Milling Diagnosis Using Artificial Intelligence Approaches

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Abstract :

The Industry 4.0 framework needs new intelligent approaches. Thus, the manufacturing industries more and more pay close attention to artificial intelligence (AI). For example, smart monitoring and diagnosis, real time evaluation and optimization of the whole production and raw materials management can be improved by using machine learning and big data tools. An accurate milling process implies a high quality of the obtained material surface (roughness, flatness). With the involvement of AI-based algorithms, milling process is expected to be more accurate during complex operations.
In this work, a smart milling diagnosis has been developed for composite sandwich structures based on honeycomb core. The use of such material has grown considerably in recent years, especially in the aeronautic, aerospace, sporting and automotive industries. But the precise milling of such material presents many difficulties.
The objective of this work is to develop a data-driven industrial surface quality diagnosis for the milling of honeycomb material, by using supervised machine learning methods. In this approach cutting forces are online measured in order to predict the resulting surface flatness.
The developed diagnosis tool can also be applied to the milling of other materials (metal, polymer, ...).

Key words: milling diagnosis, machine learning, support vector machine, honeycomb core

1 Introduction

The Industry 4.0 framework needs new intelligent approaches. Thus, the manufacturing industries more and more pay close attention to artificial intelligence (AI). For example, smart monitoring and diagnosis, real time evaluation and optimization of the whole production and raw materials management can be improved by using machine learning and big data tools [1]. An accurate milling process implies a high quality of the obtained material surface (roughness, flatness) [2]. With the involvement of AI-based algorithms, milling process is expected to be more accurate during complex operations.

T. Mikołajczyk *et al*. developed an Artificial Neuronal Network (ANN) for tool-life prediction in machining with a high level of accuracy, especially in the range of high wear levels, which meets the industrial requirements [3]. The particularity of their work was the combination of a multi-layers ANN model with image processing in order to reduce the potential error.

D. Pimenov *et al*. evaluated and predicted the surface's roughness through artificial intelligence algorithms (random forest, standard Multilayer perceptron) [4]: in their investigation the obtained performance depends on the parameters contained in the dataset.

M. Correa *et al.* compared the performances of Bayesian networks (BN) and artificial neural networks for quality detection in a machining process [5]. Even ANN models are often used to predict surface quality in machining processes, they preferred BNs for their significant representation capability and for the fast model building.

The work of C. Zhang *et al*. [21] focused on monitoring the condition and life of the cutting tool in dry milling environment. From de-noised vibration signal they extract some relevant features such as the root mean square, the skewness and the kurtosis in both time and time-frequency domain. Based on Neuro-Fuzzy Network (NFN), they implemented a tool wear prediction model which performs the best, with the smallest Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) compared with Back Propagation Neural Network (BPNN) and Radial Basis Function Network (RBFN) algorithms.

Z. Rui *et al*. [24] implemented a hybrid approach combining handcrafted feature design with automatic feature learning for machine health monitoring: local feature-based gated recurrent unit (LFGRU) networks. By comparison with some other methods such as the Support Vector Machine (SVM), the k-nearest neighbor (kNN), they verified the effectiveness and robustness of the proposed LFGRU model for tool wear prediction.

D. Wu *et al.* [25] have worked on cloud-based machine learning for tool wear prediction in milling. The research was about the development of a novel approach for machinery prognostics using a cloud-based random forest algorithm. Their experimental result have shown that despite the fact that random Forests give the best accuracy for large dataset, parallel random forest algorithm has the best ratio training time/accuracy. Future more, they will predict tool wear with other machine learning algorithms such as support vector machines as well as to make a comparison with their actual algorithms.

For machining result prediction, similar algorithms could be used but the recurrent problem is how to increase the accuracy of those algorithms. K. Javed. *et al.* [26] have worked on an enabling health monitoring approach based on vibration data for accurate prognostics. They have shown that prognostic efficiency is closely related to the extracted features and by the same way proposed a method for enabling features that can lead to simple and accurate prognostics.

