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Research Article

Machining Parameters and Toolpath Productivity Optimization Using a Factorial Design and Fit Regression Model in Face Milling and Drilling Operations

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Very commonly, a mechanical workpiece manufactured industrially includes more than one machining operation. Even more, it is a common activity of programmers, who make a decision in this regard every time a milling and drilling operation is performed. This research is focused on better understanding the power behavior for face milling and drilling manufacturing operations, and the methodology followed was the design of experiments (DOEs) with the cutting parameters set in combination with toolpath evaluation available in commercial software, having as main goal to get a predictive power equation validated in two ways, linear or nonlinear, and understanding the energy consumption and the quality surface in face milling and final diameter in drilling. The results show that it is possible to find difference in a power demand of 1.52 kW to 3.9 kW in the same workpiece, depending on the operations (face milling or drilling), cutting parameters, and toolpath chosen. Additionally, the equations modelled showed acceptable values to predict the power, with p values higher than 0.05 which is the significance level for the nonlinear and linear equations with an R square predictive of 98.36. Some conclusions established that optimization of the cutting parameters combined with toolpath strategies can represent an energy consumption optimization higher than 0.21% and the importance to try to find an energy consumption balance when a workpiece has different milling operations.

1. Introduction

According to Energy Information Administration (EIA) [1], 27203 Trillion BTU was the total energy consumed by the industrial sector in 2018. The aerospace, automotive, and plastics industries use machining processes to produce metallic parts for different manufacturing purposes [2]. To improve energy consumption efficiency in manufacturing systems, several researchers have focused their work on identifying the primary variables involved in machining [3]. Several analyses to assess the environmental impacts of machining processes have been carried out to better understand the behavior of the energy consumed. Some authors have found that the energy required for material removal is very low when compared to the total energy of the machine tool operation [4]. Therefore, several researchers have focused their work on finding ways to reduce this total energy rate. Guo et al. [5–7] analyzed the surface quality and energy consumption of a turning process; the aforementioned research tested a workpiece made of steel 11SMnPb30 and found that the best cutting parameters ranged as follows: a table feed of 0.05–0.3 mm/*r*, an axial depth of cut 0.5–1 mm, and a cutting speed of 80–800 m/min. To understand and minimize energy behavior in the milling processes, different operations have been studied. These previous works have proposed face milling improvements based on efficient toolpaths and energy consumption [8–10]. These improvements were such as the optimization of surface milling regarding cycle time, as well as the study of toolpath selection as a critical factor [11, 12]. Investigation in the optimization of machining parameters trying A6061 aluminum and using the response surface methodology based on particle swarm optimization not only led to finding an optimal combination of machining parameters but also that the spindle speed variable is the most influencing in surface roughness, power consumption, and cutting force. This alternative study showed ±7% of error [13]. Mathematical power prediction has been proposed, based on experimental models of infinitesimal cutting force during the machining process in order to obtain the power consumption, where the data were divided into spindle rotational, feed motion, and idle power, and the error of mean power was 0.208% [14]. Other studies aimed at the development of a mathematical model to know the power demand in face milling has considered both the cutting parameters and the flank wear [15]. Additionally, an artificial intelligence model was proposed in order to monitor the main drive power in the CNC machine in real time. The surface roughness and measuring the flank wear of the cutting tool were the main output variables considered, and random forest techniques had an accuracy between 33 and 44% [16]. Other techniques have considered the multi-optimization analysis, using the same roughness surface methodology, using titanium Ti-6A1-4V, as well as the surface roughness values. This model made it possible to know the power consumption with a correlation coefficient higher than 90% [17]. Other relevant studies consider the laser surface texturing (LST) technique in combination with the addition of nanoparticles (NPs) to the cutting fluid for getting better results in terms of reducing the spindle load (power demand) and reducing the tool wear in relation to surface roughness and thus finding that it is possible to improve the milling process up to 11% [18]. Some studies have successfully used milling processes with more than one machining type, determining different cutting parameters for the primary geometry features of their case studies [19, 20]. Behrendt et al. [19] propose a procedure for machine tool selection based on energy consumption, while Helu et al. [20] evaluate green machining technologies based on sustainability and cost. Li et al. [21] have investigated workpieces with different machined features to identify relevant factors. They found that critical factors are cutting parameters optimization, process planning, and job shop scheduling. The analysis that they have carried out has proved that the toolpath selection impacts both the material removal power and the air cutting times. For a process, which includes more than one milling feature, it is necessary to select different cutting parameters for each feature, based on material, cutting tool, and toolpath [22, 23]. The power required by a milling operation depends on parameters like spindle speed, feed rate, depth of cut, and transversal cut [24]. Different investigations have proposed energy consumption predictive models based on cutting parameters to estimate surface roughness [25, 26] and tool wear [27]. In order to optimize machining processes, different statistical techniques were used. With the use of either nonlinear or linear polynomial models, it is possible to model power behavior. Amongst these techniques are design of experiments (DOEs), Taguchi, nondominated sorting genetic algorithm (NSGA), and response surface.

This paper reports on a research aimed at modelling the power consumption of the face milling and drilling operations in terms of cutting parameters. This is relevant because such power demand models assist in defining cutting parameters in order to achieve the required quality of surface, which is key in manufacturing processes and adequate productivity rate. The energy consumption is also considered as a factor. Besides, the work reported successfully identifies facing and drilling toolpaths with the lowest power demands and employs DOE to define tests that were carried out to calculate the constants of the desired models. The methodology used by the authors identified that nonlinear equations provided a better fit than linear equations for the machining operations studied. Additionally, the combination of the cutting parameters and toolpath is more suitable to improve a machining process.

2. Power Demand Background

Several researchers have worked on understanding power consumption on machine tools. Draganescu et al. attempted to develop a model for the spindle motor's efficiency η using the following equation, which relates the p_c, minimal cutting power, with p_{mc}, the power consumed by the spindle drive motor [28]:

$$\eta = \frac{p_c}{p_{\mathrm{mc}}}. \tag{1}$$

Gutowski et al. [4] determined the power consumed in a machining operation using the following equation, which estimates p, total power, with p_o, idle power, $\dot{m}$, the rate of material processing, and k, a constant:

$$p = p_o + k\dot{m}. \tag{2}$$

Different authors [4, 7] have analyzed machining power demand composed of three components:

(i) *Standby Power*. It is the constant power consumed by a machine tool whether material is being cut or not. The electrical components of a machine that always consume power are its controller, its computer panel, and its lights.

