Front. Mech. Eng. 2021, 16(2): 221–248
https://doi.org/10.1007/s11465-020-0627-x

REVIEW ARTICLE

Xingzheng CHEN, Congbo LI, Ying TANG, Li LI, Hongcheng LI

Energy efficient cutting parameter optimization

Abstract Mechanical manufacturing industry consumes substantial energy with low energy efficiency. Increasing pressures from energy price and environmental directive force mechanical manufacturing industries to implement energy efficient technologies for reducing energy consumption and improving energy efficiency of their machining processes. In a practical machining process, cutting parameters are vital variables set by manufacturers in accordance with machining requirements of workpiece and machining condition. Proper selection of cutting parameters with energy consideration can effectively reduce energy consumption and improve energy efficiency of the machining process. Over the past 10 years, many researchers have been engaged in energy efficient cutting parameter optimization, and a large amount of literature have been published. This paper conducts a comprehensive literature review of current studies on energy efficient cutting parameter optimization to fully understand the recent advances in this research area. The energy consumption characteristics of machining process are analyzed by decomposing total energy consumption into electrical energy consumption of machine tool and embodied energy of cutting tool and cutting fluid. Current studies on energy efficient cutting parameter optimization by using experimental design method and energy models are reviewed in a comprehensive manner. Combined with the current status, future research directions of energy efficient cutting parameter optimization are presented.

Keywords energy efficiency, cutting parameter, optimization, machining process

Received September 2, 2020; accepted December 14, 2020

Xingzheng CHEN, Li LI
College of Engineering and Technology, Southwest University, Chongqing 400715, China

Congbo LI (✉)
State Key Laboratory of Mechanical Transmission, Chongqing University, Chongqing 400044, China
E-mail: congboli@cqu.edu.cn

Ying TANG
Department of Electrical and Computer Engineering, Rowan University, Glassboro, NJ 08028, USA

Hongcheng LI
College of Advanced Manufacturing Engineering, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

1 Introduction

Manufacturing is a pillar industry supporting the national economy. It creates considerable wealth but consumes substantial energy and causes serious environmental pollution. Taking China as an example, the manufacturing industry accounts for approximately 30% of the gross domestic product while it consumes more than 45% of the total energy and is responsible for approximately 30% of the total CO_2 emissions [1]. Among the various industry sectors, mechanical manufacturing industry is extremely energy intensive. It consumes more than 70% of the total energy of manufacturing industry [2]. Although the mechanical manufacturing industry consumes a huge amount of energy, its energy efficiency is relatively low. Numerous studies indicate that the energy efficiency of mechanical manufacturing process is usually less than 30% [3]. Hence, effectively reducing energy consumption and improving energy efficiency of the mechanical manufacturing industry are urgent problems to be solved.

In a mechanical manufacturing workshop, machine tools are the executors used to handle the workpieces [4]. They are the primary energy consumers. In China, approximately 7 million machine tools are available, and their total energy consumption is more than twice of the installed capacity (22.5 million kW) of the Three Gorges hydropower station, which is the largest hydro power station in the world [5]. To reduce energy consumption of machine tools, there are mainly two methods. The first method is to design energy efficient machine tools and replace the existing ones in the mechanical manufacturing workshop. In this area, the International Organization for Standardization published a standard "*Machine tools — Environmental evaluation of machine tools-Part 1: Design methodology for energy-efficient machine tools*" in

2017 to give guidelines for designing energy efficient machine tools [6]. The detailed methods for designing machine tool components, such as spindles, hydraulic system, and chip conveyor, are included in this standard. However, obsoleting all the energy intensive machine tools in a short time is a difficult task for mechanical manufacturers due to the investment of these facilities. Hence, optimizing the machining process with energy consideration becomes an alternative method.

In the work reported by Newman et al. [7], they found that the energy consumption of a machining process can differ by at least 6% of the total energy consumption of machine tool in low load and is likely to grow to 40% at high load. This condition indicates that the energy consumption of machine tools is highly dependent on cutting load. Inspired by this, many researchers investigated the relationship between the cutting load and energy consumption of machine tools. An interesting conclusion shows that when the machine tool, cutting tool, and cutting condition are determined, cutting parameters are the dominant factors influencing the cutting load [8]. Small cutting parameters can reduce the cutting load and decrease the power consumption of the machine tool because power consumption is calculated by cutting force (i.e., cutting load) multiplied by cutting velocity.

However, the energy consumption in a machining process is the integral of power consumption over machining time. Small cutting parameters can decrease power consumption but increase machining time, resulting in an uncertainty of the energy consumption. In the work presented by Camposeco-Negrete [9], they found that a small cutting velocity, cutting depth, and feed rate can reduce the power consumption of a machining process. However, a high feed rate should be used when the cutting velocity and cutting depth remain in small values to minimize the energy consumption of the same machining process. Hence, cutting parameters should be properly selected to reduce the energy consumption of the machining process.

