Using Machine-Learning techniques and Virtual Reality to design cutting tools for energy optimization in milling operations

David Checa[1], Gorka Urbikain[2], Aitor Beranoagirre[2], Andrés Bustillo[1*], Luis Norberto López de Lacalle[2]

[1] Department of Computer Science, University of Burgos, Burgos, Spain

[2] Department of Mechanical Engineering, University of the Basque Country, UPV/EHU, Spain

[*] Corresponding author: email: abustillo@ubu.es, phone: +34 947259358

Abstract

The selection of a proper cutting tool in machining operations is a critical issue. Tool geometric parameters are essential to milling performance. However, the process engineer has very limited experience of the best parameter combination, due to the high cost of cutting tool tests. The same holds true for bachelor studies on machining processes. This study proposes a new strategy that combines experimental tests, machine-learning modelling and Virtual Reality visualization, to overcome these limitations. First, tools with different geometric parameters are tested. Second, the experimental data are modeled with different machine-learning techniques (regression trees, multilayer perceptrons, bagging, and random forest ensembles). An in-depth analysis of the influence of each input on model accuracy is performed to reduce experimental costs. The results show that the best model with no cutting-force inputs performed worse than the best model with all the inputs. Third, the most accurate model is used to build 3D graphs of special interest to engineering students as well as process engineers, for the optimization of power consumption under different cutting conditions. Finally, a Virtual Reality environment is presented to train engineering students in the study of the best tool design and cutting parameter optimization.

Keywords: Multilayer Perceptron; Virtual Reality; serrated cutters; energy optimization; ensembles.

1. Introduction

Manufacturing companies must balance reliable and productive cutting processes with quality parts, in order to satisfy short delivery times from industrial partners. Maintaining high mass removal rates under proper, optimum, milling forces is a crucial issue in machining operations. Hence, the modeling of cutting forces for the prediction of machining forces under a variety of conditions is essential for optimal machining operations. Some outputs of these models are the definition of power requirements, chatter onset, optimization design for fixtures and clamping, *etc.* Strasmann cutters also known as ripping or serrated cutters, offer an efficient solution for better mass removal rates. Their main applications are productive roughing operations in various areas, such as components for machine tool structural elements, tools, and fixtures, among others.

The optimization of cutting processes using serrated cutters has followed two main approaches: either by programming the best cutting conditions or by selecting the most suitable cutting tool.

The first strategy has been extensively explored and summarized in recent reviews (Vallavi M S, Gandhi N, and Velmurugan 2015), while the bibliography related to the second approach is much more limited (Tehranizadeh and Budak 2017; Urbikain Pelayo and Olvera Trejo 2020). The reason for this imbalance between research efforts into both approaches is due to the high costs of testing many different cutting tools under the same cutting conditions. While the first approach requires only one cutting tool for testing tens of different cutting conditions (*e.g.*, by changing feed rate and rotation speed), the second approach would require an inordinate number of specially manufactured tools for testing. Process engineers will therefore have very limited experience or criteria to decide upon the best combination of geometrical tool parameters and will generally rely on the tool manufacturer's recommendations. Cutting process modeling might be the only alternative solution to costly extensive experimental tests.

The mechanistic model was the first type of model used to optimize tooling processes and tool design. In their seminal work Engin and Altintas (Engin and Altintas 2001) described the fundamental points on the mechanics and the dynamics of milling cutters. Their models proved to be very useful and adaptable and were therefore extended towards more complex tool geometries. For instance, Budak (Budak 2003) analyzed the behavior of variable helix pitch tools and found productivity growth regions with respect to conventional straight end mills. More recently, mechanistic approaches when merged with either numerical methods or with FEM have led to important chatter research-related results. For instance, Ozkirimli et al. (Ozkirimli et al. 2016) reported good agreement with experimental results after having adapted the zero-th order semi-discretization method through a speed average time-delay term in their model that reproduced regular and irregular tooling patterns. Likewise, Tunc (Tunc 2018) proposed a generalized milling model using a combination of FEM, stereolithographic (STL) slicing and Receptance Coupling Substructure Analysis (RCSA) for analyzing chatter in robotic milling. Urbikain (Urbikain 2019) analyzed the behavior of complex barrel tools under static and dynamic conditions.

This strategy has been also followed regarding serrated or undulated profiles. The model proposed by Campomanes (Campomanes 2002) tested both the mechanics and the dynamics of serrated tools with sinusoidal forms. It took no account of the full tool geometry and its effects, preferring the linear edge force model to account for milling forces. The mechanistic cutting prediction model proposed by Zhang et al. (Zhang et al. 2003) divided the solid end-mill into axial disks. Grabowski et al. (Grabowski, Denkena, and Köhler 2014) also presented a model for forces and stability that took account of friction and rubbing effects. They included edge force coefficients for the computation of the cutting forces. Merdol and Altintas (Merdol and Altintas 2004) addressed the fundamentals of the mechanics and the dynamics of serrated endmills. They developed a mechanistic cutting force model to predict cutting forces and utilized the model to analyze the effects of tool geometry on basic quantities such as chip thickness, cutting force, power and vibrations. Imani et al. (Imani, Sadeghi, and Kazemi 2008) proposed real-time finite element analysis to study the stability of interrupted (low immersion) milling processes. In their work, they investigated the helix angle and its effects on cutting forces. In turn, Dombovari et al. (Dombovari, Altintas, and Stepan 2010) examined serration effects on milling stability using semi-discretization algorithms. In turn, Koca et al. (Koca and Budak 2013) used the Linear edge-force model for force modeling and the first order semi-discretization method for stability prediction with serrated end mills. They used Brute Force Search and the Differential Evolution Method to investigate serration parameters for improved stability. Recent investigations can be found on the margins for machining quality improvements based on the properties of the serrated profile (Tehranizadeh and Budak 2017) and on the serration shift angle between cutters (Urbikain Pelayo and Olvera Trejo 2020).

Machine-learning techniques can also be considered for cutting-process modeling. Machine-learning techniques have the advantage of generalizing the models to new conditions, thereby reducing the number of expensive experimental test that have to be performed. When the output of a machine-learning model is a continuous variable, the prediction problem is commonly called regression. Many machine-learning techniques have been developed for regression tasks: Artificial Neural Networks (ANN) (Yegnanarayana 2004), Regression Trees (RT) (Quinlan 1992) and Ensembles (Kuncheva 2014). The accuracy of these techniques equals other traditional approaches and the techniques themselves are more flexible for many manufacturing processes such as surface quality (Benardos and Vosniakos 2003) and tool wear (Chandrasekaran et al. 2010) prediction in machining operations. However, there are few studies that have modeled power consumption as an output, although recent studies have shown that the energy consumption of the drive is the most critical factor for the eco-impact of a machine-tool when its whole lifecycle is considered (Dietmair et al. 2010). However, sensitivity towards eco-impact and power consumption is very recent in industry and the modeling of power consumption is not as extensive as the prediction of surface quality and tool wear. In this sense, Lechevalier et al. (Lechevalier et al. 2018), in one of the rare studies on power consumption modeling with machine-learning algorithms, proposed an ANN-based methodology to generate analytical models for energy consumption in milling processes.

Tools can be properly designed once cutting process models are prepared, following either of those two approaches –analytical modelling and machine-learning techniques-. Tool design is studied and optimized through many different direct/indirect indicators of cutting-process quality. In the first group, we find surface quality; surface and average surface roughness parameters, Ra and Rz, are often the output functions. Tools that are optimized for the best surface accuracy are, however, finishing end-mills with a slight MRR. Such models tend to use empirical models and Taguchi techniques (Kumar 2018, Kumar et al 2019), but are not so useful in terms of relating surface roughness to tool geometry. In most cases, a surface function is built for the surface roughness parameter, depending on the cutting parameters rather than the tool geometry. Those models are only capable of describing the tool at the surface with a very coarse consideration of tool parameters (tool diameter, number of flutes, …). They can hardly be used in practice to improve tool design. In the second group, cutting forces are considered a relevant indirect parameter to assess process quality. Authors often try to reduce either the peak of the cutting forces or the average total force or both; the key variable is mainly the resultant force on the horizontal XY plane (as a lower force tends to be registered on the Z axis) (Tehranizadeh and Budak 2017, Urbikain and Olvera 2020). This criterion is selected when the aim is to improve tool life and to reduce tool costs. Controlling and reducing cutting forces is associated either with roughing or with finishing operations, because roughing operations are time-consuming operations and finishing operations may lead to chatter vibrations. Regarding the latter, chatter avoidance (or chatter-free region maximization) can also be a tool-design criterion (Comak and Budak 2017). However, chatter likelihood depends on a number of variables from one operation to another; for instance, cutting force directions, displacement direction, which in fact depend on the cutting parameter, tool geometry, *etc.*

Among these criteria, energy optimization has gained ground over recent years. As sustainable manufacturing promotes competitiveness, manufacturers of consumer goods are increasingly involved in the environmental challenge (Wippermann et al. 2020). Improving the energy efficiency of manufacturing processes is a trend -if not a must- for goods manufacturers. In this sense, models for cutting power prediction and estimation have been created and adapted to various manufacturing processes. Gutowski et al. proposed a pioneering thermodynamic model in (Gutowski et al. 2006). These authors proposed the summation of a constant term (for idle spindle running) and a variable one for the power formula, which was proportional to the Mass Removal Rate (MRR). Later, models were developed both for turning and for milling processes (Li and Kara 2011). Regarding the latter, Balogun and Mativenga (Balogun and Mativenga 2013) presented a very rigorous approach towards minimizing energy requirements. These authors modelled cutting power and studied the effect of toolpaths through milling tests and power measurements. Liu et al. (Liu et al. 2015) conducted an empirical study of total power modelling. However, the experimental agreement was only verified in slot-milling operations. They then presented a power model quality indicator that related energy consumption and surface roughness (Liu et al 2016), achieving very good agreement and even proposed a direct relation between both input-output parameters. Shi et al. (Shi et al 2019) proposed an improved model for power prediction that was successfully applied to the milling of titanium alloys, with very low errors.

