generation. In this chapter, case studies of drilling of CFRP/CFRP stacks for aeronautical assembly are presented to investigate and discuss the influence of drilling parameters, tool type and geometry on tool wear development, hole quality and surface integrity, and the opportunity to implement advanced sensor monitoring procedures for tool condition monitoring based on the acquisition and processing of thrust force and torque signals.

Keywords: FRP composite materials, drilling, assembly processes, CFRP/CFRP stacks

1. Introduction

In the aeronautical industry, aircraft weight reduction is essential to meet environmental and cost requirements related to lower emissions and fuel consumption. The use of innovative light-weight materials such as fiber-reinforced plastics (FRP) has then significantly increased in recent aircraft components [1].

The assembly of FRP components for the aeronautical industry is generally performed by means of mechanical joining processes like riveting, which offer higher performance and less challenges compared to welding and adhesive joining techniques. As a consequence, hole making is a central process since a large number of holes is required to allow for riveting of aircraft components. Mechanical drilling using conventional or innovative drill bits is the most commonly employed hole making process for FRP components, although alternative nontraditional machining processes, such as laser and water-jet machining, have been developed in the last years [2, 3].

Despite the large application of FRP mechanical drilling processes, still efforts are required to optimize them since tool wear typically develops very fast, and severe damages can be easily generated on the workpiece, affecting material integrity and surface quality [4–7].

Numerous critical defects such as geometric/dimensional errors, entry/exit delamination, interlaminar delamination, fiber pullout, uncut fibers, spalling, and cracking and thermal damage can be generated by drilling of FRP laminates [8–11]. Drilled holes of low quality result in out-of-tolerance assembly and long-term weakening of structural properties, which are not acceptable in the aeronautical sector. Tight geometrical/dimensional tolerances and surface integrity need to be met as they are a key requirement to guarantee the functionality of the assembled components.

In the last years, several research studies have investigated the role of drilling process parameters, including cutting speed, feed rate, drill bit geometry, and composition, on the output product quality, with particular reference to carbon fiber-reinforced plastic (CFRP) laminates, which are the most commonly utilized in aerospace applications [1, 12].

Different types of tools, distinguished by diverse geometry and material, have been investigated for FRP composite drilling. A complete analysis of delamination produced by drills of different geometry, including traditional twist drills and innovative drills as candle stick drill, saw drill, core drill, and step drill was reported in [13]. To reduce the high wear rate of the sintered carbide drills, TiN and DLC coatings were employed in [14] for drilling of CFRP laminates, studying material damage, thrust force, and torque generated during processing. The experimental results showed that tool wear or damage was not significantly improved by using coatings. In [15], the performance of uncoated and diamond-coated carbide tools was investigated: the diamond coating provided significantly better results achieving a tool life 10–12 times higher than uncoated carbide drills and much higher cutting speeds (170 m/min against 56 m/min).

Drilling of CFRP laminates was also investigated in [16] to identify the most suitable drilling parameters satisfying the hole quality requirements, including surface integrity and roughness, hole roundness and diameter error, showing that the thrust force and the delamination damage were in agreement with the tool wear zones.

The studies in [17] on high speed drilling of CFRP laminates using K20 carbide drill bits under different drilling parameters (spindle speed and feed rate) showed that feed rate has a major influence on thrust force, push-out delamination, and hole diameter, whereas spindle speed is one of the key factors of the drilled hole roundness.

A thorough study on the cutting mechanism and the influence of cutting parameters on delamination in CFRP drilling was presented in [18], showing that thrust force is highly dependent on feed rate because higher feed rates cause greater undeformed chip thickness, while delamination is dependent on both spindle speed and feed, and the effect of feed is amplified at higher spindle speed.

Efforts have also been spent to model the thrust force engaged in drilling, recognized as a major factor affecting the quality of drilled holes [15, 19, 20]. However, modeling was most often limited to drilling of unidirectional laminates with simple geometry drill bits, and complex mathematical relationships were required to fully describe the complex mechanisms occurring during drilling of fiber-reinforced plastic laminates.

In this framework, the aim of this chapter is to investigate more complex industrially relevant FRP drilling processes such as drilling of multidirectional CFRP/CFRP stacks for assembly of aircraft fuselage panels, discussing the employment of innovative procedures based on the multiple sensor process monitoring for cognitive tool wear prediction and hole quality assessment.

2. Drilling of CFRP/CFRP stacks for aeronautical assembly

In the aeronautical industry, in order to assemble two CFRP components, the latter are typically superimposed and then drilled together in a "one-shot" process so as to allow for easier subsequent riveting avoiding misalignment issues. Accordingly, to reproduce the real operating conditions of the aeronautical industry, wide experimental campaigns have been focused on drilling of CFRP/CFRP stacks made by two overlaid CFRP laminates [21–23].

In the following subsections, drilling of CFRP/CFRP stacks for aeronautical assembly is discussed with reference to experimental studies on the influence of drilling parameters, tool type and geometry on tool wear development, hole quality and surface integrity, and the opportunity to implement advanced sensor monitoring procedures for tool condition monitoring based on the acquisition and processing of thrust force and torque signals.

2.1. Tool wear monitoring

In the aeronautical industry, the practice for CFRP/CFRP stack drilling is typically based on manual drilling processes, where tools are replaced largely in advance to avoid any risks of material damage due to early tool failure, since severe geometrical and dimensional tolerances need to be met, and surface integrity is crucial. To fully exploit the entire tool life and increase the productivity of the aeronautical industry through a higher automation of drilling processes able to preserve the integrity of the workpiece, a reliable on-line tool condition monitoring procedure is required [21].

With the aim to perform tool condition monitoring in drilling of CFRP/CFRP stacks, different methodologies have been developed [21, 22, 24]. Such methodologies are based on the employment of multiple sensor monitoring systems for the acquisition of thrust force and torque sensor signals to be used for tool wear estimation. The different procedures of advanced sensor signal processing and feature extraction implemented in the time and frequency domain are described in the following sections. On the basis of the features extracted from the force and torque sensor signals, it is possible to develop an artificial neural network (ANN)-based cognitive paradigm for pattern recognition with the aim to find correlations between the extracted sensor signal features and tool condition [21, 22, 24].

2.1.1. Analysis of cutting force and torque signals in CFRP/CFRP stack drilling

Advanced methodologies for tool condition monitoring were developed with reference to an extensive experimental campaign of drilling of CFRP/CFRP stacks for aeronautical industry assembly [21–26]. The CFRP/CFRP stacks employed in the tests were made of two superimposed symmetrical and balanced laminates of 5 mm each. The laminates consisted of 26 unidirectional prepreg plies made of Toray T300 carbon fibers and CYCOM 977-2 epoxy matrix, with stacking sequence $[\pm45_2/0/90_4/0/90/0_2]_s$ and a 0°/90° fiberglass fabric (80 g/m^2) on the top and bottom. Following vacuum bag molding and autoclave curing, the laminates displayed an uneven surface finish on the bag side. To test the hardest condition, as requested by the industry, CFRP/CFRP stack drilling was performed by facing the laminates with their uneven sides [21].

The drilling tests were performed on a CNC drilling center with a 2-flute 6.35 mm diameter with 125° point angle twist drill made of tungsten carbide (WC).

