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Experimental characterization of energy consumption in 5-axis milling machine and developing optimization strategy

Sunil Kumar Maurya[a]*, Gianni Campatelli[b], Massimo Veracini[c]

[a]*University of Firenze, Santa Marta 3, Firenze - 50139*
[b]*University of Firenze, Santa Marta 3, Firenze – 50139*
[c]*Baker Hughes, Via Felice Matteucci, 2, Firenze - 50127*

* Corresponding author. Tel.: +393534500679. E-mail address: sunilkumar.maurya@unifi.it

Abstract

The optimization of machining processes is of paramount significance because of its pivotal role in modern manufacturing. Efficient machining techniques not only enhance product quality but also reduce costs and environmental impacts. This study focuses on the experimental characterization of energy consumption in a 5-axis milling machine and the simulation of possible solutions to reduce it. The first step is to understand the key drivers of energy consumption which is crucial for enhancing energy management and optimization. This was achieved by developing a mathematical model that uses the most common machining parameters as input using a Response Surface Methodology experimental test plan and an analysis of the contributions of the auxiliary systems to the overall energy consumption. As a second step, the effectiveness of different solutions was simulated considering different application scenario, like the type of operations. Such solutions include the introduction of duty cycle strategies for some auxiliary systems and the optimization of process parameters.

Keywords: Milling, Optimization, Energy consumption, Experimental characterization, Response Surface Methodology

1. Introduction

In recent years, the growing importance of sustainability and energy efficiency has led the industry to focus on optimizing energy consumption in manufacturing processes. Energy-intensive assets such as milling machines play a vital role in the manufacturing industry and have a significant impact on overall global energy consumption [1]. Knowing the energy consumption characteristics of milling machines and identifying key drivers, can provide valuable insights for energy management and improved efficiency. Such activities are already a part of the Industry 4.0 initiative [2], and the application of these technologies and methodologies can substantially improve the overall efficiency in terms of energy consumption in manufacturing processes [3].

In addition, the global strive towards sustainable manufacturing is steadily increasing due to two important factors: political and economic pressure to become carbon neutral in a specific target time, and second one being diminishing natural resources that are pushing industries to produce less waste and be more efficient.

The key factors that contribute to energy consumption in 5-axis milling machines include process parameters, such as feed rate, tool geometry, cutting speed, depth of cut, material of the tool and workpiece, and cutting environment [4]. Because a machine tool is a very complex system, the contribution that affects the energy consumption is multiple and includes not only the spindle, but also the auxiliary systems that play a relevant role in the performance of the process. Dahmus and Gutowski [5] evaluated these contributions to assess the energy sink of such process, evaluating the relative importance of each contribution. An important contribution is a proper machining process, which is strongly dependent on machine size, tools, and process parameters [6]. Once this information

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is available, a generic energy consumption model can be developed for milling processes, which estimates the energy consumption based on power characteristics and parameters extracted from numerical control codes [7]. Kara et al, [8] formulated a theoretical framework to describe the correlation between energy consumption and process variables in the context of material removal procedures. The researchers meticulously handpicked a set of eight distinct machining devices, considering both dry and wet cutting scenarios, to showcase the efficacy of their proposed methodology. A regression-based power consumption model can also predict in-process power consumption which is derived from the correlation between the material removal rate (MRR) and specific energy consumption (SEC) [9]. In addition, the authors of this paper have put forth proposed a model for estimating SEC with the intention of reducing energy consumption during the phases of part design and process planning [8]. Such models already show the possible energy consumed during the milling process and the significance of the environmental footprint it inflicts.