(ii) *Component Power*. It is the power required to achieve the desire spindle speed and feed rate and is needed to carry out each tool change and power the coolant pump.

(iii) *Machining Power*. It is the power used to remove material.

There exist different alternatives to name each part of the power used by a CNC machine. For example, equation (3) shows the total power consumed by a machine tool. The constant power is the equivalent to the standby state which includes unloaded motor, coolant pump, computer, and fans. The variable power includes the required power to move the spindle and carrying out jog and tool change. Finally, the force necessary to remove the material is the cutting power, Cutting P in equation (3), which is equivalent to the machining power. On the other hand, the constant power, Constant P, plus the variable power, Variable P, equal the tare power [4]:

$$T.\ \text{Power} = \text{Constant } P + \text{Variable } P + \text{Cutting } P. \tag{3}$$

2.1. Models to Predict Surface Roughness and Power Consumption. Different statistical techniques [29, 30] have been used to model the relationship between output variables and cutting parameters in machining processes. These techniques have showed their advantages on accuracy and simplicity. To establish a regression model for a particular phenomenon or behavior, it is necessary to set up selective experiments, considering output variables as dependent and input variables as independent [31]. Next, data are collected from running experiments, and an equation, i.e., a regression model, is defined based on a statistical analysis of measurements. There exist several regression models, i.e., first order, second order, and nonlinear models. In the particular case of nonlinear models, their constants can be calculated using the method of least square on the results of experiments [31]. Fang and Safi-Jahanshahi [26] proposed a nonlinear model (fit regression model), to predict the surface roughness as a variable dependent on the cutting speed, feed per tooth, and depth of cut, as follows:

$$y = x_1 \cdot a^{x_2} \cdot b^{x_3} \cdot c^{x_4}. \tag{4}$$

In equation (4), the dependent variable is y; x_1, x_2, x_3, and x_4 are constants; and a, b, and c are independent variables. The experiments documented in [26] reported an average error for equation (4) of 3.86%, and constants x_1, x_2, x_3, and x_4 started with a value of one. The Levenberg–Marquardt algorithm was used to find the optimum fit values. The following equation was used to solve the Levenberg–Marquardt algorithm:

$$\delta(k) = \left(V^T V + kD\right)^{-1} V^T (y - \eta), \tag{5}$$

where k is a conditioning factor and D is a diagonal matrix with elements of $V^T V$. The direction of $\delta(k)$ is intermediate between the direction of the Gauss–Newton increment ($k \longrightarrow 0$) and the direction of steepest descent, as follows:

$$\frac{V^T (y - \eta)}{\left\| V^T (y - \eta) \right\|}, \quad (k \longrightarrow \infty). \tag{6}$$

This paper contributes to the understanding of the power and energy behaviors as functions of machining process strategies and cutting parameters. Two milling operations are studied, facing and drilling. In order to identify which one consumes less power, three strategies are tested for facing and two for drilling. Next, DOE is used to define experiments, and the Levenberg–Marquardt algorithm with a least square estimation is employed to help in calculating the constants of linear and nonlinear models that lead to the final total power estimation. Additionally, measurements of surface finish achieved during the experiments and a nonlinear model for tare power are reported.

3. Experiment Setup

Figure 1 shows the use of the DOE methodology followed in this work to model the energy consumed by face milling and drilling.

3.1. Case Study Specification and Cutting Tool Selection. The process comprised two operations: first, face milling, consistent on getting a flat area, perpendicular to the axis of the spindle, with a depth of cut of 3 mm; second, a drilling operation applied on nine Ø 14 mm holes with a depth of 25 mm, in a rectangular array of 3 × 3. The machining process to manufacture the part was defined using the commercial software Mastercam® × 8. The face milling operation was performed using different toolpath strategies for each of them: dynamic, zigzag, and one-way. This operation was carried out in one step, i.e., only one facing stage, while the drilling operation was defined first using the counterbore toolpath cutting option and then employing the chip break. Table 1 shows the experiment about material and cutting tool.

The experiments here reported (Tables 2 and 3) implemented the use of air to remove chips during the process because the color of the chips was blue, which meant that due to the settings selected for the cutting parameters, the friction between the tool and the material was not too high.

