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CRITICAL REVIEW

Optimization techniques for energy efficiency in machining processes—a review

Fatima Zohra El abdelaoui[1] · Abdelouahhab Jabri[1] · Abdellah El Barkany[1]

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Abstract
Metal working process is one of the main activities in mechanical manufacturing industry; it is considered as a major consumer of energy and natural resources. In material removal process, the selection of cutting parameters and cooling or cutting liquid is necessary to save energy and achieve energy efficiency as well as sustainability. During the last two decades, the number of publications in this field has rapidly increased and has shown the importance of this research area. This review paper identifies and reviews in detail a total of 166 scientific studies which exhibit original contributions to the field and address multiple energy efficiency challenges. The recently developed models of energy consumption and different materials used in the machining process are presented. Therefore, this study describes various techniques for modeling and optimizing machining operations such as turning, milling, and drilling. Modeling techniques, experimental methods, multi-objective and single-objective optimization methods, and hybrid techniques optimization are presented in a detailed manner compared to previous review papers where only energy models are discussed. It can help practitioners and researchers to select the most appropriate approach for the desired experience and to highlight the progress of these methods in terms of machining energy efficiency. Additionally, this paper provides a review of different cutting fluids adopted in machining processes. This paper assists researchers and manufacturers in making advantageous technical decisions that have substantial economics in terms of energy saving.

Keywords Energy efficiency · Machine tool · Optimization methods · Lubrication · Cutting parameters · Cutting metals

1 Introduction

During the last decades, climate change is felt in the four corners of the world. Human being and animals are facing serious droughts, recurrent heat waves as well as rising sea levels. Nowadays, politicians and decision makers are now more and more aware of the negative impact of energy consumption and its threat to the global ecosystem. However, there are still efforts to be made as the demand for energy is supposed to increase by 50% between now and 2050 [1]. According to the United Nations Framework Convention on Climate Change (UNFCCC), countries worldwide are strongly urged to limit manmade temperature rise to 2 °C [2]. Moreover, as industries account for about 31% of primary energy demand and 36% of CO_2 emissions [3], managers have to consider energy consumption at each level of decisions (strategic, tactical, and operational levels).

Mechanical manufacturing processes such as casting, forming, and machining are the most used to obtain mechanical parts in automotive, aerospace, and marine sectors. Machining activity which consists of different operations to achieve the desired shape with dimensional and geometrical accuracies allows for saving energy consumption and achieving an efficient process in terms of performance indicators. First, it is necessary to define what energy efficiency is. In current language use, efficiency is defined as the relationship between output and input [4]. Analogously, many authors have defined energy efficiency and energy efficiency indicators [3, 5, 6]. Energy efficiency is defined in the ISO 14955 standard as the "ratio or other quantitative relationship

✉ Fatima Zohra El abdelaoui
fatimazohra.elabdelaoui@usmba.ac.ma

Abdelouahhab Jabri
abdelouahhab.jabri@usmba.ac.ma

Abdellah El Barkany
abdellah.elbarkany@usmba.ac.ma

[1] Mechanical Engineering Laboratory, Faculty of Sciences and Techniques, Sidi Mohammed Ben Abdellah University, Fez, Morocco

between an output of performance, service, products, or energy, and an input of energy" [7]. For the industrial sector, it is defined as "the relationship between useful process output and energy input into a process" [8].

Technically, up to two-thirds of total consumed energy in machining operations is not exploited since it is converted into heat [9]. The rest is consumed by feed axes, accessories, idle motors, controllers, and other fixed electronic items [10]. Statistics from the US Energy Information Administration [11] show that energy consumption related to machining operations accounts for more than 20% of the total energy consumption of the manufacturing industry [12, 13]. To make benefit and stay competitive, industrials have to make more efforts to adopt strategies that can help to reduce energy consumption.

This review aims to tackle this challenge and provide recent studies and advances in this area. A detailed analysis is conducted in this paper, to help manufacturers to achieve greener and more economical production, as well as academic researchers, make technical decisions about future studies. In addition, this article highlights the workpiece materials and the used cutting tools. Furthermore, this literature review focuses on optimization and modeling techniques adopted in machining operations to minimize energy consumption. Finally, as part of saving energy and respecting the environment simultaneously, this paper presents advances in lubrication and cooling techniques.

The rest of this paper is organized as follows: Section 2 analyzes existing review articles related to saving energy in the manufacturing industries. The research methodology adopted in this study is described in detail in Section 3 as well as a descriptive analysis of selected articles. Section 4 provides a structured analysis of the studied machining operations and their technological parameters such as materials and cutting tools. Section 5 gives a synthesized summary of the adopted optimization and modeling techniques. Section 6 presents the different techniques of lubrication used in machining process. Finally, the paper ends with a conclusion.

2 Preceding review studies

To date, various review papers have been published showing the significant efforts that have been made toward energy saving. Furthermore, several review papers focusing on energy consumption in manufacturing are published and each one is tackling this topic from different angles. In this section, existing review studies are investigated and compared to provide valuable insights as well as position our study. This investigation can begin with [14], which provide an overview of energy consumption in traditional and advanced manufacturing techniques. The authors analyzed the electrical energy consumed per unit volume production for conventional bulk-forming, subtractive, and additive processes. Zhang presented a literature review of energy efficiency in manufacturing systems [15]. According to this author, additional efforts should be made at global level by rapid design, construction, and reconfiguration of a machining system, or at process level by optimizing machining processes based on a selection of cutting parameters, optimizing material use, reducing cutting fluid consumption, and cutting energy. One year later, and particularly for machine tools, Yoon et al. developed a novel hierarchy of energy saving techniques for a single device level (only for machining centers), to propose steps and a direction for energy saving technologies [16]. This classification is based on "assessment and modeling," "control improvement," "software-based optimization," "cutting improvement," "hardware-based optimization," and "design for the environment." According to this study, needless peripheral device operation should be reduced in order to consume less energy, and avoid losses of energy in electrical, mechanical, and hydraulic/pneumatic.

Zhang conducted a comprehensive review on energy efficient machine tools, which included energy loss analysis, modeling, and evaluation of machine tool energy performance [17]. The author concludes that a new energy monitoring approach must be developed to improve the performance of a machine tool with various operation conditions and also minimize waste by selecting optimal machining parameters. Limitations and major barriers of existing techniques are presented as long as potential enhance energy efficiency of machine tools.

Peralta et al. presented a review on sustainability of machining process taking into account improvements of the manufacturing technologies in different phases: design, modeling simulation, optimization, and assessment [18]. Goindi et al. provided a systematic, critical, and comprehensive review of all aspects of dry machining, including also the sustainability aspect of machining [19]. This study discussed both the benefits of using dry machining and limitations such as cutting tool life, workpiece geometrical accuracies, and surface roughness. The authors also suggested directions to make dry machining more sustainable, profitable, and adaptable to product manufacturers. Zhou et al. presented a review on the use of technologies or sensors required to achieve energy efficiency in manufacturing operations at the unit process, shop floor, and supply chain levels [20].

Zhou et al. proposed a comprehensive review of the energy efficiency of machine tools [12]. This research focuses on three models: linear cutting energy consumption models based on material removal rate, detailed parameter cutting energy consumption correlation models, and process-oriented machining energy consumption models. Zhao et al. proposed a critical review of energy consumption in a machining process, the purpose of this review study is to describe predictive methods and saving strategies of energy consumption for sustainable manufacturing [21]. May et al. presented a comprehensive review on energy management in manufacturing with main axes related to energy management, namely drivers and barriers, information and communication technologies, strategic paradigms, supporting tools and methods, manufacturing process paradigms, and manufacturing performance tradeoffs [22]. Lingling et al. presented a comprehensive literature review which deals with operational strategies to improve energy efficiency of CNC machining [23]. Optimization of cutting parameters, tool path, process planning, and job shop scheduling are identified as the significant factors for energy efficiency. Moradnazhad et al. presented a comprehensive review of energy-saving strategies to increase efficiency of machining operations [24]. The relationship between process variables and energy consumption, and optimization of cutting parameters are identified and summarized.

Later on, Menghi et al. presented a systematic review on energy assessment methods and tools, three main groups according to ISO 50001 are analyzed, and relating works are synthesized (energy analysis, energy assessment, and energy-saving measures) [25]. Recently, review studies are intensified in this area with various categories like comprehensive and systematic reviews. Narciso et al. provided a literature review of methods reported in the scientific literature to investigate the potential value of industrial data using machine learning tools to achieve the objectives related to energy efficiency [26]. Pervaiz et al. focused on the role of energy consumption and then examined the influence of cutting tools, part materials and lubrication on the sustainability of the machining process [27]. The authors stated that the machining process sustainability can be enhanced by integrating different innovative approaches related to energy and material consumption of tools and parts. Aqib et al. proposed a state of the art on sustainable machining processes based on the application of various coolants/lubricants [28]. The authors then reviewed technologies for evaluating and modeling energy characteristics as well as overall strategies for saving energy. Sihag et al. presented a systematic review of machining energy focusing on six hierarchical level models and proposed directions towards sustainability of machine tools improvement based on a real time energy data monitoring [29].

Daniyan et al. focused in their review on life cycle assessment (LCA) of machine tools to minimize energy consumption and increase environmental sustainability [30]. However, the studied machine tools are not only CNC machines or conventional machines but also flexible and reconfigurable machine tools. Yusuf et al. conducted a review of energy saving models and their implementation for energy minimization problems in production and scheduling [31]. Strategies to minimize energy consumption are also discussed and minimization energy models due to the transient state of machine tools need more efforts to achieve sustainable manufacturing. Walther and Weigold gave the state of the art of approaches to predict energy consumption in industrial manufacturing, this study focuses on approaches like "system boundary," "modeling technique," modeling focus," "modeling horizon," "modeling perspective," "modeling purpose," and "model output"; however, It is not specifically devoted to machine tools or machining process [32].

This review of existing papers related to saving strategies in machine tools energy consumption shows how authors tackled this challenge from different perspectives. Moreover, it is a crucial step to present the main contributions of the present systematic review as well as differences compared to the others. This review is a step towards providing practitioners and academicians with a structured review based on approaches and techniques used to achieve minimum energy consumption for machining operations on both conventional machine tools and CNC machines. The main contributions of this paper are:

- Explores the existing research study related to machining operations and the specific studied variables as well as objective functions.
- Identifies the studied materials and different cutting conditions adopted in the literature.
- Provides a detailed analysis of optimization approaches and used parameters.
- Highlights the use of various lubrication and cooling techniques for minimal energy consumption.

3 Literature search strategy and descriptive analysis

As mentioned in the above section, our research focuses on the consideration of energy efficiency in process planning phase for material removal operations. Keyword searches are the most common method for identifying relevant bibliography; it is based on the method of combining words using common Boolean operators in order to carefully select research samples. Our search was conducted in indexed scientific electronic databases:

Web of Science (WoS): It is the oldest, most widely used and trusted database of research, publications, and quotes in the world. Based on the Science Citation Index created by Garfield [33].

- Scopus: It is a comparable multidisciplinary database that was introduced by Elsevier in November

2004 [34]. The major difference with WoS is that all Scopus content can be accessed through a single subscription without any modulation. Although Scopus also comprises content from a number of particular databases, including Embase, Compendex, World Textile, Index, Fluidex, Geobase, Biobase, and Medline [35].
- Google Scholar integrates documents from two different "collections": the open web and content from publishers and scientific societies. Google Scholar recognizes that articles can appear on the Web in different forms. For example, an article may first appear as a pre-publication on the author's homepage and then be published in a commercial publisher's journal. Google Scholar attempts to aggregate these instances and allows for the selection of the appropriate version. One of the main advantages of GS is the immediate availability of articles, no matter where they deposit [36].