To assess the impact of the cutting parameters on the machinability of the CFRP stack laminates as concern tool wear and hole quality, different cutting conditions were adopted for the experimental drilling tests: feed = 0.11, 0.15, and 0.20 mm/rev; spindle speed = 2700, 6000, and 9000 rpm. For each cutting condition, 60 holes were realized with the same drill bit in order to evaluate the tool wear development.

During the experimental stack drilling tests, a multiple sensor monitoring system was utilized, consisting of a Kistler-9257A piezoelectric dynamometer to acquire the thrust force along the z-direction, Fz, and a Kistler-9277A25 piezoelectric dynamometer to acquire the cutting torque about the z axis, and T. A National Instruments NI USB-6361 DAQ board was employed to digitalize the analogue signals acquired by the force and torque sensors at 10 kS/s.

Figure 1 shows an example of thrust force signal acquired during the CFRP/CFRP drilling tests. Both the force and torque sensor signals displayed high frequency oscillations as those highlighted in **Figure 2**. This characteristic, not observed when drilling homogeneous and isotropic materials, is associated to the anisotropic nature of the CFRP laminates, which exhibit superior mechanical properties along the fiber directions.

As shown in earlier studies on cutting of FRP composites, the fiber orientation with regard to the cutting direction regulates the mechanism of chip formation and the quality of the cut surface [5]. Based on the angle formed between the cutting edge and the carbon fibers, also known as fiber cutting angle, different cutting modes can be identified [27].

In CFRP drilling, the fiber cutting angle changes during a half revolution of the drill, and the interaction mechanism between the tool and the laminate varies accordingly, causing diverse conditions of mechanical loading and resulting surface quality [27]. As a matter of fact, loading is influenced by cutting edge geometry and cutting mode and therefore varies during a drill revolution, as observed in the sensor signals acquired in CFRP drilling, which display high amplitude oscillations.

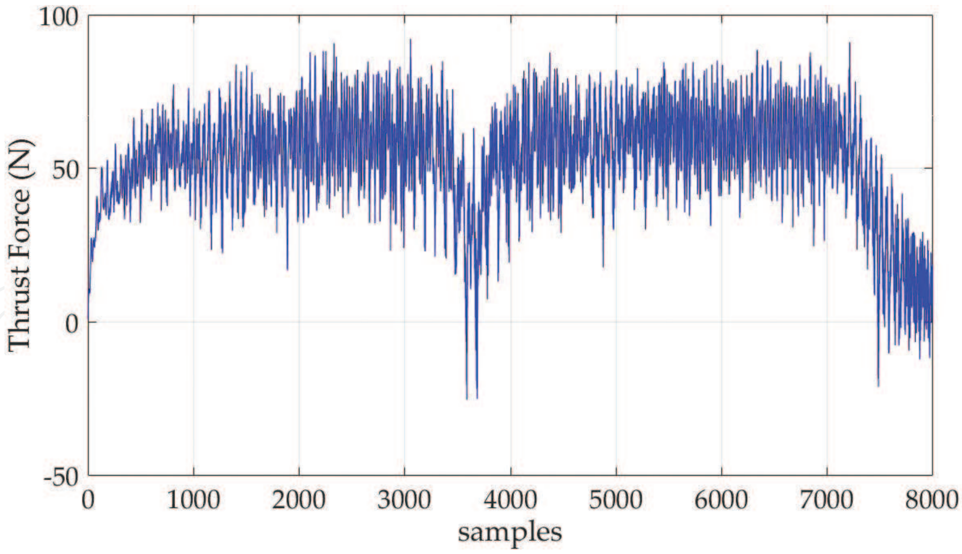

Figure 1. Thrust force sensor signal in CFRP/CFRP stack drilling (6000 rpm–0.15 mm/rev).

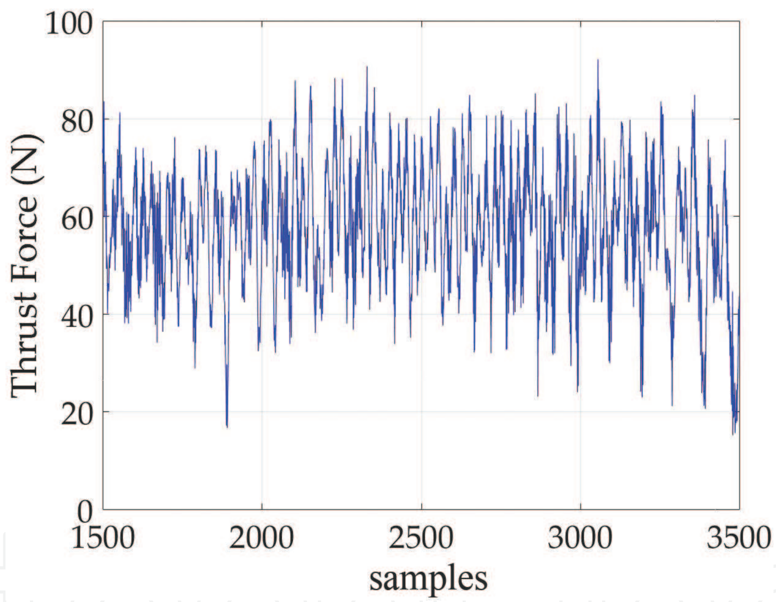

Figure 2. Enlarged thrust force signal: high frequency oscillations (6000 rpm–0.15 mm/rev).

Experimental studies have been performed with the aim to model the relationship between fiber cutting angle and cutting force in drilling of unidirectional CFRP laminates, obtaining the calculation of force coefficients as a sine wave function of 2θ, where θ is the fiber cutting angle [28]. In [27], in order to investigate the effect of local feed force on delamination in drilling of unidirectional CFRP laminates, a model was proposed by resolving cutting forces into steady and transient components, the first associated to the progressive engagement of the cutting edge, and the second associated to the cutting modes. Drilling of multidirectional CFRP laminates is far more complex: different cutting modes take place at the same time along the cutting edge, due to the diverse fiber orientations of the multiple plies simultaneously cut by the drill cutting edge.

Because of the overlap of different cutting modes in both space and time, the high amplitude oscillations that can be observed in the thrust force and torque signals acquired during drilling of the multidirectional CFRP laminates are the sum of multiple waves having a phase difference dependent on the different fiber orientations (e.g., 0, 45, 90, −45°) and having an amplitude related to the number of plies with same fiber orientations concurrently cut by the drill cutting edge.

2.1.2. Sensor signal feature extraction and selection in the frequency domain and neural network pattern recognition for tool wear estimation

With the purpose to explore the complex frequency content of the thrust force and torque sensor signals acquired in the multidirectional CFRP/CFRP stack drilling experimental tests, advanced signal feature extraction in the frequency domain was carried out in [21] with the final objective to find correlations between the extracted frequency domain sensor signal features and the tool wear state. The fast Fourier transform (FFT) algorithm was applied to translate the signals into the frequency domain. Following this transformation, a number of significant peaks were detected at frequencies equal to 1, 2, 3, 4, 5, and 6 times the revolution frequency of the tool. For instance, on the FFT of the thrust force signals acquired in the CFRP/CFRP stack drilling tests carried out at 6000 rpm and 0.15 mm/rev, in which the revolution frequency is 6000 rpm/60 = 100 Hz, the tallest frequency peaks were found at 100, 200, 300, 400, 500, and 600 Hz, that is, 1x-6x the revolution frequency, as visible in **Figure 3**.

As regards the torque signals, the tallest frequency peaks were found at 1x-4x the revolution frequency (100, 200, 300, and 400 Hz).

