Qualitative estimation of the roughness using automatic learning algorithms in a drilling operation

Aitor Duo Zubiaurre[1] – aduo@mondragon.edu -- Tlfn. 627859865
Erika Domínguez Romero[1]
Larraitz Azpitarte Aranzabal[1]
Javier Aperribay Zubia[1]
Mikel Cuesta Zabaljauregui[1]
Ainhara Garay Araico[1]
Rosa Basagoiti Astigarraga[1]
Pedro J. Arrazola Arriola[1]
[1] Mondragon Unibertsitatea, Faculty of Engineering, Loramendi 4, 20500 Arrasate – Mondragon (Gipuzkoa), España.
Received: DD/MM/AA – Reviewed: DD/MM/AA -- Accepted: DD/MM/AA - DOI: https://dx.doi.org/10.6036 (To be completed by Editor)

Abstract
Within the framework of industry 4.0, the aim is to develop collaborative human-machine environments in order to achieve greater adaptability to the variability of cutting processes by making efficient use of available resources. For this, the use of the existing information in the data obtained from the cutting processes is fundamental. The control and visualization of scientific parameters (acoustic emissions, cutting powers, vibrations, shear forces...) related to industrial parameters (tool wear, roughness, microstructure...) in drilling processes is of great importance. Drilling processes are carried out in the final stages of the production of a part, which often results in a critical operation. Using an experimental setup, where both internal signals and the acoustic emissions signal are acquired and using automatic learning algorithms, a qualitative estimate of the quality of the hole made is obtained. Given the demands of some sectors in which it is necessary to check the roughness of the machined surface and taking into account the requirements to be met by manufacturing companies, obtaining an estimation of the state of the machined surface is an advantage in terms of decision-making.

Keywords: Roughness, acoustic-emission, machine-learning, drilling

1. - INTRODUCTION

The rise of the demand on the precision of the components machined with a sustainable approach is one of the problems that the machining area has to face. The decision making regarding the critical events that could occur during the cutting process has to be done as soon as possible, being the automatization of this task one of the keys to save money. This is why, the monitoring of the cutting processes becomes so crucial. With the correct data analysis tools, the virtualization and the process control, a transformation is on its way for the machine tool area towards an automatized environment.

The drilling process is one of the most critical processes for the machining processes because it corresponds to the final stages in the fabrication of one component and there is a risk of it to be defective in case of not taking preventive measures indicating the current state of the process [1]. The drilling is a continuous cutting process where one or two cutting edges remove the desired material volume through chip removal.

The tool wear is one of the most studied problems regarding the cutting process monitoring [2]. The most frequently used signals are the cutting forces, vibrations, acoustic emissions or the sound pressure. All these signals are external to the cutting process and more or less invasive to some point. The dynamometer is used mostly for research purposes because its use, assembly and calibration, in industrial environments could be a problem [3]. As an alternative, Corne et al. [4] proposed to use the head power because it maintains a strong relation with the cutting forces and less invasive than a dynamometer. Diniz et al. [5] proposed to stablish a relation between the wear of the tool and the acoustic emission, successfully checking that the standard deviation of the acoustic emissions is related with the tool wear. Duo et al. [6] showed that there is a relation between the torque of the Z axis acquired from the machine and the thrust force. Feed torque measurement is an alternative to feed force measurement as it is less expensive to acquire and does not require invasive systems.

Acoustic emissions is the most precise signal and is defined as the elastic energy released spontaneously during a local change, dynamic and irreversible in the micro structure of the material [7]. Marinescu et al. [8] propose a system to detect anomalies in surfaces generated in milling stating that acoustic emissions have the power to detect anomalies for the monitoring of defects on the working surface of the material, unlike other signals. Vibrations and sound pressure signals have the characteristic than they measure phenomena that occur at a frequency lower than 10 kHz. Acoustic emissions are affected by high frequencies, from 50 to 500 kHz. This is why acoustic emissions detect phenomena with high precision. In Fig. 1, it can be observed the precision or scope of every signal commonly used during the monitoring process of the machining process.