However, most energy optimization models for tool design are based on relating chip load (*i.e.*, Material Removal Rate –MRR-) and the resultant cutting force with cutting power. Such mechanistic-based models can be very time-consuming and very often involve too much local to specific machining operations (slot milling, conventional straight cutting tools, soft materials…) and conditions (no tool wear, no chatter, *etc.*). Machine-learning models can only be of sufficient accuracy when fed with extensive experimental data to set their parameters and for model validation. Based on the above limitations of both approaches, a novel combination of power consumption obtained from a mechanistic-based model and small volumes of experimental data is proposed in this study using machine-learning techniques that simulate high-cost experimental models. The target applications are time-consuming rough milling applications where surface roughness cannot be the primary magnitude. Power consumption, which is related to MRR and cutting forces, is 1) a scalar quantity that is easier to process than some other parameters; and 2) it is easily measured with inexpensive devices (unlike cutting forces that need dynamometers). Therefore, power consumption will be used in this study as the main criterion. Besides, machine-learning techniques can be adapted to variables with different meanings and origins, so the proposed methodology can also be extended to other output variables, such as surface roughness, cross XY average force component and any other chatter-related variables.

However, the development of prediction models for manufacturing tasks is not the only challenge to the optimization of factory production. As manufacturing tasks are multivariable problems (Benardos and Vosniakos 2003), new technologies are needed for the visualization of high dimensional data. Some recent reviews outline this requirement, searching for solutions such as Augmented Reality (Bottani and Vignali 2019) and 3D printing (Ford and Minshall 2019). This challenge is mirrored in academic spheres: how to improve teaching methodologies so that (engineering) students can enhance their comprehension of (manufacturing) problems. As a cheaper alternative to Augmented Reality and 3D printing, Virtual reality has proven itself to be a highly effective technology for training and learning (Makarova et al. 2015). Improvements in hardware and associated technologies, coupled with lower costs, have led to a great expansion of Virtual Reality over recent years, and its progressive introduction at all educational and training levels. The use of virtual reality techniques in educational environments can produce an increase in student interest and prepare them for their future professional career (Checa and Bustillo 2020). There are many examples of virtual reality teaching and training experiences that include CNC procedures for engineering students to practice without fear of failure (Checa and Bustillo 2020), and for practical experience with a specific machining task (Nathanael et al. 2016). Virtual reality is also a suitable medium for visualization tasks (Pelliccia et al. 2016) as well as a medium in which to explore 3D learning environments, where the interaction with the content is a key factor (Valdez et al. 2015). In this way, the students learn not only the theoretical methods, but also the structure of the technical systems and the technological processes, preparing themselves better for practical professional work (Van Bibber and Bahr 2018).

During their undergraduate studies, process engineers lack practical experience of the influence of cutting tools and their geometrical parameters on the energy consumption of machining processes. As recent studies have outlined (Gani et al. 2018), new learning tools that can evaluate these influences are necessary. The combination of machine-learning techniques and virtual reality environments are, in this case, especially interesting, because they can simulate many new geometrical conditions with a very limited experimental data. The accuracy of the models might be limited for industrial use, although sufficient for students to extract useful information and patterns on the influence of geometrical parameters of a tool on cutting performance. Besides, the high immersion effect of Virtual Reality and its high interactivity with the prediction models can increase student learning rates.

This research proposes a new strategy based on experimental tests, machine-learning modelling and Virtual Reality visualization to overcome this lack of experience in the selection of the best cutting tool. First, different cutting tools were selected to analyze the effect of variable cutting geometries. Power consumption was measured in cut-off and during cutting for each test condition. Second, different machine-learning techniques were used to model the experimental data. Four types of machine-learning techniques were selected for this purpose: regression trees, multilayer perceptrons, bagging ensembles of those regressors and random forest ensembles. The most accurate model was used to build 3D graphs of direct interest for the process engineer to optimize the power consumption under different cutting conditions. Third, a Virtual Reality environment was used to train engineering students in power optimization in slot milling considering different cutting conditions and tool geometries. Figure 1 summarizes the proposed strategy.

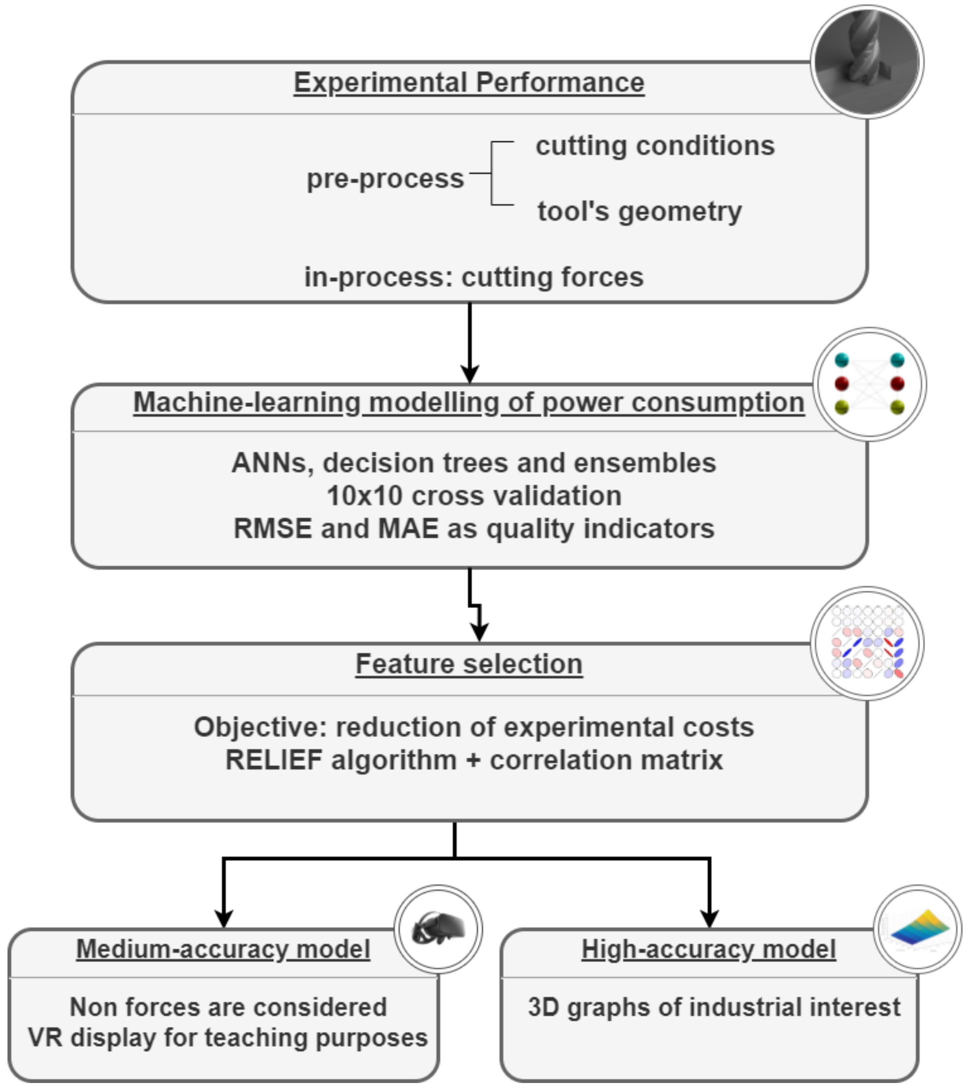


Figure 1. Scheme of the proposed strategy.

The paper is organized as follows. In Section 2, the cutting conditions and the experimental characterization of tool behavior will be presented. Milling tests will be performed and spindle speed power consumption levels will be measured. Then, the dataset extracted from the milling tests will be presented in Section 3 together with the machine-learning techniques used to model the dataset. In Section 4, the results of the modelling process will be presented as well as the best way of applying the model in industry and for teaching engineering. Finally, the most relevant results of the research will be summarized in the Conclusions and future research lines will be proposed.

2. Experimental set up

The procedure for the characterization of cutting tool behavior will be described in this section. It will cover the characterization tests including tool selection, cutting parameter selection, and experimental tests performed on Al 7075-T6 aluminum alloy workpieces in a 3-axis machining center.