Over the past 10 years, many researchers have been engaged in cutting parameter selection for minimizing the energy consumption of the machining process. A first line of work focused on the cutting parameter optimization by using experimental design method. With this method, the relationship between cutting parameters and energy consumption can be revealed and a set of optimal cutting parameters for energy saving can be obtained. This method is easy to implement but is prone of being trapped into local optimal points [10]. To this end, another group of work conducted cutting parameter optimization on the basis of energy models. The optimization process of this method is complicated, and the results are highly dependent on the prediction accuracy of energy model and the performance of optimization algorithm [11].

The motivation of this work is to perform a literature review about energy efficient cutting parameter optimization. It can be regarded as a comprehensive reference for readers from academy and industry. The energy characteristics of machining process and existing energy efficient cutting parameter optimization methods are summarized. The advantages and deficiencies of each method are presented, and some future research directions are introduced. The remainder of this paper is organized as follows. Section 2 analyzes the energy characteristics of machining process. Section 3 presents the energy efficient cutting parameter optimization by using experimental design method. Section 4 shows the energy efficient cutting parameter optimization by using energy models. In Section 5, recommendations for future research are presented, followed by the conclusions in Section 6.

2 Energy consumption characteristics of machining process

As mentioned by Dahmus and Gutowski [12], any system analysis should start with the boundary definition of the system. In energy efficient cutting parameter optimization, the energy boundary of machining system should be clearly identified first because shifting the energy boundary alters the optimal cutting parameters for the machining process window [13]. From the current literature about cutting parameter optimization for energy saving, the focused energy boundary of these studies is different. Some studies [14,15] only focus on a part of the electrical energy consumption of machining process, and other studies [16,17] explore the total electrical energy consumption and the embodied energy of cutting tool and cutting fluid. Hence, to gain a better understanding of the existing works about energy efficient cutting parameter optimization, the energy boundary and energy characteristics of machining process should be analyzed.

Machining is a process in which a material is removed from a workpiece with a cutting tool to shape it into a desired form. As shown in Fig. 1, a large amount of electrical energy is needed by a machine tool to keep the movement of machine tool components and to overcome the deformation force of material and the friction between the cutting tool and workpiece. In some machining processes, the friction between the cutting tool and workpiece is extremely severe, and cutting fluid is usually used for lubrication. However, this method can only decrease the friction rather than eliminating it. The cutting tool is worn due to continual inevitable abrasion, and the cutting fluid is invalid due to the pollution of rusted chips of workpiece and cutting tool. This condition leads to an inevitable consumption of the embodied energy of cutting tool and cutting fluid, which is the energy used to produce the material of cutting tool and cutting fluid. Hence, from the machining system point of view, the energy consumption boundary of the machining process includes the electrical energy of machine tool and the embodied energy

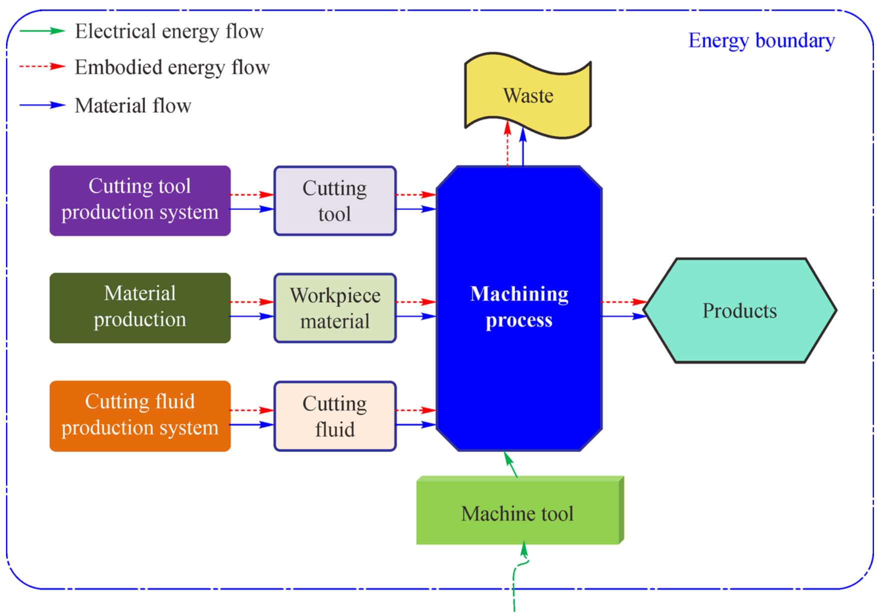

Fig. 1 Energy boundary of the machining process.

of consumable materials, such as cutting tool and cutting fluid. The workpiece material and its shape are determined on the basis of process requirements. The machining process have minimal chance to reduce the embodied energy consumption of workpiece material. Hence, in energy efficient cutting parameter optimization, the main focuses are the electrical energy of machine tool and the embodied energy of cutting tool and cutting fluid [18–20].