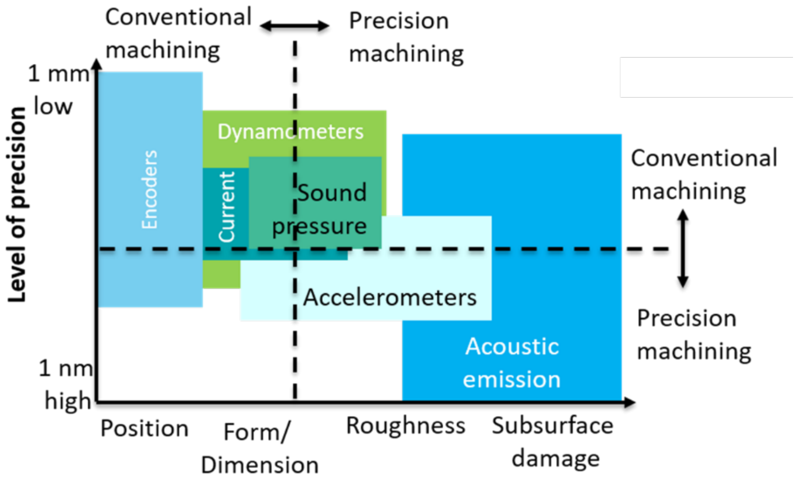


Fig 1: Measurement accuracy for each sensor (Modified from Dornfeld et al.[9]*)*

Other aspects as the roughness or the damage in the final surface could be affected by the cutting tool wear. Pimenov et al. [10] studied the milling process and found that roughness goes worst along the tool wear. In drilling processes, in the other hand, the friction of the chip and the periphery of the drill against the generated surface eliminates the generated profile, this is why, the tool wear does not need to be necessarily related with the obtained roughness. Eckstein et al. [11] analyse the drilling process in Inconel 718 not only for the drilling process, but also for the reaming. The roughness tend to be similar in both processes but better results are obtained in the reaming process. The roughness goes better in the first stages for both processes and it is suggested that this tendency is due to the rounding effect of the cutting edges. During the different operations, the only modified parameter is the tool geometry, so that the tool wear is not only the removal of the material using the tool in the cutting-edge flank face but a removal of the material in all areas exposed to the cutting.

Automatic learning algorithms offer the capability to learn from machining process behaviour using for that information extracted from data acquired during previous executions of the same process. Suresh et al. [12] use genetic algorithms to optimize the roughness of the machined part, concluding that it is a useful tool to optimize the cutting conditions and obtain the desired surface. Venkata Rao et al. [13] developed a system to optimize the cutting conditions in boring processes using vibrations signal with the aim to enlarge the useful life of the tool and minimize the roughness of the generated surface. In this study, they conclude that using a Neural Network, it is possible to create a system that allows changing the tool before the cutting process before it starts to become worse. Kilickap et al. [14] created a model based on response surface methodology and minimizing the result using a genetic algorithm, they obtain the cutting conditions necessary to minimize the roughness of the machined surface.

The analysed papers were mainly dedicated to the prediction of the tool wear and to the prediction of the roughness in other operations as milling or boring. However, the drilling is a complex process where other factors as chip evacuation are relevant. The periodicity of the roughness profile disappears in drilling processes, making the development of prediction models more difficult for this operation. Due to the few papers dedicated to the prediction of the roughness for drilling processes, this work is dedicated to explain a methodology that can be useful to create models, which describe the roughness of the machined part. The main aim of this work is the development of an automatic learning model able to describe the surface roughness of the machined part using acoustic emissions. Next sections will explain the methodology used for the acquisition and extraction of characteristics which predict the state of the surface of the hole. Following section will explain the obtained results and conclusions reached during this study.

2. - MATERIAL & METHODS

In this section, details about the experimental setup used are presented, besides that, the analysis of the roughness of the machined part in relation to the signals acquired during the drilling of Steel with composition 35CrMo4LowS. Based on the energy of the acoustic emissions generated on every machine revolution, a prediction was made about the range of roughness where the hole is expected to be.

2.1.- EXPERIMENTAL SETUP

A Lagun B1050 vertical machining centre was used for the experimental trials. During the installation of the experimental setup, an acoustic emission sensor, Kistler 8152C, was installed. In addition to this signal, internal signals of the machine were also acquired (Z axis torque, electrical and mechanical spindle power and tool tip position, speed, acceleration and jerk) just to check their relevance related to the surface integrity. For these experimental trials, drill bits Kendu BH04.5D of 8 mm diameter were used. Each tool was re-sharpened to obtain a geometrical shape representing a certain flank wear. Overall, 4 tools were used, i) a new tool, ii) a drill bit with a 0.1 mm wear, iii) a drill bit with a 0.2 mm wear and iv) a drill bit with a 0.3 mm. 5 holes were done with each tool, with a cutting speed Vc= 40 m/min and a feed rate f=0.07 mm/rev, being the holes 5 mm depth. The total number of holes during the trials were 20. In Figure 2, brief representation can be seen of the setup used in this work.

