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State-of-the-art review of energy consumption in machining operations: Challenges and trends

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ABSTRACT

Conventional machining operations such as turning, drilling, milling, grinding, etc. consume significant amounts of energy which can vary depending on many factors. Such factors include the levels of cutting parameters, the use of coolants and their types (i.e., water- or oil-based coolants, cryogenics, cold air), types of material being machined and its properties, and size and geometrical complexity, among others. Therefore, it is very important to determine effective ways to minimize energy consumption during conventional machining operations. This article provides an overview of energy consumption and improvement in energy efficiency in various conventional machining processes by an embodied energy analysis from primary and secondary consumption sources. The energy consumption in conventional machining processes can be reduced by better control of the primary and secondary consumption sources and by using more efficient machining-assisting technologies and equipment, or through the continuous monitoring and control of energy usage at different stages of the machining process including that consumed in infrastructure and other less directly related factors. The article also presents challenges and future trends regarding energy consumption and control using available and emerging techniques in the manufacturing industry.

1. Introduction

According to the United Nations, the world population is projected to reach 9.8 billion by 2050, which is 2.5 times greater than it was in 1960 [1]. This could result in a global energy crisis and make energy management the most important industry to meet the needs of our civilization [2]. The primary causes of the energy crisis are overpopulation, inadequate infrastructure for power generation and the use of renewable energy sources, overconsumption or energy waste (lack of awareness to conserve energy), and a lack of proper energy storage [3,4]. The energy crisis is detrimental to political, social, and economic development [4]. Industrial power consumption accounts for 42 % of global consumption [5], while industrial manufacturing accounts for 23 % (out of 42 %) of energy consumption and plays a major role in the global economy [5]. Another report published more recently by BP (British Petroleum) on the energy outlook until 2050 shows different scenarios regarding the share of total final energy consumption in 2050, showing that the industry will be responsible for 38–40 % [6]. Moreover, the industry sector, regardless of different scenarios, will still occupy a larger proportion of energy consumption and carbon emissions worldwide, as shown in Fig. 1.

Optimizing the different energy resources and their consumption could partially resolve the energy crisis [7]. As a result, many studies in the open literature have looked into ways to reduce energy consumption in various manufacturing processes such as additive manufacturing [8], machining [9–11], casting [12,13], metal forming [14], and welding [15]. In addition, the electrical consumption of machine tools accounts for 75 % of electricity consumed during manufacturing [2]. Energy consumption in a machining system occurs at different stages (machine tool levels, machining operational characteristics, and machine tool component breakdown), resulting in significant changes in

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manufacturing costs [16,17]. Filippi and Ippolito were the first to point out the significance of energy efficiency using machine tools [18]. Their work aimed to perform various operations with ten different numerically controlled machine tools, resulting in higher energy requirements for a machine tool than the calculated theoretical energy. Automatic machine tools reduced machining time by 60 % [19]. Table 1 summarizes energy consumption at various stages in a machining process. Some studies have reported that higher material removal rates can improve energy consumption efficiency but at the expense of reduced surface quality [20–22]. The work material properties determine the energy consumption of the machining process [23]. Furthermore, the geometrical surface complexity and machining process can have an impact on energy consumption [24]. The complexity of the surface geometry and the required machining processes influence energy consumption which also requires using experienced operators [24,25]. Higher precision machine tools can create complex geometries geometric structures, but also increase the overall energy consumption [25].

Alloys with higher hardness and density such as Titanium alloys consume more specific cutting energy than steel, copper, aluminum, and magnesium alloys as shown in Table 2. Increased hardness due to ceramic reinforcement in metal matrix composites (MMCs) results in increased EC [34]. When compared to cutting parameters (feed rate and cutting speed), the weight percentage of reinforcement in MMCs was the most important factor in increasing EC [34]. However, the optimal setting of cutting variables can reduce the EC for different materials [35].

Table 3 displays the parameters influencing the efficiency of the machining process and EC. EC during the entire machining process is computed based on energy consumed by the spindle, feed, tool operating system, cutting environment, and fixed energy (power required to activate the machine tool components ensures readiness of operations) consumed by the system [27,36]. Detailed insights into improving energy efficiency by reducing energy losses during machining operations are discussed, with recommended solutions in the subsequent sections.

2. EC sources in machining and the efficiency of energy utilization in cutting processes

Conventional machining, a key manufacturing process, requires energy to complete the material removal process. This energy is not only consumed in overcoming the friction between the cutting tool and the workpiece but also in powering the machine tool itself as shown in Fig. 3. The role of cutting fluids, often perceived merely as lubricants, extends beyond reducing friction and tool wear. Li et al. [50] provided insights into this, indicating that although cutting fluids helps decrease friction, their overall effect on energy consumption is complex, taking into account the energy needed for their manufacturing and disposal.

From a broader systems perspective, Yi et al., 2015 [52] link various CNC machining components to energy consumption and carbon emissions, encompassing cutting tools, fluids, and electrical consumption. This holistic view is crucial in understanding the interconnected nature of machining processes. Priarone et al., 2016 [53] discussed the limited options for minimizing energy consumption, underscoring the significance of efficiently tuning cutting parameters. They emphasize that as machining operations grow in complexity, energy efficiency strategies must encompass both the reduction of direct power usage of machine tools and the inherent energy of tools and fluids. Abdelaoui et al. [54] reviewed methods for turning, milling, and drilling in the context of modeling and optimizing machining operations. They highlighted the importance of selecting optimal operating conditions, including control parameters and machining environment, to achieve energy efficiency and sustainability. Their comprehensive analysis of 166 scientific studies addresses multiple energy efficiency challenges and presents recently developed EC models for machining processes. The dynamic nature of EC in machining processes is highlighted by Li et al. [27], which noted the fluctuations in energy usage corresponding to different machine tool operations. This variability, stemming from intermittent activation of machine components, is further elaborated by Zhou et al. [2]. In this regard, they proposed two analytical frameworks for energy analysis: machine tool components and machining states (Fig. 4). Chen X et al. [51] argue for the predominance of the latter, demonstrating its effectiveness in revealing energy consumption patterns and aiding in the development of consumption models.

Zhang et al. [55] performed experiments on the high-speed dry milling process to examine specific cutting energy and surface roughness (SR), offering valuable insights into the achievable range of specific cutting energy across different materials. This research contributes to the understanding of energy efficiency in high-speed machining processes. Their findings underscore the importance of tool coating and material selection in reducing energy consumption, thereby enhancing the overall efficiency of the machining process. The machining states framework, as explored in previous studies [2,17] offers an insightful exploration of energy consumption patterns, making it adaptable for optimization strategies. This approach not only explains the mechanisms of energy consumption but also highlights potential trends for enhancing energy efficiency. In this regard, Chen et al. [51] provided a

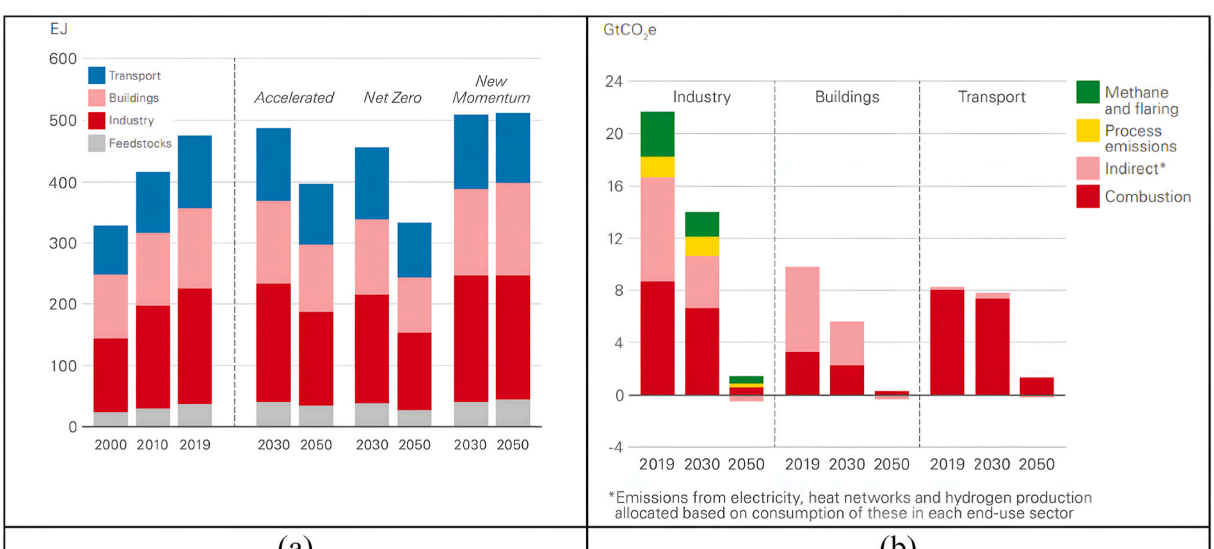

Fig. 1. BP2023 outlook on energy consumption scenarios showing (a) Final energy demand by sector and (b) total carbon emissions by sector in Net Zero [6].

Table 1
Summary of energy consumption (EC) at various stages in a machining process.

EC at different machine tool levels [26]		
Machine tool EC	Spindle EC	Process-level EC
The practical relevance of understanding the relationship between EC parameters and cutting conditions is essential for improving the overall efficiency of machine tools [27]. 1. Control systems, 2. Cooling and lubricating system 3. Drive unit, 4. Spindle motor, 5. Manufacturing process	The EC by spindle motor for the movement of the cutting tool during machining, is of industrial relevance. Spindle alone consumes >15 % of total energy [28] Spindle energy varies with different machine tools, and analyzing the spindle motor efficiency is of industrial relevance.	At the process level 1. The energy consumed is measured regarding material removal (calculated based on process variables) and is entirely independent of machine tools [29–31]. 2. Machine tools' process variables must balance energy consumption and surface integrity [32]
Energy consumption for a machining process is measured in terms of specific energy, defined as the energy consumed to remove the unit volume of the material using Eq. (1) [17] $$\textit{Specific energy} = \frac{\textit{Energy consumed}\ (\mathrm{E})}{\textit{Volume of material removal}\ (\mathrm{V})} = \frac{\textit{Power}\ (\mathrm{P})}{\textit{Material}\ \text{Removal Rate}\ (\mathrm{MRR})}\ \left(\frac{W.\mathrm{min}}{mm^3}\ or\ \frac{J}{mm^3}\right). \quad (1)$$		
Specific EC by the machine tool is computed based on Eq. (2) [17] $$\textit{Specific energy for machine tool} = \frac{\textit{EC by machine tool}\ (E_M)}{V} = \frac{\textit{Cutting Power by machine tool}\ (P_M)}{MRR} \quad (2)$$	Specific EC by the spindle is computed based on Eq. (3) [17] $$\textit{Specific energy for spindle} = \frac{\textit{EC by spindle}\ (E_S)}{V} = \frac{\textit{Cutting Power by machine tool}\ (P_S)}{MRR} \quad (3)$$	Specific EC by the net cutting energy is computed based on Eq. (4) [17] $$\textit{Specific energy for net cutting}\ \text{energy} = \frac{\textit{EC by net}\ \text{cutting}\ (E_{nc})}{V} = \frac{\textit{Net Cutting Power}\ (P_{nc})}{MRR} = \frac{P_s - \textit{Air Cutting Power}\ (P_{ac})}{MRR} \quad (4)$$
EC during machining operational characteristics involves three states [33]: **Basic State**: The energy consumed to prepare machine elements or components to operate the machine tool. Example: starting the machine, air-cutting, and machine power off. **Ready State:** The transition state is activated between basic and cutting states. Example: total energy consumed for power drives, spindle movement for tool changing, setting process parameters, and movement of tool and workpiece to desired position. **Cutting State:** Electrical energy consumed to remove material from the cutting tool. Example: energy consumed during material removal by the tooltip and coolant supply. **Energy consumption when the machine tool components break down involves two types [16]:** **Constant energy (independent of machining)**: When the machine starts processing, the computer fans, pumps, servo, spindle drives, and unloaded motors require energy. **Variable energy (dependent on machining)**: energy consumption due to machining action. Note that modern machine tools such as grinding, turning, and milling machines possess major components such as servo drives, hydraulic systems, cooling and lubrication systems, control systems, and auxiliary systems [17,19] as shown in Fig. 2. It was reported that cooling, lubrication, and hydraulics consume comparatively higher energy [27].		

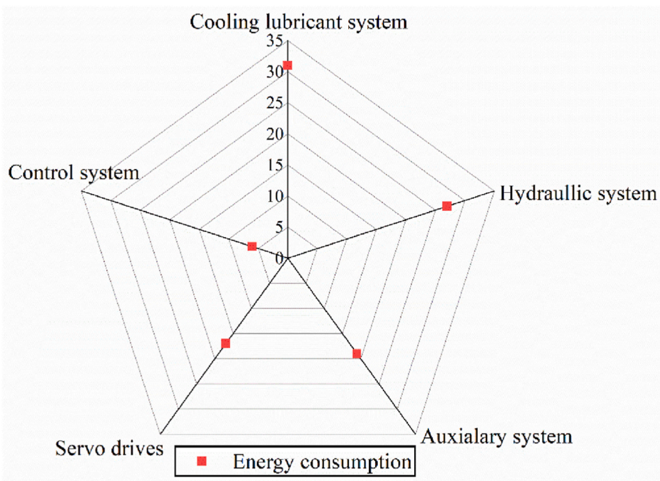

Fig. 2. EC due to break down in percentage [17].

Table 2
Specific cutting horsepower of selected engineering materials [23].

Workpiece material	Specific horsepower (hp/in.^{3}/min)
70-30 Brass	0.59
AISI 1020 steel	0.58
AISI 1112 steel	0.5
Al6061-T4 alloy	0.35
Al2024-T4 alloy	0.46
Copper	0.78
Magnesium	0.17
Type 304 stainless steel	1.1–1.9
Titanium	1.9

detailed breakdown of the machining process into distinct states, each with its unique energy profile, thereby underlining the importance of parameter selection in each state as shown in Fig. 5.

Zaidi et al. [56] analyzed the effects of machining settings on burr formation, SR, and EC, when milling aluminum alloy Al6061-T6 statistically. Their findings revealed how machining parameters affect energy usage in aluminum milling, providing complete insights into energy efficiency. The study demonstrates complex machining parameters and energy efficiency relationships, suggesting that careful optimization of these parameters can lead to significant energy savings. For instance, startup energy ($E_{startup}$), though brief, is significant due to the energy intensity of producing cutting tools and fluids [48]. emphasize the sensitivity of the entire process to optimizations in this regard. To achieve comprehensive energy efficiency in machining operations, it is imperative to consider both direct consumption and the intrinsic energy demands of tools and fluids. Ullah et al. [57] looked into the eco-indicators of cutting tools, categorizing them based on tool material, process, and geometry, and further highlighted the subcategories of each characteristic as shown in Fig. 6. They advocate for the manufacturing of an “ideal cutting tool” that balances these eco-indicators.

Furthermore, Chen et al. [58] noted that the embodied energy of the tool ($E_{tool\text{-}embodied}$) is linked to its operational lifespan, which in turn is influenced by cutting parameters and tool performance. The selection of appropriate parameters and materials can significantly reduce this embodied energy. Similarly, Wang et al. [59] discuss the embodied energy of fluids ($E_{fluid\text{-}embodied}$), constrained by production specifics. An effective energy-efficiency strategy should extend beyond operational parameters to include the intrinsic energy values of tools and fluids, optimizing their use for cumulative energy savings. In conclusion, the quest for energy efficiency in machining processes is multifaceted, involving a careful balance of cutting parameters, tool and fluid selection, and an understanding of the inherent energy consumption patterns.

Table 3
Summary of parameters affecting machining efficiency and energy consumption.

Process	Major parameters	Minor parameters
Turning [37,38]	Cutting parameter	Cutting speed, feed rate, depth of cut, coolant type, and flow characteristics
	Cutting tool	Tool geometry, cutting tool material, type of coating material, and its properties
	Workpiece material	Material, properties, and part geometry
	Cutting environment	Hot, dry, wet, flood coolant, and cryogenic
Total Energy Consumption for turning can be calculated using the following Eq. (5) [39] $EC_{total} = EC_{spindle} + EC_{feed} + m \times EC_{tool} + n \times EC_{cool} + EC_{fix}$ (5) EC_{total} = Total energy consumption $EC_{spindle}$ = EC of spindle EC_{speed} = EC by cutting speed EC_{tool} = EC by tool change system EC_{fix} = EC by fixed energy consumed m varies between 0 and 1; 0 indicates no need for tool change and 1 depicts the need for tool change n varies between 0 and 1; 0 signifies no coolant.		
Milling	Surface machining complexity [24]	Cutter: Type, material, geometry Workpiece: Size, material, geometry Equipment: Type, structure, fixture, etc. Process parameters: Tool path selection, schedule, and cutting variables
	Cutting tool [40]	Diameter, tooth, angle (helix, rake, edge, inclination, and back), nose radius
	Cutting parameter [25,40]	Cutting width, cutting depth (radial and axial), feed per tooth, and spindle speed
	Cooling methods [41]	Wet, dry, cooling control system
	Workpiece material	Material, properties, and part geometry
Total EC for milling can be calculated using the following Eq. (6) [36] $EC_{total} = EC_{spindle} + EC_{feed} + EC_{tool} + EC_{cool} + EC_{fix}$ (6)		
Drilling	Cutting parameter [42–44]	Hole depth, axial feed, cutting speed, drill material, drill geometry (flute angle and length, point angle, diameter, land width, core diameter, rake angle, gashing angle)
	Cooling methods [45]	Wet, coolant type, dry, cooling control system (flow rate, pressure, nozzle diameter, and so on.)
	Workpiece material	Material, properties, and part geometry
Total EC for drilling can be calculated using the following Eq. (7) [46]. $EC_{total} = F_Z \times d + T_Z \times \frac{2 \times n \times \prod}{60} \frac{d}{v} = Nm$……(7) n is spindle speed in rpm; F_Z is drilling force in N; T_Z is drilling torque in N; v is the feed rate in m/s; d is drilling depth in m.		
Grinding	Workpiece material	Material, properties, and part geometry
	Cutting environment [47]	Cooling medium (gas, liquids, antiadhesives, and lubricant in solid-state), delivery mode of cooling (nozzles: flood, shoe, spot, spray, centrifugal), and control system
	Cutting variables [48]	Spindle speed, effective pack density, depth of cut, and the cutting space of abrasive grits, abrasive material
	Grinding wheel [47]	Wheel material, grinding wheel geometry (width), dresser type, dressing depth and speed, and spark-out time
Total EC for grinding can be calculated using the following Eq. (8) [49]. $EC_{total} = EC_{bl} + EC_{Spindle} + EC_{Cool} = \frac{P_{bl}}{Q_w} + \frac{P_{spindle}}{Q_w} + \frac{P_{cool}}{Q_w} = \left[\frac{W \cdot s}{mm^3}\right]$ (8) EC_{bl} = EC of a base load of machine tool P_{bl}, $P_{spindle,}$ and P_{cool} = Power values of base load, spindle, and coolant Q_w be the material removal rate		

Recent studies have shed light on various aspects of this complex interplay, offering new insights and models for optimizing energy consumption. As machining technologies evolve, so must strategies for energy efficiency, ensuring that these critical manufacturing processes are sustainable and environmentally responsible.