2.1 Electrical energy consumption of machine tool

In a machining process, the electrical energy consumption of a machine tool caused by the temporal power demand is complicated with dynamic change [21]. This condition is because the machine tool components are not all running throughout the whole machining process but activated in accordance with the processing requirements. To study the energy characteristics of the machining process, the electrical energy consumption is usually classified in terms of composition system, machine tool components, and machining states [22]. As shown in Fig. 2, the methods to classify electrical energy consumption based on machine tool components and machining states are the most widely used among the energy analysis methods. The energy analysis method based on machine tool components divides the energy consumption of a machine tool into several parts. Each part is related to the power consumption of the activated machine tool components and their running time throughout the machining process. Similarly, the energy analysis method based on machining states classifies the total energy consumption into different segments on the basis of machining states (i.e., startup state, standby state, spindle acceleration/deceleration state, air cutting state, and cutting state, as shown in Fig. 2). The energy consumption of each segment is calculated on the basis of the activated machine tool components in each machining state and the duration time of each machining state. The research perspectives of the two methods are fairly the same. However, after a perusal of current literature, it is found that most of the existing studies about energy efficient cutting parameter optimization are based on machining states. This condition is because this method is convenient for analyzing the energy characteristics of the machining process and modeling the energy consumption with respect to cutting parameters. Hence, this work mainly concentrates on the energy analysis method based on machining states. Interested readers can refer to the work reported by Zhou et al. [22] and Zhao et al. [23] for other energy analysis methods.

As stated previously, the machining states of a machining process are usually divided into startup state, standby state, spindle acceleration/deceleration state, air cutting state, and cutting state, as shown in Fig. 2. Accordingly, the research community decomposes the machining process into six parts to analyze its electrical energy consumption characteristics. Energy efficient cutting parameter optimization is conducted. The detailed energy breakdown is as follows:

1) Startup energy E_{startup}. When a machine tool is turned on, the machine tool components, such as inverters, servos, and computer numerical control system, are warmed up [24]. The energy consumption of these components is usually complex with dynamic changes, but the total startup energy E_{startup} is fixed and can be measured through experiments.