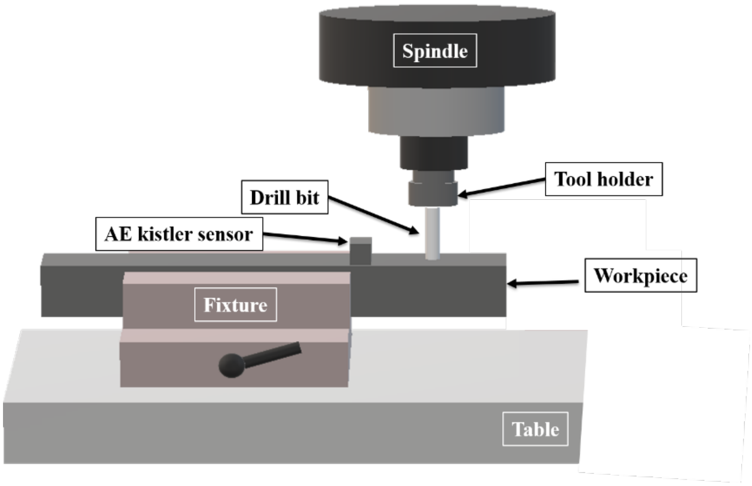
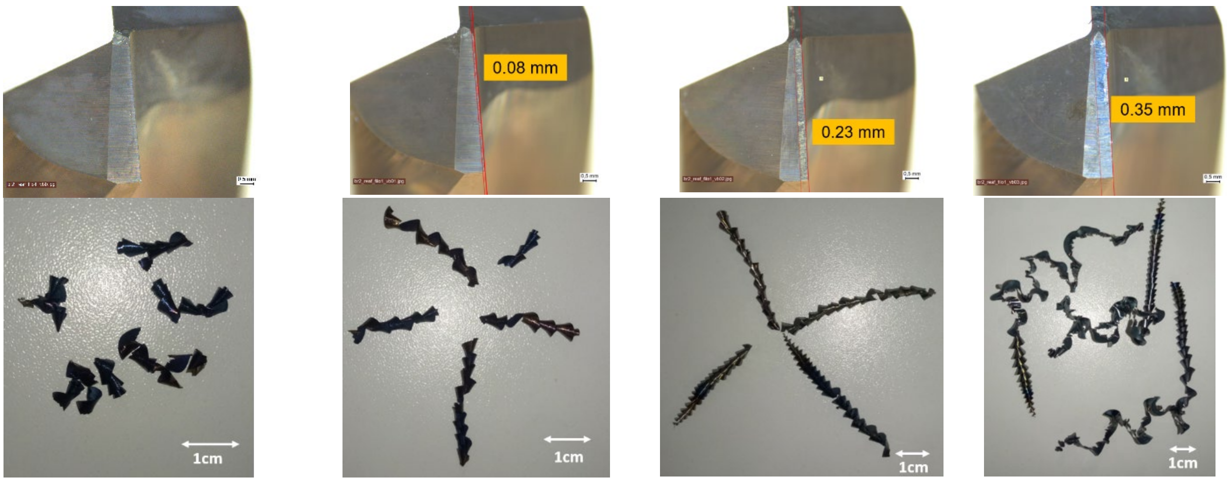


Fig 2: Experimental setup used for the experimental trials in drilling process.

During the execution of these trials, the chip was gathered to observe if it was any change on its generation during the machining process. Fig. 3 shows the geometry of every tool used and the chip generated during each drilling process. At the beginning of the process (Fig. 3a), while the tool remains new, the chip tends to have a shape of helicoidally conic fragments [15]. As the wear of the tool increases, the chip tends to be longer, maintaining the helicoidally shape, (Fig. 3b,c). when the tool shows more wear, (Fig 3.d), the chip tends to show the same shape as in previous stages but, as the process goes ahead drilling the hole, the chip does not break so easily and losses the basic shapes, showing some problems at the time of evacuating it.



a) Vb=0 mm   b) Vb=0.1 mm   c) Vb=0.2 mm   d) Vb=0.3 mm

Fig 3: tools and chips extracted for every 5 holes drilled with every tool

The roughness was measured with a profilometer Alicona IFG4 3D based on ISO 4287-1997 standard. For these measurements, the first and last holes were extracted with Electrical Discharge Machining (EDM) to subsequently cut them in two parts in the precision cutting machine, and the desired surface measured. The results of these measurements are shown in the next Fig. 4.

