MM Science Journal | www.mmscience.eu
ISSN 1803-1269 (Print) | ISSN 1805-0476 (On-line)
Special Issue | HSM 2025
18th International Conference on High Speed Machining
October 15-16, 2025, Metz, France
DOI: 10.17973/MMSJ.2025_11_2025129

HSM2025-44834

DATA ANALYSIS FOR ENERGY-EFFICIENCY IN TURNING AND MADS AGENT SYSTEM SOLUTION

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Abstract

In an era where industries are increasingly prioritizing sustainability and efficiency, optimizing manufacturing processes is mandatory. Among these processes, lathe operations are widely used in industry and consume significant amount of energy. This research investigates the monitoring of a turning process, focusing on real-time data analysis with the final aim of achieving a more sustainable and energy efficient machining process. Using an integrated agent framework for monitoring of machining outputs, the machining parameters such as spindle speed, feed rate and depth of cut are optimized. A Multi-Agent Distributed System (MADS) is created and implemented for real-time data acquisition, filtering, storage and visualisation. Comprehensive analysis of energy consumption data during cutting intervals led to the identification of energy distribution patterns and inefficiencies. Additionally, insights into the progression of tool wear made it possible to identify consumption, specific to the cutting operations, in order to define predictive maintenance strategies and thereby reducing operational downtime. The results are contextualised with KPIs that provide information on process optimisation, including recommendations on energy saving parameters and cost reduction opportunities, thereby enhancing decision-making in machining operations.

Keywords:

Sustainable machining, Monitoring, Energy Efficiency, Turning, Predictive Maintenance, Industry 4.0.

1 INTRODUCTION

Manufacturing plays a major role in industrial CO_2 emissions and global energy consumption.. Recent studies [Duflou 2012 et al.] emphasise that the sector accounts for around 84% of industrial CO_2 emissions and over 50% of global energy use, highlighting the need for adopting sustainable practices. Improving energy efficiency in machining, especially in turning processes, which are widely used and energy intensive, is crucial for lowering manufacturing costs and increasing sustainability. Despite the potential of Industry 4.0, a 2020 global survey showed that 52% of manufacturers lack the expertise and culture to implement these technologies, and only 28% have done so successfully [Liu 2022 et al.]. Accessible, modular solutions like MADS can therefore support a smoother transition toward digital and data-driven manufacturing.

This study reveals that a significant part of energy consumption in turning operations derives not from the cutting phases, but from non-cutting phases such as tool repositioning, spindle acceleration, and idle periods. The data collected from the industrial case study analysed in this work show that cutting energy corresponds only to the 21.9% of the total energy consumption, highlighting the potential to optimize the remaining 78.1%.

Moreover, although it is possible to lower the power demand by lowering spindle speed and feed rate, it has been observed that the total energy consumption may increase due to longer machining times, suggesting the necessity for selection of dynamic process parameters. These results highlight the requirement for smart, real-time control of machining settings to balance power demand, production, and tool health.

The present study proposes the implementation of a Multi-Agent Distributed System (MADS), as a real-time monitoring system for industrial applications suitable for turning operations monitoring. MADS enables real-time monitoring, adaptive parameter control and facilitates data acquisition, filtering, storage, and visualization, thus guiding operators toward easier decision-making and leading to improved energy efficiency and predictive maintenance capabilities.

As adapted for turning processes, MADS is easy to set up and offers accessible information, making it well-suited for integration within production line monitoring systems in manufacturing industries.

Experimental measurements conducted under varying cutting conditions have shown that robust predictive models for total machine energy consumption can be developed [Li 2011 et al.]. Recent studies on machinability in turning processes [Ni 2023 et al.] confirm that cutting parameters, especially feed rate and depth of cut, significantly influence cutting force, temperature, and energy usage, reinforcing the importance of real-time parameter optimization. Furthermore, to create cutting power-based energy consumption models, it is necessary to precisely differentiate idle and cutting power [Shi 2020 et al.]. These models, by dynamically considering parameters such as spindle speed and cutting power contributions, demonstrate that flexible and accurate energy models lead to superior results in modern machining analysis [Shi 2020 et al.]. Easy access to a large amount of information, increases process accuracy and energy efficiency [Xu 2018 et al.].