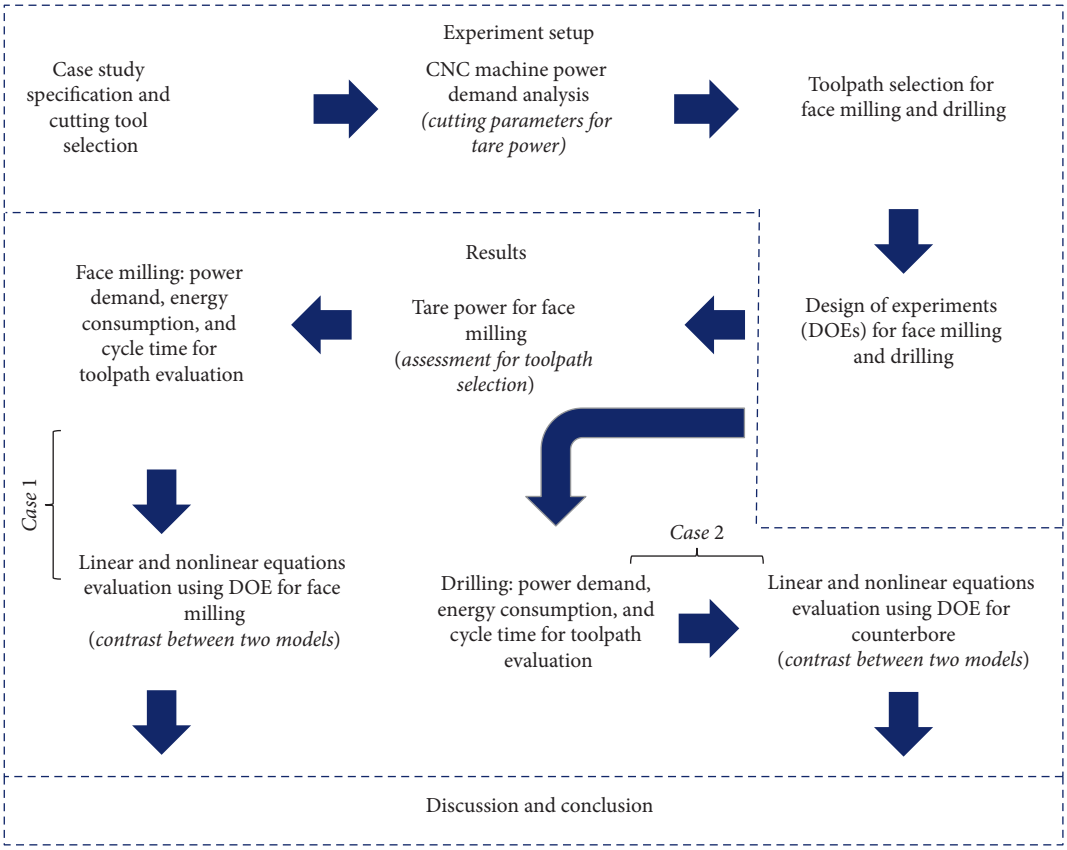

Figure 1: Methodology followed for this research.

Table 1: Details of the experiment.

Workpiece dimensions	180 mm × 150 mm, depth 30 mm, AISI 1045 medium carbon steel, hardness, Brinell 163
Workpiece material	Carbon 0.43–0.5% max, manganese 0.6–0.9% max, silicon 0.05% max, phosphorus 0.04% max, and sulphur 0.050% max
Chemical composition	ISO code IP240-1200-XA 1630 a solid carbide square end mill with effective cutting edge: 4, cutting diameter: 12 mm, flute helix angle: 35 deg, corner chamfer width: 0.2 mm
Tool material	ISO code 860.1-1400-040A1-PM 4234 a solid carbide drill with cutting diameter: 14 mm, hole tolerance: H8, point angle: 147°, chip flute length: 60 mm

Table 2: Cutting parameters used in the DOE for tare power.

Parameters	1	2	3
Spindle speed (rpm)	2005	5777	9549
Feed rate (mm/min)	802	2607	4412

3.2. CNC Machine Power Demand Analysis, Surface Roughness, and Drilling Holes. The experiments were set up on a milling machine Haas VM3. The power was measured using a three-phase energy analyzer Fluke® 430 series II, which is a portable device, complemented by alligator clips and current clamps to connect it (Figure 2). The measurement equipment took data every second, sending information to the computer, and analyzed in the Fluke® PowerLog software.

A portable surface roughness tester Mitutoyo® SJ-210 (Figure 2) was used; the instrument was set to measure under ISO 4287 : 1997 the arithmetical mean roughness value (Ra) with a resolution of 0.006 μm, cutoff wavelength λc of 0.8, roughness sampling length of 0.8 mm, the mean groove spacing RSm (mean peak width) of ×5 and 0.05 mm/s speed, stylus tip radius of 5 μm, and measuring force of 4 mN to measure the surface quality. The procedure can be described as follows: the first step consists on taking three samples in

Table 3: Cutting parameters for the DOE for the face milling and drilling operations.

Parameters		Level		
		Low	Medium	High
Face milling	v_c, cutting speed (m/min)	315	350	385
	a_p, depth of cut (mm)	0.5	1.0	2.0
	f_z, feed per tooth (mm)	0.15	0.175	0.2
Drilling	Cutting speed (m/min)	315	350	385
	Feed (mm/r)	0.15	0.175	0.2

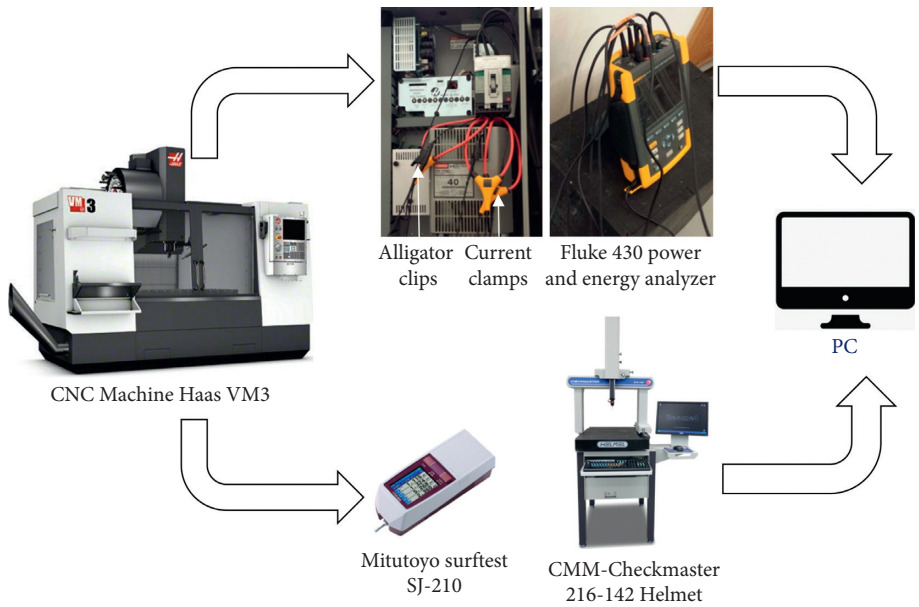

Figure 2: Schematic representation for collecting data.

different points along the flat facing machined area; the second step is to repeat three times the measure in the same points and finally is getting the average between the measurements that were obtained. The drilling holes were measured with a Checkmaster® 216 142-Helmet with resolution (Figure 2) 0.5 μm, coordinate measuring machine using a Renishaw sensor adapted to M2 Ø 4 mm ruby ball, stainless steel stem, and L 20 mm; the data were collected and analyzed using Geomet® 101 software. The procedure followed begins with collecting the first 3 data points at or near the bottom along the axis of a cylinder, secondly collecting the last 3 data points at or near the top, then repeating twice the measure in the same points, and finally getting the average between the measurements found.

The breakdown of the power of the CNC machine used was analyzed using the measurements that were obtained with the power analyzer.