K. Durmus [27], by using neuronal networks, worked on the prediction and the control of surface roughness in CNC lathe using artificial neural network. His study has concluded that artificial neural network (ANN) can produce an accurate relationship between cutting parameters and surface roughness. Based on the ANN training model, he could find the best machining parameters for obtaining a desired surface roughness.

By also using neuronal artificial neural network M. Azlan [28] has developed a surface roughness prediction models for end milling machining, in the logic to find the best ANN network structure for surface roughness prediction.

Another approach consists to measure and analyze the drive power (for example by current measuring) [31], which is not applicable in our experiment. In this paper few artificial intelligence methods are tested: random forest (RF), standard Multilayer perceptrons (MLP), Regression Trees, and radial-based functions.

In our work, a smart milling diagnosis has been developed for composite sandwich structures based on honey-comb core. The use of such material has grown considerably in recent years, especially in the aeronautic, aerospace, sporting and automotive industries. Recent development projects for Airbus A380 or Boeing 787 confirm the in-creased use of the honeycomb material. But the precise milling of such material presents many difficulties.

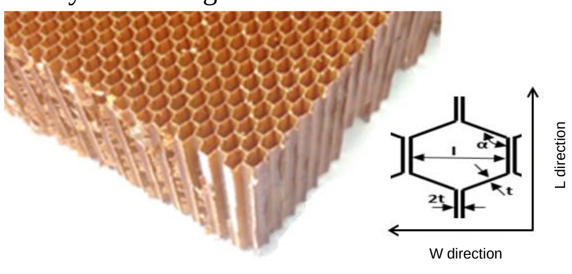
The objective of this work is to develop a data-driven industrial surface quality diagnosis for the milling of honeycomb material, by using supervised machine learning methods. Therefore, cutting forces are online measured in order to predict the resulting surface flatness.

2 Description of the experiments

2.1 Workpiece material and tools

The workpiece material studied in this investigation is Nomex® honeycomb cores with thin cell walls. It is produced from aramid fiber dipped in phenolic resin (Fig. 1). The honeycomb cores consist of continuous corrugated ribbons of thin foil bonded together in the longitudinal direction. The aim of such a process is to create a structure allowing lightness and stiffness together thanks to the hexagonal geometry of formed cells. Figure 1 illustrates the geometric characteristics of the honeycomb core. The use of honeycomb material in sandwich composite is limited by the fragility of each wall of the honeycomb, which influences the quality of obtained surfaces after machining [7, 8, 9].

Honeycomb designation: **A10-72-5OX**



Density [Kg/m3]	Cell size l [mm]	Wall size t [mm]	Angle α [°]
72	5	0.08	100

Figure 1: *Nomex*® honeycomb cores and the main geometrical characteristics

The Nomex® honeycomb machining presents several defects related to its composite nature (uncut fiber, tearing of the walls), the cutting conditions and to the alveolar geometry of the structure which causes vibration on the different components of the cutting effort [10].

It is clear that the use of ordinary cutting tools and also the mechanical and geometrical characteristics of honeycomb cores will have a crucial effect on machinability and on the quality of the resulting surface [11]. In fact, ordinary cutting tools for machining honey-comb core produce generally tearing of fibers and delamination of cell structures. Subsequently, these cause a reduction of bond strength between the skin and the honey-comb core, and thus a weaker joint for composite sandwich structures.

In our study, the used milling cutter is provided from our industry partner, the EVATEC Tools Company. As shown in figure 2, the used EVATEC tool is a combined specific tool with two parts designed to surfacing/dressing machining operation. The first part is a cutter body made of high speed steel with 16 mm in diameter and having ten helixes with chip breaker. This tool part is designated by Hogger. The second part is a circular cut-ting blade made of tungsten carbide with a diameter of 18.3 mm and having a rake angle of 22° and a flank angle of 2.5°. These two parts are mechanically linked to each other with a clamping screw.