This seemed to confirm the tight connection between the peaks of the signal frequency transform and the effect of the cutting angle variation during the drilling process due to the several fiber orientations in the multidirectional laminates.

The amplitudes of the identified force and torque frequency peaks with increasing number of holes were investigated, showing a notable growth of some of the peaks, as shown in **Figure 4** with reference to the thrust force signals of the experimental drilling tests carried

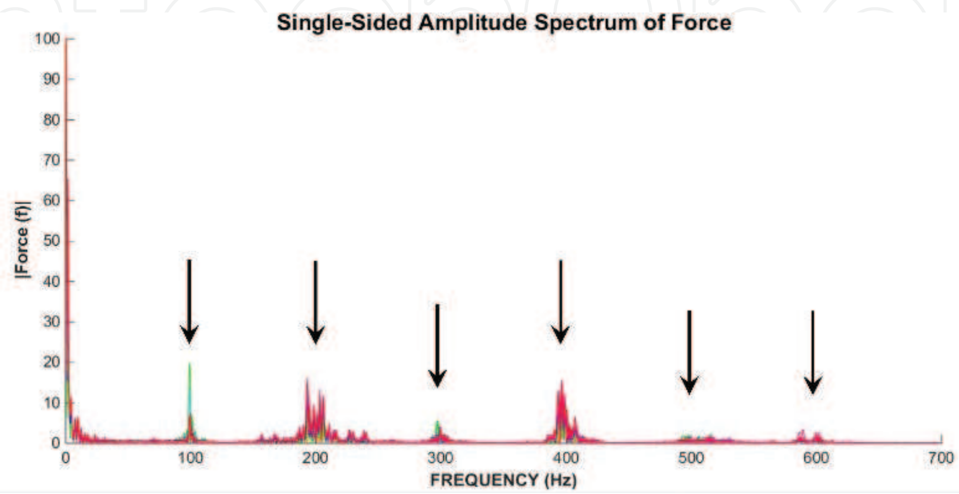

Figure 3. Single-sided amplitude spectrum of thrust force signal (6000 rpm–0.15 mm/rev) [21].

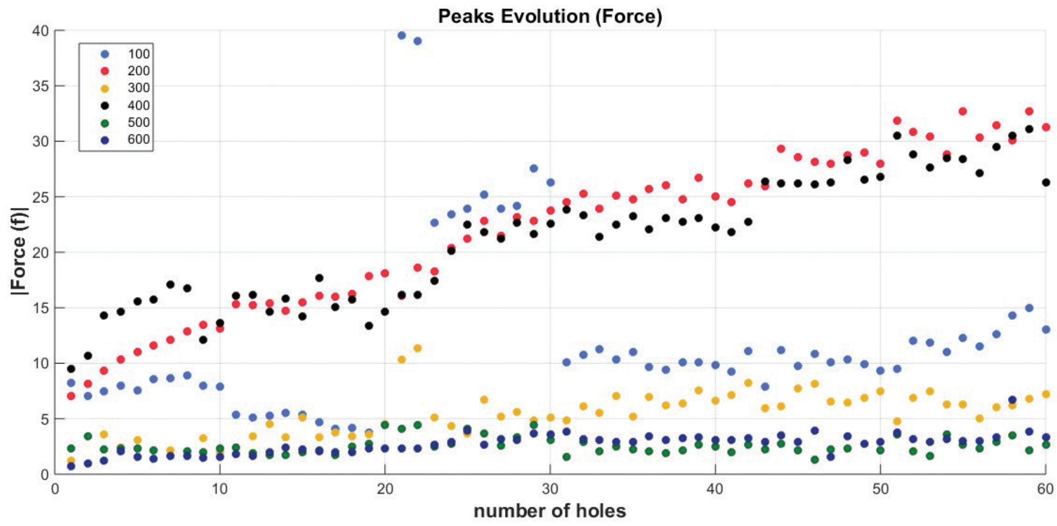

Figure 4. Amplitude of the peaks detected in the frequency transform of the thrust force signal vs. hole number (6000 rpm–0.15 mm/rev) [21].

out at 6000 rpm and 0.15 mm/rev, suggesting a potential correlation of the frequency peak amplitude with tool wear progression.

A statistical feature selection procedure based on the Pearson's correlation coefficient was applied to evaluate the statistical correlation between the extracted features and the output tool flank wear, VB.

Substantial correlations with tool wear state were identified for the following set of features: $Fpeak_{2x}$, $Fpeak_{4x}$, $Fpeak_{6x}$, $Tpeak_{2x}$, and $Tpeak_{4x}$. The subset composed the first three features extracted from the thrust force signal displayed the highest correlation with tool wear. The selected features were used to build two different feature pattern vectors, FPV_1 and FPV_2, to feed cognitive paradigms for the estimation of tool wear. FPV_1 was made of three features extracted from the thrust force signal, and FPV_2 was a sensor fusion feature pattern vector containing the five features extracted from the thrust force and the torque signals.

The FPVs were fed to three-layer cascade-forward backpropagation artificial neural networks (ANN) to find correlations between the extracted and selected frequency domain sensor signal features and tool wear state through pattern recognition [29]. ANN training was performed using the Levenberg-Marquardt optimization algorithm. Each FPV was associated to its corresponding flank wear (VB) to create input-output vectors for ANN learning. For each drilling condition, 60 input-output vectors (i.e., one for each drilled hole) were built to create the related ANN learning set. Training and testing were performed with different ANN configurations by varying the number of hidden layer nodes. In particular, the number of hidden layer nodes was varied between 3, 6, and 9 for FPV_1 and 5-10-15 for FPV_2, that is, equal to the 1, 2, and 3 times the number of input features.

Cross validation of the NN was carried out by means of the leave-k-out method with $k = 1$. The global pattern recognition performance was evaluated by merging the recognition rates achieved across all trials.

The ANN performance was evaluated in terms of mean square error (MSE), that is, the variance of the differences between the VB values predicted by the ANN and the target VB values. The very low MSE values, between 9.82E-07 and 1.57E-05, confirmed the robust correlation between the sensor signal features extracted in the frequency domain and the tool wear, due to the interaction between the drill bit and the anisotropic CFRP material.

Through pattern recognition based on the frequency domain signal features extracted from the multiple sensor monitoring signals, the ANN accurately reconstructed the tool wear curve. **Figure 5** presents the reconstructed tool wear curve for the drilling test performed at 6000 rpm and 0.11 mm/rev, obtained by applying the leave-k-out method with $k = 1$ to the ANN with three hidden layer nodes trained with the three features extracted from the thrust force signal (MSE = 1.57E-05). **Figure 6** presents the reconstructed tool wear curve for the same drilling test obtained by applying the leave-k-out method with $k = 1$ to the ANN with 5 hidden layer nodes trained with the five features extracted from the thrust force and the torque signal (MSE = 3.79E-06).

For all drilling conditions, the sensor fusion pattern vector FPV_2, including frequency domain features coming from both thrust force and torque signals, provided better results than FPV_1.

The accurate tool wear curve reconstruction achieved by the ANN can be effectively utilized to determine the end of useful tool life through on-line diagnosis during CFRP/CFRP stack drilling, identifying the transition of the tool flank wear between the second and the third phase of the wear curve.

2.1.3. Sensor signal feature extraction and selection in the time domain and neural network pattern recognition for tool wear estimation

Sensor signal feature extraction can also be carried out in the time domain with the aim to find correlations between the extracted sensor signal features and the tool wear state.