The current review was based on following search keywords: ("manufacturing*" AND "cutting parameters*" AND "energy*" OR "optimization*" OR "material removal*" OR "turning*" OR"milling*" OR "drilling*" OR "lubrication*") in the article title. The results of the first search on Scopus gave us 588 documents while on Web of Science the result was 293 043 documents. Then, a temporal limitation was retained, and we only consider articles published before the year 2022. Furthermore, the articles are limited to the English language only, and articles related to the field of engineering, energy, material science, and environmental science. This type of filtering reduces the number of articles in Scopus to 516 and the number of articles in Web of Science to 105,779. For quality reasons, books and book series were excluded; at this stage, 378 journal articles are conserved. To verify that this number of articles is included in our topic and to eliminate the suspicion that they are, we read the abstract, introduction, and summary. In the next step, we checked the entire article and eliminated 240 irrelevant articles; subsequently, the number of items decreased to 166. The search process is illustrated in Fig. 1. Next, a descriptive analysis of these 151 items was performed and presented in the following sections.

4 Journals and year of publication distribution

Our research study shows that the 166 articles were published in many different scientific journals (37 journals). Thirty percent of these articles are published in the "International Journal Cleaner Production"; which can be explained by the fact that the focus of the journal is on two topics: research and practice of cleaner production. In addition, 14% of the articles are published in the "International Journal of Advanced Manufacturing Technology," due to the interest of this journal for articles dealing with topics related to advanced manufacturing technologies, and 6% are published in "International Journal of Precision Engineering and Manufacturing." The other 50% are distributed in 34 different journals, such as "Procedia CIRP," "Journal of Materials Processing Technology," "Journal of Engineering Manufacture," "Journal of Intelligent Manufacturing," and "International Journal of Production Research." The journal distribution of publications is shown in Fig. 2.

Articles related to energy efficiency and optimization of cutting parameters were first studied by Draganescu et al. [37]. Five years later, Bhattacharya et al. published a paper estimating the effect of cutting parameters on energy consumption in the milling process [38]. Since 2013, researchers have prioritized energy efficiency in the manufacturing sector, which explains the increase in the number of articles published from 1 to 7. It can be noted that the number of articles published in 2019 is very high, with a total of 27 articles. The peak of articles dropped to 16 in 2020 and 14 in 2021 due to the COVID-19 crisis. In terms of cooling and lubrication techniques, [39, 40] were the first researchers to introduce "cryogenic lubrication technology" in the turning process. Three years later, a paper on the use of MQL techniques in milling was published [41]. Later on, three researchers also used MQL in machining; six papers were published in 2020, and three papers were published in 2021. The distribution of publications by year is shown in Fig. 3.

5 Energy consumption models

Machine tool energy consumption characteristics are actually predicted with high accuracy thanks to the development of exact mathematical models; various energy modeling of the machining processes have been conducted during the last year. In this section, the relevant models are presented and these two definitions are necessary:

- Material removal rate (MRR) is the amount of material removed per time unit.
- Specific energy consumption (SEC) is the energy consumed to remove 1 cm^3 of material.

The first research paper related to machining energy modeling was proposed by Bayoumi and Hutton [42] where SEC is studied as machining efficiency. Nine years later, Draganescu et al. [37] developed a new model attempting to establish relationship between energy consumption of a vertical-milling machine and MRR for machining aluminum alloy as expressed by the following equation:

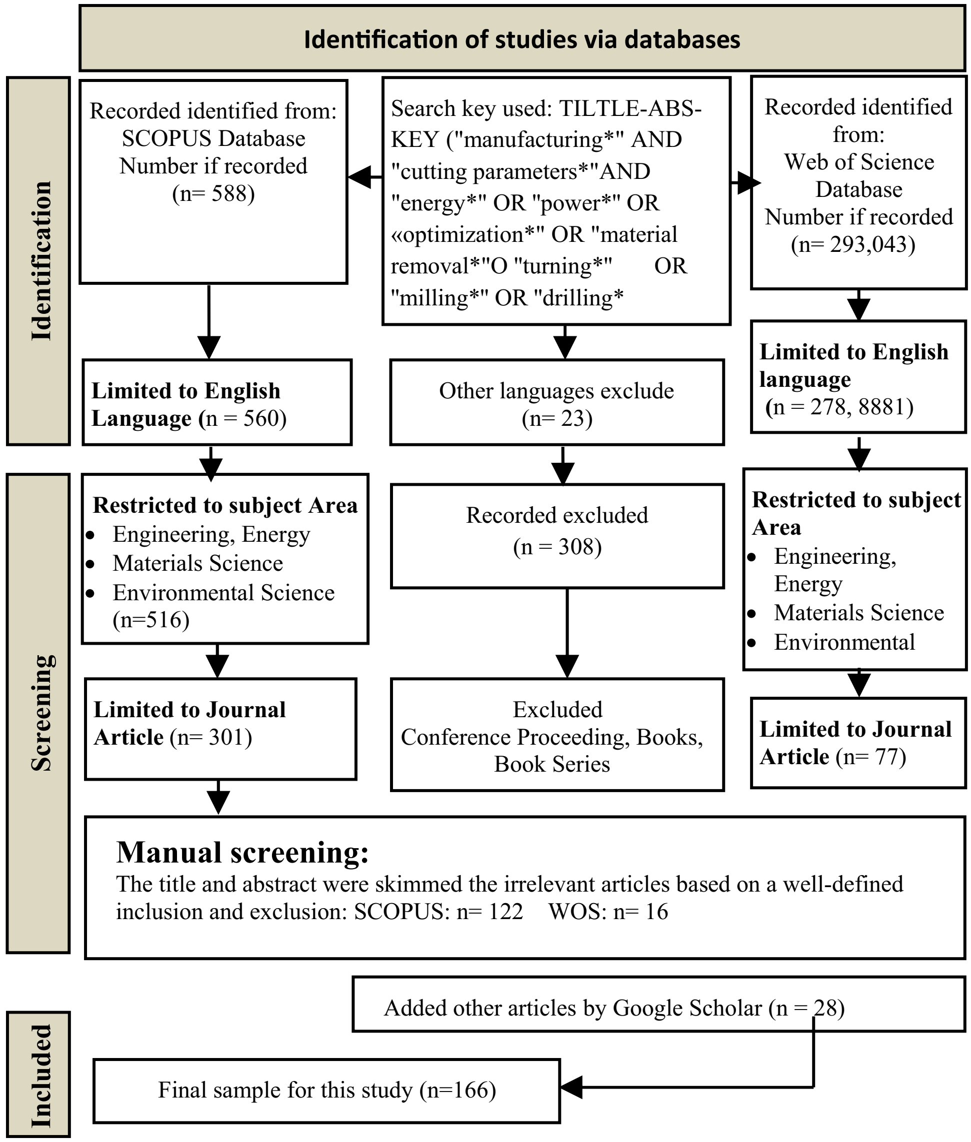

Fig. 1 Flow diagram of adopted research methodology

$$E_{cs} = \frac{p_c}{60\eta \mathrm{MRR}} \tag{1}$$

However, this work was limited to the main spindle drive motor, whereas other auxiliary motors with an efficiency less than 1 also consume energy. Gutowski et al. [9] tried to separate energy consumption into two parts: constant energy and variable one, which is proportional to the MRR. In this work, authors proposed a theoretical SEC model based on thermal equilibrium approach for turning process, the first term in their energy equation which is constant as well as the coefficient of the second term are not clearly defined and not tested on other machining processes.

Li and Kara [43] proposed an inverse model aiming to provide an accurate relationship between MRR and SEC as expressed in the following equation:

$$\mathrm{SEC} = C_0 + \frac{C_1}{\mathrm{MRR}} \tag{2}$$

where C_0 and C_1 are constants related to the studied machine tool. The proposed model is subsequently studied in milling process [43] and grinding process [42]. The authors carried out various tests to find coefficients for 8 different machines in both turning and milling processes. The results show that C_0 varies from 1.494 to 3.730 and C_1 from 2.191 to 2.445 for turning; in milling operations, C_0 varies from 2.411 to 2.845 and C_1 from 0.971 to 0.997. However, SEC in this work is measured during the cutting period; the other machining periods such as start-up, stand-by, clamping, and positioning periods are ignored; according to the authors, these periods consume less than 10% of the total energy. However, this study like the previous one is limited to the dry cut and not validated for machining hard materials which causes an

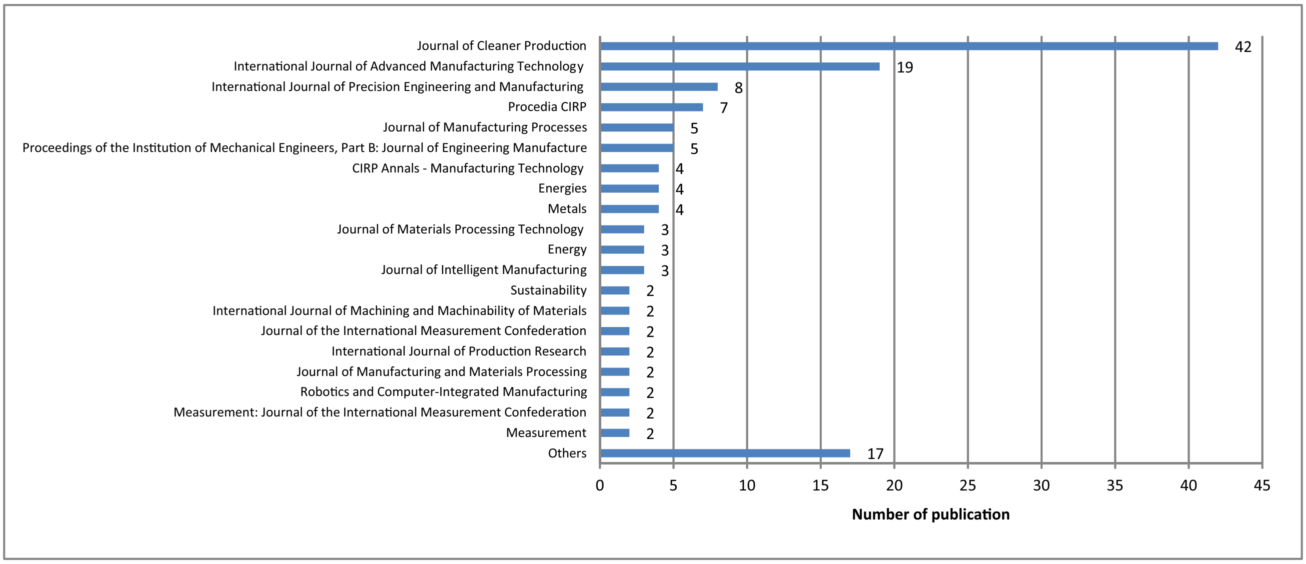

Fig. 2 Distribution of publications per journal

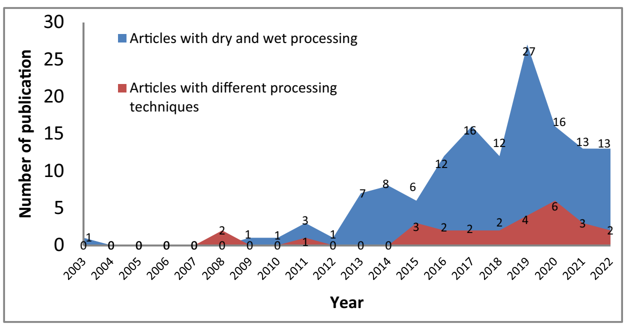

Fig. 3 Distribution of annual publication

increasing energy consumption since it requires more energy related to the coolant pump. Up to now, the authors only focus on the cutting period.