2.1. Tool selection

The group of chatter-resistant solid end-mills can be classified into four main types each of which reduce the regenerative effect thus improving chatter performance: alternating pitch cutters, Strassman or roughing cutters, trapezoidal cutters, and bi-helix cutters. In this study, our attention is focused on the second and third groups. Strassman cutters are cylindrical tools with helical forms. In addition to tool diameter D, helix angle β, and number of cutters Z, the major parameters are the amplitude A and the wavelength L of the sinusoid. An additional pair of parameters are needed for the trapezoidal tools: the upper width of the trapezoid, sometimes described as a percentage of the wavelength period, ε, and the angle of the trapezoid's flank, ϑ. Figure 2 describes these parameters on both tool types.

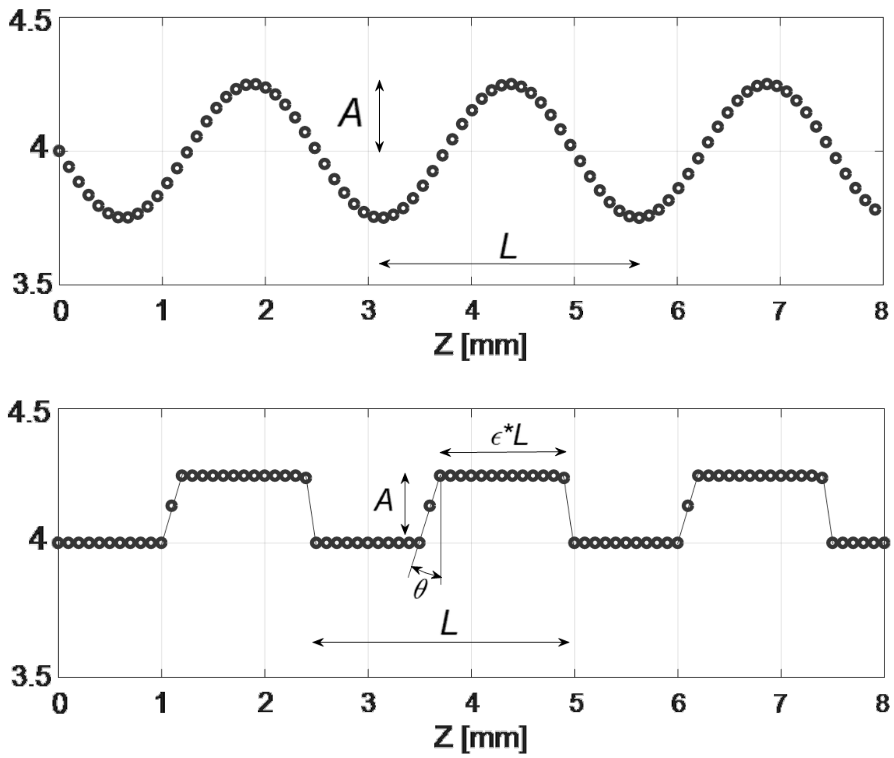


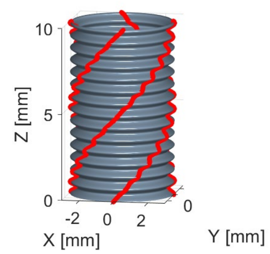
Figure 2. Geometrical parameters in sinusoidal and trapezoidal solid end-mills (β=45°).

Quotes were requested from various tool suppliers for a serrated aluminum alloy cutting tool, so as to ensure identical cutting conditions. The only constraint was the tool diameter: D = 8 mm (larger diameters increase their cost). Three tools from three different suppliers were selected as the best option for the milling of Al 7075-T6, in view of the manufacturers' recommendations. The suppliers of tools #1 and #2 recommended the most specific solutions for the machining of Al 7075-T6. The supplier of tool #2 recommended the tool for aluminum, but not for other materials, while the supplier of tool #3 recommended the P group for the use of its serrated tool, although it also included the S group. Finally, tool #4 was recommended for stainless steels or titanium-based alloys, but was selected here to test the influence of the geometry.

There were differences between the three tools: number of teeth Z = 3 or 4 and helix angles from 30-45°. The most interesting feature of the roughing cutters was their serrated profile. All the tools were measured using a digital microscope. Table 1 summarizes the geometrical data of the tools.

No internal lubricant was used. Besides, not all the types are available with internal lubrication and the tool cost would be doubled.

Table 1. Main geometrical parameters.



Tool number	Number of teeth Z	Helix angle β	Serration parameters
1	3	40°	A=0.10 mm; L=1.30 mm
2	3	45°	A=0.12 mm; L=1.30 mm
3	4	30°	A=0.20 mm; L=1.35 mm
4	4	45°	A=0.20 mm; L=1.20 mm; ε=0.625; θ=45°

2.2. Experimental tests

A good practice to maintain chip load under a certain control is to compensate the a_p and the a_e parameters. For comparative purposes, the tools will be tested with identical machining parameters: cutting speed, V_c, in m/min; axial depth of cut, a_p, in mm; radial depth of cut, a_e, in m/min; and, feed per tooth and revolution, f_z, mm/rev. The same feed per tooth was in all cases selected, because of the different number of cutters. Table 2 shows the cutting conditions for the experimental tests.

Table 2. Cutting parameters for the characterization tests.

Tool number	a_p [mm]	a_e [mm]	f [mm/rev]	N [rpm]
1	1-3	8	0.09-0.36	3,000-6,000
2	1-3	8	0.09-0.36	3,000-6,000
3	1-3	8	0.12-0.48	3,000-6,000
4	1-3	8	0.12-0.48	3,000-6,000

A conventional 3-axis machining center (Kondia B640) was used for the cutting tests. Cutting forces were measured with a Kistler dynamometer (9255B). Additionally, a power sensor was installed in the electrical cabin of the machining center (Figure 3). This device extracts instantaneous direct readings from the intensity running on each of the three phases. The power consumption can then be obtained, as it is proportional to the intensities. Figure 3a shows the main elements: the supply voltage (230VAC), the U-V-W phases of the motor spindle, the Hall effect sensor holes, the sensor phase connections and laptop Ethernet wiring. Figure 3b shows an example of a cutting test. The program is executed and paused in cut-off condition (before the tool penetrates the workpiece). The spindle rotates at the programmed spindle speed where P_0 is the measured power. Then, the operator runs the program at the programmed feed rate. Cutting forces and power consumption are monitored and recorded until the tool leaves the workpiece and the spindle speed is stopped.

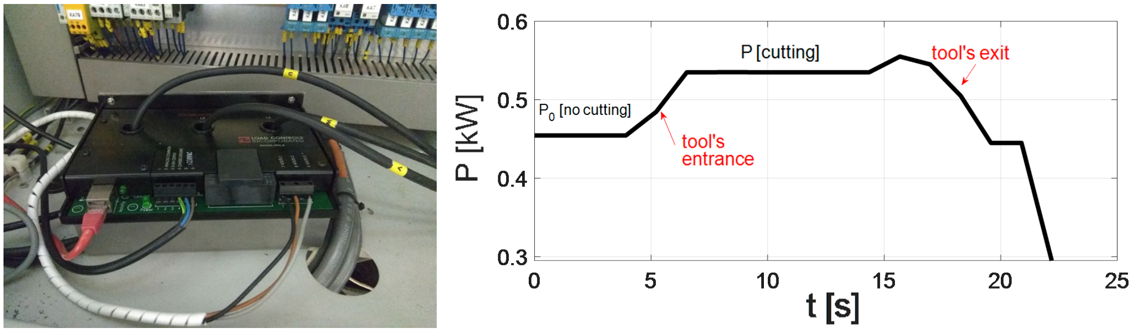


Figure 3. a. UPC-E power sensor; b. Monitoring spindle's power consumption.

3. Modeling

This section describes the dataset extracted from the experimental tests and the machine-learning techniques used for the prediction of the selected dataset outputs.

3.1. Dataset description

A dataset was compiled from the experimental set up described in Section 2 with inputs of three different types: cutting conditions, cutting tool features, and cutting force measurements. Besides, the dataset includes three measurements of the power consumption shown in Figure 3b: its value before the cutting process begins (P_0), its average value during the cutting process (P) and the result of subtracting the value before the cutting process from the value during the cutting process or the power consumption directly related to the cutting process (P_c). The power consumption directly related to the cutting process is calculated as the difference between the average value of the power consumption during the cutting process and its value before the cutting process begins (P_c= P-P_0). The dataset comprised 5 inputs or attributes related to the cutting conditions, 6 inputs describing the tool geometry, and 4 attributes measured during the cutting process that can provide information on tool wear. About cutting conditions the selected attributes were the: feed per tooth and revolutions (f_z), feed rate (f), spindle rotating speed (S), cutting speed (V_c), and the axial depth of cut (a_p). Regarding the tool geometry, the selected attributes were the number of teeth Z, the helix angle β, and the serration parameters A and L (amplitude and wavelength of the sinusoid, respectively). Another two attributes were added to the dataset to consider new features of the tools, such as its coating or material; these parameters are not directly related to any geometrical characteristic of the tools. *Shape* classified the tools by their serrated profile: sinusoidal or trapezoidal. *Tool* is a general identifier of each tool tested in the experiments. *Tool* provides the tool information to the machine-learning model not included in all the other inputs (such as coating type, *etc.*). Finally, the selected attributes related to process performance were the cutting forces in the 3 axial directions, F_x, F_y, and F_z, and the total cutting force, F. Those inputs were selected as the main variables because they are the ones that the process engineer can change to optimize the power consumption of the cutting process. Almost all the inputs and the outputs are considered continuous variables, although some of them take a very limited number of possible values, due to the experimental design and the limitations in the number of tools to be tested. Only *Tool* and *Shape* are nominal variables: while *Tool* takes four possible values (1, 2, 3 and 4), because four different tools were tested, *Shape* takes only two values: 1 (for sinusoidal geometry) and 2 (for trapezoidal geometry). Although the trapezoidal tool might not be completely defined by the A and L parameters, as only one tool of this geometry is used, the attribute *Shape* contains the required information for the machine learning algorithms to separate its behavior from the sinusoidal profile tools. The dataset included 116 different experiments. Table 3 summarizes both the inputs and the outputs, their units and the range of dataset values; the output variables, power consumption, are shown in bold.