Building on this, significant work has been conducted on the optimization of milling processes to reduce the adverse effects of energy consumption. Several strategies have been employed, and one such approach is to develop an energy model based on a detailed analysis of the energy consumption activities in machining processes [10]. This model can be used to assess and optimize numerical control (NC) programs for specific machining processes. Another approach is to optimize the cutting tool path itself to reduce air cuts and idle travel of axis. The influence of various programming paths on power consumption can be investigated to identify suitable programming routes to reduce energy consumption [11]. It is also important to consider the choice of optimum process parameters, such as feed rate, tool geometry, cutting speed, and depth of cut, to improve energy efficiency during machining. By selecting the optimal values for these parameters, machining performance can be improved, leading to reduced energy consumption [12]. The author presented a case for enhancing manufacturing systems through the incorporation of energy-efficient technologies, which encompassed the implementation of redesign and optimization methods, as well as their effect on production performance [13]. Other opportunities for energy reduction are provided by smart scheduling of the operation, which could affect the distribution of the inactive period of a machine, thus allowing the switch to a stand-by state with lower energy consumption. This requires a study of the stochastic distribution of the arrival time for the parts to be machined and implementation of a fit solution [14]. Indeed, the state-of-the-art regarding the energy consumption of machine tools is very large, and it is not a viable option to report a more detailed resume in this paper. However, it is important to note that most of the authors focused on the optimization of the process parameters or operation scheduling, whereas improvement actions could be carried out through an in-depth study of the consumption of auxiliary systems (refrigeration, chip conveyer belt, coolant pump, etc.) and part orientation. Although the study of machine energy efficiency is a common practice, this research focuses on two main activities. The first is the definition of a test to evaluate the difference in the consumption of the x- and y-axes, which can lead to an optimal orientation of the part [15]. The second is the analysis of the impact of the partial use of the chip conveyor that, for this specific machine, the energy consumption is not negligible.

2. Experimental Setup

For this experiment and data collection a "GF AgieCharmilles Mikron HPM 800U HD 5-axis High Performance Machining Center" was used. It was equipped with a Heidenhain iTNC 530 control unit and a chip conveyor that used two screws to remove the material from the machining chamber and an external conveyor chain to transport the chips to the degreasing unit. The material used for the tests was A182 F22 Alloy Steel (Table 1) [16].

Table 1. Mechanical properties of A182 F22 alloy steel

Property	Values
Ultimate Tensile Strength *	655 Mpa
0.2 % Yield Strength *	517 Mpa
Elongation *	17 %
Charpy Impact Toughness	42 mean/ 33 min J at –18ºC
Hardness	197 – 237 BHN (75 Ksi min)

To measure energy consumption, split core clamp-on power probes were selected, as they offer a non-invasive method for acquiring power data. These probes have a wide current-range capability, spanning from 10mA to 100A. The probes were calibrated prior to data collection to ensure accurate measurement and were associated with a voltage converter to use an NI-DAQ simultaneous sampling card and NI-9215 for the acquisition. Because the sensors measure the current in the three phases, an average of the current in the three phases was taken to calculate the power using a line-to-line voltage from a voltmeter (1).

$$P(kW) = \frac{\sqrt{3} \times PF \times I_{(A)} \times V_{L-L\,(V)}}{1000} \quad (1)$$

Where, P is the power (kW), PF the power factor, I the current (A), and V_{L-L} the line to line voltage (V)

A MULTI-MASTER solid carbide head tool from ISCAR with a treatment of TiAlN, a diameter of 20 mm, and four teeth was selected (ref number: 47552). The first test assessed the asymmetry of power consumption between the two axes to evaluate whether the efficiency of the axis movement was the same in both directions. Some differences could be due to the different mass of the axis to be moved owing to the structure of the machine. For example, with a box-in-box structure, the inner axis is lighter, and its acceleration and movement require less energy. In this case, it is interesting to concentrate the acceleration of the axis in this direction to reduce the energy consumption [17]. The toolpath for this test in given in Fig. 1. Results of this test is discussed in section 3.

For the second test scenario, the cutting parameters were selected based on Response Surface Method (RSM). RSM is a statistical technique used to model and analyse the relationship between a set of input variables (factors) and the output response of a process. RSM can be used to optimize the cutting parameters in milling by creating a mathematical model of the process. The model is created by conducting a series of experiments in which the cutting parameters are varied (table 2), and the results are measured. The experimental data were used to fit the mathematical model to the process. The model can then be used to predict the results with different process parameters and find the optimal value for SEC. These techniques help locate the optimal region within the response surface where the milling process can achieve the desired performance.

A total of 31 tests were performed with varying cutting parameters. For each test, a material length of 150 mm was machined in the same direction in a linear tool path with the cutting parameters defined in Table 2. The tests were conducted in a random order to reduce the risk of systematic errors in the results due to tool wear, and the energy consumption of each test was recorded.