2) Standby energy E_{standby}. The standby energy is

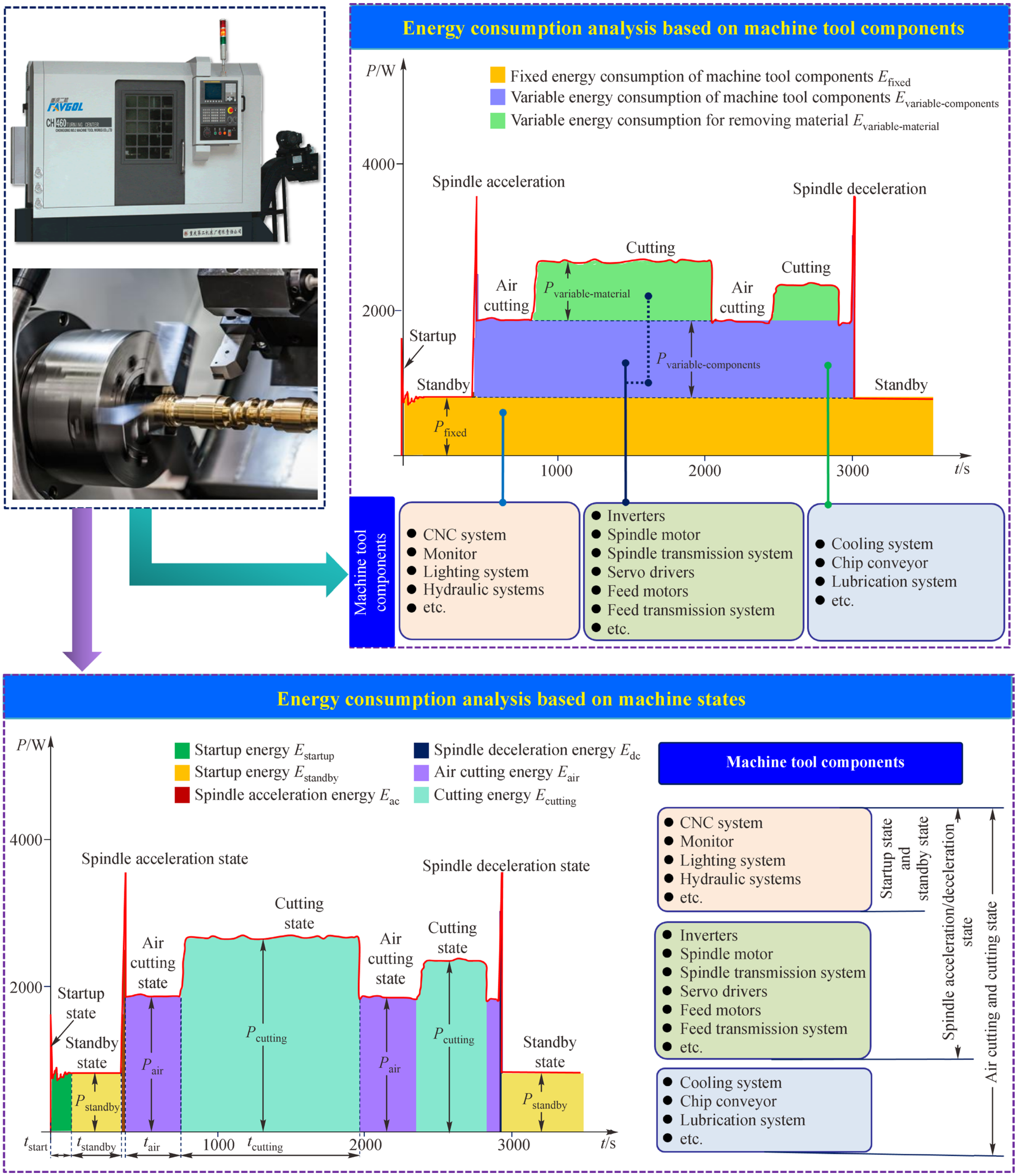

Fig. 2 Energy characteristic analysis of a machining process.

composed of two parts. The first part is used to bring the workpiece and cutting tool to the about-to cut position and to set up the numerical control (NC) program before machining [25], which is usually defined as $E_{\text{standby-preparation}}$. The second part is used to change the worn cutting tool, $E_{\text{tool-changing}}$. In a machining process, $E_{\text{standby-preparation}}$ is usually regarded as a constant, and $E_{\text{tool-changing}}$ can be reduced through cutting parameter optimization.

3) Spindle acceleration energy E_{ac} and spindle deceleration energy E_{dc}. Spindle acceleration energy E_{ac} and spindle deceleration energy E_{dc} are related to the desired spindle speed or cutting velocity [26]. However, as spindle acceleration/deceleration states are momentary. Energy consumption during these states is fairly small compared with other machining states. Some studies ignore spindle acceleration energy E_{ac} and spindle deceleration energy E_{dc} in cutting parameter optimization.

4) Air cutting energy E_{air}. Air cutting state is usually set by machine tool operators to avoid potential damage of machine and cutting tools. The air cutting energy is usually evaluated in terms of air cutting power P_{air} multiplied by air cutting time t_{air}. Air cutting power and air cutting time are related to cutting parameters. This condition provides an opportunity for machine tool users to reduce the air cutting energy through proper selection of cutting parameters.

5) Cutting energy E_{cutting}. Cutting energy is the energy consumed by a machine tool to remove a workpiece material during cutting state. Similar to air cutting energy, cutting energy is related to cutting parameters because cutting power P_{cutting} and cutting time t_{cutting} are dependent on cutting parameters. The cutting energy usually accounts for a huge proportion of the total electrical energy consumption of a machining process. In energy efficient cutting parameter optimization, some studies directly take cutting energy or cutting power as optimization objective [27,28].

2.2 Embodied energy consumption of cutting tool and cutting fluid

To produce the cutting tool and cutting fluid, a large amount of energy is consumed [29]. For example, the energy consumption to fabricate 1 cm^3 of high-speed steel (HSS), which is a widely used cutting tool material, is 755–855.9 kJ, and the energy consumption to fabricate 1 cm^3 of tungsten carbide material is as much as 8590–9723.6 kJ [30]. Hence, in energy efficient cutting parameter optimization, few researchers considered the embodied energy consumption of cutting tool and cutting fluid and optimized the cutting parameters in a comprehensive manner [31].

1) Embodied energy consumption of cutting tool $E_{\text{tool-embodied}}$. The embodied energy consumption of cutting tool is related to the tool life, which is highly dependent on the cutting parameters and machining performance of cutting tool. In a machining process, the embodied energy consumption of cutting tool can be reduced through proper selection of cutting parameters and cutting tool material [32].

2) Embodied energy consumption of cutting fluid $E_{\text{fluid-embodied}}$. Similar to the cutting tool, the production process of cutting fluid is energy intensive. In a machining process, a reasonable cutting parameter scheme can decrease the embodied energy consumption of cutting fluid [33].

3 Energy efficient cutting parameter optimization by using experimental design method

The use of experimental design method to optimize cutting parameters is vital for reducing the energy consumption of the machining process. With such a method, researchers can obtain a set of optimal cutting parameters for energy saving and derive the relationship between cutting parameters and energy consumption. In Fig. 3, the flowchart of cutting parameter optimization by using experimental design method is illustrated. The main steps are as follows.