A data-driven approach is essential for improving the accuracy of energy analysis. In particular, it allows for the separation of cutting energy from auxiliary consumption, supporting more targeted process optimizations. This methodology aligns with advanced studies in sustainable manufacturing research [Shokravi 2022 et al.] [Ragai 2022 et al.], which highlight detailed mapping of energy consumptions for customised optimisation solutions.

Additionally, by correlating energy consumption patterns with tool wear progression, this study identifies opportunities for predictive maintenance, increasingly enabled by the use of machine learning and Artificial Intelligence (AI) technologies. The relationship between wear and energy consumption can be used to create models useful for implementing real-time tool wear monitoring, proactive maintenance planning and fulfulling the objectives of reducing the incidence of unplanned downtime and maximizing tool life [Wang 2022 et al.] [Pérez 2019 et al.]. This link has been supported by different studies in which cutting energy distribution was successfully used to predict wear volume and tool degradation over time [Zhang 2016 et al.].

In addition, to improve energy performance, the system supports predictive maintenance by detecting early signs of tool wear and inefficiencies. MADS provides a modular, scalable, and flexible solution that aligns with the goals of intelligent manufacturing and supports the transition towards Industry 4.0.

Advanced sensor technologies enable the real-time monitoring and control that is required to optimize energy consumption and ensure operational reliability over time [Ibrahim 2024 et al.]. These technologies enhance energy efficiency not only at the machine level but also throughout whole industrial networks and supply chains by supporting a multi-scale systems approach [Duflou 2012 et al.].

This research presents optimization strategies derived from a real industrial case study, using key performance indicators (KPIs) to enable real-time energy monitoring and provide a practical, scalable solution. Overall, this work represents an important step toward creating manufacturing systems that are not only more energy-efficient but also more responsive and adaptive to real-time conditions.

2 ANALYTICAL MODELLING

In this section, the basic relations used during this study to calculate the energy on the turning process are presented, focusing on the interaction between cutting parameters and their effect on power demand and energy usage.

2.1 Power Consumption during cutting

The instantaneous power required for material removal P_c (W), that is a function of time, is determined by the interaction of cutting force F_c (N), which acts in the direction of cutting, and the cutting speed V_c (m/min) [Ni 2023 et al.]. This relationship is given by Eq. (1):

$$P_c = \frac{F_c \cdot V_c}{60} \tag{1}$$

Increments in cutting force or cutting velocity directly affect the power consumption. Power demand in cutting is also related to the material removal rate MRR (mm³/min) and is expressed, in cylindrical turning, as proportional to the product of the depth of cut a_p (mm), the feed f (mm) and the cutting speed Vc (m/min) [Groover 2013]:

$$MRR = a_p \cdot f \cdot 1000 \cdot Vc \tag{2}$$

Increasing any of these parameters results in a higher MRR, leading to an improvement in productivity but also an increase in the energy required for cutting. For an optimized Vc (constant), spindle speed S (rpm) changes according to cutting diameter (Di), Eq. (3):

$$S = \frac{1000 \cdot V_c}{\pi \cdot D_i} \tag{3}$$

2.2 Consumed Energy

The total energy consumed during a machining cycle, $E(t)$ (J), includes both productive (cutting) and non-productive (auxiliary) phases. It is obtained by integrating the instantaneous power P (W) over the entire process time t, as shown in Eq. (4):

$$E(t) = \int_0^t P(x)\, dx \tag{4}$$

This integral represents the cumulative energy drawn by the machine throughout the process time t, including during tool engagement, idle states, and transitions.