Figure 2: Milling cutter used for Nomex® honeycomb core ‘‘CZ10’’.

2.2 Milling experiments

All experimental milling tests illustrated in this paper were carried out on a three-axis vertical machining center Realmeca® RV-8.

Table 1: Machining center *Realmeca*® RV8 specifications

Realmeca RV8 SP		
Spindle speed max	*24 000 rpm*	
Feed rate max	*20 m/min*	
Power spindle motor	*30 kW*	
Resolution	*0.5 µm*	
Course X *Course Y* *Course Z*	*800 mm* *600 mm* *450 mm*	

The main technical specifications of this machine are given in the table 1. For assessing the performance of the machining process of Nomex® honeycomb core we monitored and measured the cutting forces generated during cutting, by using the Kistler dynamometer model 9129AA. The Kistler table is mounted below the Nomex sample in order to measure the three components of the machining force as shown in figure 3. During the measurements, the x-axis of the dynamometer is aligned with the feed direction of the milling machine and the longitudinal direction of the workpiece (parallel to core ribbons and the direction of honeycomb double wall). The three orthogonal components of machining force (Fx, Fy and Fz) were measured according to figure 3 using the Kistler table.

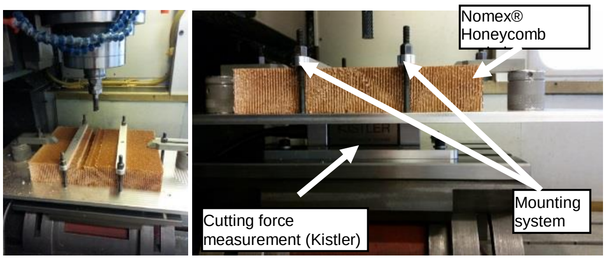


Figure 3: Experimental test setup

The milling experiment conditions are summarized in table 2. Four different speeds (high and low speeds) and four feed values were selected.

Table 2 : Milling experiment conditions

Spindle speed (rpm)	2 000	10 000	15 000	23 000
Feed rate (mm/min)	150	1 000	1 500	3 000

Two main modes of surface damage are observed (Figure 4): uncut aramid fibers along the machined surface and tearing of the walls. The appearance of the uncut fibers is a machining defect specific to the composite material which depends on the type of the fibers and their orientation. The tearing of Nomex® paper, linked to the cellular appearance of the honeycomb structure, occurs under the shear loading effect [28, 29].

Uncut fibers are observed on Figure 4 -a and -c. It is well known that the surface quality is of high importance for the use of the Nomex® honeycomb in sandwich materials. The machining defects cause a reduction of bond strength between the skin and the honeycomb core, and thus a weaker joint for composite sandwich structures.

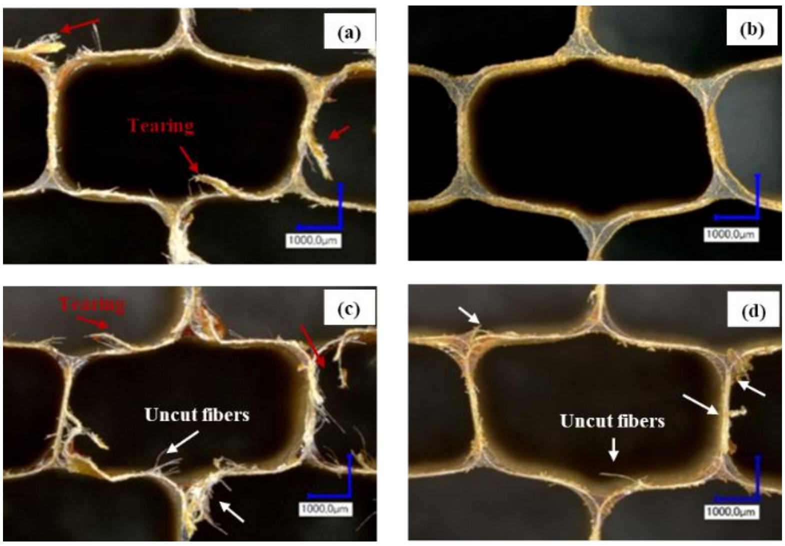


Figure 4: Obtained honeycomb machining surfaces. The case (b) represents the best milling result