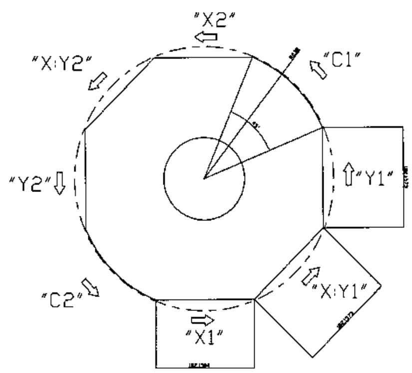

Fig. 1. Tool path

Table 2. Cutting parameters

Run	Vc m/min	a_e mm	a_p mm	a_z mm	F mm/min	N RPM
1	135	8.000	1.250	0.135	1161	2150
2	165	8.000	1.250	0.135	1419	2627
3	135	16.000	1.250	0.135	1161	2150
4	165	16.000	1.250	0.135	1419	2627
5	135	8.000	1.750	0.135	1161	2150
6	165	8.000	1.750	0.135	1419	2627
7	135	16.000	1.750	0.135	1161	2150
8	165	16.000	1.750	0.135	1419	2627
9	135	8.000	1.250	0.165	1419	2150
10	165	8.000	1.250	0.165	1734	2627
11	135	16.000	1.250	0.165	1419	2150
12	165	16.000	1.250	0.165	1734	2627
13	135	8.000	1.750	0.165	1419	2150
14	165	8.000	1.750	0.165	1734	2627
15	135	16.000	1.750	0.165	1419	2150
16	165	16.000	1.750	0.165	1734	2627
17	150	12.000	1.500	0.15	1433	2389
18	150	12.000	1.500	0.15	1433	2389
19	150	12.000	1.500	0.15	1433	2389
20	150	12.000	1.500	0.15	1433	2389
21	120	12.000	1.500	0.15	1146	1911
22	180	12.000	1.500	0.15	1720	2866
23	150	4.000	1.500	0.15	1433	2389
24	150	20.000	1.500	0.15	1433	2389
25	150	12.000	1.000	0.15	1433	2389
26	150	12.000	2.000	0.15	1433	2389
27	150	12.000	1.500	0.12	1146	2389
28	150	12.000	1.500	0.18	1720	2389
29	150	12.000	1.500	0.15	1433	2389
30	150	12.000	1.500	0.15	1433	2389
31	150	10.000	2.000	0.15	1433	2389

Where Vc is the cutting velocity, a_e the radial engagement, a_p the axial engagement, a_z the feed per tooth, F the feed speed and N the spindle speed.

3. Analysis and Results

The first analysis focused on the characterization of the machine power consumption in different states, as already defined by other authors, such as Mori et al. [18], which is crucial for understanding the contribution of time-dependent systems (such as refrigeration or numerical control) and MRR-dependent systems, such as the spindle. This clustering is functional in defining a model to predict, and sometimes optimize, the power consumption of the machining operation. In addition, the optimization will use different strategies for the two clusters; for time-dependent systems, the strategy will be to reduce the operation time, while for the MRR-dependent system, a more complex optimization will be required, considering the optimal parameters based not only on the reduction of energy consumption but also its effects on tool wear. Auxiliary consumption is presented in Table 3.

From the data acquired it is possible to create a figure similar to the one initially proposed by Dahmus and Gutowsky [5], reported in Fig. 2, it can be seen that only 24.4% of the total energy is used in the machining process and about 75% of the energy goes to the auxiliary components. Out of which a massive 27.4% energy is consumed by chip conveyer.

Table 3. Energy consumption contribution

Systems	Power (Watts)	Energy Consumed in 1 hr. (kWh)	Contribution	Cycle time
Base Consumption	2011.43	2.011	14.9%	continuous
Refrigeration	2819.43	2.819	20.9%	continuous
Chip Conveyer	3694.37	3.694	27.4%	continuous
Tool Changer	191.96	0.0111	1.4%	1 change every 10 minutes
Oil Mist	320.78	0.320	2.4%	continuous
Coolant	1158.21	1.158 ↑	8.6%	Variable
MR Process	3287.00	3.287 ↑	24.4%	Variable

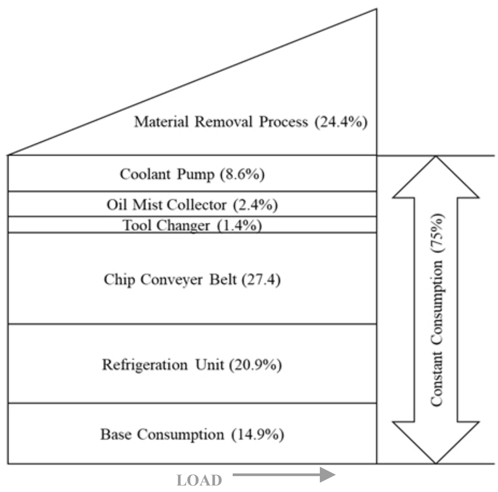

Fig. 2. Energy used as a function of material removal rate for a 5 axis CNC milling machine.