3.2.1. Total Power (kW). The total power consumed in each one of the experiments (Tables 2 and 3) was measured. Different tests in each experiment were carried out to estimate the coefficients x_1, x_2, and x_3, while a_p, v_c, and f_z are values of the cutting parameters chosen by the user to model the power consumption with a first-order model (see equation (7)) and a nonlinear model (fit regression model) (see equation (8)) and identifying the convenience of both:

$$\mathrm{kW}_{\mathrm{Total}} = a_p \cdot x_1 + v_c \cdot x_2 + f_z \cdot x_3, \tag{7}$$

$$\mathrm{kW}_{\mathrm{Total}} = x_1 \cdot a_p^{x_2} \cdot v_c^{x_3} \cdot f_z^{x_4}. \tag{8}$$

3.2.2. Constant Power. His factor was measured setting the machine to the standby state. Its value was 0.55 kW. During the experiments, the coolant water pump was turned off because the metal chips were removed by using air instead.

3.2.3. Tare Power. Face milling was used for modelling the tare power. It was measured setting the machine tool in a running condition, without removing material configured with the dynamic toolpath strategy. This toolpath was used in the study (Table 2) considering the low, middle, and high ranges that could reach the spindle speed and feed rate. So, nine tests were defined in this experiment. The data collected were used to calculate the constants of the nonlinear model proposed to estimate this energy. The model was established with spindle speed, n, and feed rate, v_f, as independent variables, shown as follows:

$$\mathrm{kW}_{\mathrm{Tare}} = x_1 + n^{x_2} + v_f^{x_3}. \tag{9}$$

3.2.4. Cutting Power. This is the necessary power to remove material. It could be determined by subtracting the tare power from the total power.

The parameters chosen in Table 2 were set under parameters mentioned in the data sheet of the CNC machine, the maximum spindle speed is 1200 rpm, while the maximum feed rate is 18 000 mm/min, and also the parameters are according to cutting tool operations suggested by the supplier. The coolant was turned off because it was not removed material.

3.3. Toolpath Selection for Face Milling and Drilling. This research considered the face milling for modelling the tare power. Cutting parameters were set as recommended by the tool supplier [32] for the facing operation. Three toolpath strategies were used: dynamic, zigzag, and one-way (Figure 3); the toolpath with the lowest power demand was identified.

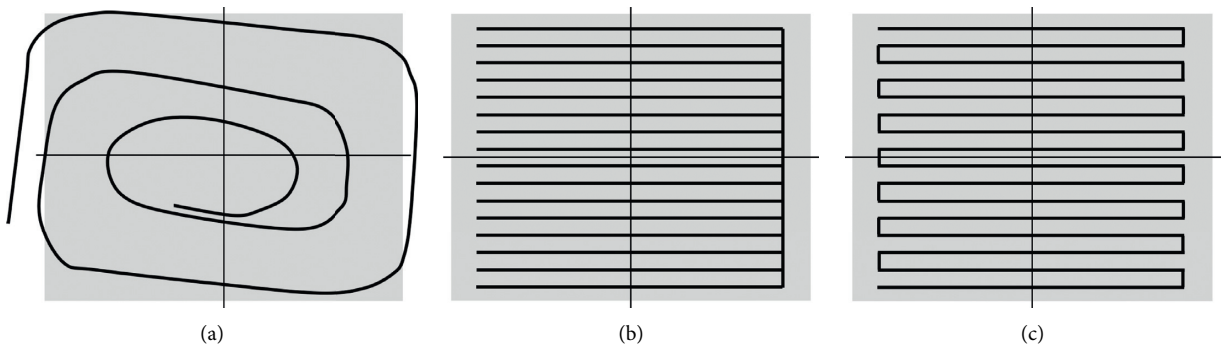

Figure 3: Toolpath strategies: (a) dynamic; (b) one-way; (c) zigzag. The drill counterbore and chip break toolpath cutting options were tested to identify the tool path strategy that required the lowest power demand.

The cutting parameters were the same for the three strategies (i.e., feed per tooth 0.2 mm, cutting speed 385 m/min, and depth of cut 0.5 mm), reaching a final depth of 3.0 mm.

3.4. Design of Experiments for Face Milling and Drilling. The cutting parameters for face milling were defined using a DOE 3^3. Table 3 shows these values. In order to obtain a satisfactory roughness, the levels of the depth of cut were set to low values: 0.5, 1, and, finally, 2 mm. The quality of surface finish achieved in the workpiece was measured.

For drilling, cutting parameters were defined with an experiment 2^3, as shown in Table 3. This operation was set with the coolant applied through the tool.

As mentioned before, a DOE 3^3 was used for face milling, and this generates 27 possible combinations of cutting parameters for the machining operation. All the values of the low, medium, and high levels for face milling of Table 3 are within the ranges suggested by the tool supplier. A DOE 2^3 was selected for drilling, which implies 9 possible combinations of cutting parameters. Again, all the values of the low, medium, and high levels for face milling of Table 3 are within the ranges suggested by the tool supplier. The results were used for the power demand and energy consumption statistical models proposed by the authors as described below.

4. Results

4.1. Tare Power for Face Milling. The statistical software Minitab® was used to carry out the nonlinear and linear regressions of the data obtained with the experiments shown in Table 3. Each one of the 27 defined tests were carried out once, to calculate the constants for equations (10) and (11). Table 4 shows the data of the nonlinear analysis solved with the Levenberg–Marquardt method and based on the results of the facing experiments using the CNC machine operating with a dynamic toolpath strategy. Table 4 also includes the estimated parameter values and their standard error.

The nonlinear predictive model equation (10), which is based on equation (9), presents $\mathrm{kW}_{\mathrm{Tare}}$ as a function of n, spindle speed, and v_f, feed rate. In the following equation, $\mathrm{kW}_{\mathrm{Tare}}$ is the tare power (i.e., constant power plus variable power):

Table 4: Nonlinear regression analysis carried out with the Levenberg–Marquardt algorithm.

Parameter	Estimate	SE estimate
x_1	0.003014	0.003773
x_2	0.639114	0.123164
x_3	0.070207	0.078683

p value: 0.623; maximum iterations: 200; tolerance: 0.00001; SE: standard error.

$$\mathrm{kW}_{\mathrm{Tare}} = 0.00301386 \cdot n^{0.63914} \cdot v_f^{0.0702071}. \quad (10)$$

Figure 4 shows over the X-axis the three spindle speeds chosen in Table 2. However, each speed is repeated three times because it was necessary to make nine tests in this experiment. For example, the spindle speed of 2005 rpm and the feed rate of 802 mm/min were tested with the three toolpaths chosen: dynamic, zigzag, and one-way; this is what the first three bars show in Figure 4, and the next three bars show the same spindle speed but with a feed rate of 2647 mm/min and the same toolpath mentioned. The tare power over the y axis, of the CNC machine, increases as the spindle speed goes up. The three spindle speeds and feed rate values specified by Table 2 were tested in the experiment. The values calculated with equation (10) to predict the tare power demand for the strategy dynamic are represented by the dotted line.