3. Improvement of energy efficiency for different aspects of machining processes

Table 4 provides an in-depth analysis of various methods for

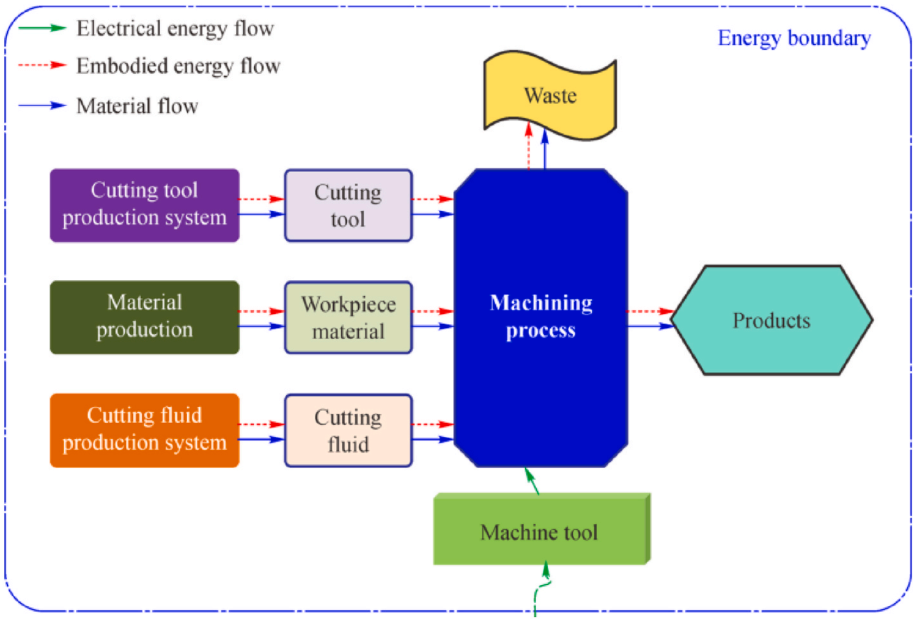

Fig. 3. Power threshold for the manufacturing procedure [48,51].

improving energy consumption efficiency in machining through cutting parameter optimization, tool characteristics, and artificial intelligence (AI) techniques. It covers various materials and machining processes, emphasizing the significant role of parameters like cutting speed, feed rate, and depth of cut. Higher speeds and feed rates increase energy usage, while tailored parameter selection substantially reduces consumption. The impact of tool geometry, material, and coating is also highlighted, showing how optimal tool choices can minimize energy consumption. Additionally, the summary discusses using AI algorithms to analyze experimental data, enabling precise determination of the most efficient cutting conditions, and demonstrating a synergistic approach combining experimental insights with AI for sustainable manufacturing practices. As a result, a detailed analysis was conducted, with a focus on cutting parameters, cutting environment, cutting tool characteristics, vibration, plasma, laser and induction-assisted machining, coating methods, and AI methods used.

3.1. Improvement of energy efficiency in machining with cutting parameters

Table 4 shown earlier also provides details of energy efficiency improvements in machining processes. There are various materials, including metallic alloys (steel, titanium, and aluminum), and composites which require different machining processes like drilling, milling, and turning. The impact of cutting parameters such as depth of cut, feed rate, nose radius, tool geometry, and cutting speed on energy consumption was analyzed. Notably, higher cutting speeds and feed rates tend to increase energy usage, while optimal parameter selection can significantly reduce energy consumption. The research also explores the use of different cutting environments and tools, highlighting the importance of choosing appropriate parameters for specific materials and machining processes to enhance energy efficiency. Li et al. [109] showed that selecting the appropriate cutting parameters during process planning can reduce energy consumption in machining by 6–40 %. In the external turning of Al7075 aluminum alloy, Bhushan et al. [68] optimized turning parameters using response surface methodology, cutting EC by 13.55 %. Chen et al. [48] focused on milling operations, incorporating the embodied EC of materials to reduce specific EC by 19.59 % in a specific case. Furthermore, optimizations in grinding, drilling, and threading parameters led to reduced EC in their respective operations, as shown by Refs. [110,111] for grinding [112], for drilling, and [113] for threading. CNC machine tool energy accounts for 99 % of manufacturing's environmental impacts, according to Zhong et al. [114]. Li et al. [50] describe the complexity of modeling carbon emissions from this energy use, linked to factors like cutting parameters and tools. Newman et al. [60] and Zhong et al. [114] suggest that optimizing cutting parameters could reduce emissions by 6–40 %. Zhou et al. [115] found that using worn cutting tools can increase carbon emissions -which are related to increases in energy consumption-by 44 %, with significant variations in cutting parameters based on tool wear. Hence, optimizing cutting parameters is crucial for reducing emissions in manufacturing. Newman et al. [60] conducted a system-level investigation, identifying various factors such as cutting tools, parameters, environment, methods, and mechanisms that affect energy efficiency in machining. Pervaiz et al. [23] emphasized strategies to minimize energy consumption, focusing on energy modeling for machine tools, operational strategies for energy reduction, techniques to lower non-processing energy, optimizing operation speed, time-of-use strategies, and overall energy consumption reduction. These methods aim to enhance sustainability and efficiency in manufacturing.

Changes in cutting parameters such as FR, CS, and DOC lead to optimizing EC in machining processes is an ever-evolving field. A synergy exists among these parameters, and by fine-tuning them, one can drastically enhance energy efficiency [17]. A crucial component of machining operations is the feed rate. This term describes the cutting tool's movement relative to the workpiece surface, significantly impacting various factors such as the energy needed, and the friction produced during machining. Most remarkably, it is the main factor influencing the forces that the workpiece and tool are subjected to during machining [67]. Camposeco-Negrete's research provides a thorough understanding of the complexities of cutting parameters and their effect on energy and power consumption [116]. The focus on fine-tuning these parameters, specifically when transitioning the objective from reducing the cutting power/energy to minimizing the surface roughness, brought forth interesting variances. Their findings indicated that the FR accounts for 87.79 % in terms of lowering EC in machining. An intriguing proposition presented is the potential to reduce energy significantly by adopting a higher feed rate [71]. However, it is not just about increasing the feed rate indiscriminately [117]. further emphasizes the significant role that feed rate play. By refining

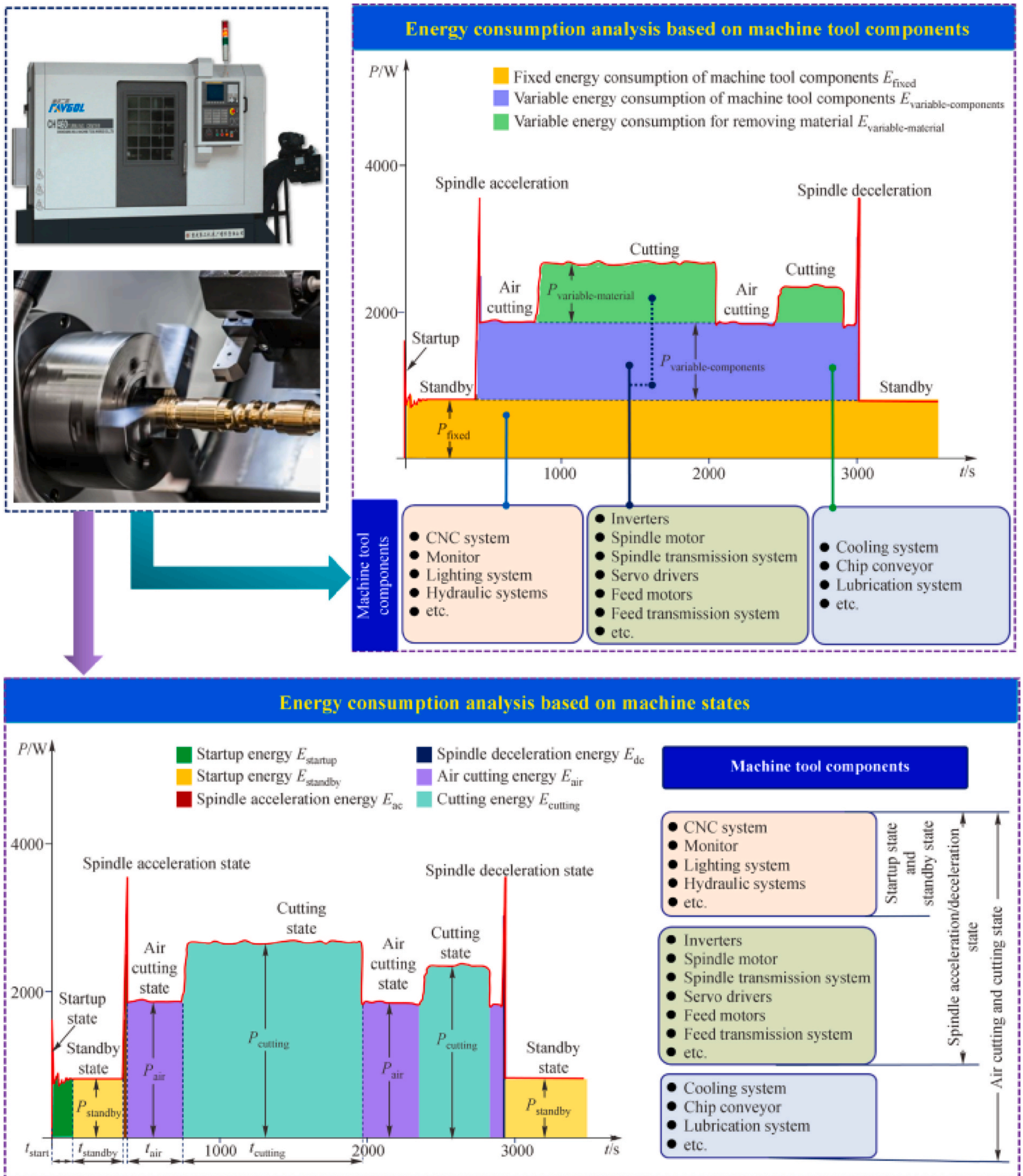

Fig. 4. Examining the energy attributes of a manufacturing procedure [51].

the cutting parameters during the dry turning of AISI 1045 steel, the results showed that the feed rate was the primary factor responsible for power consumption. They presented a distinct perspective, recommending a reduced feed rate to minimize energy consumption, and suggesting a detailed understanding of the machining process. Integrating GRA with Principal Component Analysis (PCA) provides a novel method for identifying the optimal cutting parameter setup, which can reduce power consumption by 6.59 %. A comparable study [118] concentrated on the rough turning of EN 353 alloy steel as shown in Fig. 7. Their research underscored the significant impact of the feed rate, noting that it constitutes 56.7 % of the overall energy usage in machining processes, with cutting speed being the next major factor at 31.83 %. They observed that the DOC, and nose radius contributing 6.78 %, and 1.36 % respectively, had a relatively minor influence compared to the FR and CS. To provide a more visual representation, Fig. 7 highlights the relationship between spindle speed, feed rate, and the resultant active power consumption when no cutting occurs. It is evident that both cutting parameters directly influence the active power it utilizes. The feed rate's crucial role in determining energy consumption during machining processes is not to be underestimated.

The literature emphasizes its profound impact on energy consumption and the different strategies that can be utilized for maximal energy consumption reduction [68]. Similarly, the CS, which defines the relative velocity between the workpiece and the cutting tool, provides a

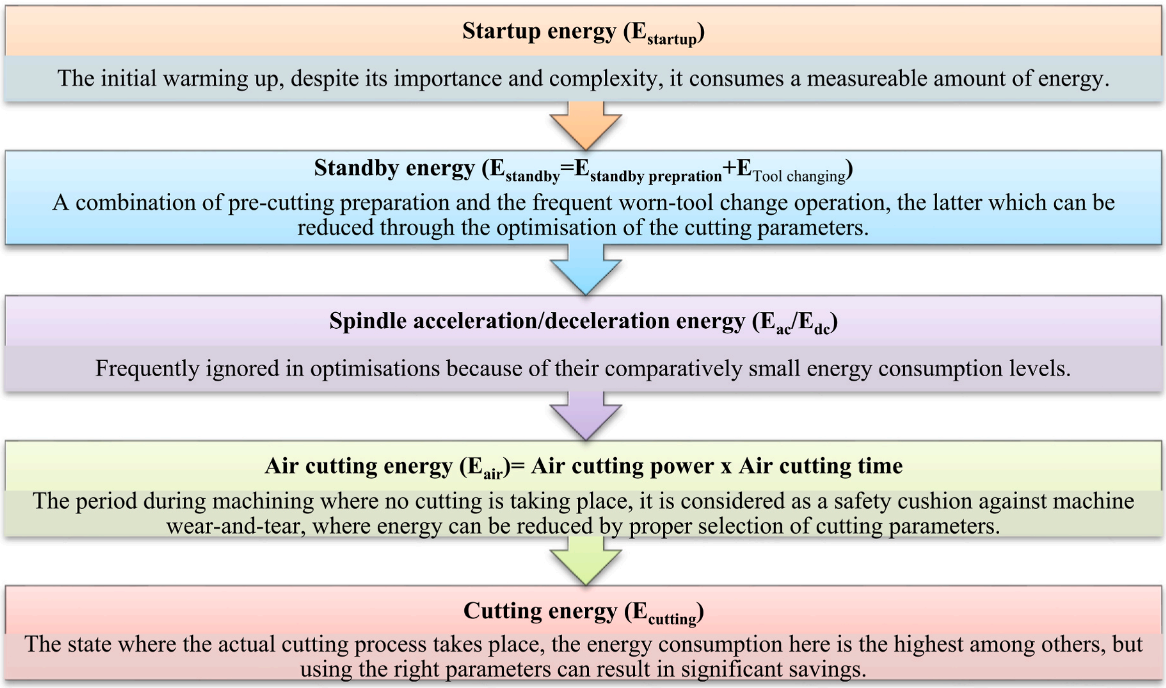

Fig. 5. The machining process states according to their electrical energy consumption characteristics [51].

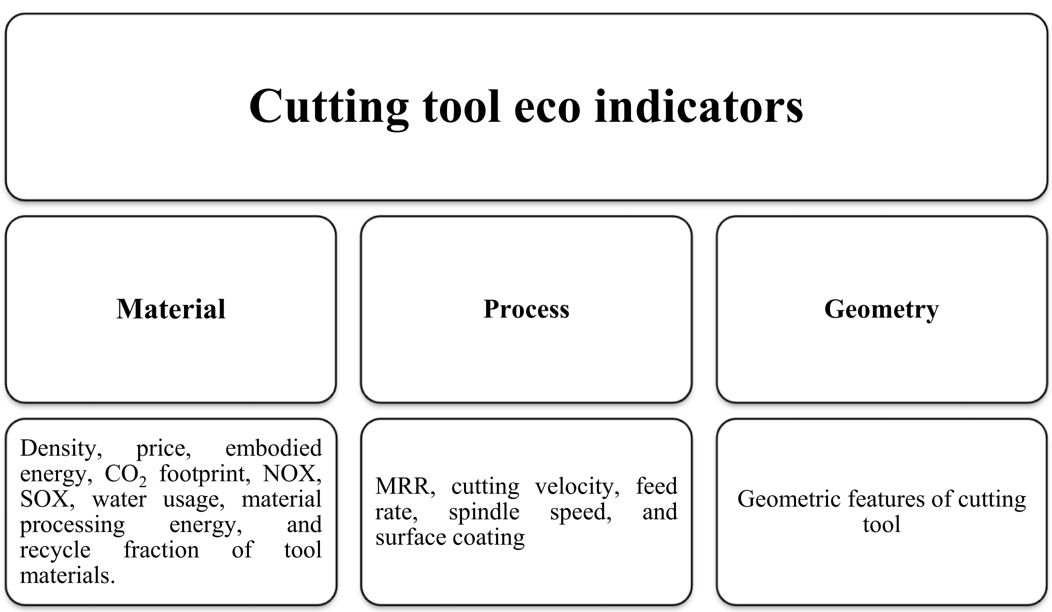

Fig. 6. Cutting tool eco indicators by [57].

detailed insight. The crucial role it plays in shaping energy consumption during machining processes cannot be ignored. Bhattacharya et al. [64] studied EC during high-speed machining of AISI 1045 steel. Their findings revealed that an overwhelming 77.4 % of the energy used was due to the cutting speed, with the depth of cut contributing to 13.2 % of the energy usage. They found that the feed rate had little impact on power usage, indicating that it should be set at the most optimal and economical level. The significance of this finding increases when one realizes that the trials were conducted in dry-cutting settings. Fig. 8 illustrates the primary influence on machine power usage, clearly indicating a proportional increase in power consumption with higher cutting speeds.

Camposeco-Negrete et al. [116] reported that while increasing the cutting speed would result in higher material removal rates, it isn't necessarily energy-efficient. Increasing the cutting speed from zero to the desired rate demands additional energy, as the study demonstrates. A compelling visualization in Fig. 9a highlights the need to minimize cutting speed to optimally conserve energy, yet this is not a universally accepted notion. As illustrated in Fig. 9b from Ref. [119], there's an upward trajectory of operational power as cutting speed increases, suggesting a roughly linear relation.

Determining the correlation between cutting speed and energy consumption is a challenging task. There is a need for a comprehensive approach that recognizes that, while increasing cutting speed may

Table 4
Summary of results of energy savings applied to different machining processes under different conditions.