In order to identify the energy used only for material removal, the cutting energy $E_c(t)$ is defined as the integral of cutting power P_c over the cutting period, when the tool is in contact with the workpiece:

$$E_c(t) = \int_{tcut_0}^{tcut} P_c(x)\, dx \tag{5}$$

Here, $tcut_0$ and $tcut$ mark the start and end of the cutting phase. Finally, the net cutting energy $E_{net}(t)$ is introduced. The objective of Eq. (6) is to isolate the energy used exclusively for chip formation. To do so, it subtracts the auxiliary power baseline P_{aux} (used for systems like coolant pumps, spindle rotation during idle, tool movements and control electronics) during the cutting period from the cutting power P_c:

$$E_{net}(t) = \int_{tcut_0}^{tcut} [P_c(t) - P_{aux}(t)](x)\, dx \tag{6}$$

This net energy value reflects only the energy directly contributing to chip formation, making it a more accurate indicator to support sustainability and efficiency evaluations.

2.3 Cutting Force Estimation

Cutting force F_c (N) can be calculated using the experimental cutting power, using Eq. (7):

$$F_c = \frac{P_c \cdot 60}{V_c} \quad (7)$$

2.4 Specific Cutting Force Estimation

To evaluate mechanical efficiency, the specific cutting force K_c (N/mm²) is defined as the ratio between cutting force F_c and area of cut (depth of cut times feed f):

$$K_c = \frac{F_c}{(a_p \cdot f)} \quad (8)$$

This parameter indicates the force which is required per unit area of material being cut. The interdependence between cutting parameters, force and energy reveals the complexity of turning processes: interdependent and critical for designing efficient, cost-effective, and sustainable machining strategies. These models collectively enable predictive analysis of tool behaviour and machining performance.

3 EXPERIMENTS SETUP AND METHODOLOGY

An industrial case is used as a motivation for this study. The results of these experiments will guide the development of energy optimization strategies for turning processes, by identifying opportunities to reduce energy consumption while maintaining machining performance. The fundings will be the inputs for the implemention of the monitoring external system supported in this research.

3.1 Experimental Set-up

Turning operations were carried out on a Huron AX MSY 300 lathe. The tool used was an 80° diamond shape double-sided, negative-style turning insert, with a chip breaker designed for medium machining of steels, and with a coated carbide for wear resistance. The insert was mounted on a left-hand turning toolholder with a 20x20 mm shank, with a 95° approach angle. Low alloy steel forged industrial raw parts have been machined.

3.2 Methodology

During machining, the machine-tool was monitored and the following parameters were recorded: active power, programmed position and actual encoder position (X and Z) and Z axis-load. The subsequent machining tests were carried out on nine parts:

- Energy consumption using the original program ($Vc = 320\, m/min$ is constant), at 50% and 100% feed to verify that, as the work load reduced, the energy is reduced;
- Power demand when machining at different spindle speeds, as well as when the spindle was operated at these speeds without material removal, to verify a_p and f influence on the consumptions;
- Analysis of the power consumption evolution with progressive tool wear;
- Reconduction of the Initial program monitoring with worn tool.

4 ENERGY ANALYSIS ON TURNING PROCESS

In this section, a power and energy analysis was conducted using the machine-tool data. The evaluation focuses on distinguishing the energy used for actual material removal from that consumed during auxiliary machine movements or idle states when machining at 100% feed.

By isolating the cutting intervals, analysing energy distribution, and comparing power usage with and without active machining, the impact of process parameters on overall energy demand is better understood.

4.1 Cutting intervals identification

The identification of the cutting intervals has been a crucial step in our analyses. The power curve shown in Fig. 1, is representing the power consumptions recorded while machining one workpiece using the optimized program in the industry (previous studies were developed to find the optimal cutting speed that increases productivity and reduces the tool wear).