2.3 Measured signals

Many milling experiences have been made in our study. For example, figure 5 shows the milling forces measured for honeycomb at 2000 rpm spindle speed and 3000 mm/min feed rate.

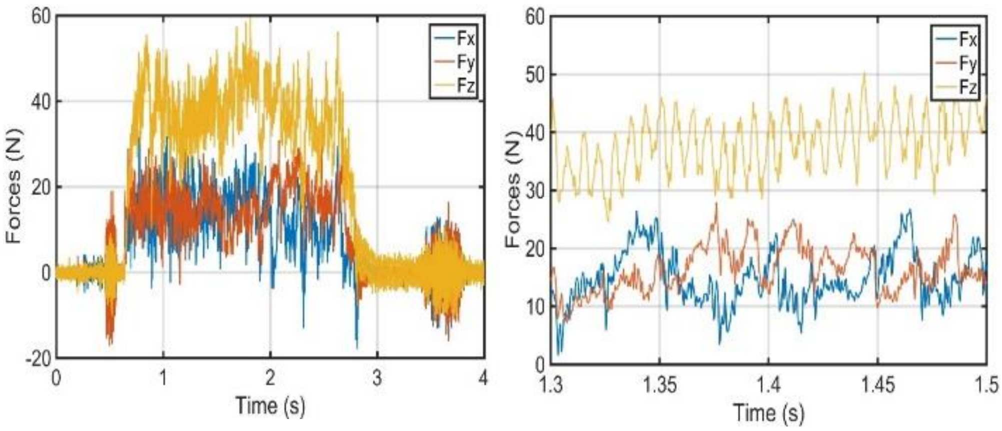


Figure 5: Milling force measurements for 2000 rpm spindle speed and 3000 mm/min feed rate: (a) during all process; (b) during 0.2s (zoom)

Cutting forces are in the order of a few Newtons, they do not exceed 60 Newtons. Generally, the force in vertical direction (Fz) is quite small, thus, it is advised that to keeping vertical forces small in milling composite due to the delamination issue. In our case, the vertical cutting force component is greater than other forces components which can be attributed to the mechanical properties of the honeycomb structure where the honeycomb structure is characterized by a better out-of-plane compression behavior than its tensile and shear strength. The evolution of cutting forces shows significant oscillations. These oscillations are caused by vacuum in the cells of the honeycomb and the angle between the cutting direction and the honeycomb cell wall direction.

Figure 6 shows the obtained evolution of the surface quality (flatness) for various combinations of cutting conditions (spindle speed and feed rate). The defect of shape is higher for low speeds. Thus, for high feed rates that exceed the 1500 mm/min, the unevenness exceeds 500 µm which characterizes the severe tearing of the honeycomb walls.

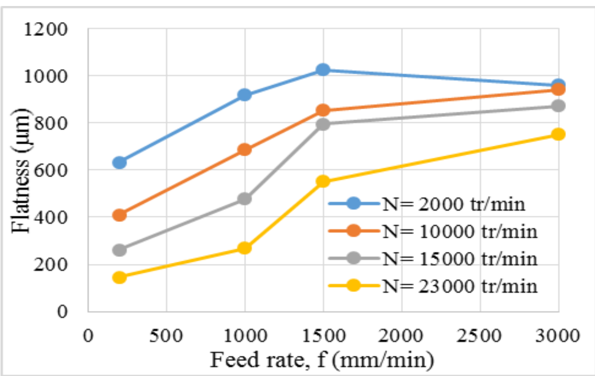


Figure 6: Effect of cutting parameters on surface flatness

Given the low level of cutting forces, the quality of the obtained machined surface allows to establish criteria for determining the machinability of the honeycomb structures. The appearance of the uncut fibers is a machining defect specific to the composite material which depends on the type of the fibers and their orientation. The tearing of Nomex® paper, linked to the cellular appearance of the honeycomb structure, occurs under the effect of shear loading [5, 12].