In [22], sensor signal feature extraction in the time domain was applied to CFRP/CFRP stack drilling performed with a traditional twist drill bit, usually employed in the aircraft industry

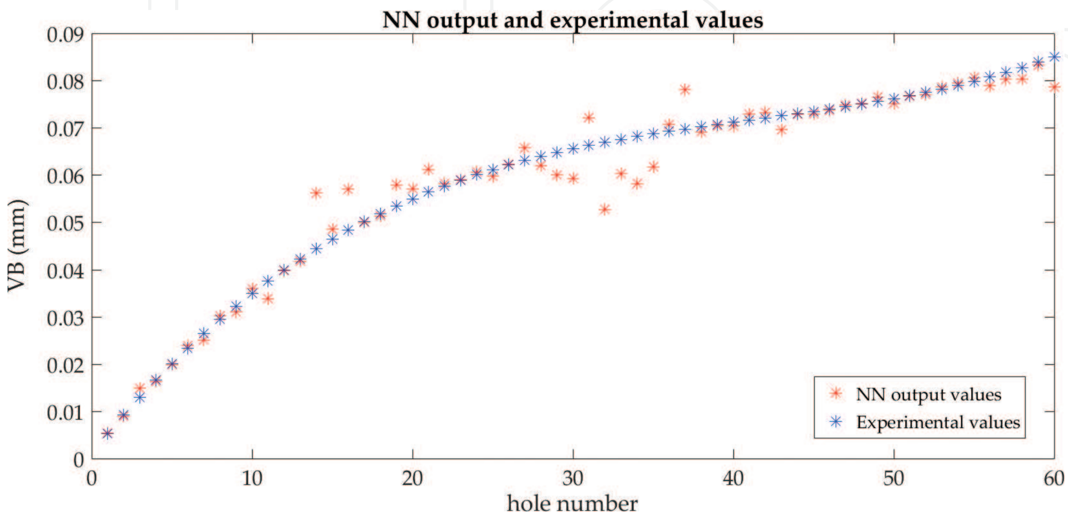

Figure 5. Reconstructed tool wear curve obtained by the ANN trained with the three features extracted from the thrust force signal (6000 rpm–0.11 mm/rev).

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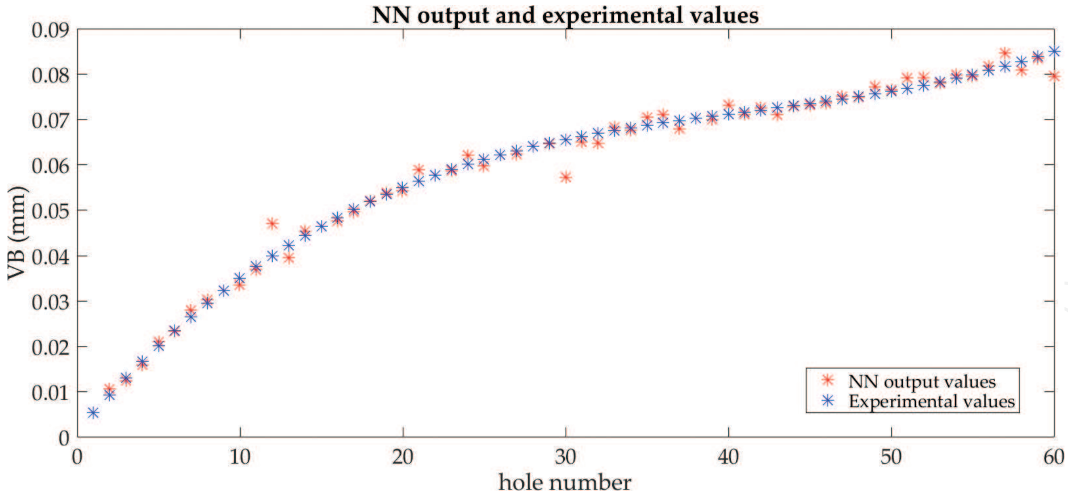

Figure 6. Reconstructed tool wear curve obtained by the ANN trained with the five features extracted from the thrust force and the torque signal (6000 rpm–0.11 mm/rev).

and an innovative geometry step drill bit. The traditional tool was a 2-flute 6.35-mm diameter twist drill with 125° point angle and 30° helix angle tungsten carbide (**Figure 7a**), while the innovative step drill bit was a 2-flute 6.35-mm diameter drill bit with 120° point angle and 20° helix angle made of tungsten carbide (WC) (**Figure 7b**). Different cutting parameters were used for the experimental drilling tests: three feed values (0.11, 0.15, and 0.20 mm/rev) and three spindle speeds (2700, 6000, and 7500 rpm).

A statistical approach in the time domain was applied for feature extraction from the thrust force and torque sensor signals acquired during the drilling tests. The following five statistical signal features were extracted: arithmetic mean, variance, skewness, kurtosis, and signal energy. For each extracted feature, the Spearman correlation coefficient, r_s, was calculated to assess its correlation with tool wear ($0 < r_s < 0.3$, weak correlation, $0.3 < r_s < 0.7$, moderate correlation, and $0.7 < r_s < 1$, strong correlation). Based on the r_s coefficient, five features showed a strong correlation with tool wear: thrust force average (F_{z_av}), torque average (T_{av}), thrust force variance (F_{z_var}), torque variance (T_{var}), and thrust force kurtosis (F_{z_kurt}).

Every 10 holes, a magnified picture of the tool was acquired through an optical measuring machine (Tesa Visio V-200) to measure the flank wear [21]. A 3rd order polynomial interpolation of the VB values was applied to reconstruct the tool wear curves for each drill bit under the tested drilling conditions (**Figures 8** and **9**).

The graphical analysis of the selected sensor signal features, with particular reference to the thrust force average (**Figures 10** and **11**), which is the most correlated feature, shows that the behavior of the features and the behavior of tool wear (**Figure 8** and **9**) display the same increasing trend with increasing number of holes. The average thrust force is higher for the innovative drill bits.

The selected statistical features were employed to construct, for each drilling condition, 60 sensor fusion feature pattern vectors (SFPVs), that is, one for each drilled hole. Each SFPV was built by combining the selected statistical signal features and the corresponding hole number, n. Each SFPV was associated to its matching flank wear value (VB) to create input-output

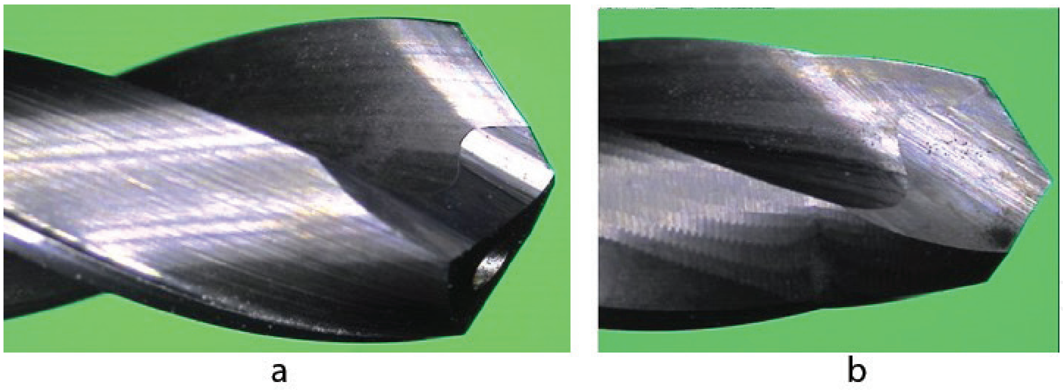

Figure 7. (a) Traditional twist drill bit; (b) innovative step drill bit [22].