Li et al. [44] tried to take into account the effect of spindle speed "n" as major factor in the energy consumption and proposed an improved model as expressed in this equation

$$\mathrm{SEC} = k_0 + \frac{K_1}{\mathrm{MRR}} + \frac{K_2}{\mathrm{MRR}} n \tag{3}$$

where "n" is the spindle speed; k_0, k_1, and k_2 are constants related to the studied machine tool. However, in this work, the authors performed experiments under dry-cutting conditions in vertical-machine center using the AISI 1045 steel as work piece material. The coefficients k_0, k_1, and k_2 of this proposed model were 5.1175, 7.7875, and 478.797, respectively. With these values, the authors are able to determine: 66.797 W as the power loss of spindle motor and approximately no power loss of the feed motor. Zhao et al. [45] adopted this model and tried to study the effect of saving energy on surface quality with the same machining process and material workpiece. Cutting parameters such as "side cutting depth," "feed rate," "cutting depth," and "spindle speed" are optimized for both surface roughness and SEC separately.

Balogun et al. [46] investigated the effect of tool wear, chip thickness, nose radius, and cutting environment on SEC for both turning and milling operations. Liu et al. [47] developed a new model to predict energy consumption in turning process, where total machining period is broken down into three types of periods: start-up periods, idle periods, and cutting periods. Liu et al. [48] proposed a new model focusing on the standby period, air-cutting period, cutting period, and energy consumption of tool changing. The aim of this work is to estimate the SEC with better accuracy, and the developed model is expressed in the following equation:

$$\mathrm{SEC} = \frac{E_{\mathrm{total}}}{\mathrm{MRV}} = \frac{\int P_{in}(t)dt}{\mathrm{MRR}.t_c} \tag{4}$$

where the term E_{total} aggregate all electrical energy consumption (J), P_{in} (t) is power loss of a machine tool (W), and t_c is cutting time (s). In this model, the total energy consumption is broken into four elements: "standby period," "air-cutting period," "cutting period," and "tool changing period." Finally, a multi-objective optimization technique is proposed which is on particle swarm to find a trade-off point between "processing time" and "energy efficiency" under technological constraints of the machining process like "tool life," "surface roughness," cutting parameters, cutting force as well as machine power limits.

The authors conclude that in the case of machining AISI 1045 steel, an increasing level of MMR leads to a low SEC and a slight increase of processing time since changing cutting tool is needed in this case. Therefore, an optimum solution to satisfy both processing time and SEC can be reached. However, it is not clear which parameter directly affects energy consumption since the MMR can be obtained from various values of cutting parameters. Huang et al. [49] focused only on the acceleration of spindle system and their impact on consumed energy in turning, milling, and drilling operations.

Zhou et al. [12] developed an improved cutting power model which is the influence of spindle speed, MRR, and cutting parameters on machining power during the milling process. The proposed SEC in a milling process is expressed in Eq. 5:

$$\mathrm{SEC} = C_1 n^{C_2} + C_3 \frac{n}{\mathrm{MRR}} + \frac{C_4}{\mathrm{MRR}} \tag{5}$$

where $C_1 \sim C_4$ are coefficients related to material and machine tool. In this study, the authors investigated the previous works related to SEC and dealt with cutting parameters as independent variables in order to obtain greater accuracy of energy modeling. This study shows that SEC mainly depends on MRR and "n" with a little sensitivity with regards to V_f, a_e, and a_p for milling process. However, tool wear is not considered in this study which could show the impact of higher machining parameter on SEC.

Chen et al. [50] developed a new model where energy is broken down into two elements: "direct energy" and "indirect energy." The first term (E_{direct}) is the energy consumed during the machining process mainly by spindle and feed motors. The second one (E_{indirect}) refers to the embodied energy of cutting tools and cutting fluids. The total energy is the sum E_{direct} and E_{indirect}. Therefore, the SEC is expressed as follows:

$$\mathrm{SEC}_{\mathrm{total}} = \frac{E_{\mathrm{direct}} + E_{\mathrm{indirect}}}{\mathrm{MRV}} \tag{6}$$

where "MRV" is the material removal volume (mm^3). For "E_{direct}," energy is decomposed to "startup energy," "standby energy," "spindle acceleration/deceleration energy," "air cutting energy," and "cutting energy." The last one is depending on cutting parameters. The authors conclude that among the parameters of MRR, "cutting speed" is the most significant parameter that influences the specific energy consumption. The effect of tool wear is not investigated, and its impact on energy consumption is not considered. Imani et al. [51] studied the milling operation considering machine tools as a thermodynamic system and expressed power consumption as a function of spindle speed "n," feed rate, and the MRR.

A recently published paper is dealing with the total energy as a separated energy consumption of a machine tool: "start-up," "standby," "spindle acceleration," "idle," "rapid positioning," "air-cutting," and "cutting" [52]. Total energy is expressed as:

$$\begin{aligned} E_{\mathrm{total}} = & \int_0^{t_{stp}} P_{\mathrm{statup}}(t)dt + \int_0^{t_{std}} P_{\mathrm{standby}}(t)dt + \int_0^{t_{stpacc}} P_{\mathrm{acc}}(t)dt + \int_0^{t_{rpd}} P_{\mathrm{rapid}}(t)dt \\ & + \int_0^{t_{idle}} P_{\mathrm{idle}}(t)dt + \int_0^{t_{tc}} P_{tc}(t)dt + \int_0^{t_{\mathrm{air}}} P_{\mathrm{air}}(t)dt + \int_0^{t_{\mathrm{cool}}} P_{\mathrm{cool}}(t)dt + \int_0^{t_{\mathrm{cut}}} P_{\mathrm{cut}}(t)dt \end{aligned} \tag{7}$$

In this model, the authors tried to overcome the limitations of the previous models by subdividing the cutting energy consumption module into the constant MRR machining process "CMRR" and variable MRR machining process "VMRR." Two operations are carried out: turning, where "cutting speed," "feed rate," and "cutting depth" are fixed for the CMRR, end facing operations, "cutting speed" was changing continuously until the tool reaches to the center of the part, and therefore, spindle speed "n" was selected with feed rate and cutting depth as process parameters in VMRR. Aluminum "Al 6061" is adopted as material workpiece for both the dry and wet conditions, and the fitting coefficients of the proposed model for different energy modules are determined with high accuracy, according to the authors.

6 Machining process optimization with energy consideration

The main objective of this section is to provide a concise and focused summary of each material removal experiment published between 2003 and 2022. This summary includes machining process, cutting tool materials, workpiece materials, cutting conditions, objective functions, and so on.

6.1 Distribution of studied machining processes

Machining operations have been considered as the core of manufacturing since the industrial revolution. The process of removing material from a workpiece is performed using cutting tools and machine tools to achieve the desired product dimensions with better surface roughness. Additionally, the processes comprise traditional techniques like turning, milling, grinding, drilling, and finishing. Our study shows that 91 researchers adopted the turning process and 60 used the milling process. On the other hand, the drilling process is only studied in 5 papers. It should be noted that 8 researchers attempted to investigate two processing techniques, 6 are for turning and milling, and three are for drilling and milling. Finally, one article found in our study that used simultaneously three types of material removal operations (milling, turning, and drilling). Figure 4 shows the machining process distribution from 2003 to 2022.

6.2 Adopted objective functions for energy efficiency

In the context of minimizing production cost, consumption of natural resources, and improving product quality, manufacturers and researchers are dealing with different objective functions which are presented in Fig. 5. It is noticed that 34% of researchers have focused on reducing "energy consumption," while 27% aimed at reducing "surface roughness." According to Aryan et al. [53], surface roughness is the best parameter for evaluating product quality. "Material removal rate" is considered an important indicator to measure productivity in CNC machining [54]; therefore, 12% of researchers minimize MRR to reduce the cost of waste recycling (chips) and ensure energy efficiency. Moreover, 7% and 5% of the studied papers are dealing with "power consumption" and "machining cost," respectively. Additionally, 5% of studies have used "energy efficiency" as an objective function. Furthermore, in some studies up to 10% of researchers include "tool wear," "CO_2 emissions," and "machining time" as objective functions to minimize.

6.3 Decision variables and optimization parameters

This section presents the common materials used in workpiece machining experiments. One of the most often studied materials for machining is steel and its variants. This is explained by the fact that 66% of researchers used this category. Alloy steel, carbon steel, tool steel, and stainless steel are the four categories of investigated steel. It is clear from Fig. 6 that carbon steel is frequently employed (38% of researchers). While 10%, 9%, and 8% of researchers, respectively, adopted stainless steel, alloy steel, and tool. In addition, 20%, 15%, and 3% of studies, respectively, used aluminum, titanium, and cast iron. The other materials such

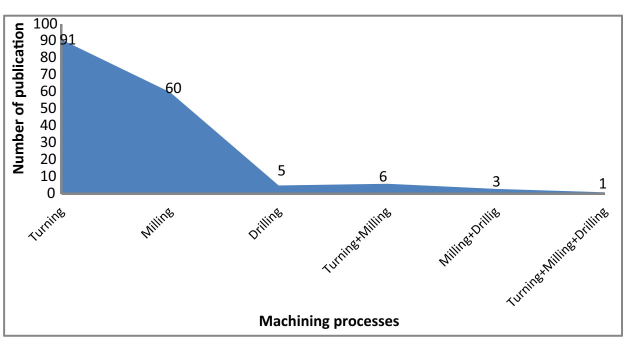

Fig. 4 Distribution of machining process

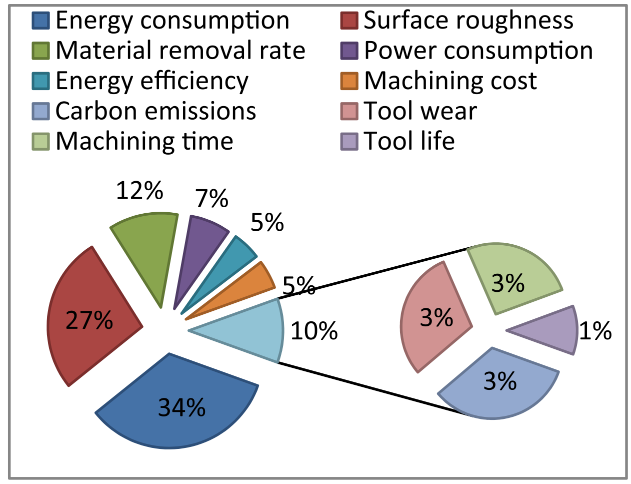

Fig. 5 Objective functions for energy efficiency

as composite, brass, and copper alloy were less adopted (6% of researchers). These materials are summarized in Fig. 6.