Workpiece Material	Machining process	Cutting tool	Cutting parameters	Cutting Environment	Method applied	Energy saving	Remarks	Ref
AA 6042	Milling	HSS	DOC: 3–12 mm; FR: 625–2500 mm/min; NoC: 1–4;	Dry	Heavy cutting	Changing process plan results in more energy savings	↑in DOC from 3 to 12 mm resulting in ↑ energy per volume removed material from 1.78 to 2.04 kg/cm3	[60]
Steel-16Mn	Milling	NR	DOC: 0.1–0.3 mm; WOC: 10–50 mm; FR: 400–800 mm/min; SS: 400–1200 rpm	Dry	Light cut, Taguchi-RSM, GA	Optimized parameters resulted in reduced energy consumption from 1.47 to 1.07 kW h	↓ of 32.07 % of energy consumption with optimized parameter conditions and processing time was reduced to 34.11 %	[61]
AISI 304 stainless steel	Turn-Mill	NR	DOC: 0.5a2 mm; FR: 0.15–0.45 mm/r; CS: 325–375 m/min	Coolant power: 700–1840 W	Taguchi-RSM	Optimized turn-mill parameters resulted in reduced energy consumption than conventional turning and milling methods alone.	Setting optimal cutting conditions reduces EC.	[62]
AISI P-20 tool steel	Turning	TiN-coated tungsten carbide	DOC: 0.2–0.5 mm; FR: 0.1–0.14 mm/rev; CS: 120–200 m/min; NR: 0.4–1.2 mm	Dry, wet, and Cryogenic	Taguchi-RSM	↑ in CS, FR, DOC, and up to middle values of NR resulting in higher power consumption	A cryogenic environment results in lower power consumption than dry and wet. NR has a negligible effect on power consumption	[63]
AISI 1045	Turning	Coated carbide	DOC: 1–2 mm; FR: 0.045–0.16 mm/rev; CS: 58–240 m/min	Dry	Taguchi	↑ in CS, and DOC resulting in higher power consumption	FR has a negligible effect on power consumption	[64]
EN-31 steel	Turning	tungsten carbide	DOC: 0.2–0.6 mm; FR: 0.06–0.15 mm/rev; CS: 39–189 m/min; NR: 0.4–1.2 mm	Dry	RSM	↑ in CS, FR, NR, and DOC resulting in higher power consumption	FR followed by DOC, NR, and CS influences the power relative to their importance	[65]
AlMg3	Milling	HSS	DOC: 0.5–1.5 mm; FR: 0.08–0.16 mm/tooth; CS:100.48–200.96 m/min;	Coolant: LUBRIMAX oil, SAROL 474 EP emulsion	Taguchi	↑ in CS, FR, and DOC resulting in higher power consumption. ↑ in flowrate of cutting fluid decreases the power consumption	DOC followed by CS, FR, and cutting fluid flow rate influences the power consumption	[66]
PEEK-CF30 composite	Turning	TiN coated	DOC: 0.25–1.5 mm; FR: 0.05–0.2 mm/rev; CS:100–300 m/min;	Dry	Taguchi-GRA	↑ in CS, FR, and DOC resulting in higher power consumption	CS, FR, and DOC were kept at 100 m/min, 0.05 mm/rev, and 0.25 mm resulting in lower surface roughness and power consumption	[67]
Al 7075-SiC composite	Turning	Tungsten carbide	DOC: 0.2–0.6 mm; FR: 0.15–0.25 mm/rev; CS: 90–210 m/min; NR: 0.4–1.2 mm	Dry	RSM-CCD	Applying the design of experiments resulted in ↓ power consumption by 13.55 % and ↑ tool life by 22.12 %.	CS is the dominant factor followed by DOC, FR, and NR for power consumption.	[68]
AISI 1050 carbon steel	Milling	Tungsten carbide	ADOC: 6–10 mm; RDOC: 0.8–1.2 mm; FR: 0.07–0.13 mm/tooth; CS: 60–100 m/min	Dry	RSM-CCD	Applying the design of experiments resulted in ↓ of power consumption	ADOC is the most significant factor followed by FR, RDOC, and CS.	[25]
AISI P-20 tool steel	Turning	TiN-coated tungsten carbide	DOC: 0.2–0.5 mm; FR: 0.1–0.14 mm/rev; CS: 120–200 m/min; NR: 0.4–1.2 mm	Cutting environment: dry, wet and Cryogenic	Taguchi	Applying the Taguchi-Fuzzy method resulted in ↓ power consumption, surface roughness, coefficient of friction, and ↑ tool life.	Cutting environment followed by DOC, FR, CS, and NR are the most dominating factors. Cryogenic coolant is favorable for all outcomes	[69]
Al 6063	Turning	Carbide	DOC: 0.4–1.2 mm; FR: 0.1–0.3 mm/rev; SS: 1250–1750 rpm;	NR	Taguchi	All factors set at minimum value tend to reduce the power consumption	↑ in CS by 50 % and decreases in tool life by 80 %. ↑ In FR by 50 % decreases tool life by 60 %.	[70]
Al 6061 T6	Turning	Carbide	DOC: 1–3 mm; FR: 0.1–0.3 mm/rev; CS: 150–250 m/min;	NR	Taguchi	↑ in CS, FR, and DOC resulting in higher power consumption	DOC is the most dominating factor followed by FR and CS.	[71]
Stainless steel	Milling	NR	FR: 15–75 mm/tooth; SS: 4000–20000 rpm	Coolant pump power: 26.5 W	OFAT-GA	Optimized machining conditions resulting in reduced energy consumption and processing time by 3.3 kJ, and 66 s.	GA determined optimal FR and SS with reduced cutting force.	[72]
AISI H13 tool steel	Milling	(Ti, Al)N/TiN coated carbide	ADOC: 1 mm; RDOC: 0.3–0.5 mm; FR: 0.05–0.2 mm/tooth; CS: 100–300 m/min	Dry	OFAT	Specific energy decreases with increasing process variables (excluding CS).	Down milling uses 8.5 % less energy compared to up milling. Finishing operations consume less energy consumption	[72]

(*continued on next page*)

Table 4 (*continued*)

Workpiece Material	Machining process	Cutting tool	Cutting parameters	Cutting Environment	Method applied	Energy saving	Remarks	Ref
AISI 4340	Turning	Tungsten carbide	WH: 31–38; FR: 0.07–0.17 mm/rev; CS: 28–89 m/min; WOC: 2–4 mm	Dry	FFD	The fuzzy rule method optimizes multiple outputs	To reduce energy consumption the FR must be increased. Compared to FR, CS and WOC have less influence.	[73]
AISI 1045 steel	Turning	Coated carbide	FR: 0.05–0.2 mm/rev; CS: 50–200 m/min; DOC: 0.5–2 mm	Dry	Taguchi	Power consumption of basic, auxiliary, and air-cutting motions relies on machine tools. EC is low at lower MRR.	Power consumption is independent of the machine tools	[74]
	Milling		WOC: 6–12 mm; DOC: 0.5–2 mm; FR: 0.03–0.12 mm/tooth; CS: 60–120 m/min			Increasing cutting parameters saves energy consumption.	Power consumption varies with different machine tools.	
AISI 1060 stee	Turning	Tungsten carbide	FR: 0.08–0.2 mm/rev; CS: 90 m/min; DOC: 0.5–2 mm; NR: 0.8–1.2 mm	Dry	OFAT	Simultaneous ↑ in DOC and FR ↓ cutting energy. Negative rake angle ↑ cutting energy	NR and cutting-edge angles are negligible for energy consumption	[75]
Cast iron alloy	Milling	TiAlN coated tool	FR: 1 mm/tooth; SS: 3000 rpm; CS: 593.76 mm/min; RDOC: 2 mm; ADOC: 1 mm;	Dry	OFAT	Energy consumption is reliant both on machining parameters, and tool path	EC can be reduced by decreasing the cutting time	[76]
AISI 1045	Turning	Al2O3/(W, Ti) C ceramic tool	FR: 0.1–0.3 mm/rev; CS: 80–140 m/min; DOC: 0.2 mm	Dry	OFAT-FEM	Cutting energy during cutting action is higher when the tool wear is higher.	FR of 0.2–0.25 mm/rev, CS: 110–125 m/min resulted in low energy consumption, better tool life, and reduced surface roughness	[77]
Al 6061-T6 alloy	Turning	Carbide tool	CS: 1250–2000 m/min; UDCT: 0.1–0.4 mm	Dry	OFAT	SCE decreases with high-speed machining conditions. 47 % of energy savings were achieved by determining optimal cutting parameters	Tool wear, geometry, and cutting fluids are to be included in the near future in estimating the SEC.	[78]
Al 6061-T6 alloy	Turning	Carbide tool	CS: 250–1000 m/min; FR: 0.1–0.4 mm	Dry	FFD	27 % of energy savings were achieved by determining optimal cutting parameters	↑ in FR and CS ↓ the SEC by 15–28 %, and 6–13 %.	[79]
S45C carbon steel	Milling	tungsten carbide	FR: 0.1–0.5 mm/tooth; CS: 50–250 m/min; DOC: 0.2–2.6 mm; WOC: 20–60 mm;	Dry	Taguchi-PSO	High CS results in rapid tool wear, and shorter tool life, resulting in increased tool-change energy consumption. Direct SEC decreases with increased FR, and DOC.	Cutting velocity is the major factor. Influencing SEC. Low values of cutting velocity result in reduced SEC.	[48]
NR	Turning	NR	FR: 0.1–0.2 mm/tooth; CS: 1–3 m/s; DOC: 1–1.5 mm;	NR	NSGA-II	Higher CS, FR, and DOC save energy consumption but increase cost due to tool wear and failure.	DOC is the most dominating factor followed by CS and FR.	[80]
AISI 316 steel	Turning	Carbon boron nitride	FR: 0.1–0.2 mm/min; CS: 110–170 m/min; DOC: 0.8–1.7 mm;	Dry	RSM-BBD, DFA	Optimal conditions resulted in 13.89 % and 6.78 % in SR and PC.	DOC is the most dominating factor in power consumption	[81]
Medium carbon steel	Milling	cemented carbide	FR: 0.1–0.6 mm/tooth; CS: 50–300 m/min; DOC: 1–4 mm;	Dry	OFAT, ES	Optimal conditions for 1st, 2nd and finish pass resulting in 5.433 j/mm3, 5.433 j/mm3, and 6.138 j/mm3.	ES minimizes energy consumption and maximizes the MRR simultaneously.	[82]
C45E4 steel	Turning	NR	FR: 0.05–0.09 mm/rev; CS: 1000–2000 rpm; DOC: 0–3 mm;	Dry	Taguchi, NSGA-III	↑ in surface roughness ↓ the SEC and energy efficiency. The surface roughness, SEC, and energy efficiency by 16.72 %, 13.58 %, and 2.5 %.	NSGA-III is an efficient optimization tool that satisfies all the responses	[83]
Steel (Grade-45)	Milling	TiAIN-coated Carbide tool	FR: 120–240 mm/min; SS: 500–2100 rpm; DOC: 0.5–2 mm; WOC: 3–9 mm;	Dry	Taguchi	SEC relies on MRR and CS and has negligible influence on DOC, WOC, and FR	The CS and additional power needed during machining action increase the cutting power estimation accuracy in a milling process	[84]
EN 353 alloy steel	Turning	TiCN and Al2O3 coated tungsten carbide	FR: 0.2–0.3 mm/rev; CS: 165.79–248.69 rpm; DOC: 1–1.8 mm; NR: 0.4–1.2;	Dry	Taguchi, AHP, Entropy, TOPSIS	The AHP method offers a better solution for improved production rate and energy consumption.	Weights determined by AHP resulted in 68.23 % energy consumption, 4.46 % for surface roughness, and 27.31 % for MRR.	[85]
Al 7075	Milling	NR	FR: 500–900 mm/min; SS: 8000–12000 rpm; DOC: 1–1.8 mm; WOC: 1–3;	NR	RSM-CCD, DFA	The optimized conditions set at FR, SS, DOC, and WOC were kept fixed to 8000 rpm, 740 mm/min, 1.8 mm, and 2.7 mm resulting in EC of 4.45 kWh per blade and 48.5 min of machining time.	The optimized conditions were confirmed with experimental values with a relative error maintained equal to less than 1 %.	[86]
AISI 1045 steel	Turning	tungsten carbide	FR: 0.12–0.2 mm/rev; CS: 103.31–174.14 m/min; DOC: 0.5–1.5 mm;	Dry	Taguchi, GA	GA determined optimal conditions (DOC, CS, and FR: 0.5 mm, 119.05 m/min, and 0.12 mm/rev) equal to 0.547 kW experimentally.	All factors were significant with a major contribution by DOC, followed by CS and FR equal to 61.71 %, 16.4 %, and 12.85 % towards power consumption.	[87]

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Table 4 (*continued*)

Workpiece Material	Machining process	Cutting tool	Cutting parameters	Cutting Environment	Method applied	Energy saving	Remarks	Ref
NR	Milling	NR	FR: 300–500 mm/min; SS: 2000–4000 rpm; DOC: 0.2–0.4 mm; WOC: 4–8;	Dry	Taguchi, GRA, LDPS	Taguchi-GRA-LDPS systematic model enhances optimization capability, minimizes particle oscillation during process optimization, and achieves better energy efficiency, ensuring reduced EC.	Taguchi method for experimentation. GRA for correlating multiple outputs to a single output and determining weights. LDPS determines the optimal solution to all outputs (MRR, cutting power)	[88]
45# Steel	Turning	Cemented carbide	FR: 0.1–2 mm/rev; CS: 80–200 m/min; DOC: 0.1–3 mm;	NR	MO-ITLBO	MO-ITLBO resulted in reduced energy consumption for machining a camshaft is 9.92 % and machining an input shaft is 12.17 %.	SEC can also be further reduced considering the interaction among the design and process parameters.	[89]
AISI 1045 steel	Milling	T5K10 (titanium-tungsten cobalt group)	FR: 0.125–0.32 mm/tooth; CS: 196.3–392.6 m/min; DOC: 1 mm; SS: 500–1000 rpm;	Dry	GRA	For resource saving the optimized parametric conditions were found to be equal to FR, CS, machining length equal to 0.125 mm/tooth, 392.6 m/min, and 5 mm.	GRA resulted the optimal conditions resulting in improved efficiency and reduced machining time.	[90]
AISI 1045 steel	Turning	Uncoated carbide	FR: 0.12–0.2 mm/rev; CS: 103.31–174.14 m/min; DOC: 0.5–1.5 mm	Dry	Taguchi, GRA, TOPSIS	Optimal machining conditions such as CS: 103.31 m/min, FR: 0.12 mm/rev, and DOC: 0.5 mm resulted in reduced power consumption by 13.41 % and increased surface roughness by 48.52 % by Taguchi-TOPSIS over Taguchi-GRA.	GRA produced better surface roughness, whereas TOPSIS improved power consumption. Differences in optimal values require validation experiments to justify the effectiveness of the model developed.	[91]
Steel- C45	Turning	NR	FR: 0.1–2 mm/rev; SS: 100–1500 rpm; DOC: 0.1–5 mm	Dry	OFAT, NSGA-II	Tuned NSGA-II parameters resulting in ↓ 38.5 % with energy consumption, and ↓ 47 % with surface roughness for the optimized parameters set at FR: 1.1 mm/rev; SS: 1500 rpm; DOC: 0.5 mm	Higher FR resulting in poor machining quality	[52]
AISI 304	Turning	Carbide	FR: 0.15–0.35 mm/rev; CS: 50–900 m/min; DOC: 0.2–2.2 mm	Coolant Power: 0.125 kW	Taguchi, GRA	The optimal condition set with DOC, FR, and CS is equal to 2.2 mm, 0.15 mm/rev, and 90 m/s. The resulting optimal conditions compared with the initial condition ↓ with 66.90 % for surface roughness, ↑ an MRR of 8.82 %, and ↓ 81.46 % for energy consumption.	The GRG model produced a good R2 value equal to 97.21 % signifies the model is efficient in conducting optimization.	[92]
stainless steel 304	Milling	Wiper inserts	FR: 0.04–0.12 mm/tooth; CS: 60–160 m/min; DOC: 0.2–1 mm; NR: 0.2–0.8 mm;	Dry	BBD, GRA	Applying BBD and GRA resulted in ↓ EC, SR, and improved PF by 34.85 %, 57.65 %, and 28.83 % compared to initial parameter settings.	The eigen values and eigen vectors could help to determine weight fractions for EC, SR, and PF equal to 0.32, 0.35, and 0.33.	[93]
ASSAB Steel	Turning	Coated Carbide	F: 0.1–0.16 mm; CS: 100–170 m/min;	Dry	FFD, Graphical optimization plot	A maximum of 50–70 % of machining energy is saved compared to traditional methods.	The optimal conditions (CS: 132.42 m/min and feed are 0.12 mm) resulted in minimizing the EC, by keeping SR and machining time fixed at 0.65 μm and 6 min.	[94]
Stainless Steel 304	Turning	HSS	FR: 0.04–0.12 mm/tooth; CS: 60–160 m/min; DOC: 0.2–1 mm; NR: 0.2–0.8 mm;	C225 soluble oil	CCD, GRA, HWOA	The best conditions resulted in better performance in CS, FR, and DOC by 42.64 m/min, 0.14 mm/rev, and 0.32 mm. Low CS and DOC produce less stress on the tool, and less temperature and power.	The optimum conditions vary with the weight factor corresponding to the individual output analyzed.	[95]
graphite iron	Milling	Al2O3+Ti(C, N) + TiN coated carbide	TW: 0.1–0.3 mm; CS: 120–520 m/min; DOC: 0.2–1 mm; FR: 0.05–0.25 mm/tooth	NR	Taguchi, VPSO, PSO, and DE	The VPSO produced global optimization. Applying the ICBR method resulted in better accuracy in CP and CV up to 91.70 % and 95.65 %.	The weight fractions for cutting power resulted from CS, FR, DOC, and TW equal to 0.32, 0.12, 0.28, and 0.27.	[96]
steel bars 9XC	Turning	Coated carbide	IA: 15–35 o; CS: 100–200 m/min; DOC: 0.1–0.3 mm; FR: 0.1–0.3 mm/rev	Dry	Taguchi, ANFIS, ASA	The ANFIS-ASA resulted in reduced EC, SR, and ↑ MRR by 50.29 %, 19.77 %, and 33.16 %.	ANFIS-ASA outperformed the ANFIS-DA approach in producing better results.	[97]
Al 7075	Milling	Carbide tools	FR: 0.0005–0.0145 mm/tooth; DOC: 0.05–115 mm; CS: 10–90 m/min	Dry	CCD, TOPSIS, AENNC	AENNC-TOPSIS resulted in many solutions resulting in improved solutions to one output and compromising solutions to another.	AENNC method can be applied to other materials, tools, and outputs and offer Pareto optimal solutions to guarantee cleaner production	[98]
Ti-6Al-4V alloy	Turning	H13 Carbide tools	CS: 50–150 m/min; DOC: 1–3 mm; FR: 0.12–0.2 mm/rev	Dry	Taguchi	CS is the dominant factor affecting the SEC.	FR, DOC at high values increases productivity with reduced SEC.	[99]

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Table 4 (*continued*)