The result of this analysis is consistent with the findings of Gutowski et al. where auxiliary equipment systems such as lubricant and chip recovery systems may require more energy than the machining operation [19]. These results can be used to identify energy hungry components and a possible strategy for optimization. Such optimization scenarios are given in the subsection 4 of this paper.

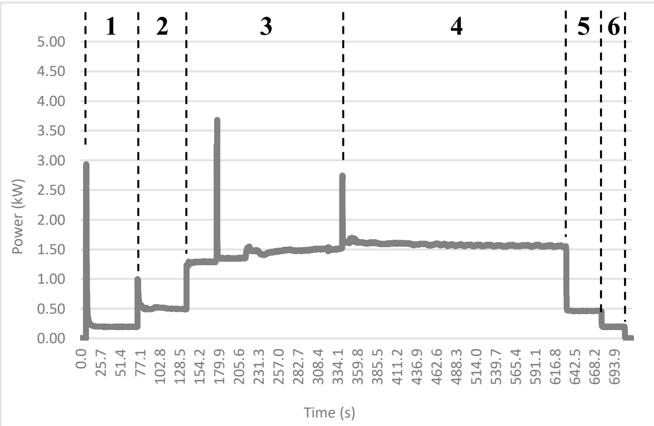

Fig. 3. Power vs Time plot for powering up the milling machine.

The tests for the power consumption of the machine in different states have been carried out in accordance with ISO 14955-2 [19] and ISO 14955-3 [20]. ISO 14955 offers a standardized approach on measuring methods in order to produce reproducible data regarding the energy supplied to a machine tool under specified conditions. The power profile graph in accordance with aforementioned ISO standard is given in Fig. 3. Different state changes are denoted by a number where 1 – Turn on main power supply, 2 – Turn on PLC, 3 – Machine warmup / pre-lubrication, 4 – Machine ready / idling state, 5 – Emergency Stop and 6 – Main power supply turn off.

Table 4 reports the values of the mean power consumption in different states and switching from one state to another. In the case of a state change, the time required for the operation was also recorded. For a state change, the energy required can be calculated as a product of the mean power and time required for the state change.

Table 4. Shutdown vs standby trade-off

Event	Cycle Time	Mean Power	Energy Consumption
STATE: Standby		1.734 kW	
STATE: Shutdown		0 kW	
CHANGE: Power-up from Standby	35 sec	1.988 kW	0.01932 kWh
CHANGE: Power-up from Shutdown	360 sec	4.413 kW	0.4413 kWh

It is important to note that the state change from shutdown to power up requires 360 s and has an energy consumption of 0.4413 kWh, while reaching the power-up state from stand-by required far less energy and a shorter time, but this higher reactiveness of the machine is counterbalanced by a constant consumption in stand-by of 1.734 kW. This means that using the standby method is convenient only when a short period of inactivity is expected. Given these data, a smart scheduling system can be employed that keeps track of the necessary down time and selects the machine status based on that. For example, if there is no work planned for the machine for a long time, it is more economical to shut down the machine, as it consumes no energy compared to a constant standby.

Another important aspect of energy consumption is energy used individually by the axis of the milling machine. Different machines can have different axis symmetry in terms of power consumption due to their positioning, weight and resulting inertia during movements [15]. In this experiment, it can be seen from the Table 5 that there is no significant difference between power consumptions of axis movements in X, Y, -X and -Y directions. The cutting operation was performed in each direction for a length of 150mm. For each operation, the cutting conditions were preselected, and the energy consumption was recorded separately.

Table 5. Power consumed per axis.