6.3.1 Experiments conducted on AISI 1045 material

To perform the machining process on the previously discussed materials and achieve the intended objective, many input parameters must be taken in consideration. Details of the experimental design of AISI 1045 are listed in Table 1. The result presented in this table makes it clear that carbide tools are frequently used for machining AISI 1045 steel, although high-speed steel (HSS) tools are rarely used in these experiences. In comparison to other techniques such as milling and drilling which are used with 38% and 6% of researchers, respectively, turning is one of the most commonly used processes (56% of researchers) for cutting and finishing AISI 1045. In this process, it is crucial to select cutting parameters with absolute accuracy. Generally, the most studied cutting parameters are feed rate (f), axial depth

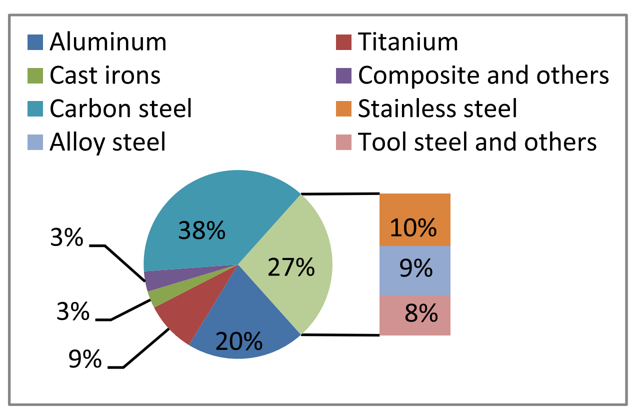

Fig. 6 Materials used in machining

Table 1 Summary of research conducted on AISI1045

Authors	Process			Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling		Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	SEC	Others	
[55]	√			Carbide		√	√	√	√			√		√					
[44]		√		Carbide	√			√	√	√	n	√	√					CE	Width of cut
[56]	√			Carbide	√	√	√	√	√					√					Feed rate, depth of cut
[57]	√			Carbide/uncoated carbide	√		√	√	√									CF	Feed rate, depth of cut
																		T	Cutting speed
													√						Cutting speed
[58]	√			Uncoated carbide	√		√		√			√				√			Feed rate
[48]		√		Carbide	√			√	√		n						√		
[59]	√			Carbide		√							√				√		
[60]	√			Carbide	√		√	√	√		SRS						√		Feed rate
[61]	√			Carbide			√	√	√			√							Feed rate
													√			√			Depth of cut
[62]	√			Coated carbide	√			√	√		TW							CO_2, PT, PC	TW
[50]		√		Carbide		√		√	√	√	n				√			Machining efficiency	Cutting speed
[63]	√			Carbide		√		√	√		n							CE, PRT	Depth of cut
												√							Feed rate
[64]		√			√		√	√	√	√	n							PRT, UEC	
[65]							√	√	√								√		Depth and width of cut
[66]		√	√			√		√	√	√	SRS							MTE	
[67]	√					√		√	√		n			√					
[68]	√				√			√	√		d			√					
[69]		√		Carbide			√	√	√		d				√				
[13]	√			Carbide	√				√		SRS							CEC	SRS and feed rate
[70]	√			Coated / Uncoated carbide	√			√	√	√								Energy loss	
[71]	√						√	√	√		N			√				Quality of process	
[72]			√			√			√		d, n			√					
[73]		√		Carbide			√	√	√	√	N				√			PC	Cutting velocity, feed rate
[74]		√		Carbide	√	√		√	√	√		√	√					CE	Width of cut
[75]		√		HSS / Carbide			√	√	√		N, m							Energy footprint, PT	
[76]		√					√	√	√								√	PC	
[77]		√			√		√	√	√		n	√				√		MC	Feed rate

Table 1 (continued)

Authors	Process			Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling		Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	SEC	Others	
[78]		√	√	Carbide/coated carbide			√	√	√	√						√			
[79]		√			√		√	√	√	√					√			PRT, CO_2 emissions	Large feed rate, large width of cut
[80]	√				√		√	√	√									CO_2, PC	
[81]	√					√	√	√	√		N			√				Machining quality	
[82]	√	√		Carbide			√	√	√	√	*n*			√					
[83]	√	√				√	√	√	√	√				√				CF, PRT	
[84]	√			Carbide	√		√	√	√			√				√			Depth of cut
[12]		√		Carbide			√	√		√	n		√				√	CP	
[85]	√						√	√	√									Energy footprint	
[86]		√				√		√	√	√	n				√			PRT	
[87]		√				√	√		√		n			√				Processing cost	
[88]	√					√		√	√		N, n			√				CO_2, PT, PC	
[38]				Coated carbide			√	√	√			√				√			Cutting speed
[89]		√		Carbide	√			√	√	√	n	√		√					
[90]	√			Carbide		√	√		√									CO_2, cost	Feed rate, cutting speed
[91]	√				√		√	√	√		TW	√			√			SCE	
[92]	√			Carbide	√		√	√	√								√		Feed rate, depth of cut
												√							Feed rate
[93]	√			Carbide	√	√	√	√	√		n			√				PT	Cutting speed
[94]	√			carbide	√		√	√	√							√			
[45]	√			Carbide		√		√	√		n							SCE	
[95]	√				√		√	√	√			√		√				Machining cost CO2emissions	
[96]	√			Carbide	√			√	√		n	√		√					
[97]		√				√	√		√			√					√	Machining time	

of cut (a_p), cutting speed (V_c), spindle speed (n), and radial depth of cut (a_e). Although, tool wear (TW), number of cutting passes (N), spindle rotation speed (SRS), number of cutting layers (m), and cutting tool diameter (d) are less taken in consideration.

According to our research, 23% of studies were to select optimal machining parameters in order to save energy with the objective functions such as specific energy consumption (SEC), cutting energy consumption (CEC), unit energy consumption (UEC), cutting energy (CE), energy consumption (EC), machining energy consumption of machine tools (MTEs), specific cutting energy (SCE), energy loss, and energy footprint. There are other objectives such as energy efficiency (EE) and machining efficiency that 10% of researchers optimized. Additionally, 19%, 10%, 9%, 3%, and 1% of research aim to minimize surface roughness (Ra), power including power consumption (PW) and cutting power (CP), CO_2 emissions, cutting force (CF), and temperature (T), respectively. Besides, material removal rate (MRR) and quality are the objective functions that 8% and 2% of researchers are trying to maximize, respectively. Also, 5% of studies aim to reduce costs including processing costs, carbon emission costs, and machining costs; thus, 3% aim to minimize time including production time (PT) and processing time (PRT).

It is noticed that the authors take into consideration in their experiments surface roughness and cutting tool wear. Moreover, the dominance of the AISI 1045 could be potentially explained by the fact that this kind of material is widely used in automobile sector as well as other industrial sectors. The next subsections deal with the other materials.

6.3.2 Experiments conducted on stainless steel material

The results of the stainless steel machining experiments are listed in Table 2. This table clearly shows that the machining of stainless steel is performed with different cutting tools such as carbide, diamond, cubic boron nitride (CBN), polycrystalline cubic boron nitride (PCBN), and high-speed steel (HSS). Carbide is the most common material tool for machining various stainless steel (AISI 304, AISI 410, AISI 316, and AISI 420). Seventy-nine percent of the authors used these materials for turning and 21% for milling in both wet and dry conditions. In most of the experiments conducted using this sort of material, V_c, f, a_e, and a_p have been widely used, while cutting force, spindle speed, tool material, and nose radius were also used in some of these experiments. Reducing energy including EC, SEC, and SCE are the main objectives of 28% of researchers; However, Ra and CF are the objectives of 20 and 8% of researchers, respectively. In addition, 10% and 8% of studies were to maximize MRR and tool life, respectively. Moreover, reducing power factor (PF), quality, temperature (T), heating rate, and PW are the goal of one paper, while cost reduction or PRT is an objective function of 5% of studies.

6.3.3 Experiments conducted on other materials

In recent years, a significant number of researchers have used different materials other than stainless steel and AISI 1045 for machining parts including aluminum, titanium, cast iron, composites, and copper, among others. Carbide, diamond, HSS, and CBN are the cutting tools used for machining these materials. Based on the results shown in Table 3, several studies performed turning and milling operations while a few studies (less than 4%) used the drilling process. In these processes, the most cutting parameters selected are cutting speed, feed, axial, and radial depth of cut. It should be noted that some researchers use additional parameters such as tool nose rotation radius (R), number of cutting tools (Z), tool angles (relief angle, inclined angle, helix angle, rake angle), tool wear (TW), nose radius (r), cutting tool diameter (d), number of cutting passes (n), burnishing force (BF), diameter of the burnishing ball (D), edge radius, relief angle, and spindle speed (n). These studies aim to find machining parameters that can reduce energy on the one hand (37% of researchers), including SEC, SCE, net cutting energy (NSCE), active energy consumed by machine (AECM), energy loss, and energy demand, and on the other hand minimize Ra (18 of studies) and maximize EE or MRR (14% of studies). Other studies (8%) optimize cutting parameters to reduce time, including cycle time, RTP, PT and machining time (MT), while 7% of studies reduce active power consumed by the machine (APCM), cutting power consumption (CPW), and cutting power (CP). In addition, some works (3%) aimed at decreasing CO_2 emissions or tool wear (TW). Wear rate, resultant force (RF), CF, PF, torque, and flank are the functional objectives that one article have reduced. One percent of researchers identified machining rate (MR), production rate (PR), quality, and tool life as maximum performance objectives. The experimental details realized with various materials are summarized in Table 3.

6.4 Experiments with nontraditional lubrication techniques

The authors emphasize the need to improve machining process in terms of economy, environment, and product quality. To achieve these objectives, several studies conducted to save energy take into account new constraints on cooling and lubrication systems. The results of the experiments made with different cooling lubrication techniques are presented in the Table 4. This table shows that conventional cutting materials such as HSS, carbide, cermets, and advanced cutting materials such as CBN, diamond, and ceramic are used for material removal operations.

Table 2 Summary of research conducted on stainless steel

Authors	Process		Material	Cutting tools	Cutting conditions		Process variables						Objective				Factors influencing the goal
	Turning	Milling			Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	SEC	Others	
[98]		√	AISI 304	Carbide		√	√	√	√		Cutting force	√			√	Tool life	Cutting fluid
[99]	√		AISI 304	Coated carbide	√		√	√	√			√	√				Feed rate, depth of cut
[100]	√		AISI 304			√	√	√	√			√	√		√		Cutting speed
[101]		√	AISI 304		√		√	√	√		Nose radius	√		√		PF	Feed rate, cutting speed
[102]	√		AISI 410	Diamond, carbide			√	√	√						√	PRT	
[103]	√		AISI 316	CBN	√		√	√	√			√		√			Feed rate
[104]	√		AISI 316	Uncoated carbide	√	√	√	√	√					√		Cost, Quality	Feed rate
[82]	√	√	AISI 304	Carbide			√	√	√	√	n			√			
[105]	√		AISI 304 AISI 410				√	√	√						√	PRT, PC	Cutting speed
[106]	√		AISI 304	Uncoated carbide	√		√	√	√	√		√	√			SCE	
[107]	√		AISI 420	Coated carbide	√		√	√	√		Nose radius	√		√		Tool life, CF	
[108]	√		AISI 304	High-speed steel		√	√	√	√			√	√			PW, CF, heat rate, T	
[109]	√		AISI 304	Coated/uncoated carbide	√		√	√			Tool material					Tool life, CF, SCE	

Table 3 Summary of research conducted on other materials

Authors	Process			Material	Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	TW		
[110]	√			AISI 52,100	Coated carbide	√		√	√	√			√						CF, Flank wear	Cutting speed
[111]	√			AISI 316	Uncoated carbide	√		√	√	√							√	√		Cutting speed
													√							Feed rate
[112]	√			PEEK-CF30	Coated carbide	√		√	√	√			√						CPW	Depth of cut
[113]	√			AL-6061 T6	Carbide		√	√	√	√			√		√					Feed rate
[10]	√			AL-7075	Carbide		√	√	√	√		r					√		Tool life	Cutting speed
[56]	√			AISI 1018	Carbide	√	√	√	√	√					√					Feed rate, depth of cut
[114]	√			AL-6061 T6	Silicon carbide		√	√	√	√									SEC	Feed rate, depth of cut
													√							Feed rate
[115]	√			EN 353 alloy steel	Coated carbide		√	√	√	√		r				√			PF	Depth of cut
																			AECM	Feed rate
[116]	√			Mild steel, aluminum, brass	High speed steel	√		√	√	√				√	√				RF	
[117]		√		AISI 1024		√			√	√	√	n			√				PRT, CO_2 emissions	Cutting speed
[118]	√			AISI 4340	Coated carbide	√			√	√			√				√			Depth of cut
														√						speed
[119]	√			POM-C	Carbide	√		√	√	√			√							Feed rate
														√					CF, CPW	Depth of cut
[120]		√		High alloy steel			√	√		√	√				√				PT	Axes feed, radial depth of cut
[60]	√			QT 500–7	Carbide	√		√	√	√		SRS							SEC	Feed rate
[121]		√		AISI 1035		√		√	√	√					√					Cutting speed, feed rate, and depth of cut
[122]		√		AISI steel	Coated carbide	√		√	√	√	√	TW							NCSE	TW
[123]		√		CGI	Coated carbide	√	√	√	√	√		TW			√					Cutting speed
[124]	√			AL-7075	Coated carbide			√	√	√				√				√		
								√		√		r	√							
[125]	√			9XC				√	√	√		Inclined angle	√		√				MR	Feed rate