Workpiece Material	Machining process	Cutting tool	Cutting parameters	Cutting Environment	Method applied	Energy saving	Remarks	Ref
Al6061 alloy	Milling	NR	SS: 5000–15000 rpm; FR: 2–3 mm/tooth; DOC: 0.1–0.2 mm;	Dry	CS–GWO	CS–GWO methodology resulted in ↓ energy consumption by 7.89 %.	Optimization has been done with limited data.	[100]
POM-C	Turning	PCD tool	CS: 188.5–510.5 m/min; FR: 0.049–0.392 mm/rev; DOC: 1–4 mm;	NR	CCD, MOGA	MOGA reduces the SEC by up to 49 %.	There will be separate optimal conditions for different operations (finish, medium, and rough) to reduce energy consumption.	[101]
Graphite iron	Milling	Coated cutting tool	CS: 120–720 m/min; FR: 0.06–0.22 mm/tooth; DOC: 0.4–2 mm;	NR	CCD	CS showed a dominant effect both on CP and SR.	NANFIS predict the data with an accuracy of 93.1 % and 93.8 % for cutting power and SR.	[102]
grey cast iron	Turning	Coated carbide	CS: 115–229 m/min; FR: 0.05–0.43 mm/rev; DOC: 1–4 mm;	NR	Brute force optimization algorithm	The Brute force optimization algorithm reduces 12.69 % of production costs, 7.51 % of SEC, and 32.11 % of production time.	The results can be further enhanced by applying other metaheuristics algorithms.	[103]
Al 7050 alloy	Milling	PVD TiAlN coated carbide tool	CS: 1000–2000 rpm; FR: 0.03–0.06 mm/tooth; DOC: 0.3–0.7 mm; WOC: 2–6 mm	Dry	Taguchi, TLBO	TLBO determined optimal values ↓ SR, and SCE by 10.95 %, and ↑ 5.2 % compared with earlier literature [Rao et al., 2013]. The ↓ SR, cutting energy, and ↑ MRR by 23.3 %, 10 %, and 13.65 % compared with [Yan et al., 2013], and ↓ SR and SEC by 2.96 % and 7.32 % [Kant et al., 2014].	Compared with experimental values optimized parameters could help to reduce SEC and improve productivity and quality.	[40]
Ti6Al4V alloy	Turning	H13 steel	CS: 50–150 m/min; FR: 0.2–0.24 mm/rev; DOC: 1 mm;	Dry	FFD	The optimal conditions (CS: 100 m/min and FR: 0.16 mm/rev) resulted in ↑ MRR and SEC by 127 % and 16 %.	Higher cutting speed is favorable for both productivity and energy consumption.	[9]
Ti 6Al-4 V (grade 5) alloy	Turning	Carbide tool	CS: 55–105 m/min; FR: 0.15–0.45 mm/rev; DOC: 1–3 mm;	Dry	Taguchi, linear regression	The optimal cutting parameters improve the prediction accuracy by 89.1 % for SR, 58.33 % for TW, and 96.75 % for SEC.	FR showed the highest influence on SR and EC, and CS for TW.	[104]
Al 6061-T6	Milling	Carbide tool	CS: 100–350 m/min; FR: 0.1–0.18 mm/tooth; DOC: 1–2 mm; NI: 1-3	NR	Taguchi	SCE can be reduced by ↑ FR, CS, DOC, and NI.	CS contributes 55 % and 47.98 % for SCE and BW in down-milling. NI contributes 68.74 % and 35 % towards SR and BW on the up-milling side	[56]
Cu/BeCrC composites	Milling	AlTiN coated inserts	RR: 0-15 wt %, FR: 0.2–0.4 mm/rev; CS: 125–175 m/min;	Dry	Taguchi, Fuzzy logic	The RR was found to be effective. Contribution with 52.71 % on EC, and FR and CS by 24.26 % and 12.85 %.	Fuzzy logic predictions ensure 20 % less time, energy, and labor.	[34]
AISI 4340 Steel	Turning	PVD-coated or uncoated carbide tool	CS: 320–575 m/min; FR: 0.1–0.26 mm/rev; CTT: coated and uncoated	Dry	Taguchi	CS contributions for SR and PC were found to be 70.53 % and 93.61 %.	Taguchi determined that optimized conditions resulted in different optimal conditions for individual outputs.	[105]
AISI P20	Turning	CVD coated carbide	CS: 160–270 m/min; SS: 728–1228 rpm; FR: 0.08–0.23 mm/rev; DOC: 0.3–2 mm	Dry, Wet	Taguchi, GRA	Reduced EC, SR, and environmental impact during the wet machining condition compared to dry operating condition.	A negligible effect of FR and DOC was observed on environmental impact.	[106]
PEEK-GF30 composite	Drilling	Zirconium oxide-coated Solid carbide	SS: 5000–7000 rpm; FR: 0.5–1 mm/rev; DT: −22 to 22 °C	Cooling compressed air system at 0 and −22 °C	FFD, DFA	Maximum desirability value corresponds to thrust force, energy, MRR, and Ft-E-MRR equal to 1, 0.88, 1, and 0.95. A desirability value close to 1 dictates the developed model is efficient.	Cooling compressed air is environmentally friendly and reduces the EC.	[107]
C45E steel	Turning	coated carbide	CS: 210–400 m/min; SS: 728–1228 rpm; FR: 0.28–0.4 mm/rev; DOC: 1.5–2.5 mm	flood cooling, MQL, and HPC	Taguchi	The contribution of DOC, CS, FR, and cooling/lubricating equal to 51.33 %, 11.32 %, 10.25 %, and 1.66 % on SCE was observed.	The optimized conditions resulted in reduced SCE compared to the initial condition.	[108]

HSS: high speed steel; DOC: depth of cut; FR: feed rate; NR: not reported; WH: workpiece hardness, UDCT: undeformed chip thickness; FEM: finite element; SCE: specific cutting energy; RSM: response surface methodology; BBD: Box-Behnken design; CCD: central composite design; FFD: full factorial design; PC: power consumption; SR: surface roughness; LDPS: Linear Decreasing Particle Swarm; MO-ITLBO: multi-objective improved teaching-learning based optimization; PF: Power factor, HWOA: hybrid whale optimization algorithm; ICBR: improved case based reasoning; CP: cutting power; CV: cutting vibration; VPSO: vibration particle swarm optimization; GRA: Grey relational analysis; PSO: particle swarm optimization; IA: Incident angle; ANFIS: adaptive neuro-fuzzy inference system; ASA: adaptive simulated annealing; NNCM: Normalized Normal Constraint method; AENNC: augmented-enhanced normalized normal constraint; DMS-PSO: dynamic multi-swarm particle swarm optimizer; FCE: fuzzy comprehensive evaluation; CS–GWO: cuckoo search and grey wolf algorithm; PCD: polycrystalline diamond; POM-C: unreinforced polyoxymethylene (acetal) copolymer; CP: cutting power; SR: surface roughness; NANFIS: novel adaptive neuro-fuzzy inference system; MOGA: Multi-Objective Genetic Algorithm; NI: number of insert; RR: reinforcement ratio; CTT: cutting tool type; PEEK-GF30: polyether-ether-ketone with glass fiber at 30 %; MQL: minimum quantity lubrication; HPC: High-pressure cooling.

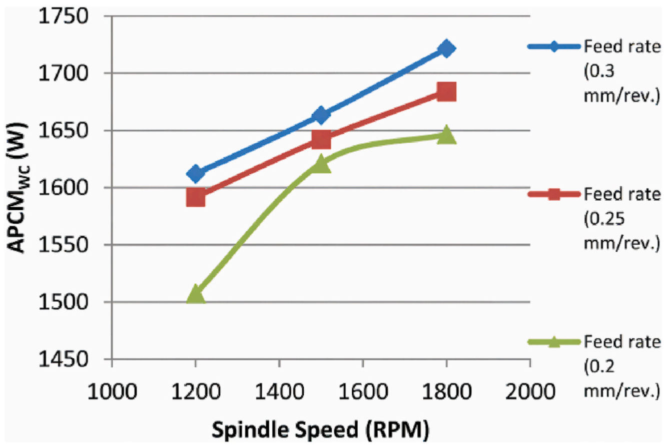

Fig. 7. Impact of cutting parameters on the active power usage of the machine in a non-cutting state ($APCM_{wc}$) [118].

increase production efficiency, it may not always be the most energy-efficient route. Exploring the depth of the cut reveals more complexities. This parameter, which represents the distance the cutting tool traverses into the workpiece, is a significant factor in the equation of energy consumption. Hanafi et al. [67] highlighted the fine balance between environmental sustainability and maintaining high surface integrity. According to their findings, the feed rate and the cutting speed were found to be the next most significant factors in predicting energy consumption, after the depth of cut as evident from Fig. 10, which shows that the depth can be responsible for up to 20.5 % of energy consumption during machining [120].

Other studies such as that reported by Korkmaz et al. [121] found that the depth of cut accounted for nearly half (49.55 %) of the power used, as illustrated in Fig. 11. This suggests that the optimal depth of cut ensures energy consumption efficiency. Their findings reinforce the idea that the depth of cut plays a crucial role in energy consumption. Additionally, cutting speed was also a notable factor, contributing to 26.03 % of the power usage. The study suggests that using the lowest possible feed rate, depth of cut, and cutting speed can reduce power consumption, thereby contributing to a more environmentally friendly approach. In their study, Ghazali et al. [122] carried out milling studies on Aluminum 6061 and identified that changes in the feed rate had a significant impact on energy consumption and were the most influential cutting parameter. They reported a reliability (R) value of 0.88 for their energy prediction model, emphasizing the precision of their findings. Şahinoğlu [123] in his study on hard turning of AISI 52100 steel, observed that increasing the feed rate and depth of cut decreased energy consumption due to shortener machining time. Specifically, they noted a decrease in energy consumption by 3.88 % under optimal conditions, highlighting the efficiency gains achievable through parameter optimization. Stojković et al. [124] examined the rough external turning of AISI 1045 steel and determined that optimizing cutting parameters reduces EC by 15.9 % compared to maximizing productivity. This finding illustrates the balance between energy consumption efficiency and productivity. Moreover, Şahinoğlu and Ulaş [125], in their study on the machining of hardened AISI 4140, found that lower feed rates and higher tool radii can lead to reduced energy consumption. They noted that a reduced feed rate leads to higher energy consumption, whereas an increased tool radius exerts a minimal impact on energy usage, offering a detailed perspective on the interaction between these parameters. These research works collectively highlight the complex interplay between different cutting parameters and their impact on energy consumption in machining operations. They show that optimizing these parameters can save a lot of energy, although the optimal settings depend on the material, machining technique, and environment. This emphasizes the need for a customized strategy in optimizing parameters to achieve energy efficiency in manufacturing processes.

Recent advancements in machine learning (ML) and AI have further enhanced the potential for optimizing energy efficiency in machining processes [126]. demonstrated the effectiveness of machine learning algorithms in developing energy efficiency models that consider both machining and configuration parameters. Their comparative study using traditional and deep learning algorithms highlights the potential for significant improvements in prediction accuracy and computational efficiency in energy management [126]. Furthermore, Lu et al. [127] proposed a reinforcement learning-based method for optimizing process parameters in CNC machining systems. Their approach, which focuses on energy efficiency and process time, successfully reduced energy consumption and cutting fluid consumption by 20 % and 35 %, respectively, showcasing the practicality and effectiveness of AI in optimizing machining processes [127]. ML and virtual reality were used to design milling cutting tools for energy optimization by Checa et al. [128]. Their experimental tests and ML modeling approach to tool design and cutting parameter optimization save more energy [109,129,130], [128]. Lastly, Abdel-Razek et al. [131] utilized an AI model to predict thermal comfort characteristics based on room occupancy, demonstrating AI's effectiveness as a tool for energy optimization. Although their study focused on room occupancy, the underlying principles of AI application can be extended to machining processes, where predictive models can significantly contribute to energy conservation [131]. The complex relationship between feed rate, cutting speed, and depth of cut necessitates a comprehensive, research-backed approach for optimal energy consumption outcomes. As technology advances and machining processes become more sophisticated, a continuous revaluation of these parameters will be required for the industry for sustainable energy consumption.

3.2. Improvement of energy efficiency in machining with cutting environment

Table 4 shown before also provides the details of a comprehensive analysis of the improvement of energy efficiency in machining processes through various cutting environments. It examines different materials and machining methods, exploring how different environments like dry, wet, and cryogenic affect energy consumption. The study demonstrates that selecting the appropriate cutting environment is crucial for optimizing power consumption and enhancing energy efficiency in machining operations. The document highlights that certain environments, such as cryogenic, can lead to lower energy consumption compared to traditional methods [132,133]. focused on sustainable machining, particularly using Al_2O_3 and graphene nanoparticle hybrid nanofluids in machining Haynes 25 alloys and AISI 52100 steel. Their research showed that increased feed rates and cutting speeds could notably decrease EC and carbon emissions by 22.17 %. They emphasize the balance between product quality, energy efficiency, and cost, advocating for energy-efficient machining processes.

In the manufacturing industry, particularly in machining processes, the emphasis on energy efficiency is increasingly paramount, driven by both economic and environmental considerations. The cutting environment, which includes the specific conditions under which machining processes occur, plays a critical role in determining energy usage. Traditional practices often rely heavily on coolants and lubricants, which, while reducing tool wear and improving surface finish, carry significant environmental and financial costs [134,135]. Recent trends in machining operations have seen a shift towards more environmentally friendly cooling technologies, such as near-dry cooling (also known as minimum quantity lubrication) and cryogenic cooling methods using CO_2 (carbon dioxide) and LN_2 (liquid nitrogen). Khanna et al. [136] explored the use of dry and liquid carbon dioxide (LCO_2) in machining glass fiber-reinforced polymer (GFRP), finding that LCO_2 effectively reduces the temperature in the cutting zone and electricity consumption, albeit with a higher environmental impact due to the energy required for

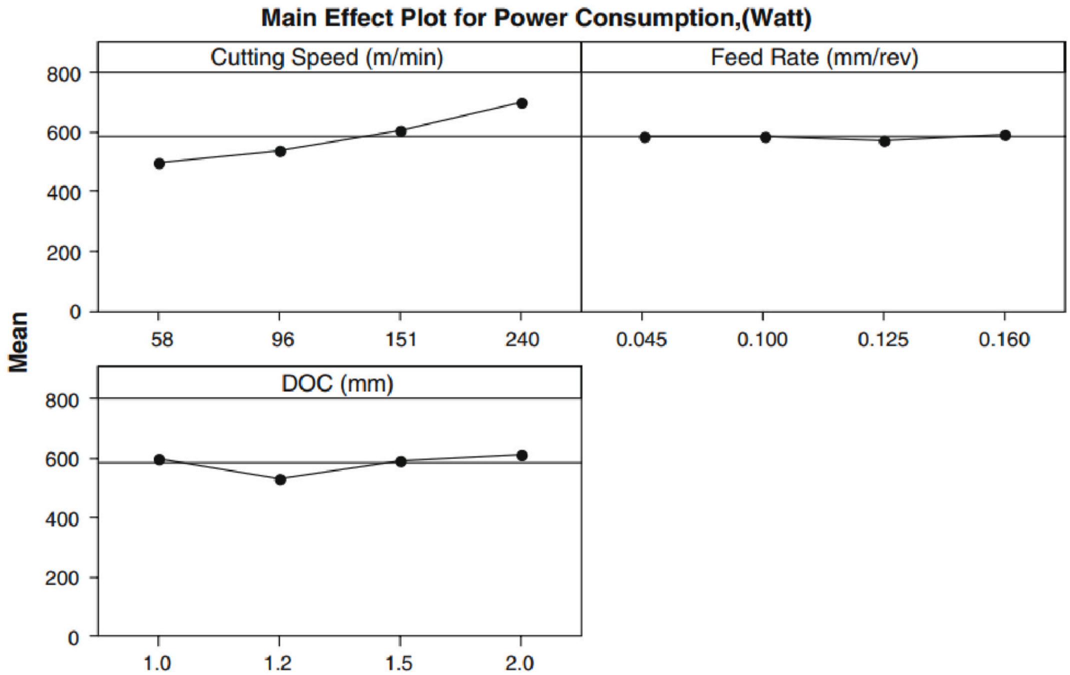

Fig. 8. Primary influence graph for device energy usage (W) [64].

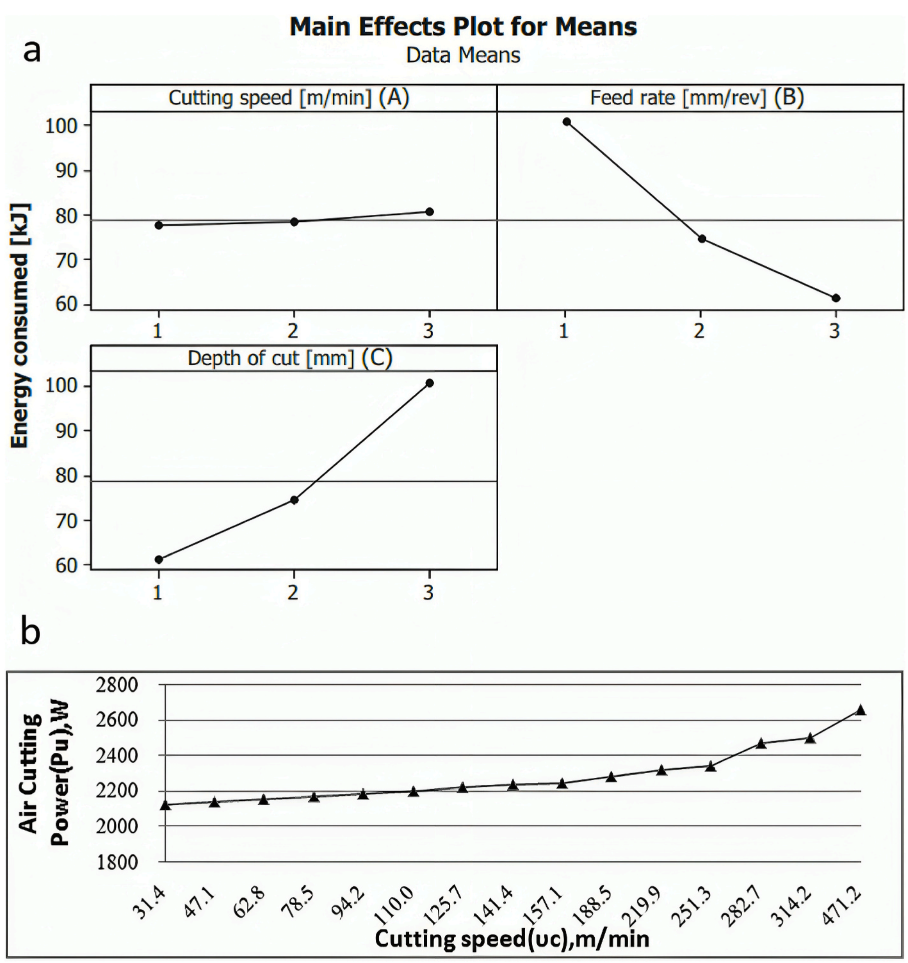

Fig. 9. a) Main effect plot for energy consumption per machining cycle [116], b) Evaluated the operational efficiency at varying cutting velocities [119].