Test No.	Unit	P-idle	P (X)	P(-X)	P (Y)	P(-Y)	X Avg	Y Avg	Diff
1	kW	3.06	3.94	3.96	3.97	3.98	3.95	3.98	-0.6%
2	kW	3.06	3.75	3.75	3.79	3.78	3.75	3.78	-0.9%
3	kW	3.06	4.48	4.86	4.52	4.89	4.67	4.71	-0.8%
4	kW	3.06	4.43	4.45	4.51	4.49	4.44	4.50	-1.2%
5	kW	3.06	4.46	4.43	4.51	4.44	4.45	4.47	-0.6%

Where, P-idle is the power in idle state (kW), P (X)&(-X) is the power during ± X axis movement (kW) and similarly P (Y)&(-Y), X-Avg& Y-Avg is the avg power of axis movement (kW), Diff is the difference between X and Y axis.

Finally, the energy consumption data was analysed using RSM. After performing the tests from Table 2, Machining Removal Rate (MRR) and Total Specific Energy Consumption (T-SEC) [21] was calculated by using the following formulas (2,3).

$$MRR = \frac{(A_e \cdot A_p \cdot V_f)}{60} \quad (2)$$

$$T - SEC = \frac{Mean\ Power_{with\ idle\ power} \cdot 60}{MRR} \quad (3)$$

Where, MRR is in mm^3/s, a_e is the radial engagement (mm), a_p is the axial engagement (mm), v_f is the feed (mm/min), T-SEC the total specific energy Consumption (kJ/mm^3), Mean Power is the measured power consumption without machine base power (kJ/s). The results of these calculations are given in Table 6.

The focus research in state-of-the-art pertaining to milling process planning has increasingly shifted towards the optimization of process parameters. Substantial evidence has indicated that the manipulation of cutting parameters, such as cutting speed, feed rate, and depth of cut, can result in significant improvement or degradation in milling performance [13]. This analysis shows how the process parameters affect the efficiency of the cutting process and the overall efficiency of the machine. From the graphs in Fig. 4, it can be seen that SEC is inversely proportional to MRR. The higher the MRR, the lower the SEC. However, even though the graphs point towards maximising the machining removal rate to reach the maximum efficiency, the machining process is constrained by factors such as tool wear, temperature control, and surface finish. In this case, the maximum efficiency is a subset of important variables, and the cutting parameters are selected in the optimum zone while maintaining the necessary constraints. This approach can lead to significant improvements in cost efficiency, tool life utilization, and energy consumption during the machining process.

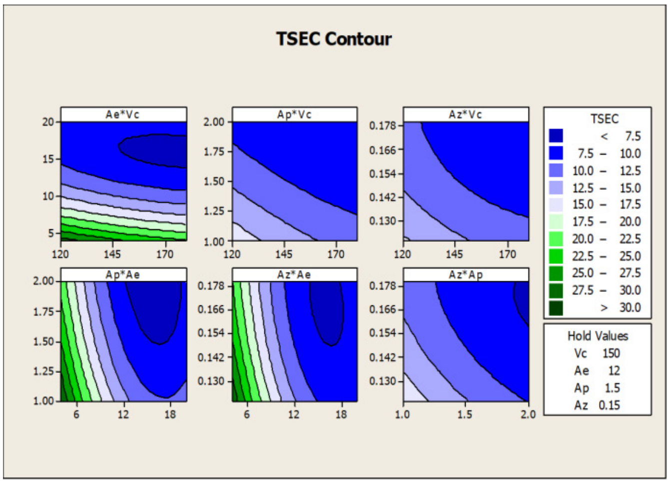

Fig. 4. Total specific energy consumption RSM contour graph

Table 6. MRR and SEC results

Test No.	Mean Power w/o idle kJ/s	Mean Power with idle kJ/s	MRR mm^3/s	T-SEC kJ/mm^3
1	2.024	4.036	193.471	1.252
2	2.160	4.172	236.465	1.059
3	2.412	4.424	386.943	0.686
4	2.616	4.628	472.930	0.587
5	2.510	4.522	270.860	1.002
6	2.918	4.929	331.051	0.893
7	2.869	4.881	541.720	0.541
8	3.419	5.431	662.102	0.492
9	2.081	4.093	236.465	1.039
10	2.256	4.268	289.013	0.886
11	2.538	4.549	472.930	0.577
12	2.818	4.830	578.025	0.501
13	2.672	4.684	331.051	0.849
14	3.080	5.091	404.618	0.755
15	3.135	5.146	662.102	0.466
16	3.790	5.802	809.236	0.430
17	2.409	4.421	429.936	0.617
18	2.448	4.460	429.936	0.622
19	2.467	4.479	429.936	0.625
20	2.441	4.453	429.936	0.621
21	2.253	4.264	343.949	0.744
22	2.673	4.685	515.924	0.545
23	1.934	3.946	143.312	1.652
24	2.957	4.968	716.561	0.416
25	2.139	4.151	286.624	0.869
26	2.200	4.212	573.248	0.441
27	2.336	4.348	343.949	0.758
28	2.681	4.692	515.924	0.546
29	2.225	4.237	429.936	0.591
30	2.225	4.237	429.936	0.591
31	2.442	4.454	477.667	0.559