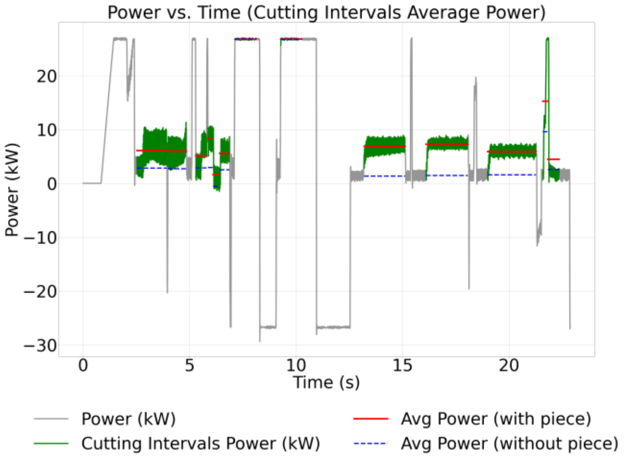

Fig. 1: Identification of cutting intervals and relative average power consumption during machining

The portions of the curves coloured in green correspond the cutting intervals, they were identified using the program code. To estimate the power consumed only by the material removal, the value of average power consumed by auxiliary sources was subtracted from the overall average value of each cutting interval sondidered.

4.2 Energy distribution

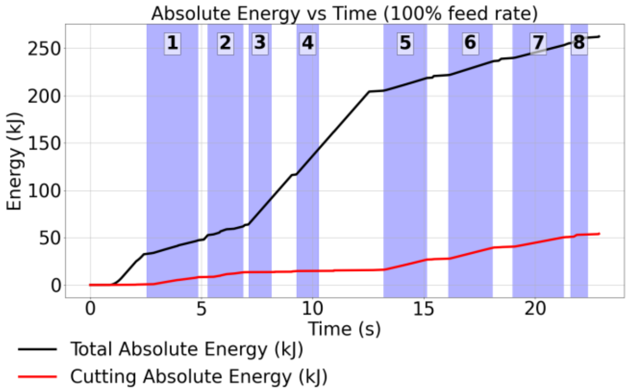

Fig. 2: Energy consumption along the machining

Based on the power measured (Fig. 1), the consumed energy during the machining program is calculated by integrating the power consumed along the machining time and the blue bands identify the different cutting stages (the eight cutting phases in the program). The black curve on Fig. 2 takes into consideration all the sources of energy consumptions.

In this industrial case, the total energy consumed by the process is 262 kJ. The red curve considers only the power during the cutting stages, thus, it includes the cutting power and the other consumptions during cutting, and it sums up to 55 kJ, which is 20.9% of the total energy. This shows that there is a high portion of energy which could be optimised and monitored.

4.3 Power consumption comparison: load and no-load machining

Power consumption presented in Fig. 1 is compared with the power consumption using the same program but when the tool is charged on the skank but is not engaging in cutting (air cutting). The energy consumed on the total machining time in air cutting is 215 kJ. One can claim that as only a small part of the energy (20%) is spent for cutting, and that the two important sources of energy in air cutting are: spindle speed (based on the optimized cutting speed) and the energy used for fast movement and tool exchange.

5 EXPERIMENT RESULTS DISCUSSION

The main outcomes of the experimental investigation are discussed in this section, focusing on how feed rate, spindle speed, and tool wear influence power consumption and energy usage.

5.1 Reduction of the feed rate

The impact of varying feed rates on power and energy consumption was evaluated by comparing machining at 50% and 100% feed rates, as presented in Table 1.

Results prove that even if the average power is smaller when machining at 50% feed rate, the total energy is higher since machining time is increased. More energy is spent to remove material and more energy is lost due to inefficiency.

Tab. 1: Comparison between 50% and 100% feed rate machining processes parameters.

Parameters	100% Feed	50% Feed	Comparison
Average Power (kW)	5	3	-20%
Cutting Energy (kJ)	46	49	+6%
Non-Cutting Energy (kJ)	216	281	+23%
Average Feed rate Force (N)	1469	1058	-39%

Tab. 2: Fc and Kc in both cases (regular and 50%).