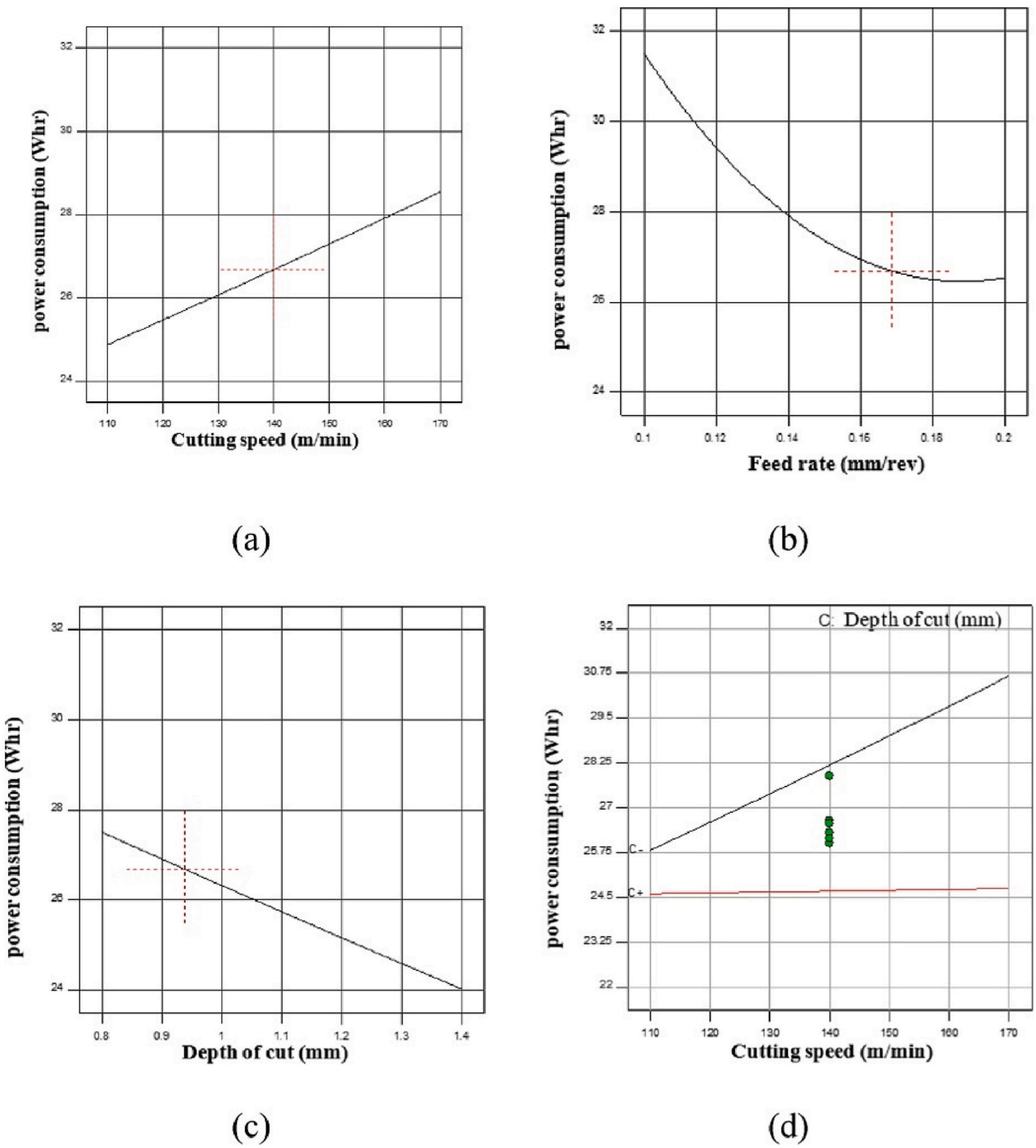

Fig. 10. Main plot of power consumption (PW) versus cutting parameters [120] (a) cutting speed (b) feed rate (c) depth of cut and (d) cutting speed interaction with depth of cut.

CO_2 condensation. This highlights the complex trade-offs in selecting cutting environments that balance energy efficiency with environmental impacts. Cryogenic machining, which utilizes extremely low temperatures, has gained attention for its ability to improve tool life and reduce thermal deformation, particularly in energy-intensive tasks like titanium machining [137]. The development of environmentally sustainable coolants, such as biodegradable oils and aqueous solutions, is also a focus, aiming to reduce ecological damage while maintaining machining effectiveness [138,139]. The integration of advanced technologies like machine learning and the Internet of Things (IoT) into machining processes is revolutionizing the cutting environment [140]. They discuss a three-tier IoT-fog-cloud model for sustainable IoT, emphasizing distributed task execution for scalability and energy management. This model can be adapted for machining processes, enhancing energy efficiency through improved forecasting and regulation of machining activities. Similarly, Musaddiq et al. explore machine learning-based resource management in IoT networks, which can be applied to optimize IoT-based machining environments for energy efficiency [141]. Despite these advancements, challenges remain in balancing energy efficiency with machining performance and the cost and complexity of implementing advanced technologies like IoT and machine learning, particularly in smaller production setups [142]. Future research is likely to focus on developing sophisticated models for predicting and optimizing cutting conditions, further advancements in eco-friendly coolants, and integrating renewable energy sources into machining operations [143,144]. In 2017, Shin et al. [145] developed a component-focused energy modeling method for real-time milling control that optimizes cutting settings to reduce machine tool EC. Energy efficiency in cutting operations has improved significantly with employing the said technology.

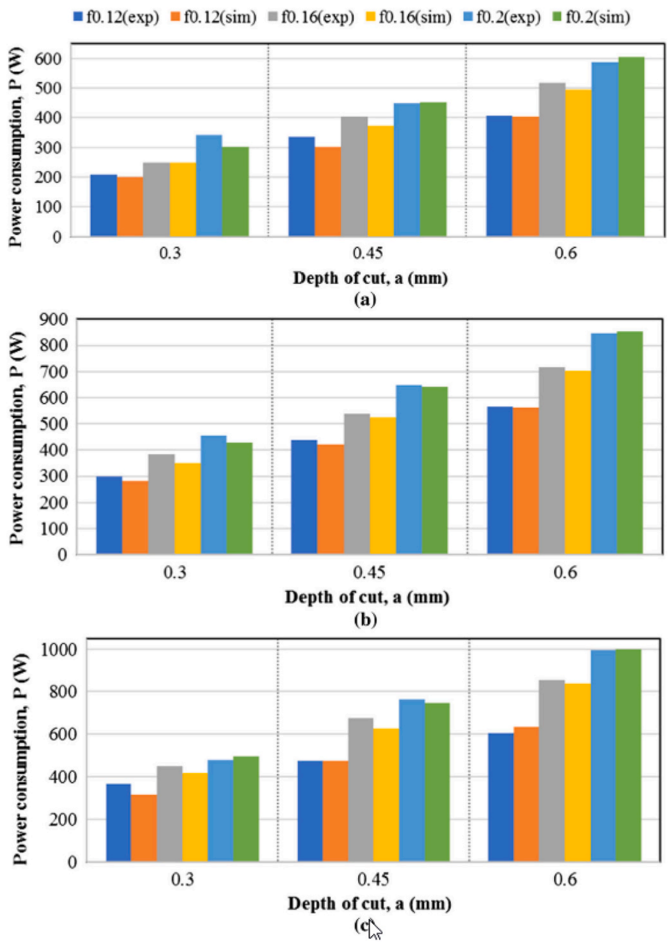

Fig. 11. Comparing experimental and simulated outcomes for P at a V = 120, b V = 170, and c V = 200 m/min [121].

Balogun et al. [146] analyzed the machining energy requirements and demonstrated that a flood-cutting environment reduces the specific energy coefficient by 28 % compared to dry cutting, leading to a 7 % overall decrease in machining energy demand [146]. Shin, Suh, and Stroud's (2015) green productivity concept in process planning focuses on eco-friendly practices to enhance energy efficiency and lessen environmental impacts in the metal-cutting industry [147]. This approach integrates assessment and prediction models with conventional planning techniques to balance productivity and environmental sustainability [147]. Ghandehariun et al. [148] also applied exergy analysis to assess sustainability in machining, focusing on turning operations to enhance environmental footprint. The study of vibration characteristics in machining processes also contributes to understanding and improving energy efficiency. Chen et al. [149] researched the vibration characteristics in the hardened steel precision machining process, providing insights into controlling vibration in hard-cutting technology. Furthermore, in Ma et al. [150] conducted a comprehensive study focusing on the EC and efficiency in machining operations, particularly turning, milling, and drilling. Their research centered on the energy aspects of metal cutting, with a specific emphasis on the turning of ANSI 4140 steel. All cutting parameters (speed, rake angle, nose radius, and edge radius) significantly affect the energy consumption analyzed through finite element simulation experimental trials. In addition, increasing the rake or decreasing the nose radius reduces energy consumption. Additionally, the research highlighted that while edge radius and rake angle greatly affect cutting efficiency, cutting speed and nose radius have minimal impact. High cutting speed, a large rake angle, and small edge and nose radii are recommended for minimizing the energy consumption, and a small edge radius and a small rake angle for maximizing efficiency. However, it's essential to consider that these optimal cutting energy conditions may negatively impact tool life, highlighting the need for a balanced approach in selecting cutting conditions and tool geometry that considers multiple objectives [150].

In conclusion, the cutting environment in machining operations offers significant opportunities for improving energy efficiency. The adoption of dry and near-dry machining, advanced cooling methods, environmentally friendly coolants, and the incorporation of modern technologies such as machine learning and IoT can lead to considerable advancements in reducing the energy impact of machining processes. However, the challenge lies in balancing these advancements with economic feasibility and environmental considerations, which will be a key focus for future research.

3.3. *Improvement of energy efficiency in machining with cutting tool characteristics*

Table 4 also emphasizes the role of cutting tool characteristics in improving energy efficiency in machining processes. It highlights how various tool features, such as geometry, material, and coating, significantly impact energy consumption. The study suggests that selecting tools with optimal characteristics for specific materials and machining operations can lead to reduced energy usage, thus enhancing overall process efficiency. The choice of cutting tools is presented as a crucial factor in achieving energy-efficient machining, suggesting a potential area of focus for further advancements in sustainable manufacturing practices. The size and geometry of cutting tools, encompassing variables such as tool nose radius, rake angle, and clearance angle, play a pivotal role in machining. Each factor significantly influences the cutting process and, consequently, energy consumption. With rising environmental concerns and an escalating energy crisis, optimizing these parameters for energy efficiency is becoming increasingly important. Wang et al. [151] highlighted the influence of the tool's rake angle in high-speed machining. Their experiments demonstrated that specific energy consumption escalates as the rake angle decreases, coupled with a reduction in the thickness of the undeformed chip as shown in Fig. 12. This finding underscores the importance of selecting an appropriate rake angle for energy efficiency. However, the ideal rake angle may vary depending on the material and machining method, suggesting a need for a more nuanced approach in its application.

Similarly, Wang et al. explored the impact of clearance angle on specific energy [152]. Their results indicated a significant influence of the clearance angle on cutting force and energy, particularly when the angle was less than 10° (Fig. 13a and b). This study emphasizes the importance of optimizing the clearance angle, though its applicability may vary with different materials, indicating a need for material-specific adjustments.

Ma et al. [150] used finite element modelling to study the impact of the nose radius on the energy consumption and cutting efficiency during turning of ANSI 4140 steel. As seen in Fig. 14a, an increase in the nose radius increases the cutting energy by approximately 9 % within a 0.4 mm–2.4 mm range, mainly due to friction. Despite friction only accounting for about half the shear energy, its 25 % rise significantly contributes to the cutting energy increase. The nose radius increase significantly affects the main cutting force, causing the deformation to become more complex and reducing the average uncut chip thickness - akin to the well-known size effect. Fig. 14b shows a slight reduction in energy efficiency with an increase in the nose radius due to the associated cutting energy increase, suggesting that adjusting the nose radius could aid in reducing the friction energy. This study suggests that while increasing the nose radius can impact energy efficiency, a balance must be struck considering the material type and friction energy.

The role of surface texturing, particularly nanotextured surfaces, represents a frontier in cutting tool technology. Recent advances in machining techniques, as reviewed by Refs. [153,154], include the

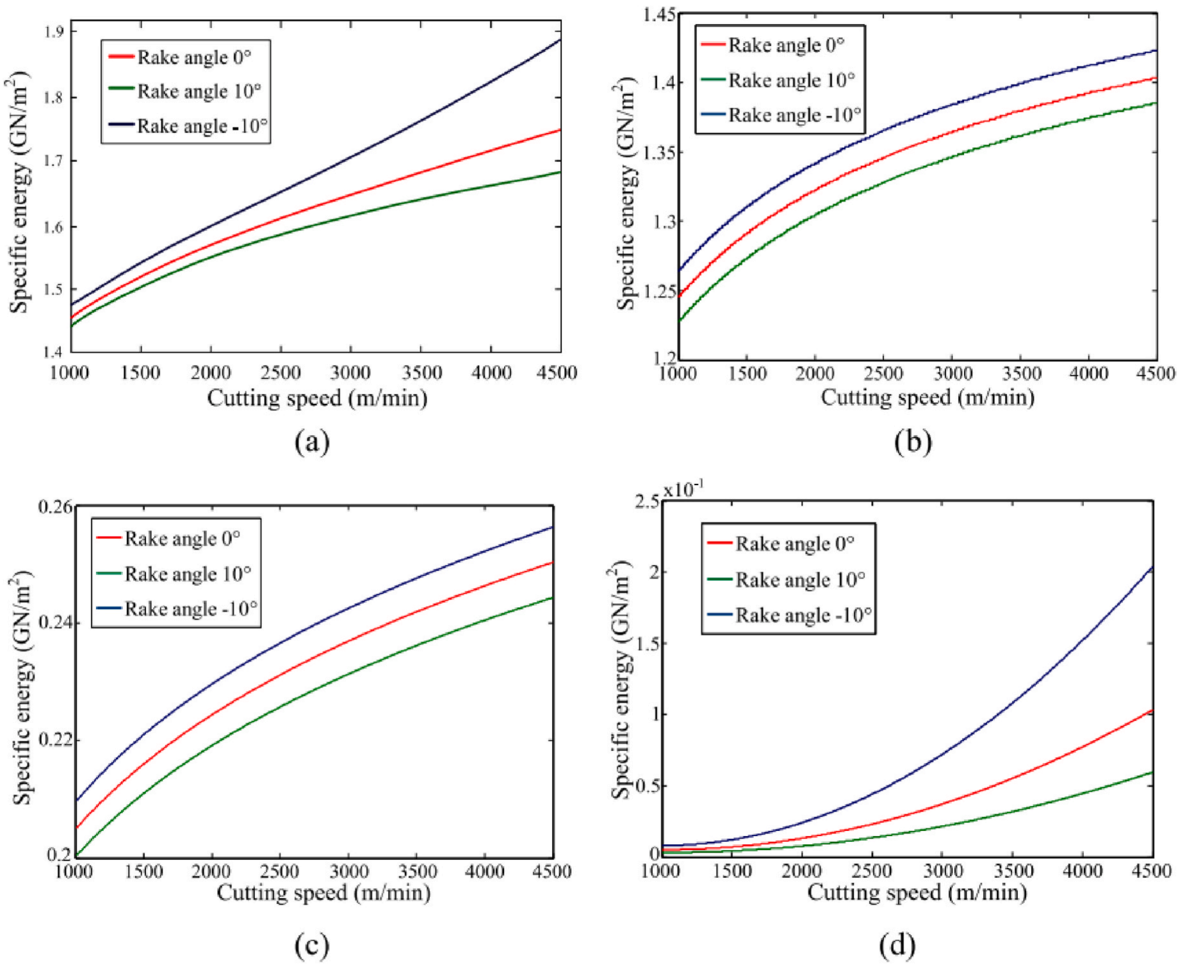

Fig. 12. Changes in total specific energy and its three components under varying tool rake angles during high-speed machining: (a) overall energy; (b) energy from plastic deformation; (c) energy due to friction; (d) kinetic energy of the chip [151].

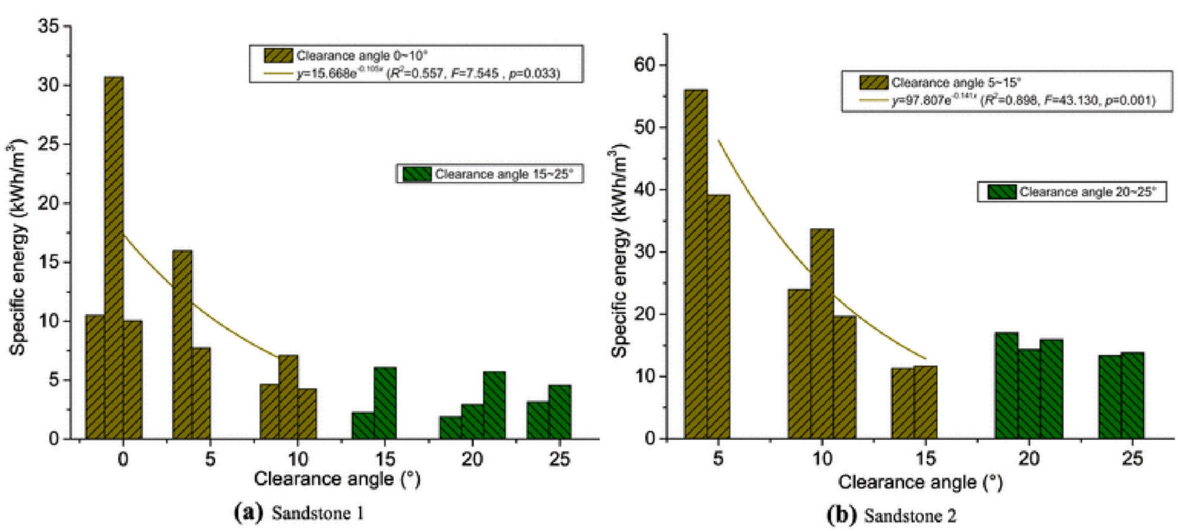

Fig. 13. The relationship between specific energy and clearance angle [152].

potential application of nanotextured surfaces, which can significantly reduce friction and improve energy efficiency. This aligns with the findings of Farooq et al. [154] and Nur et al. [155] which demonstrated that nanotextured surfaces could offer substantial reductions in friction, thereby enhancing energy efficiency. The research focuses on an often-overlooked parameter: the nose radius. Their methodology, on the other hand, is heavily reliant on finite element simulation, which, while precise, may not account for real-world machining complexities. The findings clearly show that increasing the nose radius is not the only way to improve energy efficiency. For realistic energy savings, a careful

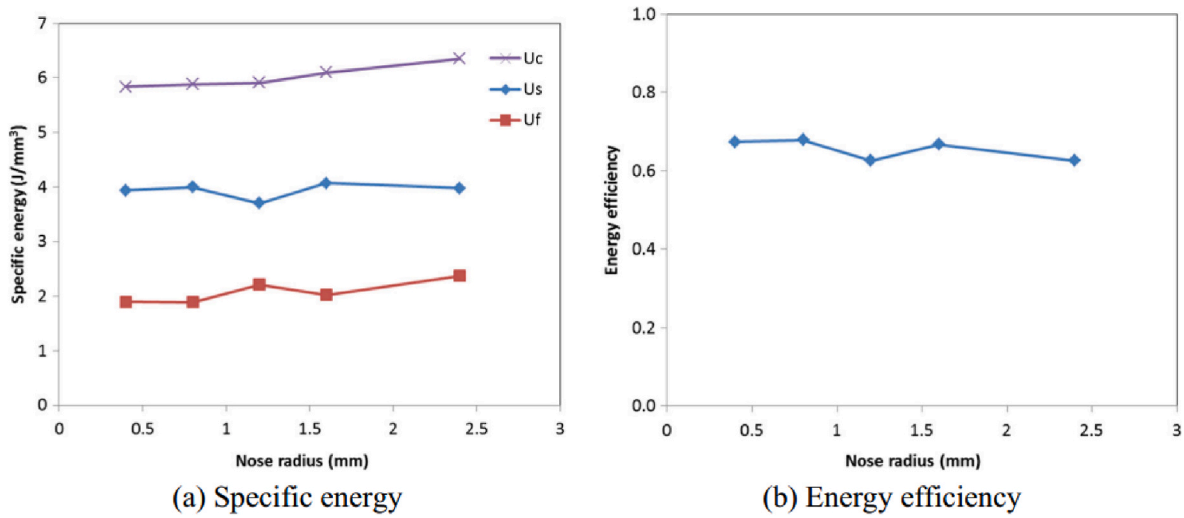

Fig. 14. Changes in specific energy and energy efficiency relative to nose radius. a. Specific energy. b Energy efficiency [150].

balance between nose radius and material type should be investigated, with friction energy taken into account. Obtaining the best surface texture could decrease the reliance on traditional oil-based lubricants usually required for achieving various degrees of friction. Thus, surface texturing also contributes to promoting ecological balance [156]. Arulkirubakaran et al. [157] demonstrated that textured tools, particularly those with perpendicular grooves, were more energy-efficient across various conditions as shown in Fig. 15. This finding points towards the potential of tool texturing in reducing energy consumption, especially in dry machining conditions.