Table 3 (continued)

Authors	Process			Material	Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	TW		
[126]			√	Galvanized steel	Steel			√	√	√		Helix angle	√							Cutting speed
[127]		√		AL-7075	Solid carbide		√	√		√		r		√	√				Quality	
[128]	√			AL-6061		√		√	√	√			√		√					Feed rate, depth of cut
[129]		√		AISI 1050		√		√	√	√	√								SEC	
[54]		√		N.S.(*)					√	√	√	n		√					CP	
[130]	√			AISI 5132,BDS 4880	Steel	√			√	√		n							SEC	Feed and depth of cut
[131]		√		Aluminum alloy			√		√	√	√	n					√		PRT	
[70]	√			AISI 80-55–06, AL-6061	Coated / Uncoated carbide	√			√	√	√								Energy loss	
[53]	√			AL-6082	High speed steel	√			√			Flank angle, n							MT	Feed rate
														√						Cutting speed
					Carbide														MT	Cutting speed
														√						Feed rate
					Cobalt									√					MT	Cutting speed
[23]		√		N.S.(*)	HSS				√	√	√	n			√					
[132]		√		AISI H13		√		√		√		n, r		√					SCE	Depth of cut, feed rate
[133]		√		Al-7050-T7451		√		n	√	√		Cutter radius, Flank angle				√				Cutter radius
[134]	√			Ti-6Al-4 V	Uncoated carbide	√		√	√	√			√	√					SCE, Wear rate	Cutting speed, feed rate
[135]	√			AISI 5140				√	√	√					√				MC, CT	Feed rate
[102]	√			AISI 410, AISI W110, AISI 4340				√	√	√									SEC, PRT	
[136]		√	√	N.S.(*)					√	√	√	n							CO_2 emissions, PRT	
[137]	√			AISI 4140				√		√		Edge radius, rake angle, relief angle, r				√			SCE	

Table 3 (continued)

Authors	Process			Material	Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	TW		
[138]	√			EN 353 alloy steel	Carbide		√		√	√		r, n	√	√		√			AECM, PF, APCM	
[103]	√			AISI 316	CBN	√		√	√	√					√					
													√							Feed rate
[139]	√			N.S.(*)				√	√	√					√				Noise emission, Cost	depth of cut
[140]	√			AL-6061 T6				√	√	√			√	√					SCE	Cutting feed
[141]	√			Ti-6Al-4 V	Uncoated carbide	√		√	√	√									SCE	Feed rate
																			CP	Cutting speed
[142]		√		Titanium alloy	Carbide			√	√	√			√	√			√	√		
[37]		√		ALSi10Mg																
[143]	√			AL-6061, AL-6082, AL-7075	Carbide			√	√										CO_2 emissions	
													√							Depth of cut
[144]		√		Manganese steel				√	√	√	√								CO_2 emissions	Depth of cut
[145]		√		Al-6061					√	√	√	n			√					TW
[146]		√		AL-7075					√	√	√	n							MT	Width of cut
															√					Spindle speed
[147]	√			Ti-48Al-2Cr-2Nb, Ti-6Al-4 V		√	√	√	√	√									PRT, cost, energy demand, CO_2	
[43]	√	√		Brass, mild steel		√	√	√	√	√	√				√					
[148]		√		Aluminum alloy	Carbide		√		√	√		n	√		√				MT	
[149]		√		Aluminum alloy				√	√	√	√								PR, MC, SCE	
[150]	√			AL-6061	Carbide	√		√	√	√									SEC	Feed rate
[151]		√		N.S.(*)			√		√	√	√	n		√		√			Spindle average temperature	
			√							√										
	√									√	√									

Table 3 (continued)

Authors	Process			Material	Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	TW		
[152]		√		AL-7050-T7451	Coated carbide	√		√											SCE	
[153]	√			AISI 1040		√		√							√					
[154]	√			N.S.(*)				√	√	√					√					
[155]		√		Copper alloy											√				Cycle time	
[105]	√			AISI 1018, AISI 5140				√	√	√									SEC, PRT, PC	Cutting speed
[156]	√			40XC			√	√	√	√		Inclined angle	√			√			CT	Feed rate
[157]		√		Titanium alloy		√	√	√	√	√					√					
[158]	√			POM-C	Carbide			√	√	√									SCE	Feed rate, cutting speed
[159]	√			AISI 1018	Carbide	√	√	√	√	√					√					Feed rate, depth of cut
[160]	√			AISI 1040	Coated carbide		√	√	√	√		r					√			Cutting speed
[161]	√			Aluminum alloy	Coated carbide	√		√		√			√				√			Feed rate, cutting speed
[162]		√		AL-6061 T6		√		√	√	√			√						SEC	feed rate, depth of cut
[163]		√		Aluminum alloy	High speed steel				√	√		n	√		√					
[164]		√		AISI 52,100	PCBN	√		√				Z, R							SCE	
[165]		√		CGI		√		√	√	√			√		√					Cutting speed
[166]			√	AISI 4140	Carbide		√	√	√			Tool type	√						Torque, thrust force	
[93]	√			Aluminum, HT250	Carbide	√	√	√	√	√		n			√				PT	Cutting speed
[167]	√			EN-GJL-350	Carbide			√	√	√		N			√				PC	
[168]		√		Al-7050	Carbide	√			√	√	√	n	√	√	√					
[169]	√			Ti-6Al-4 V	Uncoated carbide	√		√		√									SCE	
[170]	√			Al 6061	Carbide	√	√	√	√	√					√					
[171]		√		Aluminum alloy	Carbide		√	√	√		√	n							SEC, machining cost	
[172]	√			Ti 6Al-4 V		√		√	√	√			√		√					Feed rate
																		√		Cutting speed

Table 3 (continued)

Authors	Process			Material	Cutting tools	Cutting conditions		Process variables					Objective							Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	V_c	a_p	f	a_e	Others	Ra	MRR	EC	EE	PW	TW		
[52]	√			Al 6061		√	√	√	√	√					√					
[173]		√		Al 6061-T6		√		√	√	√			√						SEC	
[174]	√			Ceramic		√		√		√					√					
[175]		√	√	Q235			√	√	√	√					√				CO2emissions	
[176]	√			AISI P20	Carbide		√	√	√	√	√		√	√	√					
[177]	√			AISI 4340	Coated/uncoated carbide	√		√		√		Tool type	√		√					Cutting speed Tool type
[178]		√		30CrMnSiNi2A steel		√		√	√	√	√		√						SCEC	

Half of the researchers performed turning operations, while 35% and 8% used milling and drilling processes, respectively. These processes are carried out in various cutting conditions such as dry machining, minimum quantity lubrication (MQL), cryogenic cooling, hybrid cooling (MQL + LN2), high-pressure coolant (HPC), hybrid nanofluid-assisted MQL (HNFMQL), mono nanofluid assisted MQL (NFMQL), nanofluid small quantity cooling lubrication (NFSQCL). Cutting speed, feed, axial depth of cut, radial depth of cut, spindle speed, lubricant flow rate, cutting environment, and nose radius are the parameters selected in the material removal operations. These studies aim to find processing parameters that can reduce surface roughness on the one hand (27% of researchers) and on the other hand reduce energy (21% of studies), including CSE, ACE, EC, and SCE, and maximize MRR (8% of studies). Other studies (6%) optimized cutting parameters to save time; including cutting time (CT) and cycle time, while 3 papers maximized tool life. Additionally, one paper was aimed at reducing burr height, flank wear, T, thrust, and CO_2 emissions. PW and TW were the objective functions for 8% and 6% of researchers, respectively.

This table shows that MQL and NFMQL are gaining more attention in recent years compared to cryogenic for saving energy. Moreover, papers deal with hard materials to demonstrate the interest of using these advanced cooling technologies compared to conventional methods.

7 Modeling and optimization techniques for energy saving

For mechanical manufacturing processes, optimal cutting parameter selection is considered to be one of the most essential energy conservation strategies. Newman et al. noted that the variation of the cutting settings causes a noticeable difference in the energy consumption during machining operations [203]. About 6–40% of overall energy consumption can be decreased by optimizing cutting conditions, tools, and tool trajectory [86]. In addition, reasonable selection of processing parameters can also help to improve tool life, to decrease production costs and CO_2 emissions, and to enhance production efficiency [204]. Optimization of cutting parameters in machining operations (turning, milling, drilling) is carried out in two steps: modeling the relationship between input–output and process parameters and determining the optimal cutting parameters [205]. In this section, the adopted optimization and modeling techniques are presented with their used parameters.

Table 4 Summary of studies conducted with various cutting conditions

Authors	Process			Material	Cutting tools	Cutting conditions			Process variables					Objective						Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	Others	V_c	a_p	f	a_e	Others	Ra	MRR	SCE	EC	CF	Others	
[179]		√		Al-6061T6	Uncoated carbide			MQL	√	√			MQL flow rate, table feed rate	√	√					Depth of cut
																			Flank wear	Feed rate
[180]	√			Inconel-825	Coated carbide			MQL	√	√	√		MQL	√					CT, TW	MQL
[181]	√			Titanium (grade-2) alloy	Coated CBN			MQL	√		√		Approach angle	√				√	TW	
[182]	√			AISI 431		√		MQL	√	√	√			√					CSE	
[41]		√		EN AW 5754	High-speed steel	√		MQL	√	√	√		Lubricant flow rate	√					PW	
[183]	√			Ti-6Al-4 V	Uncoated carbide	√	√	MQL	√	√	√						√			
[184]		√		AISI 1045		√		MQL	√	√	√		Flow rate			√				Flow rate
[185]			√	PEEK-GF30	Carbide			MQL	√		√		n, temperature		√		√		Thrust force	
[186]	√			AISI 1040	Ceramic	√	√	MQL	√	√	√			√						Tool type, cutting environment,
															√					Tool type, cutting velocity, feed, and depth of cut
																	√			Cutting velocity, feed and depth of cut, Cutting environment
[187]		√		AISI 4140	Carbide			MQL	√	√	√		MQL flow rate	√						MQL flow rate
																√				Cutting speed
[188]	√			AISI 1045	Coated carbide		√	MQL,HPC	√	√	√					√				Depth of cut, cutting speed, feed rate
[189]		√		AISI 1045	Carbide			NFSQCL	√	√	√	√		√	√				ACE	Width of the cut
[190]		√		AISI H13	Carbide			NFMQL	√	√	√		Workpiece hardness	√					CT, CP	

Table 4 (continued)