Hole #1 Hole #5

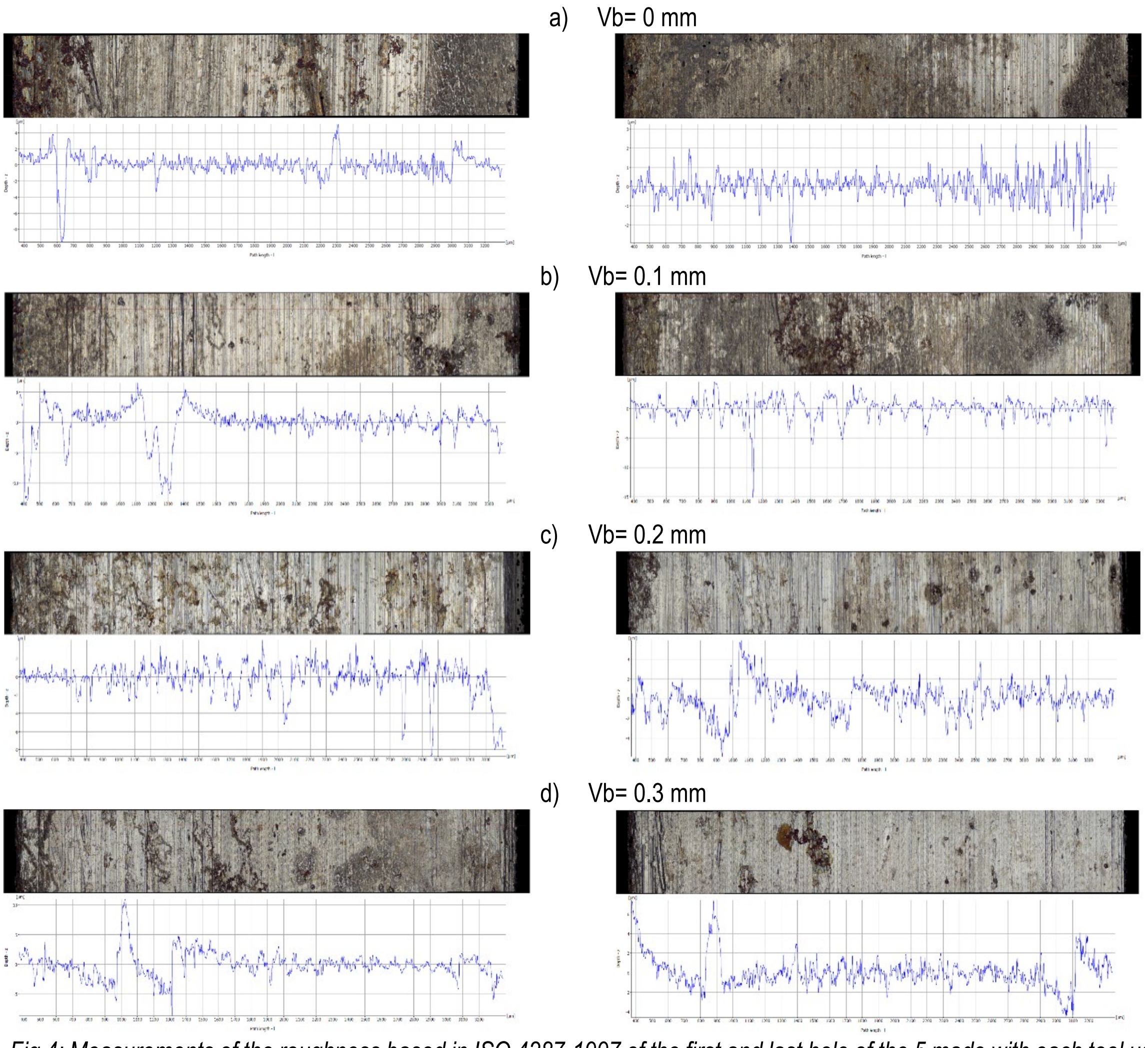


Fig 4: Measurements of the roughness based in ISO 4287-1997 of the first and last hole of the 5 made with each tool used during the experimental trials.