Moreover, the application of nanotextured anti-reflection technologies in solar panels provides an interesting parallel to machining [158]. The significant improvements in energy output due to these technologies suggest similar potential benefits in machining applications. In the context of optimizing energy efficiency, Zhu et al. [159] focused on the spiral milling of wood plastic composites and their energy efficiency. Their approach to optimizing milling conditions for energy efficiency can provide insights into the application of nanotextured surfaces in machining. Furthermore, Gao et al. [160] described a discrete energy consumption path model technique to optimize tool pathways for energy efficiency. This technique emphasizes the significance of taking energy efficiency into account in all facets of machining, including the application of cutting-edge surface technologies like nanotexturing, even though it is primarily focused on tool path optimization. The integration of these advanced technologies into machining processes represents a significant step forward in the pursuit of energy efficiency. The use of nanotextured surfaces offers a promising avenue for reducing friction and energy consumption. This approach is not only beneficial for the environment but also for reducing operational costs, making it an attractive option for industries looking to enhance their sustainability practices. Furthermore, the exploration of different materials and their responses to various tool geometries is crucial. The studies by Wang et al. [150,152] Ma et al. provide a foundation for understanding these relationships, but further research is needed to develop comprehensive guidelines that can be applied across different materials and machining processes.

In conclusion, the optimization of cutting tool characteristics for energy efficiency in machining is a complex and multifaceted challenge. It requires a careful balance of tool geometry, material properties, and cutting conditions. Future research should focus on developing adaptive strategies that consider the interplay of these variables to EC in optimizing machining processes. The potential of nanotextured surfaces, in particular, represents an exciting area of research that could lead to significant advancements in the field.

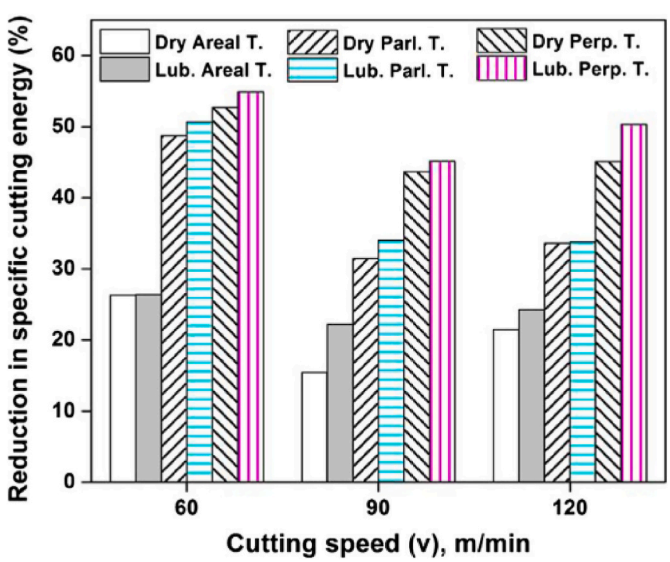

Fig. 15. A decrease in particular cutting energy (%) for various cutting velocities in both dry and lubricated circumstances [157].

3.4. *Improvement of energy efficiency in machining with tool material including coating*

Table 4 highlights how important tool material and coating are for increasing machining energy efficiency. It suggests that using tools made from advanced materials and applying appropriate coatings can considerably reduce energy consumption. The choice of tool material and coating is critical, as they directly affect tool wear, cutting forces, and heat generation, all of which influence energy usage. Optimal selection of tool materials and coatings for specific machining applications is presented as a key strategy for achieving more energy-efficient manufacturing processes. The choice of tool material and the type of coating applied to the tool showed a significant impact on energy efficiency in machining processes. Pervaiz et al. [161] assessed the effect of TiAlN-coated and uncoated carbide inserts when machining Ti-6Al-4V alloy across a range of machining conditions. The conditions covered a variety of cutting speeds and feeds and incorporated three specific machining environments: dry, mist, and flood. When it came to dry machining, the uncoated inserts outperformed in achieving a better surface finish at all cutting speeds. However, for mist cooling tests, the energy consumption was reduced when using TiAlN-coated inserts due to reduced friction in the cutting zone. The TiAlN coating played a crucial role in decreasing the friction coefficient between the tool and the workpiece, more noticeably at increased cutting speeds. Consequently, the TiAlN-coated inserts demonstrated lower energy usage, most prominently at these elevated speeds. The study demonstrated an intriguing contrast between uncoated and TiAlN-coated carbide inserts, particularly in dry and mist-cooling environments. Coated tools are thought to perform better in most situations. This research, however, highlights the importance of assessing specific machining conditions. While TiAlN-coated inserts showcased energy efficiency in mist cooling due to better friction management, they were outperformed by uncoated ones in dry machining. This is pivotal for industries as it emphasizes the need for careful selection based on conditions rather than general assumptions. Tool-material selection based on machining conditions can lead to significant energy savings, especially when considering large-scale industrial applications.

Applying a coating to a cutting tool enhances both its cutting speed and tool life. Gu et al. [162] previously conducted a study on the impact of these coatings on the tool life of inserts designed for face milling. They measured the tool life increases for TiN, TiAlN, and ZrN coated inserts against uncoated ones, correlating to the duration of wear-free cutting. This increase varied with feed per tooth and cutting speed, marking tool failure at 0.1 mm flank wear. TiAlN was most effective, extending tool life by up to 70 times, followed by TiN with a 35-time increase, and ZrN with a fourfold increase, compared to uncoated inserts. As a result, it can be concluded that coatings do more than just improve cutting speeds; they also extend the life of cutting tools, resulting in significant energy savings [163]. The work also emphasized the improved longevity offered by various coatings, with TiAlN (Titanium Aluminum Nitride) coatings demonstrating notably better performance. Their research advocates the application of coatings and highlights the considerable differences in their effectiveness. TiAlN coatings significantly extend the life of tools compared to other coatings, which is beneficial both economically and environmentally. Longer-lasting tools require fewer replacements, resulting in less operational interruption and reduced energy use. Furthermore, the increased durability of these tools helps to decrease manufacturing waste and the energy needed for producing additional tools [162].

Neugebauer et al. [42] investigated the relationship between energy efficiency and tool life during drilling operations, taking into account differences in tool and coating materials. They reported that the price of these tools varied between 3.30 and nearly 68 EURs, depending on the materials used for both the tool and its coating. Energy efficiency was determined based on the percentage of energy used in cutting relative to the total energy consumed, varying from 4.3 % to 17.3 % depending on the tools employed. Meanwhile, the cost of each meter of drilling varied as well, ranging from 1 to 8 EUR. The study found an inverse relationship between tool cost and energy efficiency: as Material Removal Rates (MRR) increased and dry machining was used, energy efficiency improved, though at a higher cost. Fig. 16 depicts a direct energy-based comparison of drilling operations performed with various power classes of drilling tools. Note that, the correlation between higher energy efficiency and high MRRs, which imply more effective material removal, but it also implies a negative relationship with tool costs. This presents a problem for sectors trying to strike a balance between operating expenses and sustainability objectives. Higher MRRs and dry machining can improve energy efficiency, but the initial tooling cost may increase as a result. With less energy used for operations, the long-term advantages might, however, exceed these upfront costs.

Zolgharni et al. [164] demonstrated how applying custom-tailored Diamond-Like Carbon (DLC) coatings can improve performance and save energy in cutting tools. They were able to produce drill bits with a 25 % reduction in swarf clogging, a 36 % reduction in energy consumption, and a five-fold increase in tool longevity by streamlining the coating process. When evaluating the total energy used during the machining process, a study by Fratila drew comparisons between near-dry machining, utilizing tools coated with TiN, and flood machining which involved uncoated tools [165]. The results showed that near-dry machining consumed only 0.52 kWh, compared to 0.67 kWh used in flood machining for producing identical components. It's important to highlight that dry machining generally necessitates the use of coated tools. In process design, it is crucial to consider both the energy requirements and the manufacturing costs. The specific conditions and outcomes of the machining process are depicted in Table 5.

Fratila et al. study [165] serves as a testament to the evolution of machining strategies. The energy savings observed in near-dry machining using coated tools, as opposed to flood machining with uncoated tools, advocate for a strategic move towards modern machining practices. A shift towards near-dry machining can yield significant energy savings in the long run. This highlights the importance of continuous innovation and the adoption of efficient practices in manufacturing. The research consistently shows a movement towards improving energy efficiency in machining operations. Coatings, especially TiAlN (Titanium Aluminum Nitride) and DLC (Diamond-Like Carbon) are crucial for extending tool life and saving energy. However, there's no universal solution; the best coating depends on the specific conditions of each machining operation. Industries need to move away from traditional thinking and evaluate the actual conditions they face, adopting solutions that are customized for their needs. While some energy-efficient tools may be more expensive initially, their ability to save energy and reduce costs over time makes them a worthwhile investment for sustainable machining practices.

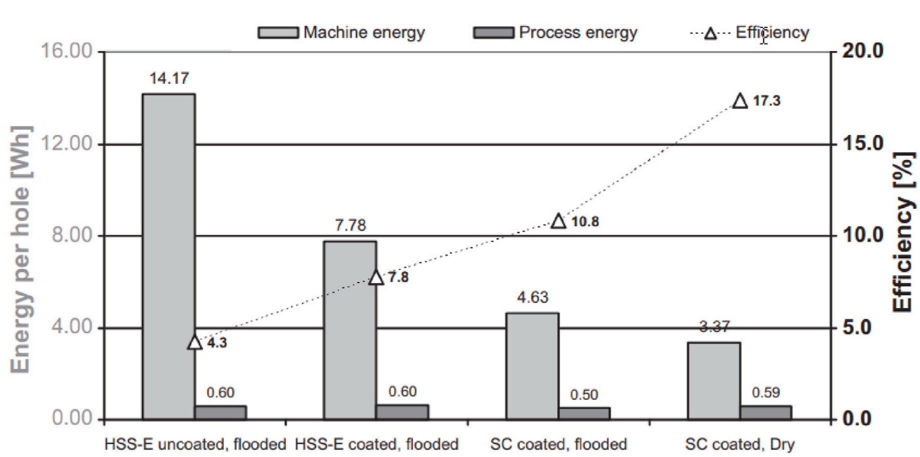

Fig. 16. Assessment of energy usage [42].

Table 5
Results obtained during the process of gear milling under various cutting conditions [165].

Type of process	FM gear milling	NDM gear milling
Tool	ø: ~90 mm EMo5Co5 uncoated tool material	ø: ~110 mm EMo5Co5 with TiN coating material
EC for 1 kg machined materials (equivalent for machining of 8 wheels)	0.67 kWh	0.52 kWh
Workpiece	16MnCr5 alloy steel material Weight: 1032.4 g	–
Cutting variables	Depth: 6.18 mm Speed: 130 m/min Feed: 2.4 mm/rev	–
Cutting Time	0.6 min	–
Machine tools	PE 50CC22Q CNC milling machine	–
Cutting fluids	Rotanol oil 100 l/min (recirculated)	Vegetable oil 0.4 ml/min (minimal quantity lubrication)
Power measurement device	HIOKI 3165	–
Gears parameters	Gear weight: 907.8 g, Modulus – 2.75 mm, Maximum number of teeth – 37, ø: ~110 mm, Teeth breadth – 19 mm	–

3.5. Improvement of energy efficiency in machining with vibration, plasma, laser, and induction-assisted machining operations

Emerging technologies like vibration, thermal, and hybrid-assisted machining have the potential to greatly enhance the energy efficiency of machining operations. Their objective is to improve the machining process by altering the tool-workpiece interaction, thereby decreasing the energy needed for material removal. Jiang et al. [166] conducted research on the precise energy usage in Ultrasonic vibration-assisted grinding (UVAG) for optical glass. Their findings suggest that UVAG is capable of both decreasing the energy needed during the grinding phase and significantly minimizing the time taken in the polishing stage that follows. Fig. 17a illustrates energy savings of 13,579.4 J/mm^3 and a saving rate of 84.8 % at a 5 μm cutting depth, reducing to 6371 J/mm^3 and 50.6 % at 20 μm. Fig. 17b illustrates that energy savings rise with wheel speed, maintaining a consistent saving rate of around 74 % between 15 and 35 m/s. Fig. 17c depicts an increase in both energy savings and the saving rate from 9846.1 J/mm^3 at 64.3 % to 14,593.3 J/mm^3 at 84.8 % as the feed rate escalates from 40 to 80 mm/s. UVAG effectively reduces process energy consumption.

Wang et al. [167] extended the concept of ultrasonic vibration to study the grinding process of γ-TiAl intermetallic compounds in what was called "Ultrasonic Vibration-assisted High-Efficiency Deep Grinding (UVHEDG), resulting in a 38.69 % reduction in grinding force and 39.05 % decrease in temperature compared to conventional high-efficiency deep grinding (HEDG). This study underscores the potential of ultrasonic vibration in reducing specific grinding energy and improving surface quality, which is crucial for energy-efficient machining processes. According to Chen et al. [166], when the depth of cut (ap) is 15 μm and grinding speed (Vs) is 25 m/s UVAG's clear advantage is its ability to reduce energy consumtpion during the grinding and polishing processes due to specificity to particular materials, like optical glass, could be a disadvantage. The study shows that even though UVAG can be a promising process, more material-specific research is required. The idea that incorporating vibrations into machining processes may very well be a path towards sustainable manufacturing is supported by the steady trend towards energy savings. Thermally Assisted Machining (TAM) is gaining popularity due to its effectiveness. An external source of heat is used in the TAM process to soften materials that would otherwise be difficult to machine before the cutting tool is applied. The three main variants of the TAM process have been the focus of research, each differing in the type of heat source used: Laser Assisted Machining (LAM), Induction Assisted Machining (IAM), and Plasma Assisted Machining (PAM) [168]. Lee et al. [169], studied the effect of machining parameters and their impact on energy efficiency for Ti–6Al–4V alloy under plasma-enhanced machining. The study concluded the best conditions for machining are a feed rate of 50 mm/min, a spindle speed of 12,000 rpm, and a depth of cut of 0.2 mm. Their research also showed that the energy efficiency of plasma-enhanced machining, in terms of mechanical energy and specific cutting energy, improved with the introduction of a preheating stage, compared to the conventional machining process. The energy efficiency of PAM was examined by gauging the specific cutting energy, identified to be 32.9 N/mm^2 for PAM. In a comparison to Conventional Machining (CM), the energy efficiency for PAM was found to be more than 60.26 % (Fig. 18).

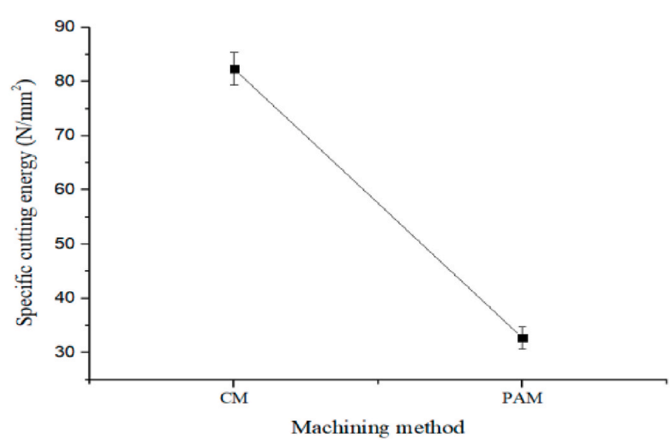

Fig. 18. Outcome of distinct cutting power in both CM and PAM [169].

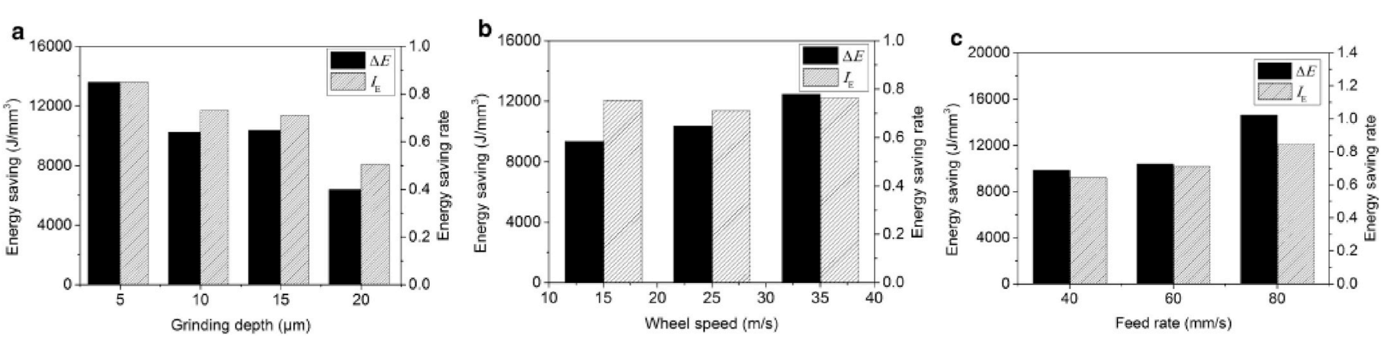

Fig. 17. Predictions of energy savings in UVAG: a. With grinding speed (V_s) at 25 m/s and workpiece velocity (V_w) at 60 mm/s; b. When the depth of cut (a_p) is 15 μm and workpiece velocity (V_w) is 60 mm/s; c.

In their study on Laser-Induced Plasma Micromachining (LIPMM), Zhao et al. [170] examined how using overflow water assists in modulating microchannel morphology during femtosecond laser-induced plasma processing. This research highlights the potential of LIPMM in creating microchannels with favorable morphological characteristics, which is crucial for large-scale production and energy-efficient machining. TAM is emerging as a leader in energy-efficient machining, but it is not without challenges. The authors contend that while preheating stages in Plasma-Enhanced Machining are beneficial, they require more energy input initially. Yet, the long-term savings, as highlighted in their study, are indisputable. TAM's trajectory is clear: refining the method to maximize energy efficiency while minimizing initial energy investments. Ahn et al. [171] focused on evaluating the performance of Laser Assisted Machining (LAM) against traditional machining methods. This involved contrasting the specific cutting energy at various depths of cut, taking into account the speed of the spindle's rotation and the feed rate. In a direct comparison of all conditions with the usual processes, LAM outperformed in aspects like energy consumption and cutting power. When the cutting depth was fixed at 0.2 mm, the specific cutting energy in LAM was reduced by up to 60 %. The primary reason for this significant reduction can be linked to the notable decrease in friction on the cutting tool's edge due to material softening from the laser's thermal source. Furthermore, Fig. 19 illustrates the comparative specific cutting energy of LAM and traditional machining under baseline conditions.