Table 3. Dataset attributes and outputs, range of variation, and units.

Variable	Abbreviation	Range	Units
feed per tooth and revolution	f_z	0.03-0.12	mm/rev/Z
Feed rate	F	0.09-0.36	mm/rev
Spindle speed	S	3000-6000	rpm
Cutting speed	V_c	75.4-150.8	m/min
Axial depth of cut	a_p	1-4	mm
Tool identifier	*Tool*	*1, 2, 3, 4*	None
Number of teeth	Z	*3,4*	None
Helix angle	B	30-45	°
Amplitude of sinusoid (serration parameter)	A	0.2-0.25	mm
Wavelength of sinusoid (serration parameter)	L	1.2-2	mm
Serrated tool profile	*Shape*	1(sinusoidal),2(trapezoidal)	None
Cutting force in X direction	F_x	17.61-193.48	N
Cutting force in Y direction	F_y	32.95-396.89	N
Cutting force in Z direction	F_z	-174.91-4.62	N
Total cutting force	F	39.28-466.65	N
Power consumption before cutting	P_0	**0.44-0.56**	**kW**
Power consumption during cutting	P	**0.5-1.82**	**kW**
Power consumption due to the cutting process	P_c	**0.05-1.26**	**kW**

3.2. Machine-learning techniques

Different families of machine-learning algorithms were tested in this research, to identify the one that produced the best model for the prediction of the power consumption in slot milling operations. All the experiments were performed using the Weka software tool (Hall et al. 2009).

First of all, the regression trees (Quinlan 1992) were tested. Regression trees are structured in a first root node that split the trunk into two or more branches, some levels of internal nodes that form the upper branches of the tree and the terminal nodes called leaves. The root and the internal nodes include a dilemma related to one of the input attributes, asking the final user to evaluate whether the input value of a certain attribute is higher or lower than a calculated threshold. Following one branch, the final leaf will provide a prediction of the output by means of a linear model of the input attributes. The so called M5P is the regression tree implementation included in Weka Software (Quinlan 1992).

Secondly, ANNs were considered, because of their well-known capacity as universal function approximators (Hornik, Stinchcombe, and White 1989). ANNs are built from small computational nodes, called neurons. Each performs a weighted transformation of the inputs to evaluate the output that is linked to an activation function. ANNs are inspired by biological neural networks that learn from previous experience. The most common ANN type is the MultiLayer Perceptron (MLP) (Bloch and Denoeux 2003) with a linear activation function. Neurons are split into a minimum of three layers. While the first layer receives the inputs or attributes of the dataset, the last one calculates the output value of the ANN. In the middle, the so-called hidden layers evaluate the hidden patterns in the dataset, discarding background noise. Despite their high accuracy for complex processes, ANNs present a serious drawback: they have many parameters that require an ideal value to be tuned for each industrial task. If not supervised by an expert, this tuning process will involve lengthy trial and error. At this point ensembles offer better solutions, because their sensitivity to parameter tuning is lower so that fewer parameters will need tuning (Bustillo et al. 2011).

Ensembles consist of a combination of many single models (called base models), such as regression trees and ANNs. The base models are trained with different datasets and their outputs are combined for improved predictive accuracy (Kuncheva 2014). One of the first ensembles to be developed is Bagging (Breiman 1996). In Bagging, each base model is trained with a bootstrapped subsample of the original data set with replacement (*i.e.*, an instance may appear many times or not at all in a specific sample). The output is generated as a linear combination of all the base model predictions. Two main issues to achieve an accurate Bagging-based model are the use of very unstable and fast base models. A base model is unstable if slight differences in the training dataset produce very different prediction models. The speed requirement is due to the need to build thousands of models during the training stage of the predictor. Considering those two requirements, regression trees are commonly used in Bagging ensembles, although other basic models, such as ANNs, can also be used for that purpose. Random Forest is a second type of ensemble that provides very good results with regression trees as base models (Breiman 2001). In Random Forest, the base models are random trees. Random trees are a subtype of regression trees, where only a random subset of the attributes is considered to take the decision in each node. With this strategy, each random tree provides a different prediction model, because the division of the training data into subsets provides samples for training each random tree.

Besides these three families of machine-learning techniques, two additional prediction models were selected as baseline methods to compare the performance of the machine-learning techniques: a naïve approach and a linear regression. The naïve approach, when predicting a continuous output, uses the mean value of the output in the training dataset as a fixed prediction of the output, regardless of the input values. A linear regression model was also considered as a baseline in this research, because the relationship between power consumption and some process inputs, such as rotation speed and feed rate, can be considered linear for certain reduced variation ranges of those process inputs [2-4]. The references in Weka software to both approaches are ZeroR and Linear Regression, respectively. As an expected result, the prediction error of any machine-learning model should be significantly lower than those of the baseline methods, to ensure that those techniques really provide reliable prediction models.

4. Results and industrial implementation

Firstly, the methodology used to train the machine-learning models and for their validation will be presented. Secondly, the results of the prediction models generated from the experimental dataset will be discussed. Finally, the industrial and teaching implementation of these models will be presented.

4.1. Machine-learning modeling procedure

Before building a prediction model with machine-learning techniques, it is necessary to define 1) the quality indicators that will be used to evaluate the model accuracy; and, 2) the training and validation scheme of the algorithms. Two quality indicators have been selected in this research: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Both indicators were selected because the bibliography on prediction models for manufacturing tasks is split between the researchers who prefer RMSE (Mia and Dhar 2016; Wang et al. 2016; Oleaga et al. 2018) and the researchers who prefer MAE (Willmott and Matsuura 2005; Mikołajczyk et al. 2018; Grzenda and Bustillo 2019). The RMSE and the MAE units are the same as the predicted target units, in our case kW, which facilitates the evaluation of model performance: the lower the RMSE and the MAE values, the better the model. RMSE and MAE are calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y)^2}{n}}$$

$$MAE = \frac{\sum_{t=1}^{n}(\hat{y}_t - y_i)}{n}$$

where n represents the number of instances of the test subset, i refers to the instance used for the current prediction, $\hat{y}_i$ is the predicted value, and y_i is the actual value of the output variable.

A 10x10 cross-validation scheme (Kohavi 1995) was selected for training and validation due to the small size of the dataset. Accordingly, the prediction model is only evaluated with new data (data that has not been used in the training stage) while the training and validation process is repeated 100 times with different random subsets of the dataset to assure statistical independence of the models with the selected subsets for the training and validation stages.

Finally, before analyzing the accuracy of each machine-learning model, the tuning process of its parameters should be described. From among the selected machine-learning techniques, MLPs are the models that show the highest sensitivity to parameter tuning (Bustillo et al. 2011), while ensembles are almost insensitive to that process, as they are averaged models. Therefore, a grid search of the main MLPs parameters was performed to find their best combination. The variation ranges of the MLPs parameters were:

- Number of neurons in the hidden layer: from 2 to 10 in steps of 1.
- Momentum: from 0.001 to 0.5 in steps of 0.005
- Learning rate: from 0.01 to 0.5 in steps of 0.005
- Training time (number of epochs): from 100 to 700 in steps of 100

For the other parameters, the default options in Weka were used. All the calculations were performed with a workstation equipped with an Intel Core i7 6700 3.4-GHz processor with 16 GB RAM and a NVIDIA Titan Xp GPU.