4. Subsystem Optimization Scenario

This study also considers the optimization of subsystems as a part of a holistic approach to improve a machine's performance. As shown in the contribution graph in Fig. 2, the chip conveyor consumes 27% of the total energy and is in constant operation during a machining cycle. It is common practice to start the system with the machining cycle and keep it running until the part is removed or when the machine is in standby. This leads to a significant energy loss.

In most cases, the production rate of the chip is not high enough to motivate the continuous use of the chip conveyor, and an analysis of a scenario where a partial use of the chip conveyor is suggested has been carried out. This requires the introduction of a duty cycle in the activation of the chip conveyor, which can be implemented both during the writing of the GCODE or by introducing an external system that can control the chip conveyor based on process parameters. For example, a possible control logic could define the duty cycle based on MRR because a higher MRR condition will result in higher chip production and a higher risk of clogging if the chip conveyor is turned off. To compare the energy savings when applying this strategy, Table 5 reports the results of one hour of operation with different duty cycles. The reported values include only the chip conveyor consumption and no other energy sink, such as spindle or axis movement; hence, they are not related to tool wear.

Table 7. Suggested duty cycle for chip conveyor.

Title	Operation type	Duty Cycle	Energy Consumed by chip conveyor	Energy saving respect to original
Original	Roughing	100%	3.69 kWh	
Suggested	Roughing	70%	2.58 kWh	30.08%
	Roughing	55%	2.02 kWh	45.26%
Original	Finishing	100%	3.69 kWh	
Suggested	Finishing	20%	0.74 kWh	79.95%
	Finishing	10%	0.37 kWh	89.97%

It is important to note that the decision to make such changes to the duty cycle is based on chip volume, cutting parameters, and chip conveyor capacity. For example, if the chips are small and fragmented, the duty cycle can be significantly reduced because it is easier to extract smaller chip sizes. When it comes to finishing, running the chip conveyor at a 100% duty cycle is significantly wasted. As the chips are very fragmented and in small quantities, the chip conveyor can run at a reduced capacity as low as 10 to 20% with a reduction in power consumption for this auxiliary system by 90% and 80%, respectively. This will be a small advantage in the total energy balance, but will be easy to implement, and its effect will be enhanced by the usually high number of working hours of a machine tool.

5. Conclusion

The proposed methodology to experimentally characterize the energy consumption of 5 axis milling machine highlights some crucial aspects of the energy consumption drivers. The first important result is the importance of auxiliary systems for the overall power consumption. This means that the development of smart strategies for their utilisation could lead to a significant reduction in machine energy consumption. An example is the partial use of the chip conveyor that, for a specific machine that has complex chip removal equipment, could lead to a saving of more than 3 kW of power during normal operation of the machine, especially when finishing operations that generate low chip volume are employed. This analysis suggests that an investment to develop an automatic system to introduce a duty cycle on the activation of some auxiliaries could lead to an advantage for a manufacturing company. The analysis of the power consumption in the idle state and the time to restart the machine also shows the possibility of introducing energy-aware scheduling solutions. Although the experimental test for axis energy consumption symmetry did not show any significant difference in energy consumption between the two axes, it is important to note that this factor is machine-dependent which means that this experiment is still important when characterising a new machine.

The results also highlight that the RSM optimisation technique can be used to optimise the cutting parameters. To reduce the energy consumption of machining, the MRR must be maximised by choosing the highest possible values for the engagement depth, cutting speed, and feed rate which are feasible for the milling machine.

To further improve the analysis and implement a holistic approach, it is important to include the consumption of other resources, such as tooling and compressed air, and their effects on machine performance in terms of quality and process efficiency. In particular, for process parameter optimisation, it is necessary to determine a trade-off between tool wear and MRR.

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