LAM's ability to outperform traditional methods, especially in energy consumption, positions it favorably in the race for sustainable machining solutions. The authors emphasize the laser's role in significantly reducing friction, which in turn translates to energy savings. Yet, a broader exploration across different machining scenarios is essential to ascertain LAM's universal applicability. Choi et al. [172] used induction-assisted machining (IAM) on AISI 1045 steel and Inconel 718, both shaped into circular cones. Experiments combining ramping and contouring milling methods were carried out to evaluate the efficiency of the IAM process. This involved comparing the specific cutting energy (refers to the energy consumed per unit of MRR over time) between these methods and CM. Fig. 20 shows the specific cutting energy for both CM and IAM across different feed rates in ramping and contouring, highlighting a 34 % reduction in the specific cutting energy for IAM during ramping at a feed rate of 50 mm/min. The rate of reduction in specific cutting energy decreases with increased feed rate. IAM, as noted by the authors, showcases promising reductions in specific cutting energy in controlled scenarios. Yet, as with the other methods, the translation of these savings across diverse conditions remains a concern. IAM's ability to offer significant energy savings in particular conditions

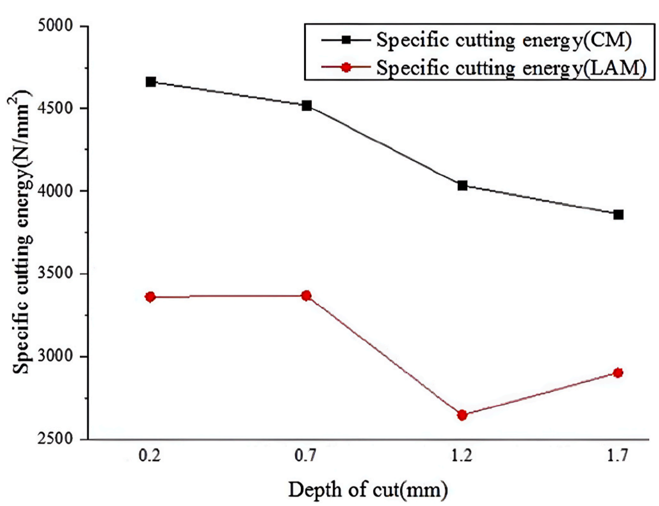

Fig. 19. Initial machining conditions' specific energy needed for cutting [171].

are indicative of its potential, but its broad-scale efficiency remains a subject for further exploration.

While there is a clear trend towards greater energy efficiency in all these emerging techniques, a balanced perspective necessitates acknowledging the challenges and the need for more extensive research. The authors argue for these techniques' transformative potential while emphasizing the importance of rigorous testing across a wide range of machining scenarios.

3.6. Employing AI techniques to determine optimal cutting conditions that minimize EC

Table 5 also presents a combined experimental and AI-based approach for identifying optimal cutting conditions to minimize EC in machining. It details how various experiments are conducted with different materials and cutting parameters to gather data. This data is then analyzed using AI algorithms, which are likely machine learning models, to identify patterns and relationships between cutting conditions and energy efficiency. The AI-based analysis enables precise prediction of the most energy-efficient cutting parameters, optimizing the machining process for reduced energy consumption. This approach illustrates the integration of experimental data and AI for enhancing sustainability in manufacturing processes. Bhinge et al. [173] utilized Gaussian process regression and machine learning to create a data-driven EC model, validated by Kim et al. [174], achieving over 94 % accuracy. Tian et al. [175] reported that the NSGA-II algorithm effectively optimizes the sequence and variables in processing to achieve a significant reduction in both energy consumption (specifically carbon emissions) and processing time. This optimization results in a 27.02 % decrease in energy consumption and a 54.65 % reduction in processing time. Tian et al. [176] also illustrated that optimal cutting parameters are influenced by tool wear conditions. As tool wear increases, the optimal parameters for carbon emissions, cost, and time in processing also rise. In situations with multiple cutting tools of different wear conditions, employing multi-objective optimization techniques such as NSGA-II, MOPSO, or integrating NSGA-II and Game theory is essential for finding the optimal balance between carbon emissions, cost, and production time. Applying AI methodologies for hybrid nanofluids (Al2O3 and graphene nanoparticle) in machining Haynes 25 alloys and AISI 52100 steel and optimizing the process variables ensure high-quality output alongside environmental and economic benefits [132,133]. Zhang et al. [177] developed an integrated model to reduce energy consumption in machining systems, merging process planning with scheduling. The model uses nonlinear process planning (NLPP) and a Therblig-based approach for energy prediction in machine tools. It aims to optimize the selection of process plans and machines for efficient scheduling, leading to energy savings. This approach's effectiveness is confirmed through case studies, showing its significant potential in lowering energy consumption in machining settings.

Optimizing cutting conditions to reduce machining energy consumption is a complex task that can benefit greatly from AI and machine learning approaches. These technologies can assist in identifying the best possible set of parameters that can lead to lower energy use while maintaining product quality and efficiency. The integration of AI in machining processes is not just a technological upgrade but a paradigm shifts towards more sustainable and efficient manufacturing practices. Recent advancements in AI have led to significant improvements in this area. For instance, a study by Yang et al. [178] has proposed a framework that integrates the Internet of Things (IoT) and ML to optimize SR, EC, and processing time in milling operations. This framework shows how AI can balance energy efficiency and product quality, emphasizing the value of real-time data gathering and analysis in machining. The study is particularly noteworthy for its holistic approach, considering not just energy efficiency but also the overall quality and time efficiency of the machining process. Building on this, Saini and Singh [179] explored the optimization of surface finish and energy consumption in

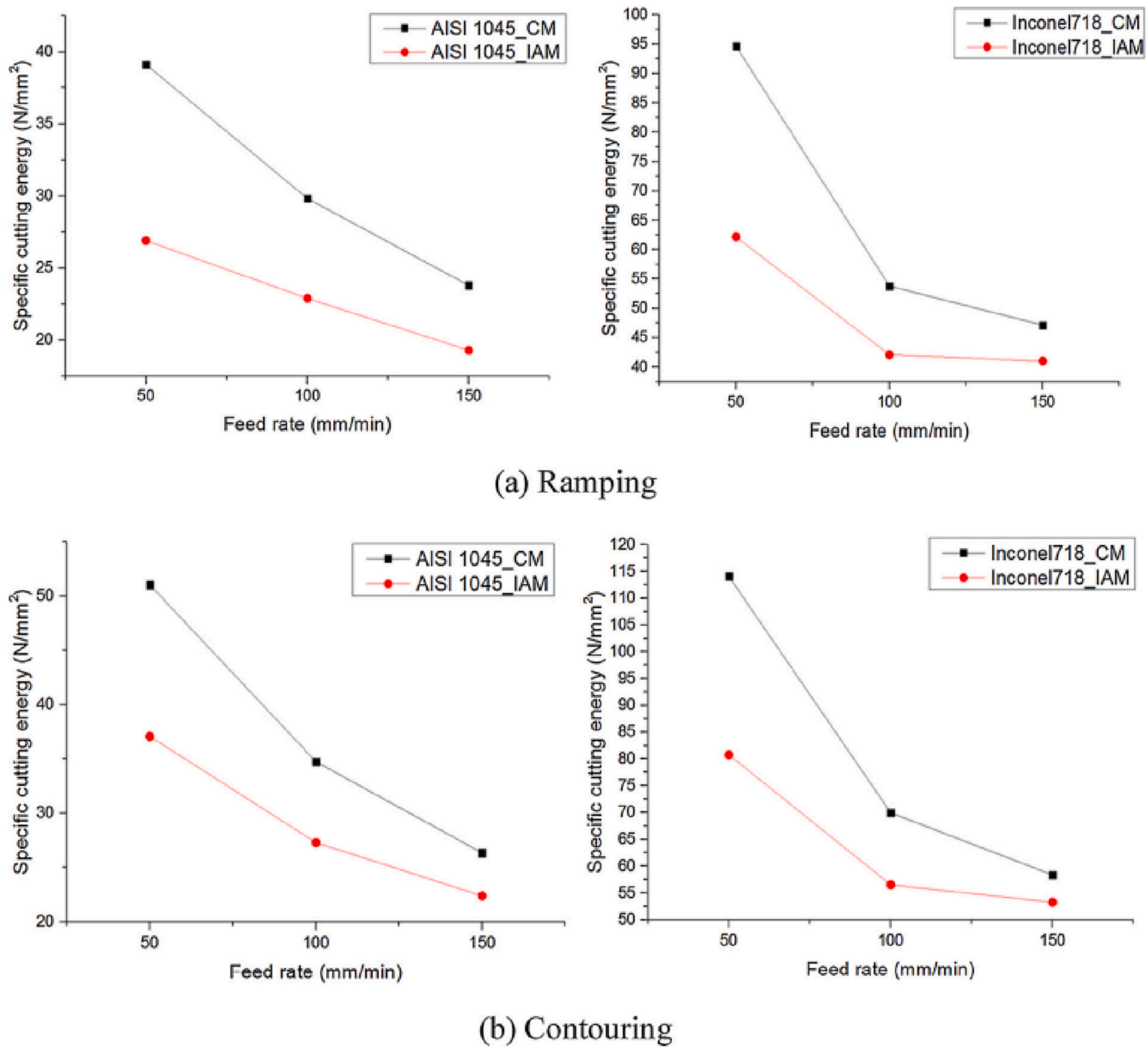

Fig. 20. The particular energy required for cutting CM and IAM [172].

CNC turning operations. Using response surface methodology (RSM), they achieved a significant reduction in energy consumption while maintaining an optimal surface finish. This study exemplifies the effectiveness of AI in optimizing machining parameters for eco-friendly operations. The work of Saini and Singh is particularly relevant in the context of CNC turning, where energy efficiency and surface quality are paramount. Furthermore, the work of Yani Zhang et al. [180] on gear machining processes using the Grey Wolf Algorithm presents a novel approach to reducing energy consumption and environmental pollution. Their model effectively identifies the most energy-efficient machining routes, showcasing the potential of AI in developing low-carbon and energy-efficient manufacturing processes. Their study is a testament to the power of AI in optimizing complex manufacturing routes, offering a significant step towards greener manufacturing practices.

In addition, Chu et al. [181] suggested a flexible method for process planning, using predictive models to estimate machining time and EC. Their approach, which utilizes a radial basis function neural network, emphasizes the importance of accurate predictions in achieving optimal process routes, thereby minimizing energy consumption and processing time. Chu et al.'s research underscores the role of predictive modeling in enhancing the flexibility and efficiency of manufacturing processes, paving the way for more adaptive and responsive production systems. Optimizing cutting conditions to reduce machining energy consumption is a complex task that can benefit greatly from AI and machine learning approaches. These technologies can assist in identifying the best possible set of parameters that can lead to lower energy use while maintaining product quality and efficiency. Recently, there has been a lot of interest in developing models that use artificial intelligence techniques to study the impact of machining parameters like cutting speed and tool geometry on things like cost, surface roughness, and time [182]. The method has the potential to increase efficiency by identifying precise cutting conditions. However, trade-offs must be made between model accuracy, time, and computational costs. Better, faster, and more cost-effective optimizations are possible as AI technologies advance. Kant et al. [183] developed Artificial Neural Networks (ANN) and Support Vector Regression (SVR) models for predicting power in AISI 1045 steel turning operations, considering various machining parameters. Using Taguchi's design methodology, 16 power-measuring experiments were conducted. Both models were compared, showing a close match with empirical data. Fig. 21 displays minor errors for the SVR model in 15 out of 16 conditions, while the ANN model had mostly below 5 % error but spiked in two experiments. The mean relative errors for ANN and SVR models were 1.75 % and 1.86 % respectively, showing the ANN model's superior performance, despite its more time-consuming setup and training process. Both models can enhance energy efficiency by providing accurate predictions for power consumption. However, the choice

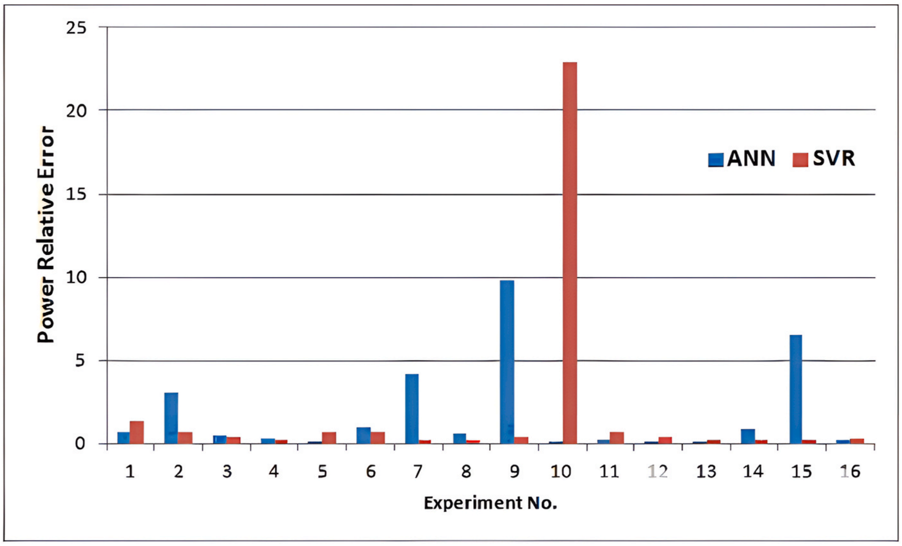

Fig. 21. Percentage of power-related error for ANN and SVR [183].

between ANN and SVR should be influenced by the specific needs of the industry and the available resources for model training and setup.

In another study, Borgia et al. [184] employed ANN to predict EC during milling. The adopted model managed to forecast the energy consumption in machining with a deviation of 2.46 %. Table 6 illustrates the mean absolute percentage error (MAPE) and the normalized mean square error (NMSE) for the trio of data sets. Based on both the MAPE and NMSE evaluations, the neural network seems to produce authentic outcomes beneficial for formulating process planning. The method offers potential energy savings by anticipating energy needs, but further refinement might be necessary to ensure the deviation remains negligible, especially for large-scale operations.

Identifying the ideal process parameters to minimize final production cost represents a significant hurdle in wood machining processes that were carried out by Tiryaki et al. [185]. The study employed ANNs to model the impact of various process parameters on power consumption during wood abrasive machining using data from existing literature. The results indicate that the neural network models accurately predicted experimental data, with a MAPE of under 2.51 % for power consumption. Furthermore, the coefficient of determination (R^2) was recorded at 0.985 when predicting power consumption using ANN modeling. These findings suggest that the proposed models can accurately anticipate power usage in abrasive wood machining (Fig. 22). As a result, this study offers valuable applications for the wood industry, as it can help to cut down on time, energy usage, and the expense of extensive experiments, by lessening the need for extensive testing. The ability to predict power consumption in wood machining can lead to substantial energy savings. Further research is needed to account for wood's variability and to generalize the model across different wood types.

Deng et al. [61] used AI to tweak process parameters to lower energy consumption. They examined the Numerical Control (NC) machine tool's energy module and developed a structure for power use during machining. Cutting Specific Energy Consumption (CSEC) was defined using these parameters. To balance processing time and CSEC, a model was crafted that combined multiple objectives into one using a quantum genetic algorithm. Fig. 23 depicts a platform used for testing energy consumption. This led to an effective compromise between processing time and energy reduction, especially when larger feed speeds and milling depths were allowed. The team achieved impressive results with a 27.21 % reduction in processing energy, a 32.07 % decrease in CSEC, and a 34.11 % reduction in processing time. This approach presents a promising way to lessen environmental harm from energy use and promote sustainable manufacturing. Their approach suggests substantial energy and time savings, pointing towards sustainable manufacturing. Diversifying the optimization strategies might yield even more robust results.

Table 6
MAPE and NMSE [184].

Data Set	MAPE (%)	NMSE (–)
Training	≈0	≈0
Testing	2.46	0.0215
Validation	0.037	0.0032

Quintana et al. [186] implemented ANNs to model energy usage in a five-axis CNC milling process. Their study highlighted the correlation between process parameters and power consumption, emphasizing the role of AI in identifying optimal cutting parameters for energy conservation. Their crucial in understanding the energy dynamics of complex CNC milling operations, offering a pathway to more energy-efficient manufacturing practices [186]. In conclusion, the integration of AI and machine learning in machining processes presents a promising avenue for optimizing energy consumption. The studies reviewed here illustrate the diverse applications of AI in various machining contexts, from metal to wood machining, and across different machining operations like milling and turning. The continuous advancements in AI technologies, coupled with the increasing availability of real-time machining data, offer significant potential for further improvements in energy efficiency in machining processes. Future research should focus on refining these AI models, improving their accuracy and adaptability to different materials and machining conditions, thereby contributing to more sustainable and eco-friendly manufacturing practices.

3.7. Analysis of carbon footprint and circular economy principles applied to machining operations

Global warming, pollution, and climate change led governments to initiate stringent regulations on industrial operations ensuring sustainable production that minimizes energy consumption and carbon emissions [187]. The term carbon footprint serves as a metric for quantifying CO_2 emissions [188]. CO_2 emissions due to industrial activities are still a major concern influencing global warming [189]. Modern industries aim at manufacturing parts (transforming raw materials into finished parts) that lower energy consumption with minimal carbon footprints [190,191]. Machining processes like milling and turning are among the most energy-intensive in manufacturing, accounting for about 75 % of

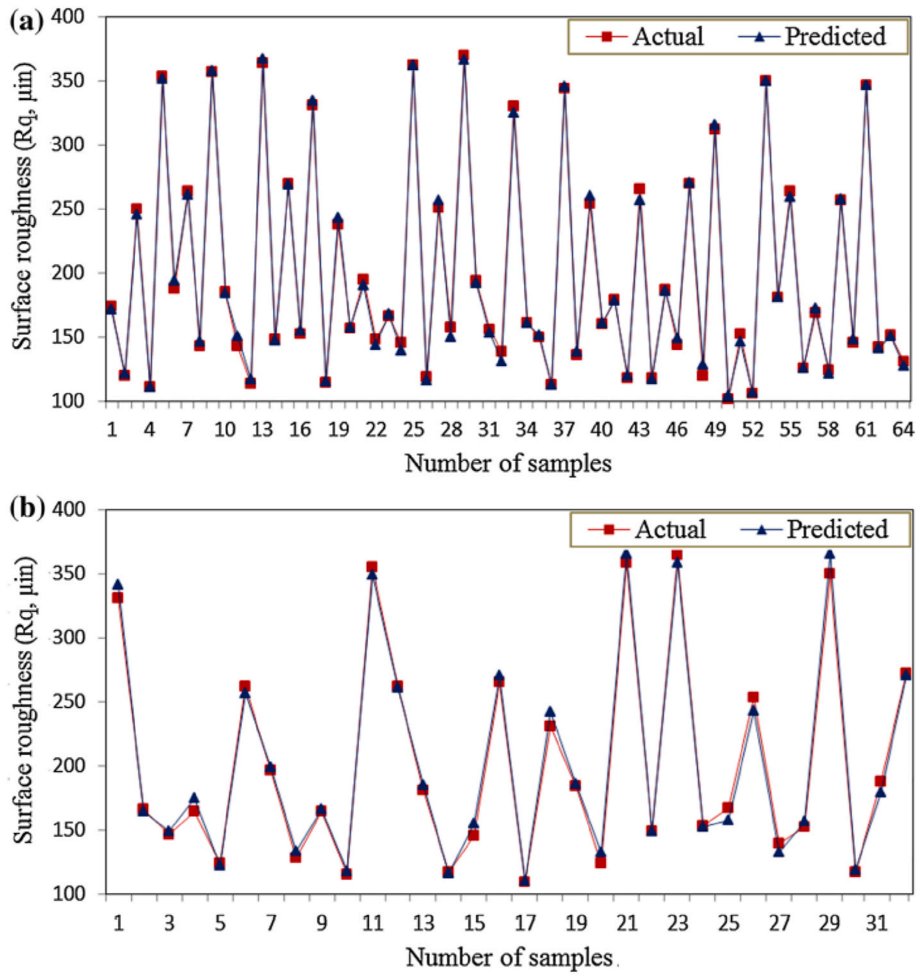

Fig. 22. Contrasting real and forecasted measurements of surface texture for (a) the training dataset, and (b) the validation dataset [185].

total energy consumption [192]. Machined parts quality (surface roughness, dimensional integrity, etc.) is influenced by machining process variables (speed, feed rate, depth of cut, and so on) and cutting environment (dry, wet, and minimum quantity lubrication) [193,194]. The sustainable use and appropriate choice of cutting fluids (oil: rice bran, turmeric, and kaolinite) minimize the carbon footprint in milling operations [192]. The machining conditions and tool path offer a substantial impact on carbon emissions [195]. Operating at a higher cutting environment accelerates tool wear, and heat generation at the tool-workpiece interface zone and reduces surface quality [196,197]. Sustainable machining ensures reduced energy consumption and carbon emission and enables production of good parts quality [198,199]. Hi-Tech (HTC) company-based clamp meter records the power consumed (in turn estimating carbon emissions) during machining subjected to different machining operating conditions [187]. Power or electricity consumption during the working phase accounts for 90 % of total life cycle carbon emissions [200]. Approximately 80 % of the weight of machine tools can be remanufactured for recycling which compensates for carbon emissions of structural materials [200]. Approximately 78 % reduction in CO_2 emissions was recorded by applying minimum quantity lubrication in grinding operation [189]. The parameters that influence the carbon footprint corresponding to the machining environment are waste disposal, and consumption (auxiliary material, raw material, and energy equipment) [201]. The carbon footprint saved (88.78 kg of CO_2 emission), which accounts for 52.15 % of the energy saved per annum, is the result of the total energy consumed under optimized conditions (turning operation) compared to that consumed under standard operating conditions [202]. The optimized machining (boring operation) process reduced the total carbon footprint of journal head machining from 529.5 kg to 497.3 kg CO_2 by saving 64 min of machining time [203]. The reduction of 32.3 kg of CO_2 (≈6.08 %) highlights the time-saving and environmental benefits. Carbon footprint represents the total amount of CO_2 released directly and indirectly because of machining activity (including materials, equipment, and personnel) accumulated throughout the various life cycle stages of a product [204,205]. Minimizing the energy consumption led to a reduced carbon footprint for the finished machining part [206]. The machining activities contributed to carbon emissions are attributed to energy consumption due to production and disposal of machined chips, cutting tools and cutting fluids [207].