4.2. Machine-Learning Modeling results

The first output to be modelled was P_0, power consumption without cutting. A linear model was able to predict the value of that output with high accuracy (RMSE of 0.0093 kW and MAE of 0.0068 kW in a 10x10 cross validation scheme). No further research was therefore required for this output and only one of the other two outputs, P or P_c, should be modeled due to their linear relationship ($P_c = P - P_0$). The linear model for P_0 considers cutting parameters, geometric features of the tool, and cutting forces, although –as may be excepted, considering the nature of the manufacturing process- the rotation speed, *S*, was the main parameter that contributed to P_0:

$$P_0 = 0.00003 * S + 0.0018 * a_p - 0.0003 * \beta - 0.0001 * F_x - 0.0001 * F_z + 0.3661$$

As P_0 can be easily evaluated, the most interesting output will be the power consumption directly related to the cutting process, P_c. Table 4 summarizes the RMSE, the MAE, and the training time of the prediction models for P_c. A tuning process of the main parameters was only performed in the case of MLPs, as described previously in Section 4.1. The best combination of parameters was found for a Learning Rate of 0.05, 2 neurons in the hidden layer, 700 epochs and a momentum of 0.2. In this case only the Learning Rate parameter played a major role in the accuracy of the prediction model, a fact that has been previously reported for similar tasks modelled with MLPs such as chatter frequency in milling (Oleaga et al. 2018) and the prediction of tool life in turning operations (Mikołajczyk et al. 2018). The prediction models can be classified into three groups considering their accuracy: low accuracy (baseline) models; medium accuracy (regression-tree) models; and, high accuracy (MLP-based) models. All the machine-learning models performed statistically better than the baseline methods. Although the Bagging ensembles usually use regression trees as base models, the low accuracy of regression trees in this case suggests the use of MLPs as base models. A significant difference between the accuracy of regression trees and MLPs might be due to better modelling by the latter of non-linear processes (Hornik, Stinchcombe, and White 1989). The low accuracy that the linear regression baseline method achieves also fits in with this explanation. The MLP model (in bold in Table 4) was the most accurate, with a very small and insignificant difference with MLP Bagging. As MLP Bagging requires no parameter tuning process, it is considered the best model for power consumption prediction with an RMSE of 10.7% of the standard deviation of the dataset (0.269 kW). Finally, the analysis of the training times provides some new interesting information. Although low in all cases due to the small dataset size, there are two characteristics that increase this indicator: the number of models to be built (ensembles should build 100 base models while regression trees should only build one model for each fold of the cross-validation scheme) and the complexity of those models (MLP models are of higher complexity than regression trees). Therefore, although bagging of MLPs is the most accurate and easily-tuned solution, its suitability in huge datasets can be questionable, due to its higher training time.

Table 4. Accuracy of the prediction models for power consumption P_c with all the input attributes.

	RMSE (kW)	MAE (kW)	Training time (s)
ZeroR	0.2702	0.206	0.01
Linear Regression	0.0899	0.0718	0.01
M5P Tree	0.0386	0.0297	0.02
MLP	**0.0282**	**0.0196**	**0.07**
Bagging (M5P)	0.0365	0.0276	0.35
Bagging (MLP)	0.0289	0.0201	1.4
Random Forest	0.0601	0.0458	0.08

Although the modeling of the power consumption, from the machine-learning point of view, might end with the identification of the most accurate model, any industrial use of this prediction would raise new questions. The first one refers to the influence of each input on the prediction model. This question can be also presented in a different way: can I avoid the use of some of the inputs and still achieve a high-accurate prediction model? If a positive answer to this question can be obtained a significant save from the industrial point of view can be achieved, reducing the number of attributes to be measured in the workshop. Besides, some inputs might repeat information presented in earlier inputs that could negatively affect the accuracy of the model.

As already outlined in Section 3.1, the input variables can be classified into three groups considering their nature: cutting conditions (5 inputs), tool geometry (6 inputs), and on-line process parameters (4 inputs). If some inputs are strongly correlated, contributing the same or very little information to the prediction model, they could be deleted from the dataset. From the industrial point of view this fact could lead to lower measuring times, reduction of on-line sensors, *etc.* The most desirable result from such an analysis would be the elimination from the dataset of the on-line process attributes, due to their higher measurement costs.

An evaluation of the feature contribution to the dataset was performed using the RELIEF algorithm (Kononenko 1994) implemented in Weka software (Robnik-Sikonja and Kononenko 1997), to study this possibility. The RELIEF algorithm was firstly developed for classification tasks and then extended to regression problems (Robnik-Sikonja and Kononenko 1997). It provides an estimation of the value of each attribute in a dataset by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same attribute, as well as the different and the same class (in classification tasks). Besides, a correlation analysis between the different inputs was completed and the correlation matrix in terms of the Pearson coefficient was calculated. Figure 4 shows the influence of each input in the output obtained with the RELIEF algorithm and the correlation matrix between the inputs using the following coding: blue = positive correlation, white = no correlation, and red = negative correlation, while the circle deformation is proportional to the input correlation, where the diagonal line refers to the maximum correlation.

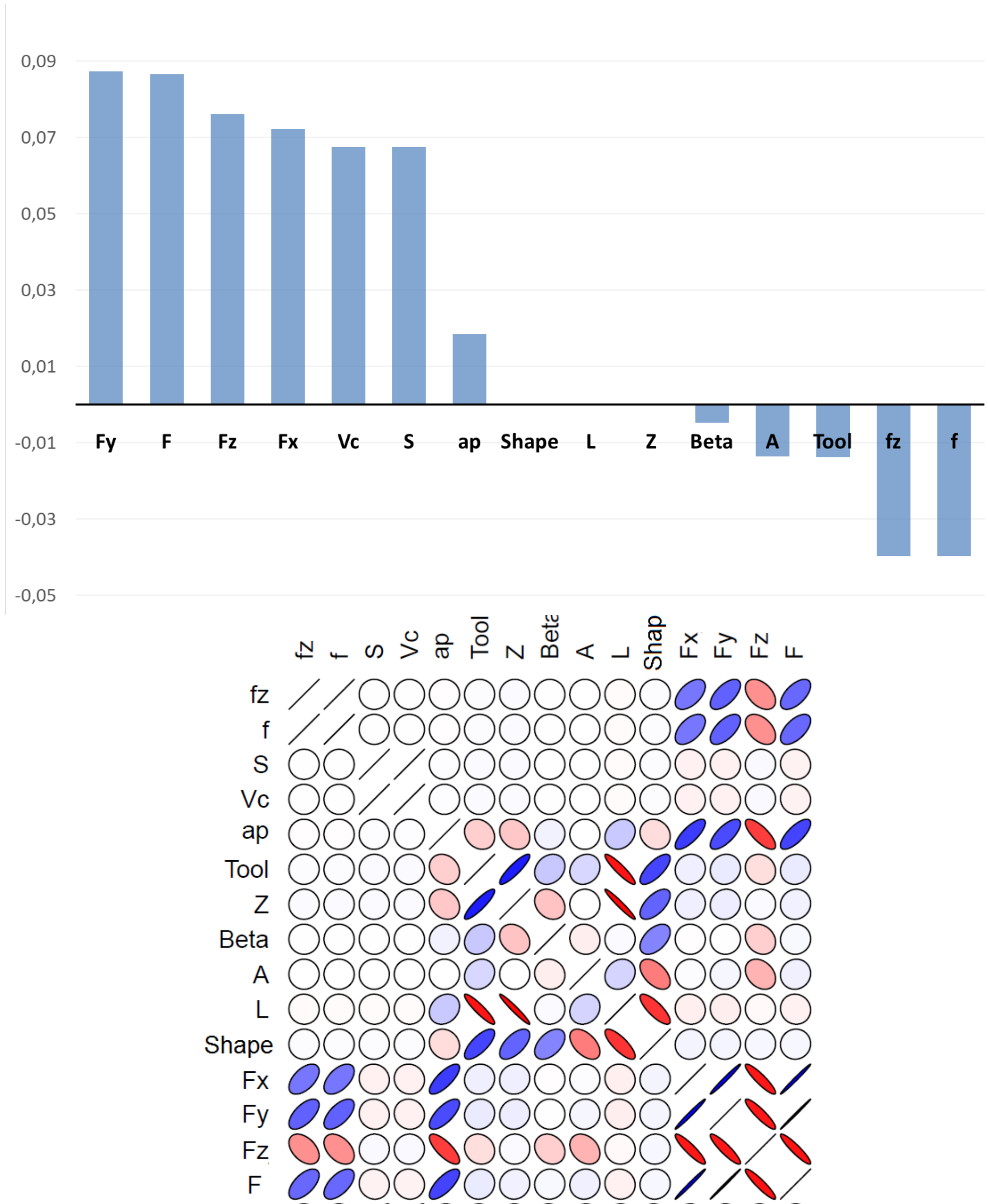


Figure 4. RELIEF analysis and correlation matrix of the dataset.

On one hand, in Figure 4 the RELIEF analysis shows the following order of importance of the inputs in the dataset (from the highest to the lowest): F_y, F, F_z, F_x, V_c, S, a_p, *Shape*, L, Z, β, A, *Tool*, f_z, and f. It is especially interesting to note that the last 5 inputs have a negative influence and might, therefore, reduce the accuracy of the model. Moreover, the correlation matrix in Figure 4 provides some extra information on the dataset. First some groups of inputs are strongly correlated (diagonals or very flat ellipses in the correlation matrix): feed rate and speed, Z, L, and *tool*, and F, F_x, F_y, and F_z. These results are expected because: 1) the speed is programed considering the selected feed rate; 2) the tool design fixes the number of teeth in terms of L; and, 3) the cutting forces will behave in similar ways, regardless of their axial direction, if very demanding cutting conditions are programmed. The lack of correlation between some inputs (white circles in the correlation matrix) is also reasonable; there was no correlation between most of the tool parameters (Z with A and β with L) and between some of the cutting parameters (*e.g.*, V_c, S and a_p

with f_z), due to the design procedure and the experimental design of the tool. But the most interesting cases are those where there is a slight or medium influence between inputs of a different nature, because the machine-learning algorithms might be able to extract the same information from both inputs or from a combination of inputs, by-passing the measurement of some attributes. In this case, F_x and F_y could be exchanged for a combination of a_p and Z, while F_z could be exchanged for a combination of a_p, β, and A. If this prediction were true, the cutting forces could be deleted from the dataset with a reduced loss of model accuracy.