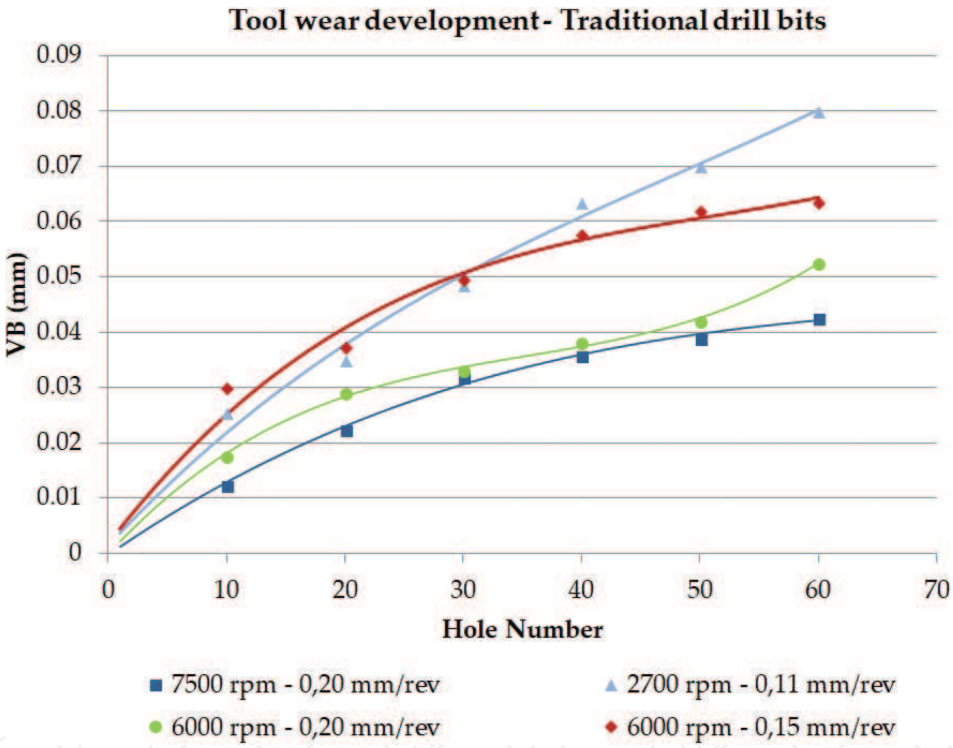

Figure 8. Tool wear values and interpolated curves. Traditional drill bits.

vectors for ANN learning. Three-layer cascade-forward backpropagation artificial neural networks (ANN) using the Levenberg-Marquardt training algorithm were setup [20]. For each drilling condition, 60 input-output vectors (i.e., one for each drilled hole) were built.

To assess the performance of the ANN in properly forecasting the upcoming tool wear values based on a restricted number of initial training input-output vectors and define the smallest number of vectors required to get a reliable tool wear forecast, the number, m, of input-output vectors utilized for ANN training was gradually increased by steps of 10 from $m = 20$ to $m = 50$.

The pattern recognition performance was measured by the root mean squared error (RMSE), that is, the sample standard deviation of the differences between the ANN predicted tool wear values and the experimental tool wear values.

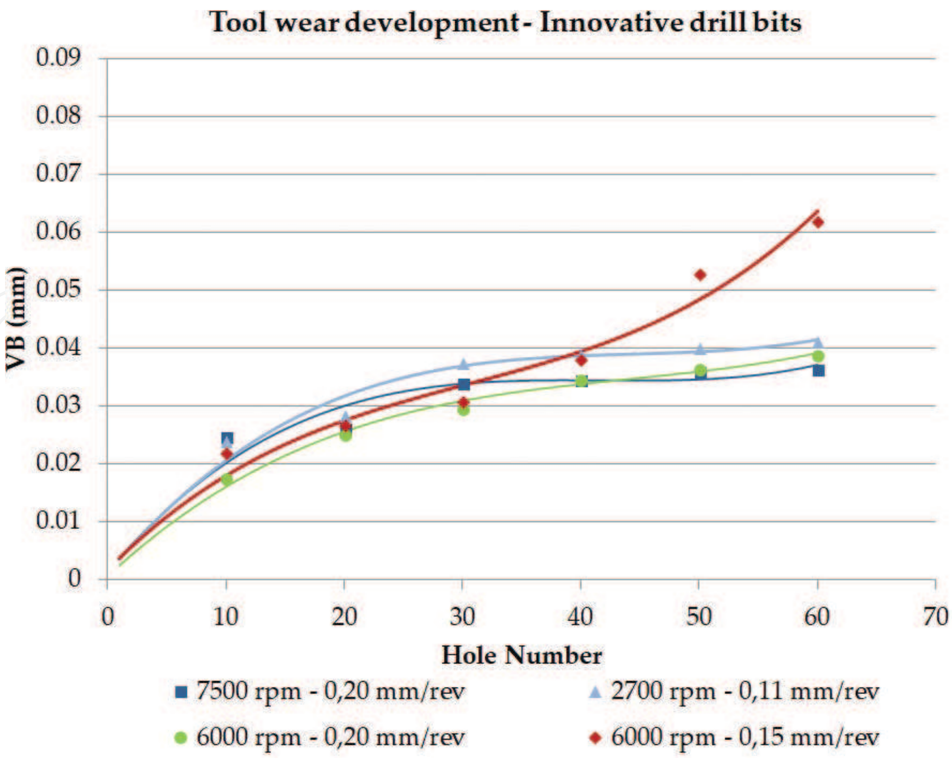

Figure 9. Tool wear values and interpolated curves. Innovative step drill bits.

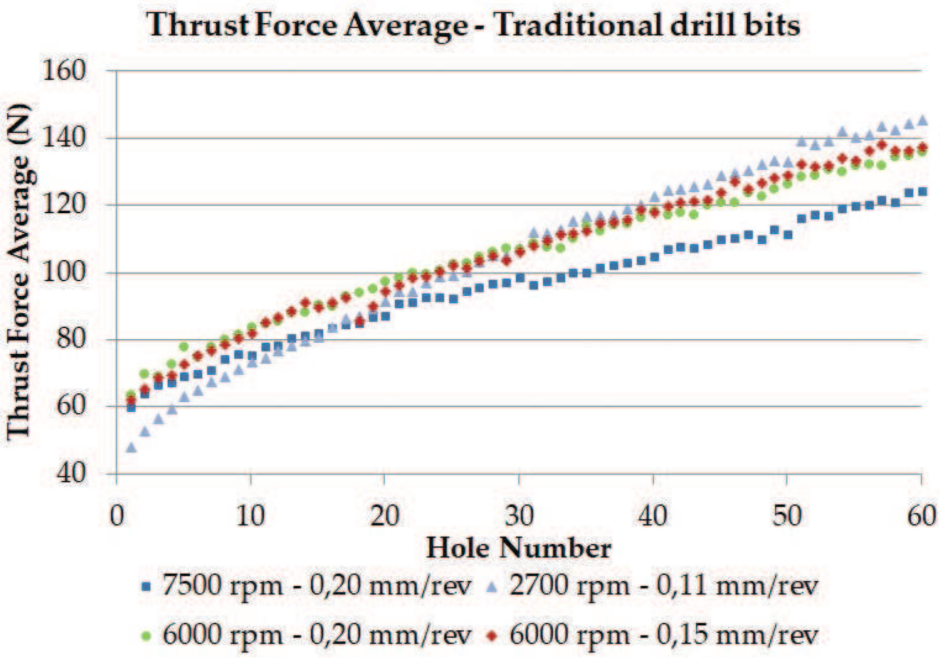

Figure 10. Thrust force average vs. hole number. Traditional drill bits.