Alternatively a surface response [30] could have been built in order to predict the milling surface quality. But close milling parameters (such as splindle speed, feed rate, depth of cut) can lead to different results, depending on the material, the quality of the machining tool, etc.

Therefore, in our approach supervised machine learning techniques (with labeled measurements for the model training) are used. These tools need the construction of features associated with the measurements.

3 Milling diagnosis using machine learning techniques

Machine learning techniques can be separated mainly in two categories [17, 23]:

- Unsupervised approaches: based only on input data (data are unlabeled). The goal is to find groups and structures in the data set, in order to classify new observations (measurements) into the different groups.

- Supervised approaches: based on input and output data (Now the data are labelled). Supervised learning algorithms can be split in two categories [23]: Classification models which partition observations in categorical groups (leads to a predictive model for discrete responses), Regression models which describe the relationship between outputs and variables through mathematical functions (leads to a predictive model for continuous responses).

A machine learning based diagnosis system consists of different steps, as indicated on figure 7.

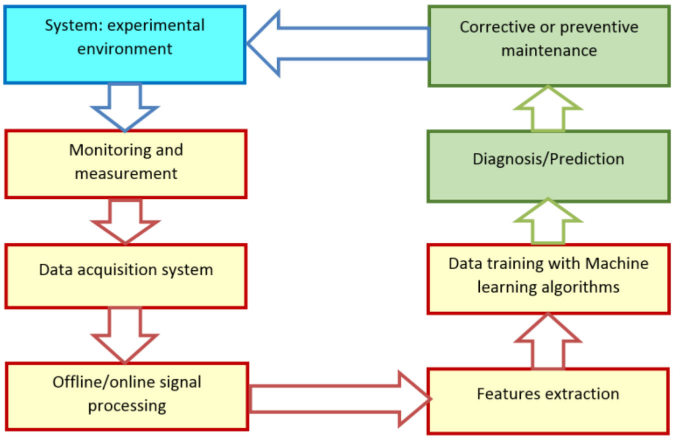


Figure 7: Workflow of a machining diagnosis system

The raw data (measurements) are firstly filtered, with low pass filters (typically with Butterworth filters order 2 or 4) in order to eliminate high frequency noises, and labeled (“obtained signals for good surface quality”, “obtained signals for bad surface quality”). Then the features are calculated offline or online (online in a real time implemented diagnosis system).

All the experiments are then split into two groups: 75% for the machine learning model training, 25% for the obtained model evaluation also called test phase in the literature (another percentage can be chosen, for example 60% - 40%, depending on the number of experiments). This can be made randomly, but the ratio “good surface quality” and “bad surface quality” must be kept in each group.

3.1 Features calculation

The features are calculated in time domain and frequency domain [6, 13] from the raw signal represented on figure 8, in steady state behavior. In fact, transient zones (that means when the cutting tool entries or exits the honeycomb core) are not taken into account.