Cutting phases	**Ap**(mm)	**fz** (mm/rev)	**Fc** (N)	**Kc** (N/mm²)
5	1.725	0.47	17304	21354
5 *	1.725	0.235	9176	22641
6	1.500	0.47	18110	25674
6 *	1.500	0.235	9780	27752
7	1.475	0.35	17782	34453
7 *	1.475	0.175	13528	52413

For Table 2, cutting force F_c and specific cutting force K_c have been calculated for cutting intervals 5, 6 and 7 of the machining programs.

Higher feed rate results in higher F_c and K_c, which can be used to estimate the efficiency of the cutting process.

5.2 Effect of spindle speed on power consumption

The program used during the experimental phase is machining the workpiece at different diameters but at constant cutting speed. Thus, the spindle must adjust its spindle speeds every time.

In order to investigate the relation between spindle speeds and power consumptions, before machining the pieces, power data have been recorded only by rotating the turning spindle at the same spindle speeds used in the machining program. The spindle speeds (rpm) used in the program were determined by applying Eq. (3) as: 1652, 1750, 1845, 2383, 2515, 3395, and 5093.

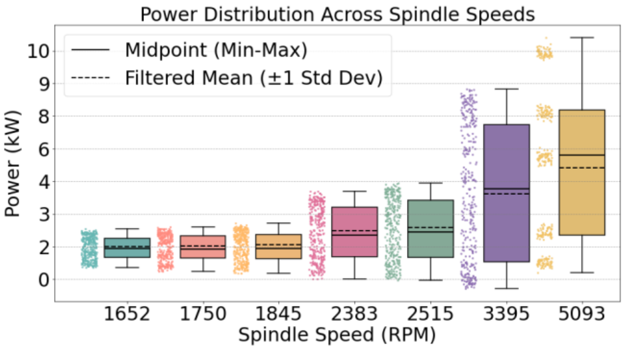

Fig. 3: Power distribution of different spindle speeds.

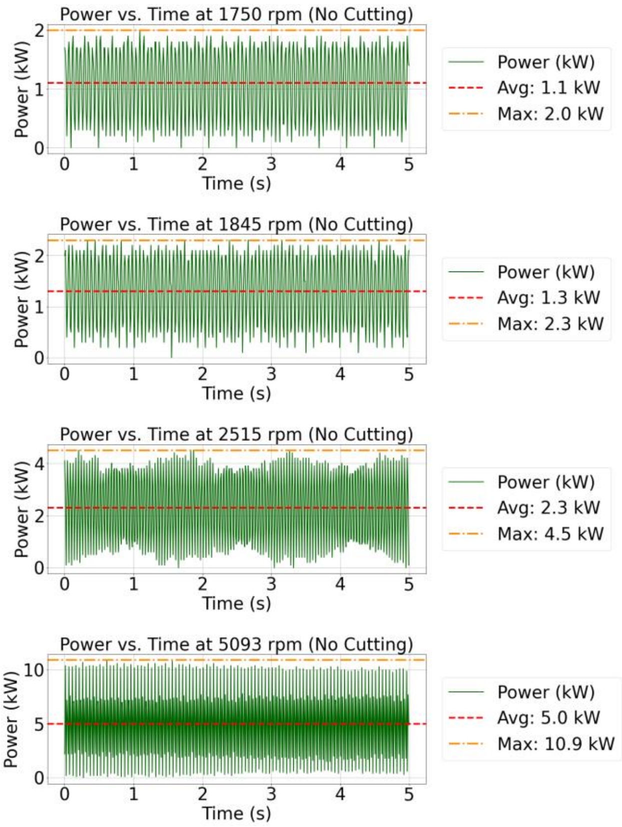

Fig. 4: Power harmonics across different spindle speeds

To simulate the same weight of the working piece during the machining operation, one piece has been placed inside the chuck, but no cutting or tool movement has been performed.