Fig. 5 shows the arithmetic mean of the roughness (Ra), the mean quadratic error (Rq) and the maximum height from peak-to-valley (Rt) for the first and last holes corresponding to each bit. As it can be observed in the figure, not necessarily a higher tool wear means a worsening of the roughness of the surface generated. The new tool is the one that a best profile generates whereas, a tool with an observed wear of Vb = 0.1 mm is the one that worst roughness generates.

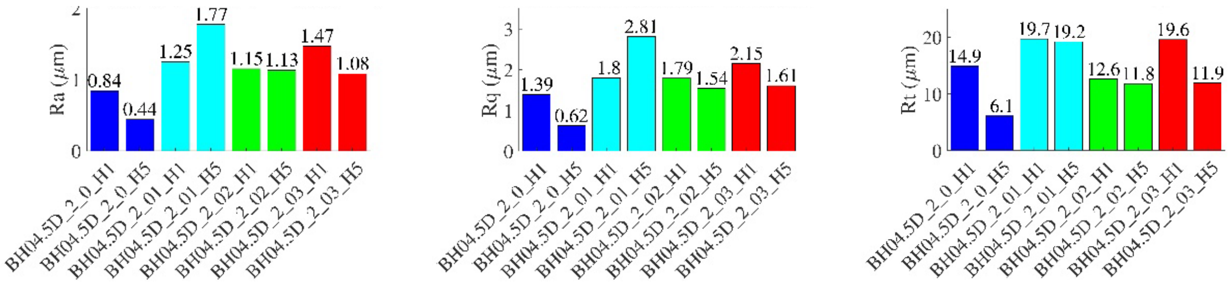


*Fig 5: Ra, Rq, Rt from the first and last hole corresponding to each tool. (Identification BH04.5D_2_(**Vb**)_H**N**, where Vb stands for the tool wear and N is the hole number).*

Based on ISO 1302:1992, different labels are used depending on the roughness measurement: R1 corresponds to roughness between [0.4; 0.9) μm, R2 roughness between [0.9; 1.2) μm and R3 roughness between [1.2; 3) μm. According to this labelling procedure, the roughness label corresponding to the holes of the new tool was 'R1' which corresponds to a roughness grade N7, a label 'R3' was the one corresponding to tools with a wear Vb= 0.1 mm , the worst roughness measured during the trials. To the holes done with tools with a wear Vb=0.2 mm, the 'R2' was given. Regarding the tools with Vb=0.3 mm, the first hole corresponds to a label 'R3' while the fifth hole corresponds to a 'R2' label. There is a lack of holes analysed in the profilometer due to the tediousness of this activity.

2.2.- AUTOMATIC LEARNING

Within the acquired signals, acoustic emissions are the ones selected to check the automatic learning algorithms performance at the time of predicting the surface roughness. As it was clear in the literature, this signal is the most sensitive one to the phenomena that could appear during the machining process and the use of this signal is extensively used oriented to the detection and prediction of micro defects.

The experiments to evaluate the performance of the algorithms used were carried out in the Weka platform [16]. Several algorithms, following different learning principles were checked. The description of these learning principles can be found in [16]. In particular, the one selected for this work were: i) Linear regression algorithms (logistic function), ii) the Naive Bayes algorithm based on probabilistic principles, iii) decision trees J48 y LMT (logistic model-based tree) and iv) instance-based learning algorithm IBk.

To evaluate the performance of these automatic learning algorithm the following evaluation metrics has been used:

Precision: also called positive predictive value, is the fraction of relevant instances among the retrieved instances.

Cohen's Kappa coefficient: is a statistic that is used to measure inter-rater reliability (and also Intra-rater reliability). It is generally thought to be a more robust measure than simple percent agreement calculation, as it takes into account the possibility of the agreement occurring by chance, a value of 1.0 meaning complete concordance.

Mean Absolute Error: is an average of the absolute errors between current values and their predictions.