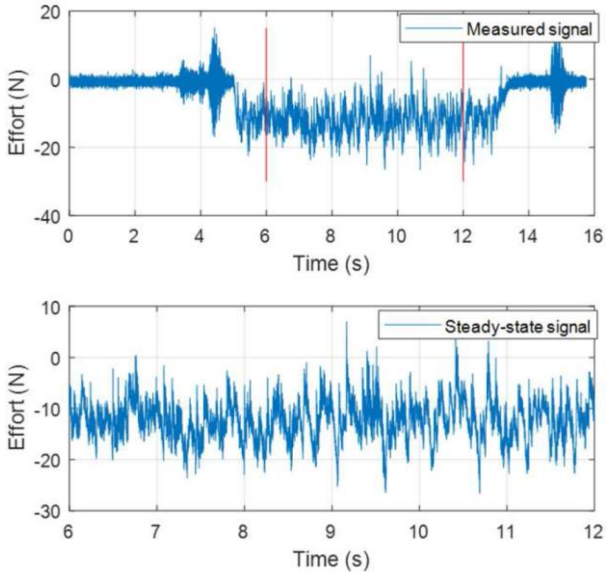


Figure 8: Measured milling force in time domain: (a) total data plot, (b) signal during steady-state phase

After a first data processing (low pass filtering), firstly 19 features are calculated in time domain for the measured milling force signal called hereafter *x*(t).

The calculated time domain features are:

- Maximum of x(t) (1)
- Minimum of *x*(t) (2)
- Difference between the maximum of x(t) and the minimum of x(t) : amplitude range (3)
- Median value of *x*(t) (4)
- Maximum of the absolute value of the signal:

$$m_{AS} = max(|x_k|) \quad (5)$$

- Interquartile range :

$$IQR = Q_3 - Q_1 \quad (6)$$

where Q_3 and Q_1 represents respectively the upper and lower quartile.
- Inter decile range :

$$IDR = D_{90} - D_{10} \quad (7)$$

where D_{90} and D_{10} means respectively the 90th ant the 10th decile. Both Inter quartile and Inter decile range are a measure of statistical dispersion of the values in a set of data.

- Average value of the signal :

$$mean(x) = \frac{1}{N}\sum_{k=1}^{N} x_k \qquad (8)$$

- Average value of the absolute value of the signal:

$$MAS = \frac{1}{N}\sum_{k=1}^{N} |x_k| \qquad (9)$$

- Average value of the absolute value of the derivative signal :

$$MAD = \frac{1}{N-1}\sum_{k=1}^{N-1} |\frac{dx_k}{dt}| \qquad (10)$$

- Variance :

$$Var = \frac{1}{N}\sum_{k=1}^{N} \left(x_k - mean(x)\right) \qquad (11)$$

- Energy of the signal :

$$E(x) = \sum_{k=1}^{N} {x_k}^2 \qquad (12)$$

- Energy of the centered signal :

$$E_c = \sum_{k=1}^{N} \left(x_k - mean(x)\right)^2 \qquad (13)$$

- Energy of the derivative signal :

$$E_d = \sum_{k=1}^{N-1} \left(\frac{dx_k}{dt}\right)^2 \qquad (14)$$

- Skewness :

$$S = \frac{E\left(x - mean(x)\right)^3}{Var^{3/2}} \qquad (15)$$

- Kurtosis :

$$K = \frac{E\left(x - mean(x)\right)^4}{Var^2} \qquad (16)$$

- Moment order i (i = 5 : 10) :

$$m_i = \frac{E\left(x - mean(x)\right)^i}{Var^{i/2}} \qquad (17)$$

- Shannon entropy:

$$E_S(x) = -\sum_{k=1}^{N} {x_k}^2 * \log_2({x_k}^2) \qquad (18)$$

- Signal rate:

$$\tau = \frac{max(x_{k=1:N}) - min(x_{k=1:N})}{mean(x)} \qquad (19)$$

Secondly another 19 features are calculated in frequency domain in a similar way for the measured milling force signal. Therefore, the Fast Fourier transform (FFT) of the signal x(t) has been calculated :

$$Y(k) = \sum_{i=1}^{N} x_i e^{-j2\pi k \frac{i}{N}}, (k = 1, \ldots, N) \qquad (20)$$

where N is the number of samples of the signal x(t).

The frequency domain features are calculated for the Y(f) signal.