First, the machining type (i.e., milling, turning, grinding, etc.) is determined in terms of the workpiece features. Second, the lubrication condition is identified in accordance with the machining requirements and the material of workpiece and cutting tool. In some machining cases, the lubrication conditions, such as dry, wet, and minimum quantity lubrication (MQL) cutting, can be regarded as a decision variable [34]. The cutting parameters that influence the energy consumption of the machining process and their feasible levels are identified in this stage. Third, experimental design methods, such as Taguchi [35], central composite design [36], and Box–Behnken [15], are adopted for generating experimental trials. These methods can guarantee the same results with fewer experimental runs compared with other techniques, such as factorial design. Fourth, a set of cutting experiments are conducted to obtain the energy consumption and/or other machining performance, such as surface roughness and tool life under each experimental trial. With the obtained experimental results, mono-objective parameter optimization or multiobjective parameter optimization is performed to obtain the optimal cutting parameter schemes. For mono-objective parameter optimization, the signal-to-noise ratio (S/N) of each trial is calculated, and the optimal cutting parameter scheme is obtained by comparing the S/N values. For multiobjective parameter optimization, gray relational analysis (GRA) or GRA coupled with principal component analysis (PCA) is adopted to generate a set of Pareto schemes. Finally, the most influential parameter for energy consumption and

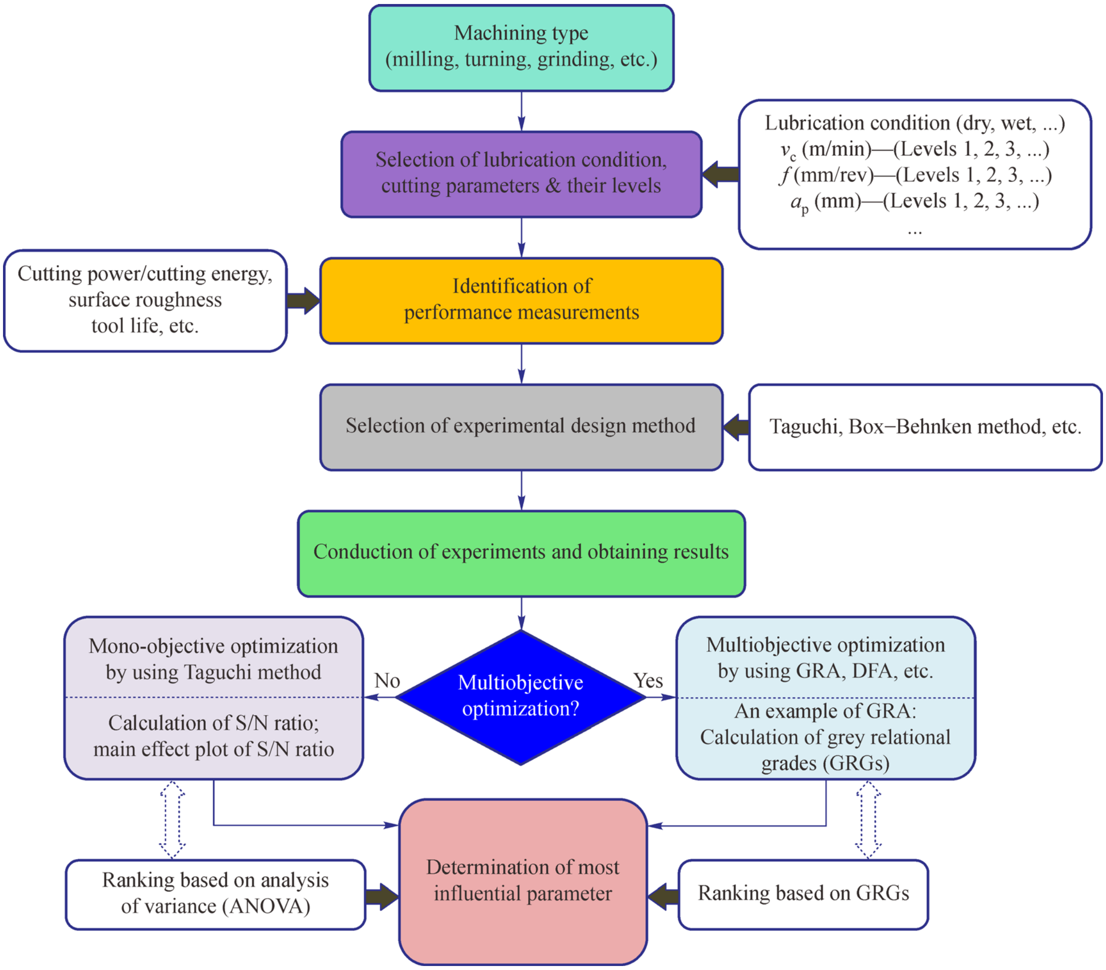

Fig. 3 Flowchart of cutting parameter optimization by using experimental design. S/N: Signal-to-noise ratio; GRA: Gray relational analysis; DFA: Desirability function analysis.

other machining performance, such as surface roughness and tool life, is determined through ANOVA or other methods, such as gray relational grade ranking.