4.2. Case 1 Face Milling: Power Demand, Energy Consumption, and Cycle Time for Toolpath Evaluation. Three different toolpath strategies, i.e., cutting options, were tested with the face milling operation using the medium values defined in Table 3, the cutting parameters were tested three times, and Table 5 shows the average values obtained.

As shown in Table 5, the toolpath dynamic consumed 0.121 kWh, which was the lowest value, and the quality surface obtained was 0.22 μm. Therefore, considering the power and energy values, the dynamic cutting option resulted in being the most convenient for energy saving.

4.3. Nonlinear and Linear Equations Evaluation Using DOE. Table 6 presents the results of the statistical analysis for the experiment defined in Table 3. Twenty-seven tests were

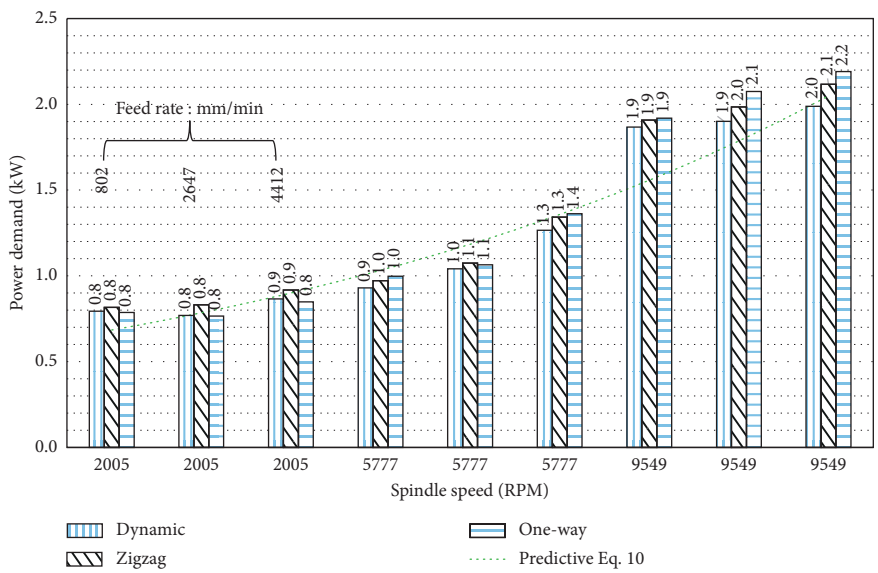

Figure 4: Experimental and theoretical tare power for the face milling operation.

Table 5: Face milling operation comparative with different cutting options.

Cutting option	Cycle time (hrs)	Power demand (kW)	Energy consumption (kWh)	Quality surface R_a (μm)	
				X-axis	Y-axis
Dynamic	0.08	1.52	0.121	0.22	0.24
Zigzag	0.10	1.55	0.154	0.20	0.28
One-way	0.07	1.99	0.136	0.21	0.22

Table 6: Nonlinear regression analysis carried out with the Levenberg–Marquardt algorithm.

Parameter	Estimate	SE estimate
x_1	0.119379	0.0296690
x_2	0.586379	0.0127844
x_3	0.660086	0.0414910
x_4	0.501722	0.0290065

Maximum iterations: 200; tolerance: 0.00001; SE: standard error.

carried out using the dynamic cutting options because it had the lowest power demand. The maximum power demand measured in the experiments was 4.10 kW, the medium value was 2.98 kW, and the lowest was 1.98 kW.

As mentioned in the previous section, the results of Table 6 were used for the model presented by equation (11), where $\mathrm{kW}_{\mathrm{Total}}$, the total power demand, can be estimated from the cutting parameters a_p, v_c, and f_z:

$$\mathrm{kW}_{\mathrm{Total-facing}} = 0.119379 \cdot a_p^{0.586379} \cdot v_c^{0.660086} \cdot f_z^{0.501722}. \tag{11}$$

Figure 5 shows that there is a normal distribution because the residual model falls on the straight line, which can be seen in the normal probability plot. Additionally, the histogram shows that the data are skewed, and the residuals are randomly distributed, which means constant variance is possible as seen in the versus fits chart. The residuals are independent from one another and are randomly distributed around the center line which means a normal behavior in the versus order chart. This tendency demonstrates the suitability of the experimental results.

Table 7 summarizes the results of the 27 experiments carried out with the DOE specified in Table 3 and shows the ANOVA data. The significance of each factor a_p, v_c, and f_z was tested. The analysis was carried out with a confidence level of 95% for all intervals. In Table 7, the p values of the three factors are significant because they are lower than 0.05, which means that the three factors are determinant for the power demand.

The surface quality produced by the 27 tests carried out, which combined different cutting parameters, was measured. The minimum average surface roughness obtained, R_a, was 0.01 μm and the maximum 0.183 μm. Therefore, these values according to indication of surface texture in technical product documentation fell between $N1$ and $N3$, which represent superfinishing and high level of finish [33].

Equation (12) shows the linear regression equation to predict the power in kW. This includes the coefficients determined using the least squares estimation, which represents the estimated change in mean response for each unit change in the predictor value:

$$\mathrm{kW}_{\mathrm{Total-facing}} = -2.296 + 1.1881 a_p + 0.005681 v_c + 8.621 f_z. \tag{12}$$