Fig. 6 shows the detailed steps for the previous feature extraction task necessary to start with the Surface roughness prediction process:

I. The signal has been filtered with a band pass filter between (50; 450) kHz, allowing the removal of low and high frequency values.
II. The precision of measurement changes for acoustic emissions depending on the location of the sensor during the trials. To avoid any problem, the data was normalized in such a way that every signal has a mean of 0 and a standard deviation of 1.
III. In case of changes of the cutting conditions, the relation between sampling frequency and the revolutions of the machine are relevant parameters. The sampling frequency varies on cutting conditions and the acquisition process depends on this factor. The energy of a signal can be considered as the relative amplitude of the signal and it can useful because it can determine the energy of the emissions.
IV. In the present study, the energy emitted in each revolution of the head of the machine is calculated(MARSE).
V. From the resulting signal, different statistical features are obtained that allow for the next step.
VI. To create an instance which corresponds to a register of the hole made.

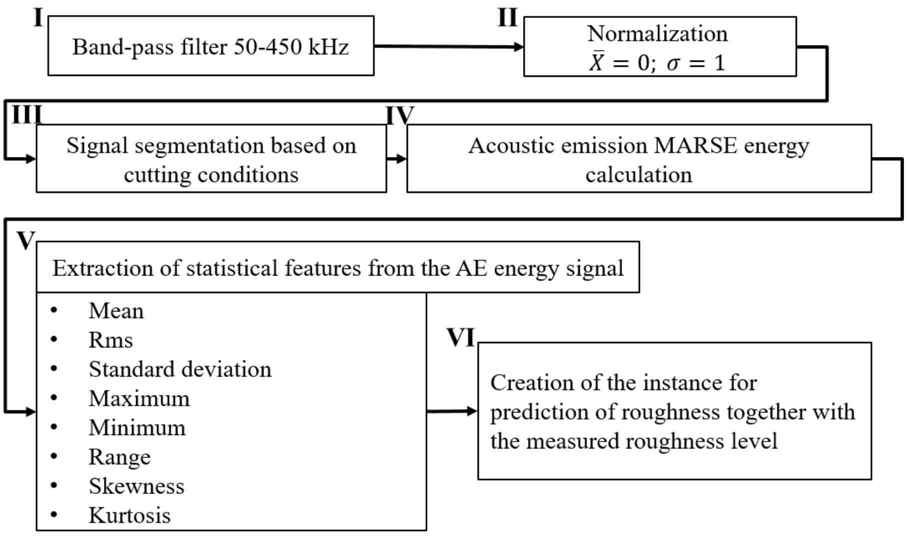


Fig 6: Feature generation process previous to the automatic learning process.

For the roughness estimation process dataset creation, a record or instance have been used for each hole made. Every record or instance has the attributes or features explained in Fig. 6 and an additional one corresponding to the target value that is going to be predicted which corresponds in this case to the roughness label, as it was described in the previous section.
Overall, only the roughness of 8 holes have been measured. As there are few instances to train the models, additional instances have been added where the label is set without any new measurement, corresponding to hole numbers 2 and 3 for Vb= 0 mm. The label value set for these instances is the same as the label on holes first and last, 'R1. At this point, we have 2 additional instances for training, 10 at all.
For the model evaluation process, apart from the 10 instances already used for training, another 7 instances, corresponding 1 of them to Vb=0, 2 to Vb=0.1 and 2 to Vb=0,2, have been added. When added, the label corresponding for roughness is, again, the same label of the first and last hole, because there was no variability on these labels. For Vb=3, as there was a variability on the values of first and last holes, no additional instances were introduced.

3. - RESULTS AND DISCUSSION

The results obtained using these algorithms suggest that the creation of an automatic roughness estimation system of the machined surface is possible. These automatic systems were trained to obtain an estimation that, afterwards, need to be compared to the real values. The results of this comparison are usually shown with a double entry table with two main entries, labels corresponding to real values (labels corresponding to roughness measured at the laboratory) that will appear referred as target and the roughness estimated by the use of the models, referred as predicted.
Table 1 shows these double entry tables called confusion matrixes, corresponding to the use of each different algorithm and besides that, previously mentioned evaluation metric values related to the results. Cells of the table in green, diagonals of these tables, recount the number of instances for which the roughness is correctly estimated by the algorithm. On the other hand, cells in red correspond to errors in the prediction, instances that corresponding to a certain roughness stablished in the laboratory become instances incorrectly labelled due to an error in the label predicted by the algorithm.