Over the past 10 years, many researchers have engaged in energy efficient cutting parameter optimization by using experimental design. The optimization steps of these optimization methods, such as Taguchi and GRA, are standardized. For clarity, the main conclusions of these studies are revealed without diving deeply into its mathematical details. Interested readers can refer to the relevant studies summarized in Table 1 for its full feature.

3.1 Related literature on cutting parameter optimization for reducing cutting power

Cutting power is the total power consumption of a machine tool during cutting state. The energy consumption of a machine tool during cutting state is related to cutting power, which is highly dependent on cutting parameter schemes. Hence, the first group of studies conducted cutting experiments to evaluate the effect of cutting parameters on cutting power. The cutting parameter schemes for minimizing cutting power are obtained, and the relationship between cutting parameters and cutting power is revealed on the basis of the experimental results. In the work reported by Bhattacharya et al. [37], they performed a set of machining experiments to investigate the effect of cutting parameters on cutting power during high-speed dry turning of AISI 1045 steel by using Taguchi method. The experimental results show that cutting velocity is the most significant factor on cutting power. A small cutting velocity can effectively reduce the cutting power of machining process. Cutting depth and feed rate have no significant effect on cutting power and should be set at their most appropriate and economical levels. Fratila and Caizar [34] investigated the influence of face milling parameters on cutting power under wet, MQL, and dry milling conditions when machining of $AlMg_3$ with HSS tool. The cutting velocity and cutting depth are significant factors influencing cutting power, whereas the effect of feed rate and lubrication condition on cutting power is insignificant. Small cutting velocity, cutting depth, and feed rate should be used to minimize the cutting power of machining process.

When optimizing the cutting parameter for reducing cutting power consumption, economic objectives, such as surface quality, tool life, and machining efficiency, should be improved or at least should not be sacrificed. Hence, some researchers shifted their focus from mono-objective optimization to multiobjective optimization. In the work presented by Hanafi et al. [28], they applied Taguchi method to optimize the cutting parameters for minimizing the cutting power and surface roughness in turning of PEEK-CF30 with TiN cutting tool. The experimental results indicate that cutting depth is the most influential parameter on cutting power. A minimum power consumption can be achieved with a small cutting velocity, cutting depth, and feed rate. GRA was used in this work to determine the optimal cutting parameters for achieving minimum surface roughness and minimum cutting power. Similarly, Kant and Sangwan [38] optimized the cutting parameters for minimizing the cutting power and surface roughness during dry turning of AISI 1045 steel. However, their conclusions are different from that of Hanafi et al. [28]. The feed rate is the most significant factor influencing power consumption. A high cutting velocity, small cutting depth, and small feed rate should be used to minimize the power consumption of the turning process. An approach coupled GRA with PCA was used in their work to find the best cutting parameter scheme for minimizing the cutting power and surface roughness.

3.2 Related literature on cutting parameter optimization for energy saving

In a machining process, the value of energy consumption is calculated by considering machining time [9]. This condition directly reflects the total energy consumed of a machining process. To this end, another group of researchers investigated the cutting parameter optimization for reducing energy consumption, and numerous studies were published. The detailed literature review is as follows:

Camposeco-Negrete [9] conducted a study to optimize the cutting parameters for minimizing the cutting power and energy consumption in turning of AISI 6061 T6 with carbide insert. A different optimization result is obtained when the optimization objective was changed from minimizing cutting power to minimizing energy consumption. For minimizing power consumption, cutting depth is the most significant factor, followed by feed rate. Cutting velocity is insignificant on cutting power. A minimum cutting power consumption can be achieved with a small cutting velocity, cutting depth, and feed rate. However, for minimizing the energy consumption of machining process, feed rate is observed to be the most significant factor, followed by cutting depth and cutting velocity. The energy consumption can be reduced by using a small cutting velocity, a small cutting depth and a large feed rate. Emami et al. [27] studied the parameter optimization in grinding of Al_2O_3 ceramic under MQL. They found that feed rate is the most significant factor on energy consumption. The energy consumption of grinding process can be reduced with a large feed rate and cutting depth. Zhang et al. [39] studied the influence of turning parameters on energy consumption under wet lubrication, MQL, and dry turning condition when machining austenitic stainless steel. The feed rate and cutting depth are the significant factors on energy consumption. Camposeco-Negrete et al. [40] optimized the turning parameters to minimize the energy consumption during turning of AISI 1018 steel under wet, MQL, and dry turning conditions. They found that feed rate and cutting depth have significant effect on energy consumption, which is similar to the findings reported by Zhang et al. [39]. Bilga et al. [41] conducted cutting parameter optimization to reduce the energy consumption in rough turning of EN 353 alloy steel with multilayer-coated tungsten carbide insert. The optimization results show that feed rate is the most dominant factor for energy consumption. Turning with a large cutting velocity, feed rate but a small cutting depth can reduce the energy consumption of the turning process. In the work presented by Altıntaş et al. [42], similar studies about cutting parameter optimization for saving energy consumption in end milling of AISI 1050 and AISI 304 steel can be found.