In general, the prediction performance improved by increasing m since, by enlarging the number of input-output vectors used for training the ANN, the latter was able to enhance the forecast of future tool wear values. Also in the case of the experimental tests carried out

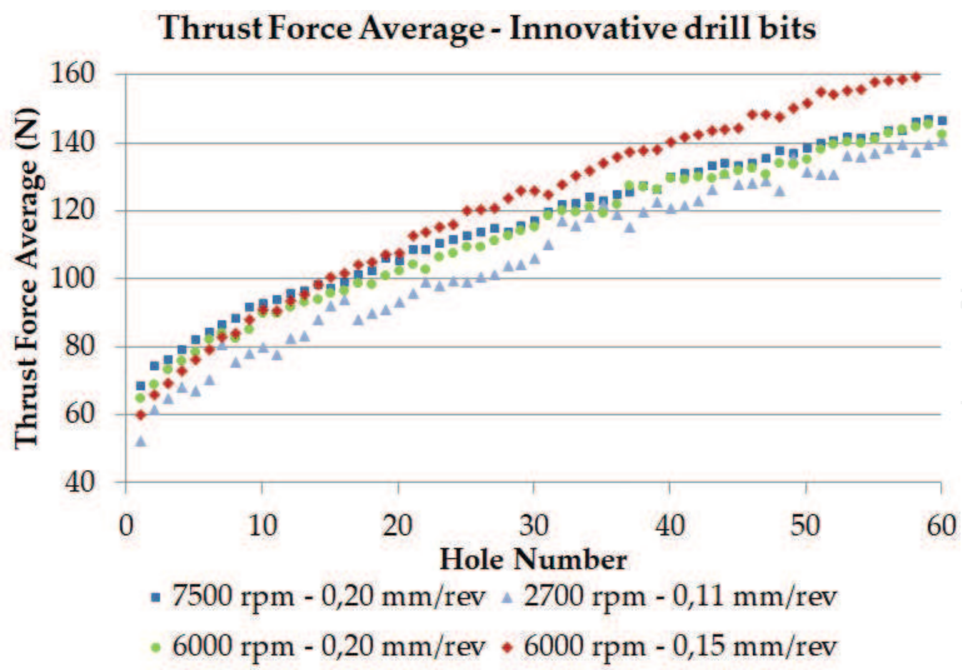

Figure 11. Thrust force average vs. hole number. Innovative drill bits.

with the innovative drill bits, the prediction performance notably improved by enlarging the number of input-output vectors utilized for training the ANN.

The best and the worst ANN prediction performances were found for the innovative drill bits. In the worst case (2700 rpm and 0.11 mm/rev), a maximum RMSE of 0.0164 for $m = 20$ and of 0.0056 for $m = 50$ were obtained due to some outliers (**Figure 12**). In the best case (6000 rpm and 0.20 mm/rev), a minimum RMSE of 0.00023 for $m = 50$ was obtained. **Figure 13** shows the tool wear curves predicted by the ANN for this case. The final curve relative to $m = 50$ is essentially overlaid to the measured tool wear curve, meaning that the ANN is capable to accurately forecast the future 10 tool wear values.

Even though the ANN prediction can be considered as more demanding in the case of the innovative drill bits, which have a more complex geometry and tool wear development, the ANN performance was still suitable, showing very low prediction errors (minimum RMSE = 0.00023 and maximum RMSE = 0.0164).

The decision making procedure for identifying the end of the tool life based on the ANN prediction can operate in a safe manner, allowing the multiple sensor monitoring procedure to be valuably utilized for on-line tool condition monitoring aimed at the implementation of a condition-based tool substitution strategy instead of a time-based strategy.

In [24], the sensor signal feature extraction methodology in the time domain was applied to drilling of CFRP/CFRP stacks performed using a traditional twist drill bit with different drilling conditions (rotational speed: 2700, 6000, and 9000 rpm and feed: 0.11, 0.15, 0.20 mm/rev).

In this case, thrust force, torque, and acoustic emission sensor signals were acquired during the experimental drilling tests. On these signals, statistical feature extraction and data fusion were implemented to construct sensor fusion pattern vectors in order to make predictions

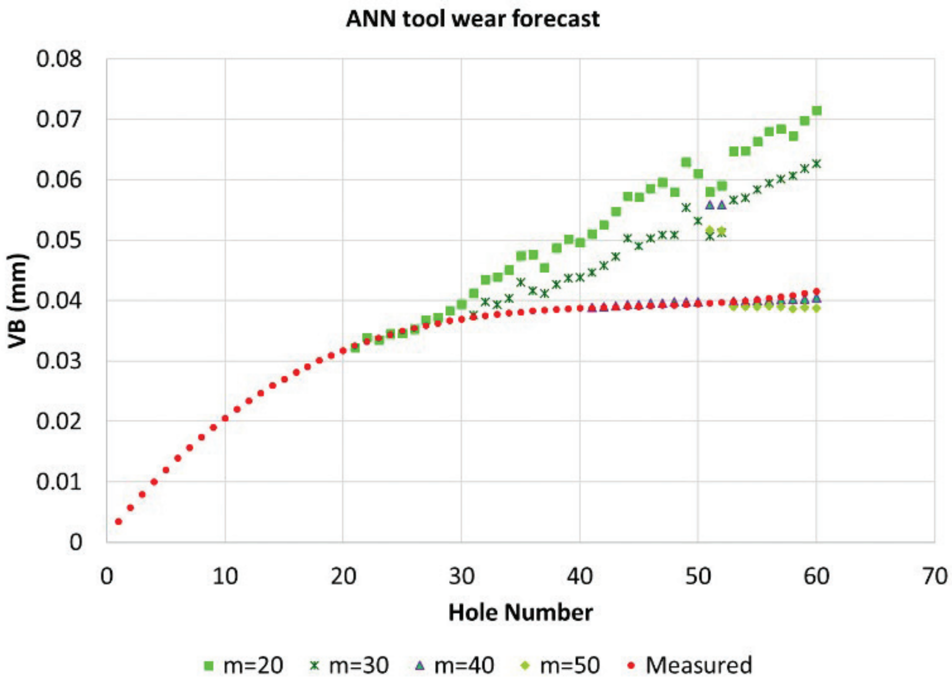

Figure 12. Worst case ANN forecast: experimental tests at 2700 rpm–0.11 mm/rev with innovative drill bit [22].