In an in-depth analysis of these predictions, the inputs were deleted from the dataset (from the lowest to the highest) following the RELIEF order and the MLP and M5P Bagging models were trained to evaluate accuracy without some attributes. Figure 5 shows the accuracy in terms of the RMSE for the MLPs and M5Ps Bagging models. On the left-hand side of this figure, the models with all the features show low errors (around 15% of the standard deviation of the dataset), on the right-hand side the models with very few inputs show high and unacceptable errors (around 70% of the standard deviation). As the RELIEF algorithm predicts: the deletion of the 5 first inputs that have a negative influence slightly increased the accuracy of the model, but the improvement was almost negligible. Interestingly, the accuracy of the model for both types of ensembles (MLP and M5P Bagging models) remained almost constant, while the models were built with at least five of the attributes: V_c, F_y, F, F_z, and F_x. Its accuracy drops drastically when any of these attributes are deleted from the dataset. Therefore, the cutting forces and one cutting parameters, V_c, might be the best and the cheapest combination of inputs for modelling this industrial process. However, the correlation factor proposes alternative solutions that could also be studied.

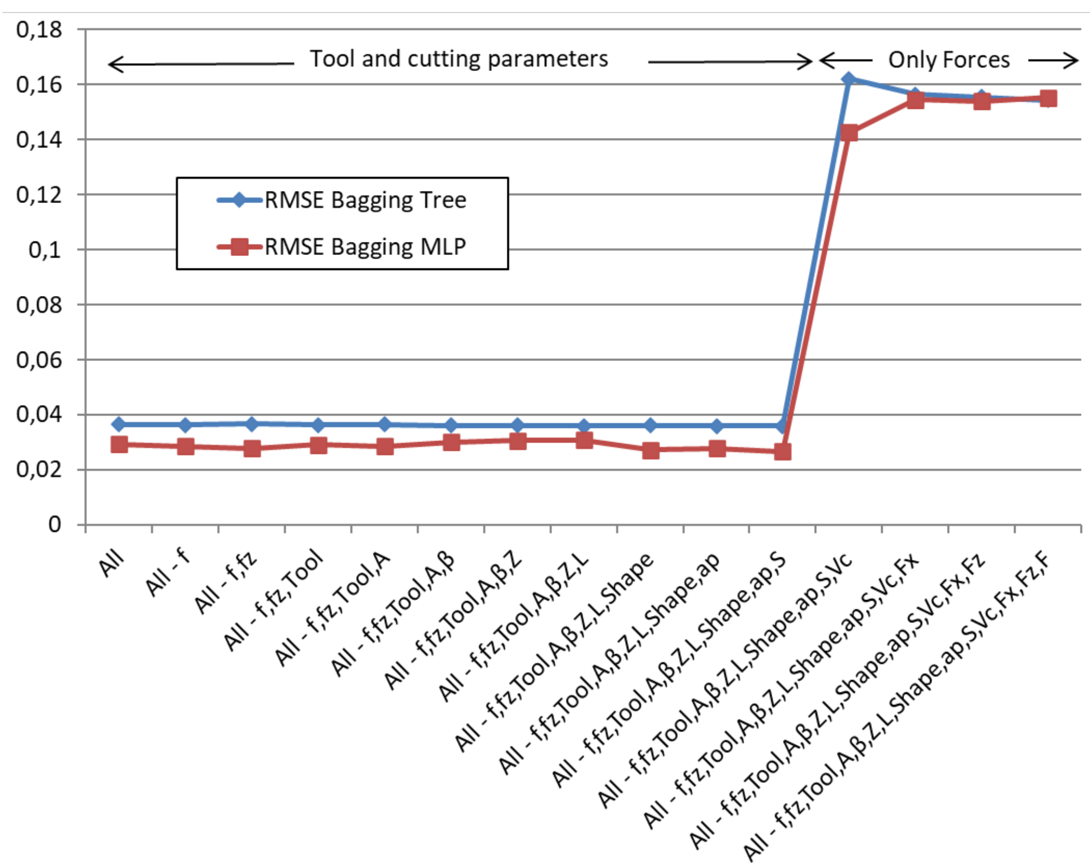


Figure 5. Effect of reducing the attributes on model accuracy.

In the search for a cheaper solution, the dataset cutting forces were deleted from the dataset and the machine-learning models were once again trained and validated. Table 5 summarizes the RMSE and the MAE of the prediction models for P_c after having deleted the four attributes related to cutting forces from the dataset. The *Tool* attribute was also deleted, due to its low influence on model accuracy according to RELIEF, and for easily interpretable models. Bold values in Table 5 outline the most accurate models. Nevertheless, as in the previous case, the parameters of the MLPs were tuned. The best combination of parameters was found for a Learning Rate of 0.3, a Momentum of 0.01, a training time of 400 epochs and 8 neurons in the hidden layer. In this case the tuning process only improved its default accuracy values by 20%, because the MLP with the default values had an RMSE of 0.0575 kW and a MAE of 0.0425 kW.

Table 5. Accuracy of the prediction models for power consumption, P_c, without force attributes.

	RMSE (kW)	MAE (kW)
ZeroR	0.2702	0.206
Linear Regression	0.1141	0.0874
M5P Tree	0.0795	0.0583
MLP	0.0450	0.0320
Bagging (M5P)	0.0683	0.0495
Bagging (MLP)	**0.0367**	**0.026**
Random Forest	0.0912	0.0669

In this case, the most accurate model (MLP Bagging) showed a 30% higher error (both for MAE and for RMSE) than the best model with all the inputs. A loss of accuracy that might be acceptable from an industrial point of view in some cases, but one that is quite acceptable for teaching purposes (the RMSE is only 13.7% of the standard deviation of power consumption in the dataset). As previously commented in the Introduction, students of mechanical engineering can benefit from testing the prediction models of medium accuracy that will give them some practical experience of the geometrical features of cutting tools and their expected effects on energy consumption in slot milling with serrated tools.

4.3 Industrial and teaching implementation

The following process is proposed, by both process engineers and students, to achieve useful models: first, only a reduced set of dataset inputs were selected; second, the best machine-learning technique was trained; third, 3D graphs were built from the trained model showing the influence of the main process inputs in the power consumption and displayed in different ways for their final use. This data dimensionality reduction approach, by means of a feature selection technique, has previously been identified as a suitable solution for visual optimization of manufacturing processes (Amini and Chang 2018).

As the model is likely to have greater clarity with fewer inputs, seven inputs were deleted from the original dataset: F, F_x, F_y, F_z, S, *tool*, and f. The four inputs related to cutting forces, F, F_x, F_y, and F_z were deleted because their values were unknown before the cutting process and they were, therefore, of no use for any pre-process prediction. Besides, those inputs can be deleted with no radical reduction of model accuracy, as demonstrated in Section 4.2. The feed rate, f, was deleted, as it provided no useful information to the model and can reduce its accuracy. The spindle rotation speed, S, was deleted, as it provided the same information as V_c. Finally, *Tool* is an input of little influence in the model and can confuse the final user because it integrates in a nominal input most of the information already included in the other parameters (L, Z, β, A, and *shape*) of the tool.

Then the best machine-learning technique, Bagging ensembles of MLPs, was trained with the dataset. In this case, the whole dataset was used for training with no cross-validation scheme, because the highest level of accuracy was sought with no requirement for accuracy evaluation. The model was generated and saved in Weka. Then, an extensive set of different input conditions for all the inputs was fed into the model and the predicted value of the power consumption was obtained.