Authors	Process			Material	Cutting tools	Cutting conditions			Process variables					Objective						Factors influencing the goal
	Turning	Milling	Drilling			Dry	Wet	Others	V_c	a_p	f	a_e	Others	Ra	MRR	SCE	EC	CF	Others	
[191]			√	AISI 1045	Coated high-speed steel			NFMQL			√		Flow rate, n	√						Feed rate
																			CF	Vibration amplitude
																			Burr height	n
[192]	√			Haynes 25 alloy				NFMQL	√		√			√			√		CO_2	Feed rate
[193]	√			AISI 51,200	Uncoated carbide			HNFMQL MQL NFMQL	√	√	√			√			√		Tool life, cost, PW	
[194]	√			Ti-6Al-4 V		√	√	Cryogenic	√	√	√			√	√	√			TW	Feed rate
[195]	√			Ti-6Al-4 V	Coated carbide	√		Cryogenic	√		√			√					CT	
[40]	√			AISI P-20	Coated carbide			Cryogenic	√	√	√		r, cutting environment						PW	Cryogenic environment
[39]	√			AISI P-20	Coated carbide			Cryogenic	√	√	√		r	√				√	Tool life, PW	
[196]		√		AISI 1060	PCBN, diamond, HSS	√	√	Cryogenic	√		√			√		√		√		Cutting speed, feed rate
[197]		√		Ti-6Al-4 V	Carbide	√	√	Cryogenic	√	√	√						√		PW, TW	
[198]	√	√		AISI 1045, Ti-6Al-4 V				NFSQCL, Cryogenic						√	√	√			Tool life, PW	
[199]	√			Ti-6Al-4 V	Coated carbide	√		Cryogenic, LN2 + MQL	√	√	√			√			√	√	MC, T, Cycle time	
[200]	√			AISI 4340	Uncoated cermet			MQL-TNL	√	√	√			√				√	TW	
[201]	√			AISI 1045				MQL	√	√	√								Machining force, cutting energy	
[202]		√		AlSi7Mg	AlTiN PVD coated	√	√	MQL	√	√	√			√					SEC	Depth of cut

7.1 Design of experiments (DoE) techniques

DoE is a statistical method for organizing and designing experiments that enables the collection of the greatest amount of data with the minimum number of experiments and the least number of resources. Generally, there are a large number of experimental designs in the literature such as Latin hypercube, Box-Behnken design (BBD), Taguchi methods, and central composite design (CCD). The studies using the experimental design are summarized in Table 5. In this table, Taguchi is widely used in experimental design (86% of researchers), while CCD is one of the most commonly used second-order models [206], used by 3 researchers. In addition, two articles used design experts, while one article adopted robust optimization and D-optimal designs, respectively.

Taguchi method requires only a small number of orthogonal test combinations, which greatly improves the efficiency of the experimental design [207]. In addition, it is an integrated approach that takes into account all the variability of materials and processes at the design stage [86]. Taguchi method is used to produce the most high-quality products at the lowest cost. It is a conventional method that allows the effective and efficient design of experiments and analysis of parameters affecting the process in the shortest possible time [53].

Taguchi uses a loss function to establish quality specifications; the value of the loss function is converted into a signal-to-noise ratio (S/N). This ratio is a powerful indicator value which offers the possibility to find the importance of the parameters involved in the studied process. It is the ratio between the signal intensity and the noise intensity, usually expressed in decibels. S/N analysis is based on three separate quality criteria which are "higher-the-better," "lower-the-better," and "nominal-the-better." For each level of process parameters, the signal-to-noise ratio (S/N) is based on the "orthogonal array" experiment, which significantly reduces the "variance" of the experiment by controlling the optimal parameter settings. The orthogonal array tables offers a set of balanced (minimum) experiments and the required results as an objective function for optimization, facilitating data analysis, and predicting the best results [208].

The experimental details using Taguchi method are summarized in the Table 6. This table shows that the lower-the-better (LTB) quality characteristic type is more useful to researchers than the higher-the-better (HTB), while the nominal-the-better (NTB) quality characteristic type is not adopted. Forty-two percent, 36%, and 11% of researchers adopted the dimension of the orthogonal table L27, L9, and L16, respectively; however, only one paper used L35, L25, L22, and L11. Additionally, "$\boldsymbol{V_c}$," "$\boldsymbol{a_p}$," and "$\boldsymbol{f}$" are the most three used common cutting parameters. It should be mentioned that 83% of the experiments were conducted for three levels, 14% for four levels, and one article for five levels.

Bilga et al. adopted in their study Taguchi techniques and ANOVA for selecting the optimal cutting parameters in order to reduce energy consumption in the turning process [115]. Fratila and Caizar used Taguchi methodology to optimize cutting fluid flow and milling parameters (axial depth of cut, feed rate, cutting speed, etc.), for $AlMg_3$ machining with high-speed steel (HSS) cutting tool to achieve better surface roughness and lower cutting power [41]. The results show that the optimal cutting conditions for reducing energy consumption are minimum depth of cut as well as feed rate, minimum cutting speed, and maximum lubricant flow rate. Qasim et al. adopted Taguchi method and ANOVA to reduce cutting force, temperature, energy consumption, and deformed chip shape [57]. Bagaber and Yusoff evaluated the machining performance of coated carbide cutting tool for machining AISI 316 hard steels under dry turning technology [103]. The influence of cutting parameters such as cutting speed, feed rate, and depth of cut is determined using the central composite plane. The results adopted with ANOVA technique showed that the energy consumption is cutting speed proportional to cutting speed and tool wear, feed rate most significantly affects energy consumption and surface roughness, followed by cutting depth. Bhattacharya et al. examined the impacts of cutting parameters such as cutting speed, feed rate, and depth of cut on surface roughness and energy consumption using Taguchi techniques [38]. The results showed that power consumption and surface roughness are significantly affected by cutting speed.

Finally, in this powerful technique, the length of the orthogonal table depends on factor levels, and it is shown

Table 5 A summary of DoE-based energy optimization research

Experimental design	Reference articles
Taguchi method	[38, 40, 41, 52, 57–59, 70, 72, 78, 82, 86, 99, 109, 112, 115, 118, 133, 141, 150, 160, 161, 164, 166, 170, 172–174, 176–178, 182, 188, 189, 201, 202]
CCD	[39, 40, 114]
Design expert	[116, 169]
Robust optimization	[71]
D-optimal design	[98]

Table 6 Taguchi parameters

References	Factors					Level of each factor			Dimension of the orthogonal table							Nature of the ratio S/N		
	v_c	a_p	a_e	f	Others	3	4	5	L_{35}	L_{27}	L_{25}	L_{22}	L_{16}	L_{11}	L_9	HTB	LTB	NTB
[112]	√	√		√		√				√							√	
[109]	√			√	Tool material	√									√	√		
[159]	√	√		√		√									√		√	
[115]	√	√		√	*r*	√				√						√	√	
[57]	√	√		√	*α*			√			√							
[118]		√		√	*n*	√				√						√	√	
[60]	√	√		√			√							√				
[70]	√	√		√			√						√			√	√	
[53]		√			*n*	√				√						√	√	
[133]	√	√			*n*	√									√		√	
[72]				√	*d, n*	√				√								
[138]	√	√		√	*r*	√				√						√		
[141]	√	√		√		√									√			
[78]	√	√		√		√									√		√	
[82]	√	√		√		√									√			
[150]	√	√		√		√				√							√	
[12]		√	√	√	SRS	√			√									
[86]		√	√	√	*n*	√				√							√	
[38]	√	√		√			√						√				√	
[160]	√	√		√	*r*	√				√							√	
[164]	√				*R*	√									√			
[59]	√	√		√		√				√								
[58]	√	√		√		√				√							√	
[61]	√	√		√		√				√								
[187]	√			√	Flow rate	√						√					√	
[189]	√	√	√	√		√				√							√	
[182]	√	√		√	*n*		√						√					
[41]	√	√		√	Lubricant flow rate	√									√		√	
[56]	√	√		√		√									√		√	
[113]	√	√		√		√									√		√	
[201]	√	√		√		√				√								
[176]	√	√		√	*n*	√									√			
[170]	√	√		√		√				√								
[172]	√	√		√		√									√			
[173]	√	√		√		√									√			
[202]	√	√		√			√						√					

from the previous table that "three levels" is the most adopted. Additionally, "V_c" and "a_p" are studied in almost all these papers related to DoE; this is shows that the authors are more aware of the effect of these variables on energy saving.

7.2 Modeling techniques

For process planning phase, methods for modeling input–output process parameters can be economically advantageous. As shown in Table 7, there are a number of popular modeling methods, including response surface methodology (RSM), radial basis function (RBF), artificial neural network (ANN), kriging, fuzzy logic theory, and bottom-up approach (BUA). In this table, it can be noticed that RSM is the most used method by researchers (82% of researchers). This method was proposed by Box and Wilson [209], and it is based on the adaptability of empirical models to experimental data and offers good empirical modeling performance. It is based on a set of mathematical and

Table 7 Modeling techniques

Techniques	Reference articles
RSM	[10, 37, 39, 40, 43, 58, 59, 61, 63, 74, 82, 86, 92, 92, 94, 100, 104, 106, 107, 110, 114, 119, 125, 129, 137, 142, 143, 146, 157, 162, 177, 180, 185–187, 187, 190, 191, 196]
ANN	[45, 148, 184]
Kriging model	[128, 132, 190]
Fuzzy logic theory	[102, 126, 174]

statistical techniques to provide the relationship between responses and input decision variables in order to maximize or minimize response attributes. Furthermore, 7% of work used ANN which solved complex input–output and in-process parameter relationships for machining control problems [205]. Moreover, "kriging" model that entails approximating the output from deterministic data and defining the outcome as the realization of a stochastic process [210] is used by three papers. Finally, the fuzzy set used by two papers plays a vital role in modeling input–output relationships and in-process parameters.

Campatelli et al. optimized process parameters using a RSM to minimize energy consumption in milling process [129]. The results showed that the optimal radial engagement value which minimizes specific energy related to cutting efficiency reached 1 mm, and the optimal feed rate per tooth value is 0.12 mm. Camposeco-Negrete improved cutting parameters for turning AISI 6061 T6 aluminum using RSM and ANOVA to reduce machine tool energy consumption and surface roughness [114]. The results of this study showed that feed rate and depth of cut are the most important variables for reducing total specific energy consumption to 14%, while feed rate is the most important variable for reducing surface roughness to 360%.

Rajesh investigated the impact of cutting settings on machine energy consumption and tool life using RSM and desirability analysis [10]. This work showed that multiresponse optimization by desirability analysis reduces energy consumption to 13.55% and increases tool life to 22.12%. The most crucial parameter is cutting speed, which is followed by feed rate, depth of cut, and nose radius. Tlhabadira et al. developed a mathematical model for energy consumption optimization using response surface methodology (RSM) [157].

7.3 Mono-objective and multi-objective optimization

One of the most prevalent and important issues in both engineering development and scientific research is optimization issues. Optimization can be divided into two groups based on the number of optimized objective functions: single-objective optimization and multi-objective optimization issues.

7.3.1 Mono-objective optimization

Several techniques used by various researchers are listed in Table 8; these methods are generally based on meta-heuristic search including genetic algorithms (GA), neighborhood cultivation genetic algorithm (NCGA), Tabu search (TS), simulated annealing (SA), gray wolf optimization (GWO), artificial bee colony (ABC), and particle swarm optimization (PSO), and evolutionary strategy (ES). In the following subsection, parameters of these techniques are well presented. Methods that researchers adopted in recent years are critically evaluated in the section below.