All the calculated features (in time and frequency domains) are normalized and stored in a table whose lines and columns respectively represent the experimental number (also called instance) and the associated feature values. The normalization has been made as follows [16]:

$$feature_{norm} = \frac{feature - mean(feature)}{std(feature)} \qquad (21)$$

This normalization leads to :

$$\begin{cases} mean(feature_{norm}) = 0 \\ std(feature_{norm}) = 1 \end{cases}$$

3.2 Reduction of the features

The obtained normalized feature table contains 38 calculated features and 3 input values for each experiment (each experiment corresponds to a row in the matrix). The input values are the tool rotation speed, the cutting speed and the depth of cut.

It is necessary to make a dimensional reduction of that feature table in order to avoid overfitting of the learning algorithm. For a set of features, dimensional reduction can be made by using two major techniques such as feature reduction and feature selection. In feature reduction the original high-dimensional data is mapping into a lower-dimensional data. So, the transformed features are linear combinations of the original features. In feature selection, an optimal subset of features is chosen according to an objective function.

For a linear supervised problem, different feature reduction algorithms could be used, such as [18]:

- PCA: Principal Component Analysis. The features are transformed into a new set known as the principal components, which are orthogonal and ordered. The first principal component retains the maximum variation that was present in the original components, the principal components being the eigenvectors of a covariance matrix.)
- CCA: Canonical Correlation Analysis (used to analyze the relation between a pair of datasets, instead of a single dataset as in PCA, by finding a linear combination of variables which have maximum correlation with each other)
- LDA: Linear Discriminant Analysis (used to find the best projection to a line in order to well separate the samples from different classes. This kind of data reduction could be also used as classifier).
- PLS: Partial Least Squares (based on the input-output correlation and the output variance. It is used to overcome the limits of PCA in regression by successively extracting factors from both X and Y such that the covariance between those extracted factors is maximized).

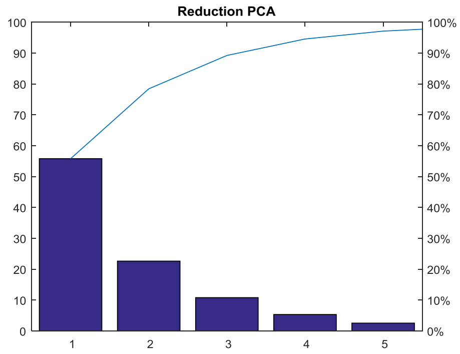


Figure 9: Pareto plot of the variance percentage

The PCA algorithm [18, 19], used in our case, has been one of the most used algorithms for dimensional reduction in industrial context. PCA can be seen as a data pre-processing method which gives a weighted reduced matrix (Zn of n-by-n dimension) where each component is a linear combination of all original variables (Xp) [18]:

$$Z^n = \alpha^{1n}X^1 + \alpha^{2n}X^2 + \cdots + \alpha^{pn}X^p \qquad (22)$$

The Z^n elements are uncorrelated and ordered by the fraction of the total information each retains. From the Zn matrix, we selected the new data table by keeping only the n-first principal component to reach a variance percentage of 99% (fig.9): we kept the first five columns

3.3 Labeled data

From the evaluation of the effect of the cutting parameters on surface flatness result (figure 6), we defined two classes of surface quality applied to the output data of each observation (see table 3) :

Table 3: Label table for the experimental observations

Label	Flatness (µm)	Qualitative value
'A‘	0 – 600	Best surface quality
‘B'	600 – …	Worst surface quality

As shown in table 3, two labels are defined, called classes. Class 'A' corresponds to the positive class, Class 'B' corresponding to the negative class. Thus, news data will be predicted using the rules below:

- If prediction probability result ≥ 0.5 : class A
- If prediction probability result < 0.5 : class B

3.4 Applied supervised learning algorithms

In this work, several classification algorithms have been implemented in the Matlab software environment [20, 21]:

- k-nearest neighbor (kNN)

- Decision tree (DT)
- Support Vector Machine (SVM)

In order to evaluate how the internal parameters of each algorithm influence their efficiency, several variants of the same algorithm have been implemented (various distances, different kernels, etc.).