Finally, Figures 6-8 were built as an example of the possible industrial use of this model. The X and the Y axis show different cutting conditions in terms of a_p and V_c, respectively. The Z axis shows the predicted power consumption for each cutting condition. For each figure, the other process inputs - *L*, *Z*, *β*, *A, shape* and f_z- were fixed. From those fixed inputs only one (f_z) could actually be changed during the cutting process, because the others refer to the tool geometry (*L*, *Z*, *β*, *A*, and *shape*), which were dependent on the selection of the cutting tool. So, these 3D graphs are quite reasonable from an industrial point of view, where the cutting tool is first selected and then the best cutting conditions are programmed. In these three figures the expected power consumption evolution was the same: a higher cutting speed, V_c, and a higher depth of cut, a_p, requires higher power consumption; the influence of those two inputs is not linear and can be modelled in quadratic terms, thereby explaining the better accuracy of the MLP models rather than the regression trees

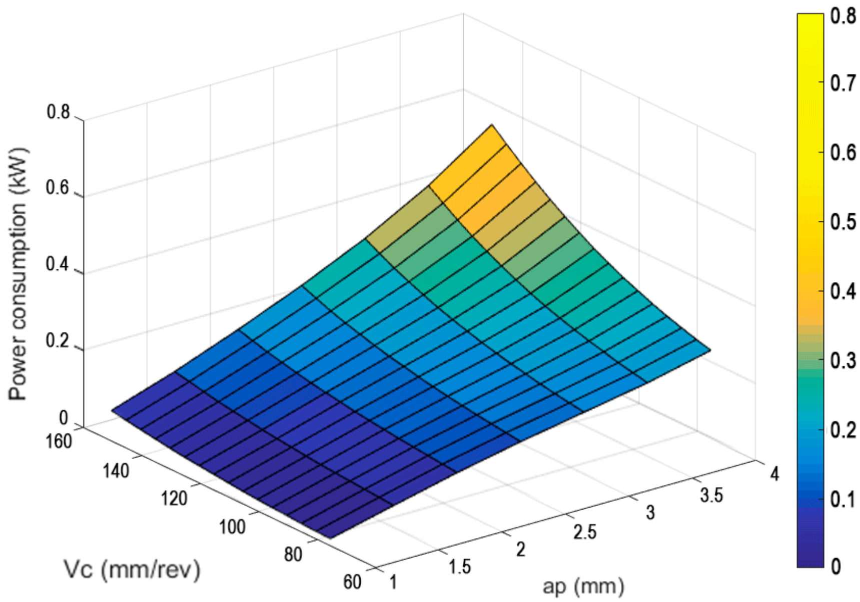


Figure 6. Predicted power consumption for a trapezoidal tool (β=40°, A=0.2, L=2).

Figures 6-8 show how a process engineer might use the prediction model. The three graphs are built for the same feed rate and revolution, f_z, (0.03 mm/rev per tooth), but for different cutting tool parameters. While Figure 6 shows the predicted power consumption for a trapezoidal tool with β=40°, A=0.2, L=2, Figures 7 and 8 refer to sinusoidal tools of L=1.3 but with different *β* and *A* values (β=40°, A=0.2 for Figure 7 and β=30°, A=0.25 for Figure 5). The three figures are built for the same number of tool teeth (*Z*=4). Comparing these three figures, the lowest power consumption, always for low values of a_p and V_c, are achieved with a trapezoidal tool with higher values of the *L* parameter (Figure 6). The influence of the *β* parameter might be low in power consumption; only the convex or concave shape of the curves for low a_p might be derived from this parameter as the comparison Figure 6-7 (convex) versus Figure 8 (concave) outlines. The influence of the *A* parameter might be especially strong for demanding cutting conditions, high values of a_p and V_c, as shown by the comparison between Figure 7 and Figure 8: while in Figure 7 (*A*=0.2) the power consumption is always under the threshold of 0.4 kW, in Figure 8 (*A*=0.25) it almost doubles this value (reaching 0.7 kW) in the worst case.

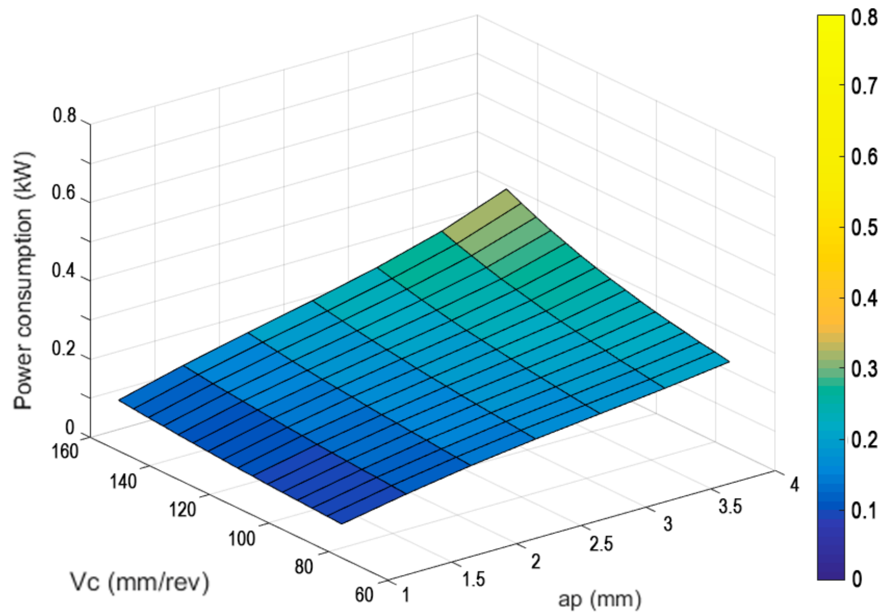


Figure 7. Predicted power consumption for a sinusoidal tool (β=40°, A=0.2, L=1.3).

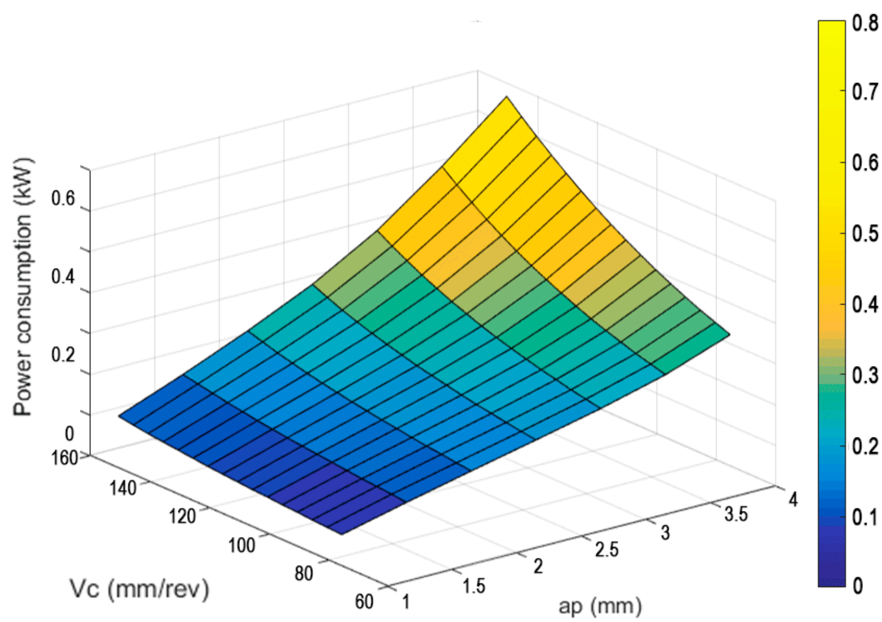


Figure 8. Predicted power consumption for a sinusoidal tool (β=30°, A=0.25, L=1.3).

Obviously Figures 6-8 are not sufficient to evaluate the influence of each geometrical parameter of the cutting tool in a systematic way; but they show how the process engineer can build different 3D graphs to compare the expected performance, in terms of power consumption, of different cutting tools proposed by the tool manufacturer for a certain cutting process.

The second proposed use of this prediction model, for the teaching of engineering students, could be done by using the same 3D graphs, but the extensive variety of inputs (5 tool parameters and 3 process parameters) might prove confusing and could complicate work on the model, making it difficult to extract clear conclusions. Therefore, a Virtual Reality interface with the prediction model was built for the students. In this interface the values of the geometrical characteristics of the cutting tools are controlled by sliders (control bars), while three 3D graphs are built for the different values of f_z, each of them representing the power consumption in terms of a_p and V_c, as in the case of Figures 6-8. The use of a Virtual Reality interface allows the student to compare the 3D graphs simultaneously from different perspectives and quick and easy control of the geometrical parameters of the cutting tool provides a quick understanding of the influence of each parameter.

A Java script was written for Weka to generate the predicted power consumption values according to the different cutting conditions. Weka generated three 2D matrices for the predicted power consumption (a_p, V_c), each for a certain value of f_z (0.03, 0.075 and 0.12 mm/rev per tooth) and for a certain set of tool parameters (L, Z, β, A, and *Shape*). This script repeated the process for 10 different values of each tool parameter, in some cases (L, β, and A), or for only two values for Z and *Shape*, as only two different values of those two parameters were tested in the original dataset. Then, these data were formatted as column-based text and imported into the game engine. Unreal Engine was used because of its external data management capabilities and easy-to-program immersive virtual reality experiences. The head mounted display was Oculus Rift with Oculus Touch interaction devices. These devices permit the user to move in a physical space limited by the scale of the room, to approach objects (the milling tools in this case) and to pick them up, as well as to interact with the parameter controls and to explore the 3D graphs from any 3D view.

The virtual environment includes 1) three 3D graphs similar to the ones presented in Figures 6-8 (X axis: a_p, Y axis: V_c and Z axis: P_c) each of them for a different value of f_z (0.03, 0.075 and 0.12 mm/rev per tooth), 2) three controllers for the main geometrical tool parameters that can be changed (L, β, and A) and a 3D model of the selected serrated tool. As the virtual environment includes three 3D graphs each of them for a different value of f_z; in this way, the student will not have the chance to change any cutting process variables and can concentrate on the analysis of power consumption as a function of tool parameter. The 3D graphs are visualized as points in the 3D space; their shape, color and size can be altered for a better representation. The user interface was designed for the easy selection of tool parameters (L, β, and A), as Figure 9.A shows. According to the parameters that are set, the user will be able to check the geometrical changes directly in the 3D model, both in the cutting tool and in the 3D graphs representing power consumption (Figure 9.B). Besides, the user can observe the cutting tool in great detail, because it is projected on a much larger scale than the real one. In this way, the changes in its geometrical parameters may be better appreciated (Figure 9.C). The 3D models of the cutting tool in all possible configurations were created by means of 3D modeling software (Blender). Figure 9.E shows a user interacting with the educational experience. The environment is neutral grey to avoid distractions with the content, and the checkered floor design defines the space in which the user can move. Finally, Figure 9.D shows the controllers of the virtual experience (Oculus touch), from which a laser beam is projected for interaction with the sliders and the 3D model of the tool.