7.3.2 Multi-objective optimization

Multi-objective optimization has many different approaches that have been proposed. However, this study only sought to the methods that were used in our reference papers, which were published between 2003 and 2021, as seen in Table 9. Forty-two percent and 29% of the researchers, respectively, used nondominated genetic sorting algorithm II (NGSA-II) and grey relational analysis (GRA). Multi-objective particle swarm optimization algorithm (MOPSO), multi-objective simulated annealing (MOSA), multi-objective genetic algorithm mode II (MOGA-II), multi-objective particle swarm optimized neural networks system (MOPSONNS), multi-objective improved teaching–learning-based optimization

Table 8 Optimization techniques

Optimization techniques	Reference articles
GA	[64, 66, 79, 83, 94, 142, 149, 180]
PSO	[50, 54, 123, 144, 184, 190]
ABC	[59, 164]
SA	[13, 68]
ES	[76]
NCGA	[156]
TS	[65]
Direct search method	[85]

Table 9 Multi-objective optimization method

Optimization techniques	Reference articles
NSGA-II/NSGA-III	[55, 62, 63, 80, 90, 91, 96, 97, 104, 137, 139, 151, 163, 189, 198]
GRA	[74, 77, 89, 100, 101, 112, 189, 194, 195]
MOPSO	[86]
MOSA	[23]
MOGA-II	[179]
MOPSNNS	[124]
MO-ITLBO	[69]
AMOPSO	[73]
AENNC	[127]
MRL	[105]
MOGWO	[93]

Table 10 Hybrid optimization method

Optimization techniques	Reference articles
AHP-TOPSIS	[199]
GRA-AHP	[134, 140]
DMS-PSO	[135]
PSO-FA	[192]
GRA-RSM	[58]
APSO-NSGA-II	[87]
CS-GWO	[145]
GRA-WOA	[108]

(MO-ITLBO), adaptive multi-objective particle swarm optimization (AMOPSO), augmented-enhanced normalized normal constraint (AENNC), meta-reinforcement learning (MRL), and multi-objective grey wolf optimization (MOGWO) are adopted for each paper.

NSGA is a popular method for multi-objective technique; it is widely adopted in various industrial optimization problem. As for manufacturing, it can give to practitioners to select the adapted solution from the pareto front. Whereas, the problems studied in these papers cannot be generalized to other similar machining process, since different machining parameters could not be the same. Here, sensitivity analysis is critical at this stage and could solve this problem.

7.3.3 Hybrid optimization method

The literature review indicates that some researchers used hybrid optimization methods; this approach is based on two techniques in order to achieve a rapid convergence of high quality. Khan et al. used the hybrid particle swarm optimization-firefly algorithm (PSO-FA) to solve nonlinear MOO problems with multiple variables for reducing specific energy, carbon emission, and product cost [175]. Furthermore, Gupta et al. introduced analytic hierarchy process (AHP) combined with TOPSIS to assess sustainability [199]. The decision criteria are cutting temperature, surface roughness, cutting force, energy consumption, and carbon emissions. Younas et al. used grey relational analysis (GRA) coupled with AHP to find the optimal combination of parameters for optimization of MRR, Ra, and SCE in turning process [134]. This study showed that the combination of these two techniques provides the best result. Song et al. proposed a MOO model for turning operations, aiming to simultaneously reduce energy consumption, machining cost, and machining time [135]. To solve this formulation, the authors proposed a dynamic multi-swarm particle swarm optimizer (DMS-PSO). Tanvir et al. used a hybrid whale optimization algorithm (WOA) to optimize cutting parameters for turning processes [108]. The results of this experience show that thanks to this hybrid algorithm, the number of experiments is greatly reduced and an optimal parameter combination is obtained. Xiao et al. optimized cutting parameters using adaptive particle swarm optimization (APSO) and NGSA-II in order to reduce energy efficiency and cost [87]; this approach assists manufacturers to make between energy usage and processing costs decision tradeoff. Kant and Sangwan used GRA with RSM to develop multi-objective predictive models to reduce power consumption and surface roughness [58]. The hybrid optimization methods are listed in Table 10.

Hybrid optimization techniques allow to develop powerful optimization tools. In one hand, the use of hybrid techniques helps decision makers to select optimal solution adapted to the process. In other hand, it can overcome the limitation of some optimization method, such as premature convergence, high computational time, and stability.

7.4 Meta-heuristics

7.4.1 Genetic algorithm (GA)

GA is based on the natural evolutionary process to solve the optimization problems, and its operating principle is "survival of the fittest." Existing literature shows that GA are effective tools for obtaining global optimums [212]. GA using basic operators: population size, number of iterations, number of generations, crossover rate, and mutation rate. The values of the GA parameters implemented by the researchers in their optimization code are shown in Table 11. It can be seen that the population size parameter takes the following values: 20, 24, 40, 50, 60, 100, and 500. Some researchers set the number of iterations to 200 and 300. For the crossover rate, the researchers set it to 5 values, 0.6, 0.7, 0.8, 0.9, and 1. Finally, the mutation rate takes a minimum value of 0.001 and a maximum value of 0.2.

Table 11 GA parameters

References	Method	Population size	Number of iterations	Number of generations	Crossover rate	Mutation rate
[180]	GA	20	1		0.7	0.05
[117]		100		50		
[66]		100	300		0.9	0.05
[64]		40		200	0.8	
[83]		100		300	0.7	0.7
[132]	AMGA	40		40	0.9	
[156]	NCGA	24		44	1	0.01
[137]	NSGA-II	20		20	0.9	
[62]		100		300	0.8	0.2
[63]		50				
[151]		100	200		0.7	0.05
[80]		500	200	1000		0.001
[139]		60			0.8	0.05
[90]		100			0.6	0.1
[96]		300		100	0.7	0.2

GA optimization technique is proposed to optimize machining parameters in multi-pass dry milling processes [117]. The objective in this study is to find a trade-off between processing time, energy consumption, and carbon emission through principal component analysis and regression analysis based on experimental data. Zhou et al. suggested using GA to optimize the cutting parameters for the end milling process [64], The aim of this work is to minimize the cutting time and energy consumption per unit of material. To reduce computation time of machining sequence search; Hu et al. adopted two algorithms which are deep first search (DFS) and GA [66]. Reducing energy consumption of the machine tool was used as objective function of this search; DFS can accurately find the optimal global solution. In contrast, GA generally takes less time to reach the best or near-optimal solution. As a result, GA is 30% or less likely to find the global optimal solution, and due to the nature of meta-heuristics, it often returns a near optimal solution.

7.4.2 Particle swarm optimization (PSO)

PSO is a meta-heuristic that allows finding the optimal solution in a reasonable processing time, except for large instances where the computation is intensive and requires considerable computing time. This method is based on “social interactions” between “agents” called “particles,” to reach a given objective in a common search space where each particle has a certain capacity for memorizing and processing information. This stochastic optimization meta-heuristic was proposed by Kennedy and Eberhart [213]. The correct configuration of the parameters of the PSO algorithm is a difficult task since it requires evaluating a large number of parameter combinations to find the most suitable settings. Population size, number of iterations, inertia weight (w), learning factors (C_1 and C_2), and velocity ranges (V_{min} ,V_{max}) are the parameters of the PSO, PSO-FA, MOPSO, and AMPSO algorithms. Table 12 lists the different parameter values adopted by some researchers; it is important to note that the selection of population size depends on the problem to be solved; in this study, there were 4 population sizes,

Table 12 PSO parameters

Reference	Method	Population size	Coefficients		Inertia weight(w)		Velocity ranges		Number of iterations
			C_1	C_2	w_{min}	w_{max}	V_{min}	V_{max}	
[144]	PSO	30	1.4944	1.4944	1				50
[184]			> 0	> 0					300
[192]	PSO-FA	50	1.5	2	0.5	1.4			100
[86]	MOPSO	60	1	1	0.4	0.9	− 1.5	1.5	
[73]	AMPSO	60	0.9	1.2	0.67				200

30, 50, and 60. Regarding the learning factor, there are in some cases where C_1 and C_2 have the same value, such as $C_1 = C_2 = 1.4944$ and $C_1 = C_2 = 1$. In other cases, C_1 was set to 1.5 and 0.9 and C_2 was set to 2 and 1.2. Researchers did not specify a maximum velocity $V_{\max}$ that could be used as an overall velocity limit affecting the PSO. Furthermore, some researchers have used in their experiences 50, 100, 200, and 300 iterations.

Deng et al. proposed the PSO approach to optimize a multi-objective optimization model, with the minimum processing time and highest carbon utilization efficiency defined as objectives; compared to the GA, PSO is more useful method in terms of accuracy and fast convergence [144]. The results of this study showed that the optimized machining parameters significantly reduce the carbon emission, processing time and remarkably improve the carbon utilization efficiency. Jang et al. used the PSO algorithm to minimize the specific cutting energy in a milling process [184]. Li et al. first analyzed the energy consumption characteristics of the multi-pass surfacing and then used the AMPSO algorithm, which aims to improve energy efficiency and minimize production costs [73]. To improve the efficiency of the PSO algorithm, Song et al. developed a DMS-PSO [135]. This multi-objective optimization model is aimed at simultaneously minimizing the energy consumption, machining cost, and cutting time of turning operation. The goal of using PSO is to obtain a fast convergence speed. However, PSO performed well in the first iteration, but it was inefficient to reach a near-optimal solution, and there was a risk of falling into a locally optimal solution. Due to these two problems, Li et al. proposed a new modified MOPSO algorithm [86]. In this study, the modified MOPSO was used to analyze the trade-offs between several objective functions: processing time and energy efficiency of the CNC machining process.

7.4.3 Cuckoo search (CS)

CS is a new nature-inspired meta-heuristic algorithm developed by Yang and Deb [214]; it is an effective approach for solving global optimization problems. CS is based on the parasitism of some cuckoo species. Moreover, the algorithm is improved by Levy flights [215], instead of a simple isotropic random walk. Recent research suggests that CS may be more efficient than PSO and GA [214].

Chen et al. used a MOCS method to solve a milling optimization model including tool and cutting parameters [75]. The objective of this approach is to reduce production time and energy consumption. For effective resolution, CS might be combined to other techniques. Zhang et al. proposed a hybrid cuckoo-gray wolf (CS-GWO) algorithm to find the best cutting parameters, intending to consume the minimum energy [145].

7.4.4 Tabu search (TS)

TS is a neighborhood method, using techniques that avoid local optima and cycles. This meta-heuristic has been developed by Fred Glover [216] and it is very successful due to the very satisfactory results obtained on a large number of problems. TS was proposed to solve multi-objective optimization models [65]; for the AISI 1045 steel milling process, this model is designed to maximize energy efficiency and reduce production time. The number of partition neighborhoods was set to 50, the length of the Tabu list was set to 7, the number of iterations was set to 100, and the number of initial solutions was set to 50.

7.4.5 Simulated annealing (SA)

SA is a meta-heuristic method that simulates the annealing process in metallurgy in order to guide the system from any initial state to the ground state with the lowest internal energy, it was created by Kirkpatrick et al. [217]. SA may be used to find the approximate value of the global minimum of a multivariate function [13]. The SA parameters are initial temperature (T_0), end temperature (T_e), temperature decreases function (T_k) and length of Markov chain (L_c). Luoke et al. used SA to find the optimal spindle speed (SRS) and feed rate that achieves the minimum machining energy consumption (MEC) of machine tools for turning operations [13]. The experimental results showed that SA can obtain the overall optimal value in a shorter computation time when the spindle speed and feed rate are 0.1 and 0.001, respectively. The optimal solution reduced the ECM to 19.28%. Hu et al. employed SA to optimize cutting parameters in order to reduce energy consumption in end face turning operation [68]. This study showed that SA has more than 96% probability of achieving the overall optimal value and can reduce energy consumption to 14.03%.

7.4.6 Grey wolf optimization (GWO)

GWO is a recently developed technique compared to the other ones, it is proposed by Mirjalili et al. [218]. This algorithm is inspired from the social hierarchy and hunting techniques of grey wolves in nature. The leadership hierarchy is divided into four types of grey wolves (alpha, beta, delta, and omega). Zhao et al. proposed the MOGWO method to find the best cutting parameters for a three-piece turning process [93]. Energy consumption and production time are optimized using these factors.

It is noticed that, in this kind of evolutionary algorithm, optimal solution is directly based on the value of some parameters: population size, crossover, and mutation rates. However, variation of these values has a great impact on the optimal solution which justifies the need of tuning these parameters in order to select the adapted value for the problem to be optimized. Moreover, the authors used a fixed number of iterations to obtain the optimal solution instead of "stopping criterion" which guarantee a better accuracy of optimal solution.