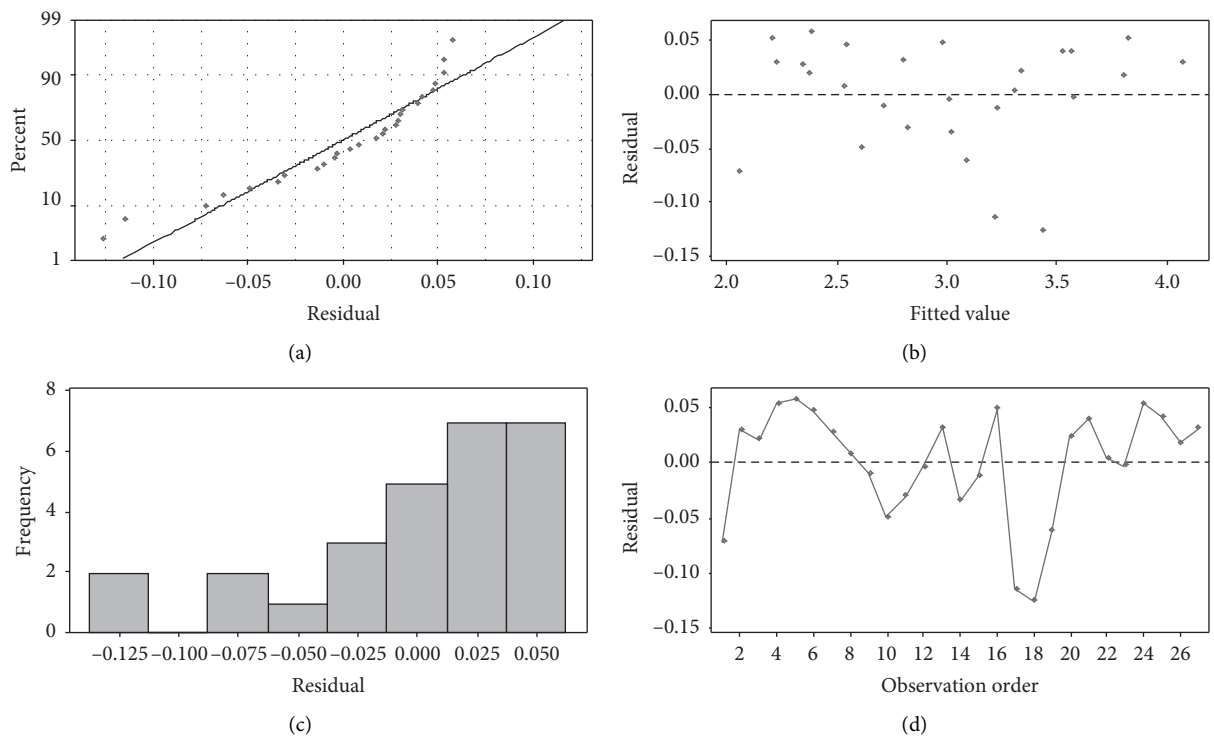

Figure 5: Residual plots for the face milling operation: (a) normal probability plot; (b) versus fits; (c) histogram; (d) versus order.

Table 7: Variance analysis of the experiment (Table 3).

Source	DF	Adj. SS	Adj. MS	F value	p value
Regression	3	7.89958	2.63319	669.94	0.00001
a_p	1	6.35191	6.35191	1616.07	0.00001
v_c	1	0.71156	0.71156	181.04	0.00001
f_z	1	0.83611	0.83611	212.72	0.00001
Error	23	0.09040	0.00393		
Total	26	7.98998			

R^2 (pred): 98.36%.

Figure 6 shows a comparison between the real power demands (denoted with green color in figure), with the linear equation prediction (equation (12), denoted with blue line in figure) and with the nonlinear equation prediction (equation (11), denoted with yellow color in figure). The figure compares the values obtained in each one of the 27 tests carried out during the experiment. Clearly, the green line is completely aligned with the yellow line, whereas the blue line shows different slight values in comparison with the real power behavior. For example, in test 2, the real value is 2.25 kW, which contrasts with the 1.97 kW estimated by the linear predictive equation.

4.4. Case 2 Drilling: Power Demand, Energy Consumption, and Cycle Time for Toolpath Evaluation. The two different drilling cutting options tested, counterbore and chip break, were compared. The tool machined the hole with a single movement when the counterbore cutting option was used. The hole was machined progressively, i.e., with a series of penetration and withdrawal movements, using the chip break option.

The toolpath counterbore consumed 0.011 kWh to produce a hole with a radius of 7.001 mm (Table 8). Therefore, considering the lower energy value, the counterbore toolpath option resulted to be just more convenient for energy saving.

4.5. Nonlinear and Linear Equations Evaluation Using DOE for Counterbore. Table 9 presents the results of the statistical analysis for the experiment defined in Table 3. Nine tests were carried out using the counterbore drilling option because it had the lowest power demand. The maximum power demand measured in the experiments was 4.12 kW, the medium value was 3.46 kW, and the lowest was 2.94 kW.

The modelling of the drilling operation was carried out for the drill counterbore toolpath based on the results of the regression analysis presented in Table 9. In the model of the operation, $\mathrm{kW}_{\mathrm{Total}}$ represents the total power demand and it is a function of the cutting drilling parameters v_c and f_n, as follows:

$$\mathrm{kW}_{\mathrm{Total-drilling}} = 0.27747 \cdot v_c^{0.486936} \cdot f_n^{0.0197716}. \quad (13)$$

Figure 7 shows that there is a normal distribution because the residuals for the model fall on the straight line, making it possible to see this in a normal probability plot. Also, the histogram shows that the data are skewed, and the residuals are randomly distributed which means constant variance is possible seeing in versus fits charts; the residuals are independent from one another, those randomly around the center line mean a normal behavior in versus order chart.