In Fig. 3 it can be noticed that the dispersion of the scattered points increases when the speed increases because of the presence of higher oscillations. As shown in Fig. 4, the power consumed is higher when we increase the spindle speeds. After comparing the power consumptions obtained by just moving the spindle, with the ones collected when machining, the effect of different f and a_p used in the program is refected in the power values.

5.3 Tool wear Analysis

During the wear test, after every machined piece, the tool has been observed with microscope. The flank wear has been measured and used to create a tool life curve.

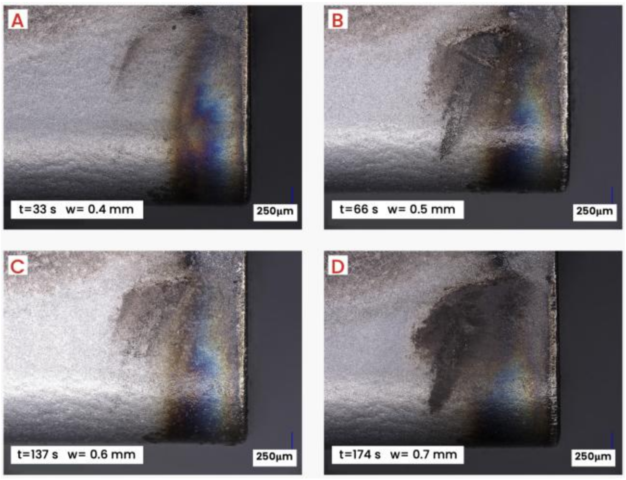

Fig. 5: Cutting tool wear images.

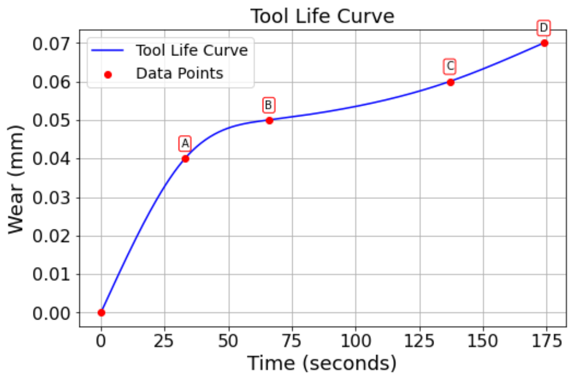

Fig. 6: Tool life curve.

Tool wear was evaluated by examining the cutting edge of the insert. Five parts were machined, with material removal gradually increased on the later parts to accelerate tool wear. During the wear test, after every machined piece, flank wear measurements were carried out using a Keyence VHX microscope, the results are shown in Fig. 5.

The corresponding tool life curve, shown in Fig. 6, displays an initial phase of rapid wear growth followed by the beginning of a steady wear phase. As expected, the curve has an initial phase of quick growth and a beginning of steady phase. To create a more complete curve that includes also a severe wear stage, additional passes should be performed.

The last workpiece was machined using the industrial program with a worn tool. Although total energy consumption showed no significant increase compared to machining with a new tool, power fluctuations were much lower. This indicates that the worn tool has partially lost its ability to engage aggressively with the material.

6 MONITORING EXTERNAL SENSORS SYSTEM

The results discussed above, were necessary to lay the foundations of what will be the parameters to be monitored with the MADS system. MADS (Multi-Agent Distributed System for Monitoring and Control of Industrial Processes) [Bosetti 2024].

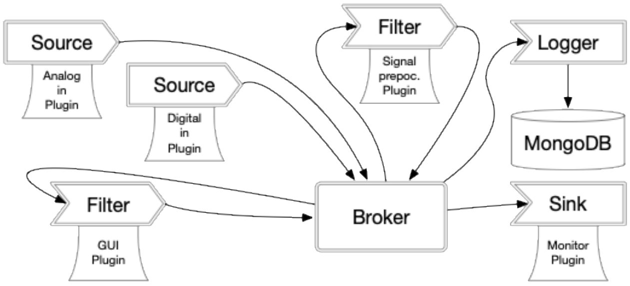

Fig. 7: MADS system structure.