The first k-nearest neighbor (KNN) was implemented by keeping the default Euclidean distance. For the same model, a limited number of neighbors (k=2) have been applied. Another training model consisted to weight each observation (the rows of our data set). Moreover the KNN algorithm has been modified by using the Chebyshev distance.

The first used decision tree algorithm is a fitted binary classification decision tree. Then the tree has been pruned to obtain a pruning tree of level 2.

Two SVM algorithms have been implemented using different kernel functions. The first one is a linear SVM which is the default function for a two-class data set. The second one is the Gaussian SVM algorithm which is a normalized polynomial kernel.

4 Obtained results

4.1 Results of the trained models

The different machine learning algorithms (with their adapted tuning parameters) are applied to the normalized labeled training data set (75% of the total experiments). The obtained trained models are then tested on the labeled test data set (25% of the total experiments). The objective is to find again the labels of the test data set: table 4 shows the accuracy result of each algorithm.

Table 4: Prediction error for the normalized data set

Algorithms	Accuracy
KNN	83.4%
KNN k=2	81.3%
Weighted KNN k=2	83.4%
Chebychev KNN k=2	87.5%
Tree	99%
Pruned tree	66.67%
Linear SVM	83.4%
Gaussian SVM	66.67%

From table 4 we can observe that the classical decision tree classifier leads to the best trained model for predicting new data. But when that same algorithm was pruned, it lost an accuracy of 32.33%. The pruning can be necessary in the case of a real time implementation.

Table 5 shows the accuracy result of each algorithm performed with the reduced normalized data set obtained from the PCA.

Table 5: Prediction error for the normalized weighted data set obtained by PCA

Algorithms	**Accuracy**
kNN	99%
kNN k=2	85%
Weighted kNN k=2	98.2%
Chebychev kNN k=2	87.5%
Tree	99.2%
Pruned tree	66.67%
Linear SVM	99.8%
Gaussian SVM	93.8%

For the dimension reduced feature table, obtained by PCA, the algorithms gave better results: several algorithms produce high accuracy rate. Specifically, linear SVM is the most efficient with the lowest running time and the highest accuracy. It is also noticed that more an algorithm is constrained by parameters, more its performances can be reduced. For example it is the case of the pruned tree for which we limited the expansion.

4.2 Prediction results for new experimental data

We used some news experimental data set in order to evaluate the performance of the trained model. The goal is to predict online (during milling) the surface quality. Results are presented here for the trained model by using the linear SVM classifier algorithm.

Table 6: Performance of the prediction using SVM classifier

	Predicted class		
Actual class	A	B	
A	TP = 83%	FN = 17%	100%
B	FP = 0%	TN = 100%	100%

(TP: true positive rate; FN: false negative rate; FP: false positive rate; TN: true negative rate)

Table 6 shows the percentage of true positive rate and false negative rate obtained from the evaluation of the prediction. The negative class B was the best predicted class. Despite the fact that linear SVM algorithm lost in performance for data set with large predictors (i.e. large number of features), it has been the most accurate algorithm with the best prediction rate and the lowest training time.

5 Conclusion and further works

It is known that the milling's performance is qualified by evaluating the roughness or the flatness of the resulted surface. In this work, different supervised machine learning algorithms have been implemented and compared. To do this, features were firstly calculated from measured milling forces and then each Artificial Intelligence (AI) - based model has been trained by the labeled set of features. From the prediction results, SVM algorithm seems to be the most efficient diagnosis algorithm in this application of honeycomb material milling. The developed diagnosis approach can also be applied to the milling of other material.

The next step consists to test and compare different feature reduction algorithms with measures having uncertainties, in order to have a fast real time milling diagnosis system.

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