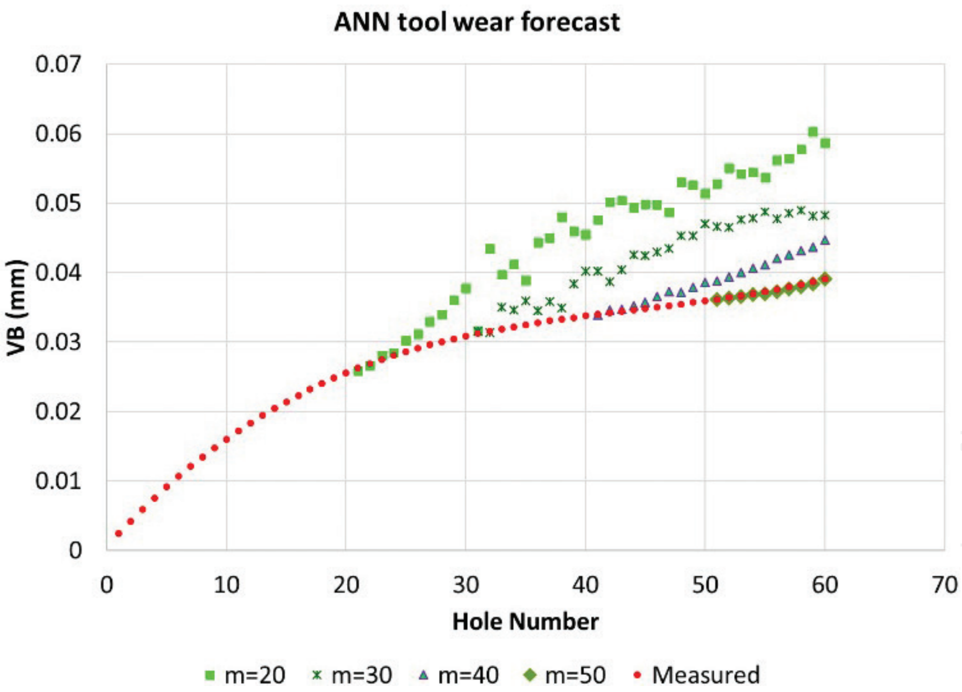

Figure 13. Best case ANN forecast: experimental tests at 6000 rpm–0.20 mm/rev with innovative drill bit [22].

about the state of the tool via artificial neural network-based pattern recognition paradigms. Based on the calculation of the Pearson's correlation coefficient, five best correlated features were identified (thrust force average, thrust force variance, thrust force skewness, torque average, and acoustic emission average), and they were utilized to form the input sensor fusion pattern vector for ANN pattern recognition. The ANN prediction of tool wear was highly

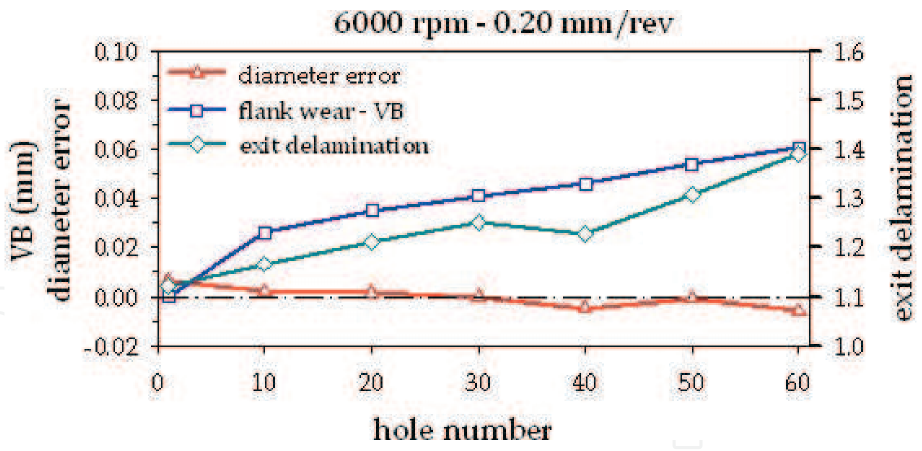

Figure 14. Exit diameter error, tool flank wear, and exit delamination (6000 rpm–0.20 mm/rev).

accurate, with an RMSE <4e-3, showing reliable correlations between fused signal features and tool wear level. The reliable predictions of tool wear development can be used to support on-line decision making on drill bit replacement need.

Moreover, the prediction of tool wear can be functionally utilized to forecast the quality of the drilled holes. The latter was assessed considering dimensional accuracy and entry/exit delamination, which both have an effect on the performance of the CFRP assembly. Dimensional accuracy was measured with reference to hole diameter error, that is, the difference between actual and nominal hole diameter divided by nominal hole diameter [30]. The entry/exit delamination was assessed with reference to the delamination factor, Fd, that is, the ratio between the diameter of the circle encompassing the damaged area and the nominal diameter of the hole [25].

The drilled hole quality evaluations were utilized to set up a criterion for tool replacement need, which is required when the tool wear is responsible for a drilled hole, the quality of which is no longer acceptable. As the lower limit of the tolerance range corresponds to the nominal diameter of the hole, any negative hole diameter error is unacceptable. For each drilling condition, the occurrence of negative hole diameter errors was detected and associated with the corresponding flank wear value and the exit delamination factor.

Under all drilling conditions, the hole diameter error became negative when the flank wear, VB, reached the typical value of 0.04 mm (see **Figure 14**). The latter can be used as a threshold to determine the need for tool change due to an undersized hole diameter. For all drilling conditions, the exit delamination factor grew with increasing number of holes and reached a value between 1.3 and 1.4 when the flank wear reached 0.04 mm. This suggests that the flank wear threshold could also be associated with the second hole quality parameter represented by the exit delamination factor.

Hence, a correspondence between hole diameter error and exit delamination factor with tool wear level was observed. As a result, via on-line prediction of tool wear during drilling, taking into account the identified flank wear threshold, the cognitive sensor monitoring paradigm can provide diagnosis and prognosis services to support decision making on tool replacement need, which is essential for drilling automation.

3. Conclusions

This chapter provided an overview of the main challenges related to drilling of fiber-reinforced plastic composite materials which are extensively employed in the aeronautical industry. Rapid tool wear is generated due to the abrasiveness of the reinforcing fibers, and different types of damages affecting material integrity and surface quality, with particular reference to delamination damage generation, are often produced by drilling.

With reference to aeronautical industry applications, where the assembly of CFRP components requires "one-shot" drilling processes so as to allow for easier subsequent riveting avoiding misalignment issues, drilling of CFRP/CFRP stacks made of two superimposed laminates was investigated.

Based on a wide experimental drilling campaign, the case studies analyzed the influence of drilling parameters, tool type and geometry on tool wear development, hole quality and surface integrity, and the opportunity to implement advanced sensor monitoring procedures for tool condition monitoring based on the acquisition and processing of thrust force and torque signals.

Diverse multiple sensor process monitoring procedures were implemented in the drilling of CFRP/CFRP stacks for the assembly of aircraft components, with the aim to support on-line decision making on tool replacement time through cognitive tool wear estimation and hole quality assessment. The monitoring procedures were based on the acquisition and processing of thrust force, torque, and acoustic emission sensor signals during the experimental drilling tests.

With the purpose to explore the complex frequency content of the thrust force and torque sensor signals acquired in the multidirectional CFRP/CFRP stack drilling experimental tests, advanced signal processing was also carried out in the frequency domain.

The sensor signal processing techniques, comprising signal conditioning, feature extraction in the time and frequency domain and data fusion, were implemented to construct sensor fusion feature pattern vectors—made of sensor signal features coming from sensors of different nature—with the aim to find correlations with tool state via artificial neural network-based pattern recognition paradigms.