In machining processes, the carbon footprint analysis involves evaluating the greenhouse gas emission (represents CO_2 equivalent) associated with all phases of machining processes. This includes direct emissions from energy consumption during cutting (raw material, cutting fluid, lubricating oil) as well as indirect emissions from the production and disposal of cutting tools, material removed as chips, coolants, and machine components (see Fig. 24). Understanding which parts of the machining process are most energy-intensive helps investigators who perform better estimate their carbon footprint and those target areas for minimization through optimization or technological innovations. In addition, understanding the machining operations that contribute to carbon emissions that significantly influence energy consumption, waste generation, economy (cost saving), and enhancing operational efficiency are of practical relevance [208,209]. Several approaches that minimize carbon emissions in machining operations (contributing directly or indirectly) are discussed below.

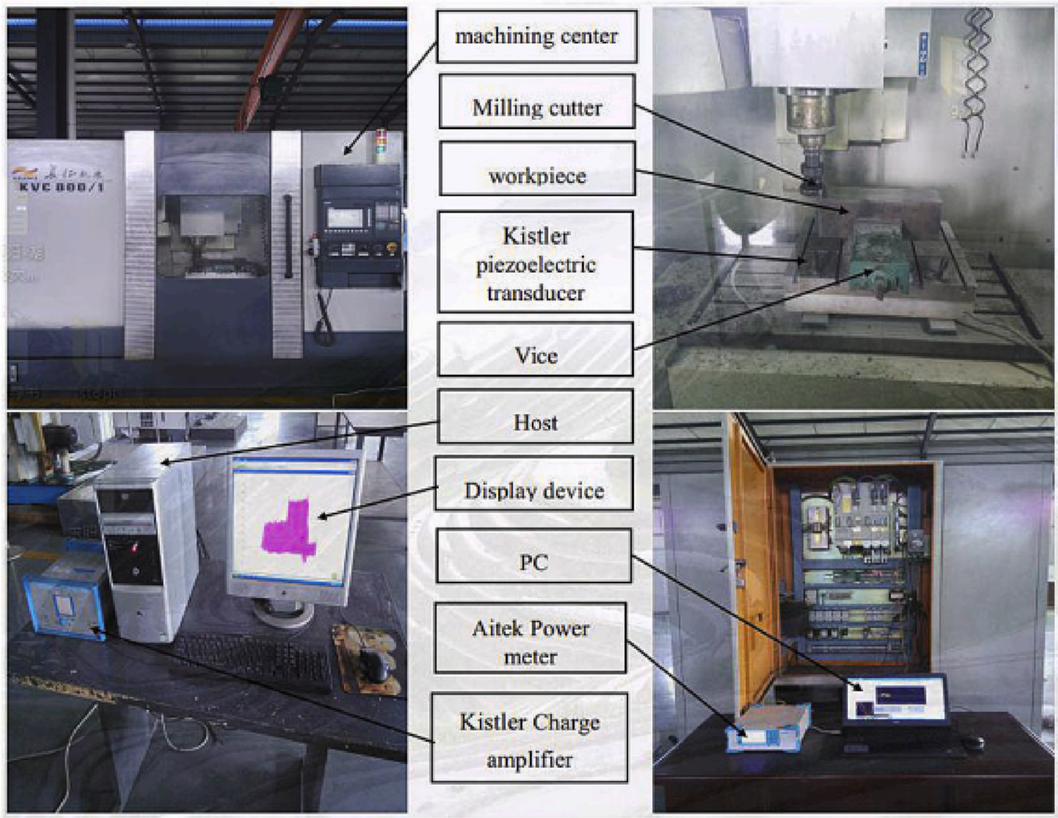

Fig. 23. Platform for testing energy usage experiments [61].

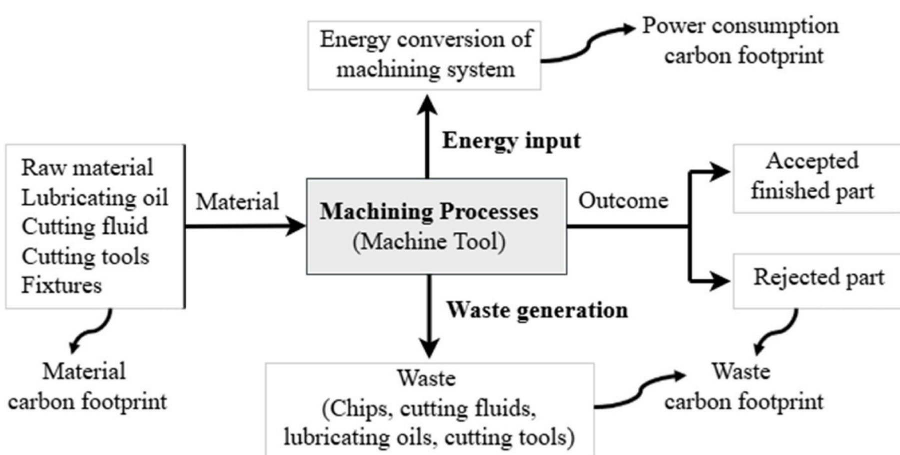

Fig. 24. Carbon footprint flow analysis of machining processes.

- Use of energy-efficient machine tools or equipment (energy recovery systems and variable frequency drives) designed for minimized energy consumption and release fewer carbon emissions [210].
- Employing renewable energy resources (solar, wind, etc.) to power machining operations minimizes the electricity-related carbon footprint [211].
- Use of sustainable and eco-friendly materials (recycled or biodegradable materials) that minimize waste generation and carbon emission [212,213].
- Use biodegradable or recyclable cutting fluids with a minimum quantity lubrication approach instead of flood coolant to minimize an environmental impact [214].
- Applying methods (artificial intelligence, statistical methods, multi-criteria decision-making methods, and so on) ensures process optimization through reduced idle time, lead time, and toolpath inefficiencies [215].
- The use of coated cutting tools, cryogenic cooling, smart sensors, and IoT-aid systems ensures real-time adaptive feedback control strategies that minimize tool wear and waste generation [216,217].
- Use of life cycle assessment approaches that track and target the phases contributing to higher emissions and reduce CO_2 emissions [218,219].
- Optimizes the transportation logistics that reduce carbon emissions in transferring raw materials, finished products, and waste [220, 221].

The circular economy transforms the manufacturing strategy from a traditional linear (take-make-dispose) to a regenerative approach that could highlight reuse, recycling, and waste minimization [222]. In machining operations, the circular economy principles are integrated with the following strategies.

- Tool life enhancement with the use of advanced coating and cryogenic cooling techniques that reduce tool wear [223,224].
- MQL and dry/near-dry machining strategies optimize the coolant strategies that minimize environmental impact and resource reuse [225,226].
- Real-time monitoring, trajectory optimization, and optimizing cutting parameters ensure energy efficiency and minimize energy consumption [198,227].
- AI-based monitoring systems enable investigators to predict tool wear ensuring reduced tool overuse and premature failure (leading to disposal) [216,228].
- A significant proportion of machinery parts (~80 %) can be remanufactured or recycled enabling industry personnel to reduce embodied carbon in structural parts [200,229].
- Machined chips and used cutting fluids that are processed or repurposed enable industry personnel to waste recovery and reduce landfill waste and emissions [230,231].

Overall, machining operation plays a vital role in ensuring overall sustainability. Limiting carbon footprint through optimized cutting conditions, intelligent monitoring, and sustainable resource (material, equipment, personnel) use potentially benefits the environment and economy. The sustainability strategies discussed above directly support the principles of circular economy, emphasizing durability, reusability, and minimizing resource input. Integrating carbon footprint analysis with circular economy paves the way for responsible and future-ready manufacturing practices.

3.8. Energy loss minimization with adaptive trajectory optimization and control strategies

Modern machining industries pay significant attention to trajectory optimization and advanced control strategies towards energy-efficient machining aiding the integration of intelligent and Industry 4.0 technologies [211,232,233]. Trajectory optimization through intelligent planning of tool paths minimizes unproductive tool movements, idle times, and machining times aiding to directly contribute that minimizes the energy consumption [234,235]. Optimized trajectory planning (smoothening acceleration and deceleration curves, reducing jerks, air-cutting, and sharp directional trajectories) significantly decreases the load on servo drives, motors, and control systems and lowers energy consumption during both cutting and non-cutting phases [236]. Adaptive and real-time feedback control systems, integrated with artificial intelligence techniques ensure dynamic adjustment of cutting parameters in response to variations in workpiece material, tool path, tool condition, and process stability [237,238]. The developed control systems prevent overcompensation and underutilization of cutting power, ensuring that only the required amount of energy is used for a given task [72,238,239]. Applying intelligent control algorithms dynamically adjust the cutting parameters (spindle speed, feed rate, and coolant flow) developed for energy-efficient systems without hindering surface quality or tool life [240–242]. Finally, the integration of trajectory optimization with intelligent control strategies led to advancement in energy-efficient machining without compromising productivity or quality.

4. Future research trends and challenges for energy saving in machining processes

This section describes the future research trends and challenges for energy efficiency in the machining process based on the understanding of past literature from the present state-of-the-art studies. Machining operations consume substantial power, impacting overall energy consumption. EC in machining can be minimized by controlling cutting parameters, cutting environment, coolant system, cutting tool geometries, coating of cutting tools, and so on. The techniques employed to minimize energy consumption utilize the statistical design of experiments and artificial intelligence tools. Employing new-age technologies renders reduced energy consumption during machining processes. A few of the potential implementation challenges as well as those extracted from the available literature are discussed below.

- Employing artificial intelligence tools (ANNs, fuzzy logic, algorithms) for predicting optimal machining conditions provides solutions to reduced energy consumption. The challenges involved ensuring the efficient interface or connectivity between the machine tool and computer for online monitoring [243,244]. The challenges in machine tool-computer interface are to handle the large number of interconnected smart devices, which consumes higher energy consumption [26]. Energy management and harvesting methods are challenging tasks for optimized energy consumption [194].
- Employing machine learning methods for determining and monitoring energy consumption is bound due to limited datasets to train and test algorithms [243]. This occurs because of ethical and legal requirements in protecting end-user power consumption datasets for promoting research. There exists immediate attention in developing novel approaches to secure and implement novel privacy-maintaining machine learning approaches.
- Developing a virtual machine tool prevents collision due to early predictions and enables training to users with parametric codes to ensure insight into the process. The graphical representation of machining centres, viz. geometric model and kinematic chain is required to create the virtual machine tools. However, increased complexities in machining centres cause users to identify the kinematic chain with dependent components [245]. The challenging task is to develop such a virtual machine tool for efficient energy consumption.
- AI and sensor technologies monitor tool wear in real-time by controlling the cutting parameters during drilling, turning, milling, and grinding. Worn-out tool during machining operation increases mechanical vibrations, resulting in chatter, damage to the work material and machine tool, and higher energy consumption. The challenging task is detecting tool wear initiation and propagation during machining operations and the best time to replace the tool ensuring a balance between part quality and total costs (tool cost, energy cost, etc.).
- Machining is a more vital production technique than conventional manufacturing routes (casting, forming, etc.) to offer better dimensional accuracy and surface integrity in the finished product. Precise selection of technological parameters such as cutting speed, feed rate, cutting tool geometry, cutting tool-workpiece, and cutting environment are essential in minimizing energy consumption.
- Many methods are proposed in the literature to select the appropriate parameters for experimentation, analysis, and optimization in machining processes. Trial-and-error experiments result in costly experiments and might result in local optimal conditions. Statistical design of experiments limits the requirements of conducting many experimental trials and thereby helps reduce energy consumption. Selecting the most influential parameters and accurate modelling methods that reduce resources and energy consumption is challenging for researchers.
- The precise selection of appropriate tool-workpiece material combinations and machining environment (dry, wet, and MQL) pave the way for reducing waste and energy consumption.
- Textures (micro-holes, grooves) on cutting tools minimize the cutting forces, friction, and contact length of chip-tool interfaces, reducing

energy consumption. The challenging task is to select the appropriate geometry of textures (width, height, edge distance, grooves, holes, texture pattern, diameter-to-depth ratio, and so on) without affecting the tool's life [246].
- The use of lubricants enriched with nano-additives or textured cutting inserts filled with solid lubricants can further improve the performance of textured cutting tools as the nano-additives remain intact on the tools' surface during machining therefore, reducing the cutting forces, friction, and energy consumption. The challenging task is to retain the thin film deposited coating against friction caused by large cutting forces between the chip-tool interfaces. However, further investigations are required in this regard to optimize combined modification effects (nano-additives/solid lubricants and textured tools) on the overall energy consumption process during machining, taking into account further implications on increased costs (recycling and treatment of the lubricant) and the impact on the environment (waste and disposal of the lubricant).
- Cryogenic cooling is a promising technology for efficiently machining difficult-to-cut materials with reduced cutting forces, tool wear, surface roughness, and friction, resulting in better energy consumption. However, the machining efficiency itself relies primarily on monitoring and controlling appropriate temperature to mitigate the side effects of subzero temperatures (i.e. dimensional changes in cutting tool and workpiece among others).
- Energy consumption data can be collected using Industry 4.0, machine learning, and image processing methods. Energy consumption data can be collected with the embedded highly sensitive sensor. Integrating or mounting such sensors close to the cutting zone poses problems due to chip formation, wear, tool breakage, etc. Addressing such issues remains a challenging task.

5. Conclusions

This comprehensive review article outlines the various types of energy consumption sources in conventional machining process and the improvement of energy consumption using different approaches in machining processes (cutting parameters, cutting tool design and properties, use of cooling technologies, using other non-conventional machining technologies and artificial intelligence), providing insights into the various aspects of sustainable machining. A detailed summary of each area of study is given and discussed, illustrating how technological advancements and different machining practices relate to one another, anticipating the combined effect of these developments on future industrial paradigms. From the review, the following can be concluded.

- Cutting parameters are a key factor in traditional machining processes, governing energy consumption levels among other things. The feed rate, cutting speed (or spindle speed), and depth of cut contribute significantly to energy consumption in machining. Many studies have been conducted to optimize these parameters to reduce energy consumption. These studies also investigated how cutting parameters and other factors (coolants, tool design, material, workpiece material, and part requirements) affect overall energy efficiency and consumption. The majority of studies are unique, which means they are only valid for that specific set of parameters and machining conditions. A broader approach that ultimately reports on energy consumption and optimization based on various factors is required. However, such an approach necessitates extensive experimental studies and resources, making it difficult to implement. An alternative would be to use numerical, theoretical, and AI models to reduce the size of the experimental design approach required to achieve ultimate solutions for energy savings in various machining processes regardless of input factors (cutting parameters, machine type, tool type, and design, workpiece material, coolant use, and so on).
- A careful examination of modern machining methods, such as the use of High-Pressure Coolant (HPC) and Minimum Quantity Lubrication (MQL), reveals a strategic shift in direction towards sustainability and resource utilization. These developments highlight the complex trade-offs between environmental concerns and operational effectiveness. MQL provides a balanced method between dry machining and high coolant consumption, while HPC shows significant promise in resource conservation and increased productivity even in the face of controversial discussions.
- The synthesis of research on tool geometry and surface texturing uncovers groundbreaking possibilities for achieving ecological harmony and energy conservation in machining processes. Nano-textured surfaces and intricate surface texturing like Diamond-Like Carbon (DLC) coatings represent the highest level of innovation, holding the promise of radically reducing energy consumption and fostering sustainable manufacturing practices, even in highly specialized applications like those involving optical glass.
- The investigation into tool materials and coatings signifies a transformative shift in machining approaches and industry norms. The comparative study between uncoated and advanced TiAlN-coated tools underscores the critical importance of selections tailored to specific contexts, unveiling new possibilities for energy conservation and eco-friendly industrial applications. This important effect on tool longevity and machining efficacy represents the convergence of economic viability and environmental conservation.
- The in-depth analysis of vibrational and thermally assisted machining techniques put forward their transformative potential in minimizing energy consumption and refining machining processes. Ultrasonic Vibration Grinding (UVAG) and Thermally Assisted Machining (TAM) represent the combination of precision and energy conservation, presenting a roadmap to sustainably optimized machining processes. However, these promising techniques come with their set of challenges, necessitating a meticulous approach to maximizing long-term energy savings while optimizing initial energy inputs.
- The integration of AI and ML in machining processes is at the forefront of industrial innovation. The deployment of models like ANN and SVR highlights the transformative potential of AI in predicting and optimizing energy consumption with a remarkable degree of accuracy. AI's adaptability and precision in configuring optimal machining parameters signify a revolutionary step towards attaining environmental sustainability and operational efficiency in manufacturing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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