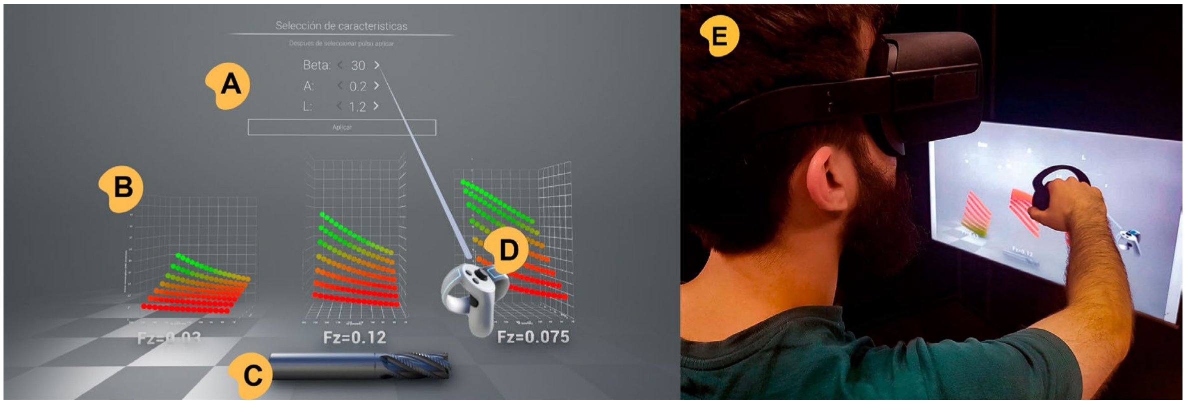


Figure 9. A: User interface for proper selection of tool parameters (L, β, and A); B: 3D graphs of power consumption; C: cutting tool; D: controllers of the virtual experience (Oculus touch); E: User interacting with the virtual environment.

The VR application is available at the following link: https://3dubu.es/en/cuttingtools/. In addition, this website includes videos of students using the virtual reality tool that can help provide a comprehensive view of how the VR application works. Figure 10 shows a practical example of two scenes of the virtual environment in which the user has selected different parameters for L, β, and A. In this example, the student has changed parameters β and A from lower (left) to higher (right) values. As there are no changes on the Z-scale of the VR application, the student can see that lower β and A parameter values increase the power consumption for high feed-per-tooth values, fz, while they have lower effects for both medium and low values of this cutting parameter. Immersion in the 3D models and VR data simulation should help to catch the attention of the students and their knowledge acquisition.

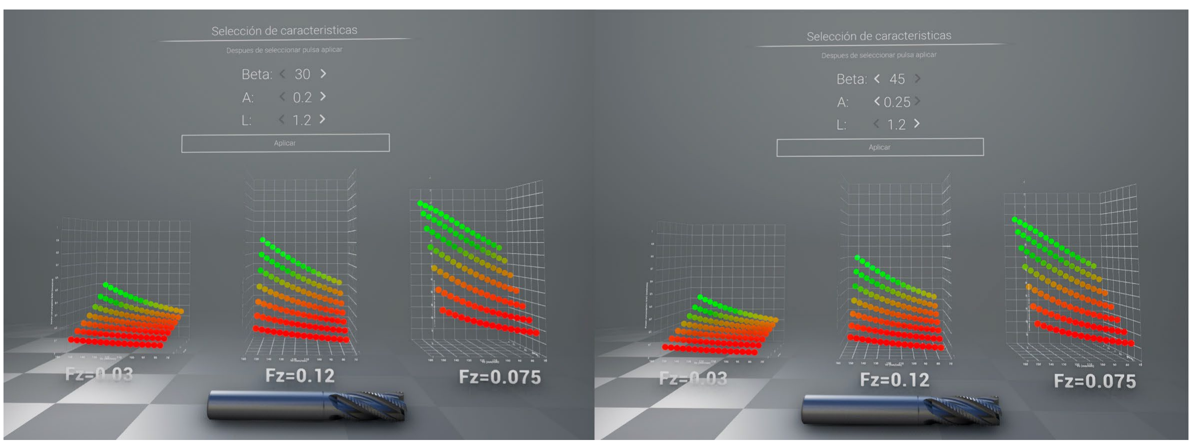


Figure 10. 3D virtual-environment power-consumption graphs.
Left L=1.2, β=30, A=0.2. Right L=1.2, β=45, A=0.25.

5. Conclusions

The selection of the best conditions for any machining operation is a critical issue in the daily activity of manufacturing, due to the high number of inputs that influence machining performance and the high costs of experimental tests. First, the use of machine-learning techniques for that industrial task has been proposed in this research relating to energy consumption optimization in the milling of Al 7075-T6 aluminum alloy with serrated cutters. Machine-learning techniques can simulate thousands of different tool geometries, a fact that cannot be achieved with experimental models, due to the reduced offer of different serrated tools on the market. Secondly, the use of different visualization techniques has been proposed for applying the trained models in two different ways: as 3D graphs for their industrial use (the selection of the best tool and the best cutting conditions) and as Virtual Reality environments for their teaching use (an understanding of the effect of tool parameters and cutting conditions on power consumption among undergraduate students). The key contributions from this study are that:

- An extensive dataset has been compiled to validate the strategy. The dataset included 116 different experiments with 15 inputs of a different nature: 5 inputs related to cutting conditions, 6 inputs described cutting tool features, and 4 inputs related to cutting force measurements. This dataset was used to train different machine-learning techniques, under a 10x10 cross-validation scheme, and for their validation. In a first stage, following consideration of all 15 inputs, MLPs showed the highest accuracy, although in view of their complex tuning processes, the alternative selection of bagging ensembles of MLPs was preferred, a model with similar accuracy but no-tuning process. Regression trees and ensembles of regression trees showed the worse performance, due perhaps to their weaker capacity at modeling complex relationships.
- In a second stage, an in-depth analysis of the influence of each input on model accuracy was completed, searching for both savings and increased accuracy in the experimental stage. This analysis was done by means of an evaluation of the feature contribution to the dataset using the RELIEF algorithm and a correlation matrix between inputs. The analysis showed no decrease in accuracy, if only five of the attributes are considered: V_c, F_y, F, F_z, and F_x. However, the accuracy of the model drastically decreases when any of these attributes are deleted from the dataset. Therefore, the cutting forces and one cutting parameter (*e.g.* V_c) might be the best combination of process parameters to extract the main information from this industrial process, for accurate prediction models based on machine-learning algorithms, although alternative solutions that might be studied were also evident from the correlation factor.
- In the search for a cheaper solution, the cutting forces were deleted from the dataset and the machine-learning models under consideration were once again trained and validated. In this case, the most accurate model (Bagging of MLPs) showed a 30% higher error than the best model with all the inputs. That accuracy loss level might not be acceptable from an industrial point of view in all workshops, but it may be acceptable for teaching purposes (the RMSE is only 13.7% of the standard deviation of power consumption in the dataset).
- The following process achieved useful models for both process engineers and students: first, only a reduced set of inputs of dataset were selected (any force unknown before the cutting process took place was not considered); second, bagging ensembles of MLPs were trained with the whole reduced dataset; third, 3D graphs were built from the trained model showing the the influence of the main process inputs in the power consumption and displayed in different ways for their final use.
- 3D graphs, where predicted power consumption is projected in terms of two cutting parameters, a_p and V_c, have shown their suitability, in that they present clear information on the effect of each geometrical parameter of the tool on power consumption. The sinusoidal amplitude A is the most critical parameter for reductions in power consumption under any cutting conditions and the geometrical shape (whether trapezoidal or sinusoidal) the lowest influence. These sorts of 3D graphs have been incorporated in a virtual reality environment displayed with Oculus Rift and equipped with Oculus Touch interfaces. It is a virtual environment in which the student can modify, by means of 3 sliders, the main

geometrical parameters (*L*, *β*, and *A*) of the tool, observing the changes in an enlarged 3D model of the serrated tool while observing the effect of power consumption under different cutting conditions.

Future work will be focused on the extension of the dataset to tools of different diameter, a higher range or number of teeth and a more extended description of the trapezoidal geometry; the objective will be the analysis of the influence of those parameters in key machining variables such as cutting forces and/or power consumption. Besides, if tool diameters are changed in the dataset, the process productivity will have a very strong variation range and the optimization of power consumption and process productivity can be studied to identify the best cutting conditions for each tool geometry, depending on different manufacturing priorities. Additionally, other parameters considered constant in this study (such as phase shift parameter between sinusoids of different flutes) could be optimized following the proposed methodology.

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