Apart from the above studies, other researches focused on multiobjective optimization of cutting parameters with traditional objectives, such as surface roughness and tool life, because energy efficient sustainable machining should not sacrifice machining economic targets. Bhushan [43] optimized the turning parameters to minimize energy consumption and maximize tool life during machining of 7075 Al alloy. Cutting velocity is observed to be the most influential factor on energy consumption. A small cutting velocity, feed rate, and cutting depth can reduce the energy consumption of the machining process. The influence of cutting parameters on tool life is different from that of energy consumption. Desirability function analysis (DFA) was used in this study for multiobjective optimization of cutting parameters to reduce energy consumption and increase tool life. Yan and Li [44] studied the multi-objective optimization of face milling parameters to maximize material removal rate (MRR) and minimize energy consumption and surface roughness. The experimental results indicate that cutting width is the most influential parameter on energy consumption. Milling with a large cutting width, feed rate, and cutting depth but a small cutting velocity can reduce the energy consumption of the milling process. The optimization results for minimum energy consumption does not necessarily satisfy the optimization criterion of minimum surface roughness and maximum MRR. GRA combined sequential quadratic programming (SQP) was used in their study to strike a balance between the three objectives. Arriaza et al. [45]

conducted a set of experiments for multiobjective optimization of milling parameters to reduce machining time and energy consumption. The experimental results show that cutting velocity is the most significant factor on energy consumption. DFA was used to find the trade-off solutions for minimizing machining time and energy consumption. Bagaber and Yusoff [46] investigated the multiobjective optimization of cutting parameters to minimize energy consumption, surface roughness, and tool wear in dry turning of AISI 316 steel. Feed rate is concluded to be the most significant factor influencing energy consumption. Turning with a large feed rate, cutting depth but a small cutting velocity can reduce the energy consumption of the machining process. DFA was used in their work to determine the trade-off solution for minimizing energy consumption, surface roughness, and tool wear. In the work presented by Suneesh and Sivapragash [47], they studied multiobjective parameter optimization for energy saving, surface quality improvement, cutting force, and cutting temperature reduction in turning of Mg/Al_2O_3 hybrid composites. Feed rate is concluded to be the dominant contributor for energy consumption followed by cutting velocity and cutting depth. Minimum energy consumption of the turning process can be achieved with a small feed rate, cutting velocity, and cutting depth. GRA and the technique for order of preference by similarity to ideal solution (TOPSIS) were used to perform multi-objective optimization. The results show that the solution obtained using the TOPSIS is better than that of GRA.

3.3 Remarks

On the basis of the literature reviewed in Table 1, the following remarks are summarized.

- The experimental results of these studies are highly dependent on specific machining conditions (i.e., machine tool, workpiece material, tool material, lubrication, etc.). The influence of cutting parameters on energy consumption varies with different machining conditions. A cutting parameter that is a dominant factor on energy consumption in a machining condition may be an insignificant one in another machining condition.
- Minimum power consumption can be achieved by decreasing the value of cutting parameters because the cutting force can be decreased with small cutting parameters. However, the strategy for selecting cutting parameter to reduce energy consumption may vary with different machining conditions. This condition is because energy consumption is the integral of power consumption over machining time. Small cutting parameters reduce power consumption but increase machining time, and the decrement or increment of energy consumption is uncertain. The measure for selecting cutting parameter to reduce energy consumption should consider the specific machining conditions.
- The relationship between cutting parameters and energy consumption is not always the same due to the relationship between cutting parameters and economic objectives (surface roughness, tool life, MRR, etc.). The optimal cutting parameter schemes for minimizing energy consumption does not necessarily satisfy the optimization criterions of minimizing surface roughness, maximizing tool life, and MRR. Multiobjective optimization is an effective method used to solve this problem.
- The optimal cutting parameters are either directly selected from existing experimental combinations or obtained by using GRA, DFA or other methods. The optimization results are dependent on the experimental settings of the cutting parameters. A risk of being trapped into local optimal points may occur [10], and the obtained cutting parameters may not be the optimal ones from the view of global optimization.