Mads is an open-source system of TCP-networked agents implementable as monolithic processes (single specific task), or as plugins (source, filter or sink). Its structure is presented in Fig. 7. Sources are executables that grab data from the field and publish them to the broker; Filters are programs that receive data from other sources, process them, and publish the results to the broker; and Sinks are executables that receive data from the broker and process them locally. An agent called *logger* saves incoming data to a MongoDB database.

6.1 MADS setup

Experimental MADS monitoring setup as been developed in the laboratory and is suggested as a monitoring system solution. This setup is used to collect data on real-time external sensors and substitute the ones from the machine.

Fig. 8: MADS setup and components.

In Fig. 8, numbered elements (1–9) correspond to the described system components:

1. Broker PC: Managing agent communication and system control;
2. Raspberry Pi 4: Edge node for real-time signal and local data storage;
3. Raspberry Pi Monitor: Live signal visualization;
4. Arduino with Sensors: Gathers data and communicates with Raspberry Pi via serial;
5. Machine Electrical Cabinet: Houses the sensors;
6. Power Distribution Box: Supplies power to Arduino, Raspberry Pi, and peripherals;
7. Portable Socket Strip: A flexible power source;
8. Ethernet Cable: Enables low-latency communication;
9. Tool Trolley: Organises the full system setup.

For this research, accelerometers and SCT-013 current sensors were installed, but other types of sensors could be considered depending on the parameters to be monitored.

6.2 Deployment of KPIs and Data Dashboard

A significant advantage of MADS system is that the recorded signals can be continuously plotted in real-time using Python libraries, offering immediate insight into current oscillations, peaks in power, or anomalous behaviours, issuing alerts if predefined limits are exceeded.

For industrial applications, data dashboards (operator panels, quality control terminals, or factory dashboards) could display real-time or historical production data, aiming to improve decision-making.

To support this objective, relevant KPIs (Key Performance Indicators) can be defined to track process performances.

In this study, based on the results obtained during the experimental phase, a set of KPIs is proposed:

- Cycle Time: Time required to complete one full machining cycle for process optimisation;
- Power Thresholds: Instantaneous power monitoring;
- Energy Thresholds: Accumulated energy consumption used to support efficiency and sustainability targets;
- Spindle Load: Continuous monitoring of motor current to detect underload or overload states;
- Cutting Force: Estimated using power data to track tool engagement and indicate wear.

7 CONCLUSION

Energy distribution analysis revealed that 79.1% of energy is consumed by non-cutting operations such as tool repositioning, spindle acceleration, and idle running. This highlights opportunities for energy-optimising strategies: reduce cutting velocity (Vc) during non-cutting phases to lower spindle speeds and power consumption; increase spindle speed during cutting to match MRR and maintain productivity; increase feed rates in time-consuming cuts and reduce them during less demanding or idle phases; and smoothen acceleration/deceleration to avoid energy spikes. When tool wear is significant, lowering Vc can reduce wear effects, extend tool life, and cut energy usage.

This research highlights the need for deep data analysis to support modern machining monitoring systems. Real-time monitoring, KPI tracking, and adaptive process control enstabilish the proposed system as a powerful IIoT tool for both sustainability and productivity.

Future work includes deploying MADS directly on production lines, integrating predictive models, enhancing sensor encapsulation, embedding edge intelligence, expanding sensor types, and programming MADS agents for advanced process interaction. This would also open up the possibility of comparing the results obtained in this study with those from a mass-production turning machine. The MADS solution can be applied across a wide range of machining processes, with multi-machine compatibility, offering a versatile step forward in real-time monitoring and Industry 4.0.

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