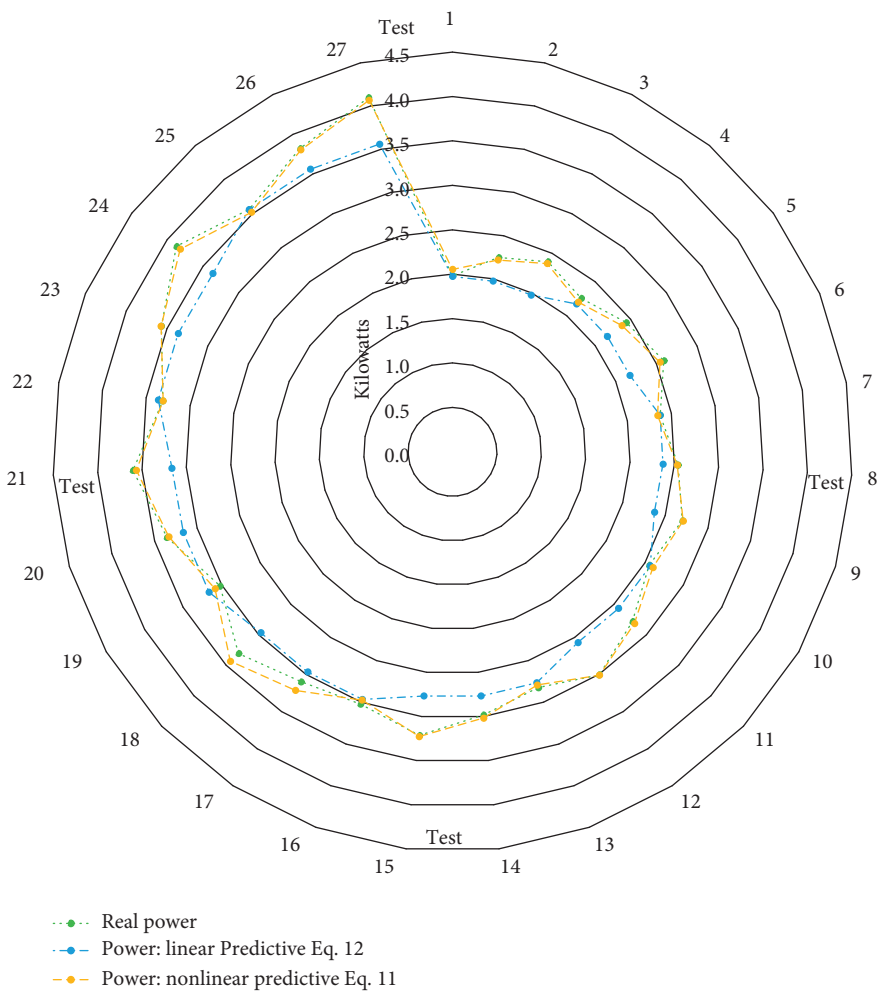

Figure 6: Face milling power real value compared against the results obtained with the nonlinear and linear predictive models.

Table 8: Drilling operation comparative with different cutting options.

Cutting option	Cycle time (hrs)	Power demand (kW)	Energy consumption (kWh)	Radii (mm)
Counterbore	0.003	3.930	0.011	7.001
Chip break	0.003	3.256	0.014	7.002

Table 9: Nonlinear regression analysis carried out with the Levenberg–Marquardt algorithm.

Parameter	Estimate	SE estimate
x_1	0.277470	0.0820493
x_2	0.486936	0.0552161
x_3	0.019772	0.0419983

Maximum iterations: 200; tolerance: 0.00001.

This tendency demonstrates the suitability of the experimental results. The data collected are the support to construct the model of equation (13) with its respective variables.

Table 10 shows the results of the 9 tests carried out with the parameters of the DOE displayed in Table 3 and also shows the ANOVA data. The significance of each factor v_c and f_n was tested. The analysis was carried out with a confidence level of 95% for all intervals. The p value of the v_c factor is significant, which means that this parameter has an important impact on power. However, the f_n factor is higher than 0.05, implying a low impact on power.

Equation (14) shows the model to predict the power generated with the regression analysis. It can be seen that drilling operations include two cutting parameters, cutting speed (v_c), and feed per revolution (f_n):

$$\mathrm{kW}_{\mathrm{Total-drilling}} = 1.661 + 0.008873 v_c + 0.367 f_n. \quad (14)$$

Figure 8 shows a comparative between the measured values of power, real powers (green color), with the values obtained with the nonlinear equation (equation (13), denoted with blue color in figure) and with the linear equation (equation (14), denoted with yellow color in figure). The blue line is aligned with the yellow line which are the predictive equations, whereas green line shows slightly

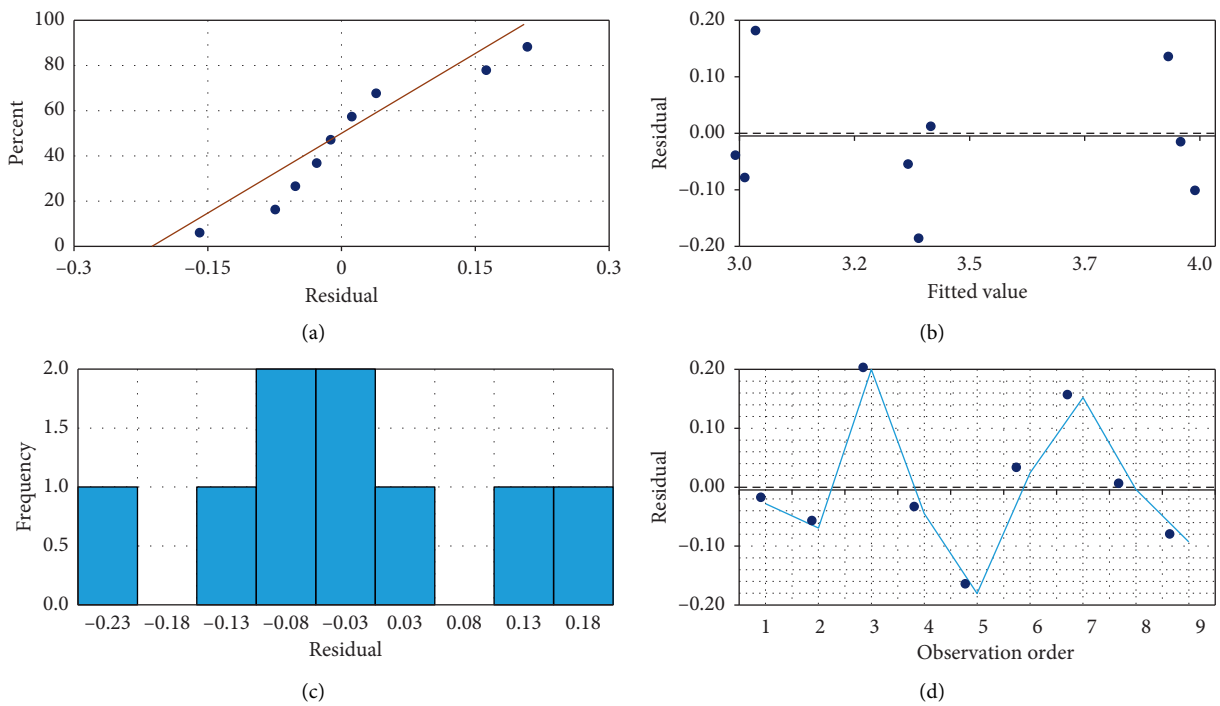

Figure 7: Residual plots of the drilling operation: (a) normal probability plot; (b) versus fits; (c) histogram; (d) versus order.