8 Optimization with cooling/lubrication techniques for energy saving

In manufacturing process, cutting fluids are used to increase tool life, decrease surface roughness, and improve overall machining process efficiency. Minimum quantity lubrication (MQL) technology improves overall machining performance in terms of cutting fluid consumption [188]. The cutting environment is an important parameter for energy consumption compared to others, as pump power in wet conditions and compressor power in MQL conditions are added for measuring the total energy [186]. To achieve environmentally friendly manufacturing, dry cutting is highly recommended [62]. In addition, dry cutting accounts for a large portion of processing costs [110], therefore, dry cutting is used for sustainable machining [211]. Figure 7 shows the different lubrication techniques used by the researchers between 2003 and 2021.

On the other hand, conventional emulsions with cooling/lubricating characteristics play a vital role to reduce tool wear, and to improve product quality, and machinability [199]. In this sense, several researchers used emulsions in the machining process namely Lu and Wang who used a mixture consisting of 5% emulsifier and 95% water by volume for the turning process of AISI 1045 steel [51, 77]. In the drilling operation of the same material, Jia et al. used a plain water-based emulsion [72]. Priarone et al. performed the turning experiments of Ti-48Al-2Cr-2Nb and Ti-6Al-4 V alloys through traditional flood cooling technology [147].

However, the massive use of emulsions is dangerous from the ecology point of view, as well as air, and water resources, which leads researchers to explore new ways to introduce biodegradable oil as an alternative to mineral-based

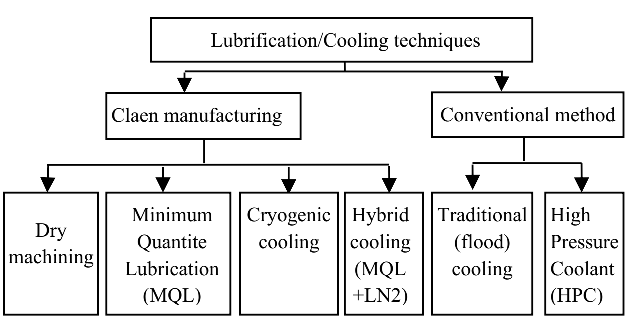

Fig. 7 Techniques for lubrication and cooling

emulsions. In the experiment of turning steel AISI 1045 [59], used a cutting fluid containing 3% vegetable oil emulsion. Also, Pereira et al. used the wet cutting lubricant which is a soluble biodegradable emulsified oil used to deal with aluminum alloy Al 7075 for milling operations [127]. In addition, Kara and Li conducted turning and milling experiments on two materials namely brass and mild steel under dry and wet cutting [43]. The coolant used in this experience contains almost no minerals and is mixed with water.

Researchers adopted various cooling/lubrication techniques in a single machining process. Mia et al. studied three types of cutting conditions for turning process of Ti-6Al-4 V alloy such as dry condition, single and double jet of cryogenic liquid nitrogen [195]. In the dry condition, no external cooling or lubrication is used, while in the single-jet condition, the cryogenic liquid nitrogen jet is sprayed onto the cutting surface, while in the double-jet condition, the jets are sprayed onto the cutting surface and the flank surface simultaneously. The results showed that cryogenic cooling jet-assisted turning operation is better than dry cutting in terms of the clean manufacturing environment, energy-saving, and improved cutting mode performance. Simultaneous application of two cryogenic nitrogen jets on the cutting surface and the flank surface is more effective than the application of a single cryogenic jet.

Gupta et al. discussed the potential of dry, LN2, and LN2 + MQL machining in turning process Ti-6Al-4 V titanium alloy [199]. The experimental results showed that in dry turning, the main costs include tooling costs and energy costs during operation. However, in the case of LN2 and LN2 + MQL cooling, these costs will be reduced because the tool wear is negligible and better results are obtained. Analysis of the results shows that LN2 plus MQL cooling consumes lower energy than dry cooling and LN2 cooling. Therefore, compared to dry cooling and LN2 hybrid cooling, LN2 + MQL gives the best results. Priarone et al. performed the turning of a Ti-6Al-4 V alloy under three conditions of wet, MQL, and dry cutting [183]. For wet cutting, the flood cooling system provides a water emulsion. For MQL, a plant aerosol delivered by compressed air is applied to the cutting area. Results showed that wet turning reduces overall energy requirements at higher cutting speeds, while dry turning is the better option to offset lubricant consumption. Under the selected cutting conditions, MQL does not appear to be a favorable solution. This is due to the consumption of air compressors, which are one of the most expensive equipment in industrial facilities. Mozammel Mia performed the end milling operation of AISI 1060 steel under the application of conventional oil and cryogenic condition through the tool by liquid nitrogen, in addition to dry cutting [196]. The experimental results showed that cryogenic cooling is more effective than dry cutting and conventional cutting oil. This cooling technology can improve surface quality, reduce the cutting force, improve the surface quality and reduce specific cutting energy, thereby improving durability. Cica et al. used three cutting conditions for the AISI 1045 steel turning process, namely flood cooling, MQL, and HPC environment, to evaluate the impact of the cooling/lubrication technique on SCE [188]. The experiments showed that the use of flood cooling increases the SCE requirements, compared to the MQL and HPC environments.

In recent years, the concept of minimal lubrication by nanofluid is adopted by Teimouri et al. [191] in the drilling process of AISI 1045 carbon steel. Also, Khan et al. dissolved smaller size graphite nanoparticles to produce graphite nanofluid in order to make the cutting fluid more efficient [193]. Thus, end milling experiments of AISI 1045 steel were conducted in MQL nanofluid conditions. The different cooling/lubrication techniques that can be used in machining processes namely: turning, milling, and drilling are summarized in Table 13.

The cutting condition proportions in material removal process between 2003 and 2022 are shown in Fig. 8. It can be clearly seen in this figure that half of the researchers employ the dry method due to its many benefits for durability, cleaner manufacturing, and human health. Additionally, 31% of machining processes use cutting fluids. Finally, over the past few years, 20% of research is moving to the use of modern cooling and lubrication technologies, such as HPC, MQL, cryogenic cooling, and hybrid cooling.

It is shown that from this literature review that, dry cutting was considered as a clean and an efficient technology compared to processes that use coolant liquids until the development of new techniques such as MQL, NFMQL, HPC, and cryogenic lubrications. The MQL cutting

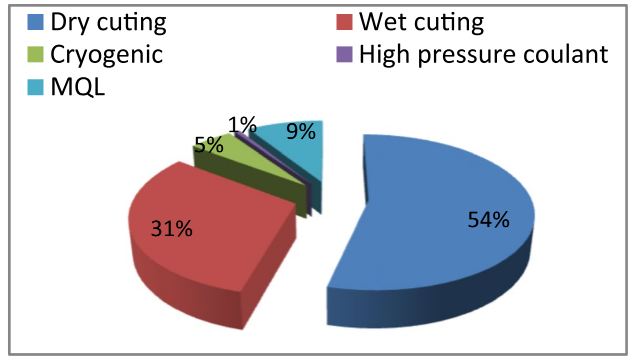

Fig. 8 Cutting condition proportions adopted

conditions enhance the cutting tool life with maximum MMR and then minimize the SEC. The use of NFMQL in machining could save up to 50% of consumed energy as it uses 1000 times less of liquid, an advanced step toward saving energy is made when the hybrid NFMQL is proposed. Moreover, a mixed lubrication based on LN2 and MQL showed an improvement of energy saving, around 16% more compared to dry cutting. The other lubrication technology such as cryogenic is also a promising cooling method since it is known as nontoxic and nonexplosive liquid, and gives also better results in terms of energy saving, productivity as well as, product quality. Finally, the HPC machining environment is attracting recently researchers, however, more efforts are needed to investigate the effect on surface roughness and energy consumption since additional power is consumed to activate the hydraulic system.

Table 13 Type of lubrication

Dry cutting	Without lubrication	[13, 41, 43, 44, 48, 50, 52, 53, 56–58, 60, 60, 62, 64, 68, 70, 74, 77, 79, 84, 91–96, 96, 99, 101, 103, 104, 106, 109–112, 112, 116, 117, 121–123, 128–130, 132–134, 133, 134, 141, 147, 150, 152, 153, 157, 159, 161, 168–170, 172–174, 173, 174, 182–184, 183, 194–197, 195, 196]
Wet cutting	Water-based emulsion	[55, 72, 147, 183]
	Vegetable-based oil emulsions	[59, 98, 127, 188]
	Conventional flood lubrication	[113, 114, 159, 196]
	Water-based cutting fluid	[43, 81, 88, 151, 186]
	Others cutting fluid	[10, 50, 56, 66, 67, 83, 86, 90, 97, 100, 104, 115, 120, 123, 131, 138, 148, 156, 160, 171, 175, 176]
Cryogeniccooling	Liquid nitrogen mono/dual jets	[39, 40, 194–196, 199]
MQL	NFSQCL	[189, 198]
	HNFMQL	[193]
	NFMQL	[190–193]
	Oil-based lubricant	[41, 179–181, 181, 184, 187]
	Others	[182, 183, 186, 188, 201, 202]
High pressure coolant		[188]
Hybrid cooling	LN_2+ MQL	[199]

9 Conclusions

In recent years, the industrial sector is gradually oriented toward a sustainable and cleaner production due to the increase in energy consumption and environmental pollution. In this context, our study provides a literature review of energy efficiency in the machining processes. In this review paper, we focused in three electronic scientific databases which are Web of Science, Scopus, and Google Scholar. A descriptive analysis of 166 papers published between 2003 and 2022 is clearly presented, a preliminary analysis shows that these articles are published in 37 scientific journals, and 2019 was an excellent year due to the large number of publications. Furthermore, the most used machining process is the conventional machining known as turning. Additionally, half of the researchers adopted AISI 1045 steel because of its low cost as well as ease of machining and "carbide" is the most commonly used cutting tool material in the studied research papers.

Studies over the past few decades have sought to provide more practical strategies for achieving energy and environmental objectives. It has been observed that the energy consumption for machining can be saved by optimizing the cutting parameters. Moreover, a reasonable selection of processing parameters can also contribute to extend tool life, reduce production costs, decrease carbon emissions, and improve production efficiency. Optimization of process parameters in machining operations (turning, milling, and drilling) is carried out in two steps: modeling the relationship between input–output and process parameters and determining optimal cutting conditions.

This work provides an overview of machining optimization methods with energy consideration, which are divided into five types, namely modeling techniques, experimental methods, multi-objective and single-objective optimization methods, and hybrid techniques optimization. Detailed definitions and descriptions are provided for all these optimization methods in order to present the regularly adopted parameters. Scientific research shows that "Taguchi" is the most widely used design of experiments (DoE) method (86% of researchers) and "response surface methodology" is the most popular modeling approach (82% of researchers). Additionally, meta-heuristics such as "genetic algorithms" and "particle swarm optimization" are commonly used for single-objective optimization, and half of researchers address multi-objective problems using "NSGA II" technique.

Since material removal process generates a lot of heat and consumes a lot of energy. In this case, an appropriate cooling liquid or cutting liquid should be used. Two types of lubrication/cooling technologies were identified from the literature review, including those used for clean manufacturing (e.g., dry machining, minimum quantity lubrication (MQL), cryogenic cooling, Hybrid cooling "MQL + LN2"), and conventional methods such as (traditional cooling, HPC). Some of these methods generate waste as well as environmental and social damage. Researchers have attempted to address machining components by integrating the three general dimensions of sustainability (economic, ecological and equity). Thus, based on experiments studied between 2003 and 2022, they reveal that revolutionary cryogenic technology offers a cost-effective and ecological solution; it is a promising metal-working technology in terms of energy saving.

Data availability Not applicable.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest Not applicable.

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