Tabla 1: Matrices de confusión y métricas de evaluación de los modelos obtenidos

Logistic function

Target \ Prediction	R1	R2	R3
R1	5	0	0
R2	0	6	0
R3	0	0	6

Accuracy	100%
Kappa coef.	1
MAE	0

Naïve Bayes

Target \ Prediction	R1	R2	R3
R1	5	0	0
R2	0	3	3
R3	1	1	4

Accurac	70.5%
Kappa coef	0.55
MAE	0.18

J48

Target \ Prediction	R1	R2	R3
R1	5	0	0
R2	3	3	0
R3	0	1	5

Accuracy	76.47%
Kappa coef.	0.65
MAE	0.17

IBk

Target \ Prediction	R1	R2	R3
R1	5	0	0
R2	1	5	0
R3	0	1	5

Accuracy	88.2 %
Kappa coef.	0.82
MAE	0.16

LMT

Target \ Prediction	R1	R2	R3
R1	5	0	0
R2	2	3	1
R3	0	0	6

Accuracy	82.3%
Kappa coef.	0.73
MAE	0.31

In general, observing the obtained results, it looks like there is a relation between the acoustic emissions and the roughness. Guo et al. [17] analyse the relation between the acoustic emissions with different output parameters in turning processes showing the relationship between acoustic emissions and the roughness. Kishawy et al. [18] mention some studies trying to stablish the relation between acoustic emissions and the surface integrity , stating clearly that is a signal with high potential for an on-line monitoring of the generated Surface. The present work reinforces this relation for drilling process.

As it can be observed in these results, the logistic function is the one with the best results. With this type of function, a classifier is created for every pair of class values, using only the instances for these two values. The output of the algorithm for a new instance is based on the estimated class value that gets more votes.

Naive Bayes algorithm follows a probabilistic approach but is not properly working in this problem, probably due to the few numbers of instances. The output of this algorithm can be distorted if during the testing process, instances appear not corresponding to any group of the known groups. The algorithm will probably associate a probability value of 0 to every known group, obtaining worst results.

The decision tree J48 improves the precision and the kappa coefficient while it maintains a similar mean absolute error. Classification trees use the divide and conquer approach, showing, generally, a good performance in training sets. Usually, the algorithm over fits to the training data and have difficulties to generalise to new data. Given the few instances in hand in this work, probably the algorithm suffers from this problem.

Finally, the logistic model tree (LMT), although it has good precision, is the algorithm with the highest mean absolute error. This model has some difficulties to correctly classify the label 'R2' but performs properly with the other labels.

The confusion matrix corresponding to the IBk algorithm shows acceptable results, misclassifying only two instances of the testing process, one from label R2 and another observation with label R3.

In general, the label 'R2' is the one that more errors generates, this label is the one corresponding mostly to the tools with a wear of Vb=0.2 mm, which generates the longest chip and where the chip evacuation becomes more difficult, generating more uncertainty about the generated surface. On the other hand, the label that more easily can be learnt from the data is the label 'R1' because it gets 100% of accuracy for every algorithm.

Although this work only deals with few instances, the algorithm show an interesting performance and we think that a system of this kind could help at the time of stablishing the evolution of roughness that a given tool geometry generates in drilling processes based in data acquired during the process .

4. - CONCLUSIONS

Acoustic emissions are used in this study to predict the Surface roughness. To stablish this relation, many parameters have been measured giving more relevance to the roughness and the wear of the tools used during the trials. There is not a clear relation between the roughness and the tool wear, but a higher tool wear makes it difficult to evacuate the chip, somehow removing the profile created by the cutting edges.

Few data was available, but the results seem to indicate that it is possible to use models that allow the estimation of roughness in drilling processes using the energy recorded by the acoustic emissions, which takes into account both, the energy produced by the cutting of the edges and the friction of the peripheral walls.

With an accuracy of 100%,within the tested models, the one with the best performance is the logistic model. In the future, it is intended to carry out a greater number of tests and measurements on a larger number of samples, favouring the robustness of the models.

It should be noted, in any case, that the measurement of roughness is a costly task but affordable in case of parts belonging to critical sectors.

ACKNOWLEDGEMENTS

This work has been developed by the group of Intelligent Systems for Industrial Systems (IT-1357-19) and the group of High-Performance Machining (IT-1315-19) of Mondragon Unibertsitatea supported by the Department of Education, Linguistic Policy and Culture of the Basque Government. This work has been carried out with the support of the Procoda project (KK-2019/00004) and has been partially funded by the PRODUCTIVE 4.0 project subsidised by ECSEL (737459) and MINECO (PCIN-2017-071).

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