The ANN performance results achieved in the case studies indicated that, for all CFRP/CFRP stack drilling conditions, by using sensor fusion pattern vectors made of selected features extracted from force and torque sensor signals, a very accurate ANN prediction of tool wear is achieved. As a matter of fact, these procedures demonstrated reliable correlations between sensor signal features and tool wear level both in the case of the features extracted from the time domain and in the case of the features extracted from the frequency domain.

The prediction of tool wear can be functionally utilized to forecast the quality of the drilled holes. As a matter of fact, a correspondence between exit delamination factor and tool wear transition between the second and third phase of the wear curve was observed. In this transition, an exit delamination factor value, Df = 1.4, was identified and set as threshold beyond which unacceptable hole quality is generated.

As a result, taking into account the identified threshold, cognitive tool wear prediction via artificial neural networks can be used for on-line decision making on tool replacement to avoid unacceptable hole quality.

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Conflict of interest

The authors declare no conflict of interest.

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References

[1] M'Saoubi R, Axinte D, Soo SL, et al. High performance cutting of advanced aerospace alloys and composite materials. CIRP Annals - Manufacturing Technology. 2015;**64**: 557-580

[2] Herzog D, Jaeschke P, Meier O, et al. Investigations on the thermal effect caused by laser cutting with respect to static strength of CFRP. International Journal of Machine Tools and Manufacture. Epub ahead of print. 2008. DOI: 10.1016/j.ijmachtools.2008.04.007

[3] Azmir MA, Ahsan AK. A study of abrasive water jet machining process on glass/ epoxy composite laminate. Journal of Materials Processing Technology. 2009;**209**(20): 6168-6173. https://doi.org/10.1016/j.jmatprotec.2009.08.011

[4] Teti R. Machining of composite materials. CIRP Annals - Manufacturing Technology. 2002;**51**(2):611-634. https://doi.org/10.1016/S0007-8506(07)61703-X

[5] Lopresto V, Caggiano A, Teti R. High performance cutting of fibre reinforced plastic composite materials. In: Procedia CIRP. Elsevier B.V. 2016; Vol. 46. pp. 71-82. https://doi.org/10.1016/j.procir.2016.05.079

[6] Ho-Cheng H, Dharan CHK. Delamination during drilling in composite laminates. Journal of Engineering for Industry. 1990;**112**:236-239

[7] Jain S, Yang DCH. Delamination-free drilling of composite laminates. Journal of Engineering for Industry. 1994;**116**:475-481

[8] Shyha IS, Aspinwall DK, Soo SL, Bradley S. Drill geometry and operating effects when cutting small diameter holes in CFRP. International Journal of Machine Tools and Manufacture. 2009;**49**(12-13):1008-1014. https://doi.org/10.1016/j.ijmachtools.2009.05.009

[9] Shyha I, Soo SL, Aspinwall D, Bradley S. Effect of laminate configuration and feed rate on cutting performance when drilling holes in carbon fibre reinforced plastic composites. Journal of Materials Processing Technology. 2010;**210**(8):1023-1034. https://doi.org/10.1016/j.jmatprotec.2010.02.011

[10] Davim JP, Rubio JC, Abrao AM. A novel approach based on digital image analysis to evaluate the delamination factor after drilling composite laminates. Composites Science and Technology. 2007;**67**(9):1939-1945. https://doi.org/10.1016/j.compscitech.2006.10.009

[11] Hocheng H, Tsao CC. Effects of special drill bits on drilling-induced delamination of composite materials. International Journal of Machine Tools and Manufacture. 2006;**46**:1403-1416

[12] Faria PE, Rubio JCC, Reis P, et al. Drilling of fiber reinforced plastics: A review. Journal of Materials Processing Technology. 2007;**186**:1-7

[13] Davim JP. Drilling of Composite Materials. New York, NY, USA: NOVA Publishers; 2009

[14] Murphy C, Byrne G, Gilchrist MD. The performance of coated tungsten carbide drills when machining carbon fibre-reinforced epoxy composite materials. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture. 2002;**216**(2):143-152. https://doi.org/10.1243/0954405021519735

[15] Iliescu D, Gehin D, Gutierrez ME, et al. Modeling and tool wear in drilling of CFRP. nternational Journal of Machine Tools and Manufacture. 2010;**50**:204-213

[16] Brinksmeier E, Fangmann S, Rentsch R. Drilling of composites and resulting surface integrity. CIRP Annals - Manufacturing Technology. 2011;**60**:57-60

[17] Krishnaraj V, Prabukarthi A, Ramanathan A, et al. Optimization of machining parameters at high speed drilling of carbon fiber reinforced plastic (CFRP) laminates. Composites. Part B, Engineering. 2012;**43**:1791-1799

[18] Phapale K, Ahire A, Singh R. Experimental characterization and finite element modeling of critical thrust force in cfrp drilling. Machining Science and Technology. 2018;**22**:249-270

[19] Karpat Y, Bahtiyar O, Deger B, Kaftanoğlu B. A mechanistic approach to investigate drilling of UD-CFRP laminates with PCD drills. CIRP Annals - Manufacturing Technology. 2014;**63**: 81-84

[20] López De Lacalle LN, Rivero A, Lamikiz A. Mechanistic model for drills with double point-angle edges. International Journal of Advanced Manufacturing Technology. 2009; **40**:447-457

[21] Caggiano A, Centobelli P, Nele L, et al. Multiple sensor monitoring in drilling of CFRP/CFRP stacks for cognitive tool wear prediction and product quality assessment. Procedia CIRP. 2017;**62**:3-8

[22] Caggiano A, Napolitano F, Nele L, et al. Multiple sensor monitoring for tool wear forecast in drilling of CFRP/CFRP stacks with traditional and innovative drill bits. Procedia CIRP. 2018;**67**:404-409

[23] Caggiano A, Rimpault X, Teti R, et al. Machine learning approach based on fractal analysis for optimal tool life exploitation in CFRP composite drilling for aeronautical assembly. CIRP Annals. 2018:1-4

[24] Caggiano A, Nele L, Nele L. Artificial neural networks for tool wear prediction based on sensor fusion monitoring of CFRP/CFRP stack drilling. International Journal of Automation Technology. 2018;**12**:275-281

[25] Caggiano A, Angelone R, Teti R. Image analysis for CFRP drilled hole quality assessment. In: Procedia CIRP. Elsevier B.V. 2017. Vol. 62. pp. 440-445. https://doi.org/10.1016/j.procir.2017.03.045

[26] Angelone R, Caggiano A, Improta I, et al. Temperature measurements for the tool wear and hole quality assessment during drilling of CFRP/CFRP stacks. Procedia CIRP. 2018; **67**:416-421

[27] Bonnet C, Poulachon G, Rech J, et al. CFRP drilling: Fundamental study of local feed force and consequences on hole exit damage. International Journal of Machine Tools and Manufacture. 2015;**94**:57-64

[28] Karpat Y, Bahtiyar O, Deger BKB. A mechanistic approach to investigate drillingof UD-CFRP laminates with PCD drills. CIRP Annals - Manufacturing Technology. 2014; **63**:81-84

[29] Teti R, Jemielniak K, O'Donnell G, et al. Advanced monitoring of machining operations. CIRP Annals - Manufacturing Technology. 2010;**59**:717-739

[30] Sadek A, Meshreki M, Attia MH. Characterization and optimization of orbital drilling of woven carbon fiber reinforced epoxy laminates. CIRP Annals - Manufacturing Technology. 2012;**61**:123-126