Table 10: Variance analysis.

Source	DF	Adj. SS	Adj. MS	F value	p value
Regression	2	1.47609	0.73805	47.09	0.00001
v_c	1	1.46422	1.46422	93.42	0.00001
f_n	1	0.01187	0.01187	0.76	0.418
Error	6	0.09404	0.01567		
Total	8	1.57013			

R^2 (pred): 93.45%.

different values in tests 3 and 7. For example, the real value in test 3 is 3.23 kW, in contrast to 3.03 kW obtained with the linear predictive equation and 3.07 kW with the nonlinear equation.

5. Discussion

Tool path strategies and cutting parameters are important factors in the power and energy behavior. It is also known that the maximum power demanded by a CNC machine is tare power [7], but it is not constant. However, if the tool path does not change, the spindle speed and the feed rate will vary depending on cutting parameters. This could be modelled with linear and nonlinear equations, in the idle CNC machine tool condition. The work reported in this paper considered the dynamic tool path strategy for facing as a basis for developing a model because its power demand was inferior to the other two milling strategies (Table 5). There was no representative difference of the surface finish obtained with each strategy, as displayed in Table 4; along the X-axis, R_a varied up to 0.02 μm and up to 0.04 μm, in the Y-direction.

As the tool path was constant in facing, the energy performance depended on the spindle speed and feed rate. Tare power was modelled with the dynamic tool path. However, the same procedure reported in this paper can be used with other machining processes and different tool paths to define the appropriate model for tare power. A nonlinear equation was used to represent the tare power as a function of cutting parameters because of the comparison of the results obtained with linear and nonlinear models reported in Figures 5 and 7.

The data collected through different experiments allowed the authors to choose cutting parameters to achieve workpiece design specifications and, at the same time, take into account low energy consumption operations. According to the data collected using different tool paths for facing, the dynamic tool path reported 1.52 kW and 0.121 kWh, the zigzag 1.55 kW and 0.154 kWh, and the one-way tool path reported 1.99 kW and 0.136 kWh. This behavior was determinant to select the results of the dynamic tool path strategy to define the model for the operation because of its low power demand.

From the face milling 27 experiments, the cutting parameters of the three tests (A, B, and C) carried out with the dynamic toolpath with the lowest power demand and energy consumption were as follows: A—$a_p = 1$ mm, $v_f = 350$ m/min, and $f_z = 0.20$ mm per tooth; B—$a_p = 1.5$ mm, $v_f = 350$ m/min, and $f_z = 0.20$ mm per tooth; and **C**—$a_p = 2$ mm, $v_f = 350$ m/min, and $f_z = 0.20$ mm per tooth. The power, energy, and roughness surface were $A = 2.59$ kW, 0.030 kWh, and 0.085 μm; $B = 3.21$ kW, 0.038 kWh, and 0.56 μm; and $C = 3.87$ kW, 0.046 kWh, and 0.66 μm. Based on these results, the values for v_f and f_z could be selected,

Figure 8: Drilling power real value compared against the results obtained with the nonlinear and linear predictive models.

and there are two options for a_p: the lowest power and energy consumption; therefore, the lowest cycle time was obtained with option A, but the best quality surface was produced with option C. So, if the surface finish achieved with A satisfies the workpiece requirements, this is the best option. Still, C is also adequate.

Drilling was tested with coolant applied to the tool, especially for removing the chip. In addition, the highest variation in ratio was 0.08 mm. However, drill counterbore required the highest value in power with 2.9 kW, reaching 3.9 kW, and on the contrary, this operation showed the lowest energy value with 0.009 kWh until reaching 0.011 kWh. Besides, the same behavior observed in the drill counterbore operations was found using the chip break strategy. Power values ranged from 2.8 kW to 3.2 kW and energy from 0.01 kWh to 0.014 kWh. The results above-mentioned showed that, in the case of drill counterbore, the variation between the lowest and the highest power was estimated in 0.97 kW and the figure for energy was estimated in 0.002 kWh. When drilling with chip break, the power was 0.376 kW and the energy 0.004 kWh. The power variation was an important measurement in this operation, especially because this behavior is a consequence of all power peaks that take place during machining.

6. Conclusions

Based on the comprehensive outcome of our investigation, the following conclusions can be drawn:

(1) The approach used in this research in terms of cutting parameters as demonstrated by the nonlinear power model is validated by the fact that the p value for the lack-of-fit test is 0.623 (Table 4), which means that this value is larger than the significance level of 0.05 or the linear model with R^2 (pred) 98.36 (Table 7).

(2) The power demand and energy consumption differences of the facing and drilling operations for the workpiece analyzed varied from 2 to 4 kW and 0.125 kWh to 0.011 kWh. In order to achieve a good balance of consumption, i.e., without big differences or peaks, it is necessary to carefully select the tool-path trajectory, cutting parameters, and cutting tools

for each machining operation required by a workpiece.

(3) Different behaviors in energy consumption derived from choosing one or another toolpath available in commercial software. The values found for dynamic toolpaths (tare power) are 1.21 kWh, as a minimum, to 1.54 kWh, as a maximum. This could represent an optimization value of 0.21% (Table 5). Moreover, regarding the behaviors in energy consumption shown when using one or another cutting parameters, the values found for dynamic toolpaths are 0.030 kWh, as a minimum, to 0.046 kWh, as a maximum (Discussion). This could mean an optimization value of 0.35%.

Further research will focus to find a correct energy balance, using equation prediction by varying the cutting parameters. More studies are necessary in order to better fit the quality of surface with energy consumption.

Abbreviations

a_p:	Depth of cut
DOEs:	Design of experiments
f_n:	Feed per revolution
f_z:	Feed per tooth
kW:	Kilowatts
kWh:	Kilowatts hour
n:	Spindle speed
R_a:	Roughness average
rpm:	Revolutions per minute
v_c:	Cutting speed
v_f:	Feed rate
ANOVA R^2 (pred):	Analysis of variance R^2, predicted.

Data Availability

The nature of the data obtained in the present investigation are of the experimental type. The equations presented in the article are of the own authorship of all those who participated in the writing of the same and come from the result of studying the theories related to the design of experiments. Addition information can be made available from the correspondence author (xavier_snk@hotmail.com) or the principal author (gminquiz@yahoo.com) upon request. There is no restriction to access such data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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