4 Energy efficient cutting parameter optimization by using energy models

In addition to energy efficient cutting parameter optimization by using experimental design method, another group of researchers established energy models with respect to cutting parameters and conducted cutting parameter optimization by using the established energy models. Cutting parameter optimization is formulated as a constrained problem within feasible parameter ranges. Evolutionary or metaheuristic algorithms are usually used in the optimization process to solve the optimization model.

Figure 4 gives the flowchart of cutting parameter optimization by using energy models. Similar to cutting parameter optimization by using experimental design method, the first step is to select a suitable machining type for machining the workpiece in accordance with its features. The second step is to identify the energy boundary and model energy consumption with respect to cutting parameters. If the optimization is a multiobjective one, the relationships between machining performance (surface roughness, machining time, etc.) and cutting parameters are modeled. A mono-objective optimization model with the only objective of energy consumption or a multiobjective optimization model with energy consumption and machining performance is established, with the constraints of machine tool, cutting tool, and surface roughness requirements. Evolutionary or metaheuristic technique, such as particle swarm optimization (PSO) or genetic algorithm (GA) is used to solve the proposed model. Note that the optimization algorithms for mono-objective optimization and multiobjective optimization models are different. An optimal solution can be obtained using the mono-objective optimization model and algorithm, whereas only Pareto solutions can be obtained with multiobjective optimization ones.

Table 1 Studies on energy efficient cutting parameter optimization by using experimental design

Category	References	Machining type	Workpiece material	Tool insert material	Lubrication	Optimization method(s)	Optimization objective(s)			Most influential factors on energy/power consumption	Minimum energy consumption can be achieved with	Minimum power consumption can be achieved with
							Power consumption	Energy consumption	Multiobjective optimization with other objective(s)			
Cutting power reduction (single-objective optimization)	Fratila and Caizar [34]	Face milling	$AlMg_3$	HSS	Dry, MQL, and wet	Taguchi method	Cutting power	×	×	v_c and a_p	N/A	$v_c\downarrow, f\downarrow, a_p\downarrow$
	Bhattacharya et al. [37]	Turning	AISI 1045 steel	Coated carbide insert	Dry	Taguchi method	Cutting power	×	×	v_c	N/A	$v_c\downarrow, f\rightarrow, a_p\rightarrow$
Cutting power reduction (multiobjective optimization)	Hanafi et al. [28]	Turning	PEEK-CF30	TiN	Dry	Taguchi method and GRA	Cutting power	×	Surface roughness	a_p	N/A	$v_c\downarrow, f\downarrow, a_p\downarrow$
	Kant and Sangwan [38]	Turning	AISI 1045 steel	Carbide insert	Dry	Taguchi method, GRA and PCA	Cutting power	×	Surface roughness	f	N/A	$v_c\uparrow, f\downarrow, a_p\downarrow$
Energy saving (single-objective optimization)	Camposeco-Negrete [9]	Turning	AISI 6061 T6 aluminum	Carbide insert	Wet	Taguchi method	Cutting power	Air cutting energy and cutting energy	×	a_p (power consumption), f (energy consumption)	$v_c\downarrow, f\uparrow, a_p\downarrow$	$v_c\downarrow, f\downarrow, a_p\downarrow$
	Emami et al. [27]	Grinding	Al_2O_3 ceramic	Diamond insert	MQL	Taguchi method	×	Cutting energy	×	f	$f\uparrow, a_p\uparrow$	N/A
	Campatelli et al. [36]	End milling	AISI 1050 carbon steel	Coated, carbide insert	Dry	RSM	×	Standby energy, air cutting energy, cutting energy	×	N/A	N/A	N/A
	Zhang et al. [39]	Turning	0Cr18Ni9 steel	N/A	Dry, MQL and wet	Taguchi method	×	Cutting energy	×	f and a_p	$v_c\uparrow, f\uparrow, a_p\uparrow$	N/A
	Camposeco-Negrete et al. [40]	Turning	AISI 1018 steel	N/A	Dry and wet	Taguchi method	×	Cutting energy	×	f and a_p	$v_c\downarrow, f\uparrow, a_p\downarrow$	N/A
	Bilga et al. [41]	Turning	EN 353 alloy steel	Carbide insert	N/A	Taguchi method	×	Cutting energy	×	f	$v_c\uparrow, f\uparrow, a_p\downarrow$	N/A

(*Continued*)

Category	References	Machining type	Workpiece material	Tool insert material	Lubrication	Optimization method(s)	Optimization objective(s)			Most influential factors on energy/power consumption	Minimum energy consumption can be achieved with	Minimum power consumption can be achieved with
							Power consumption	Energy consumption	Multiobjective optimization with other objective(s)			
Energy saving (single-objective optimization)	Altıntaş et al. [42]	Milling	AISI 304 steel	HSS	N/A	RSM	×	Cutting energy	×	f	$v_c \downarrow, f \uparrow, a_p \downarrow$	N/A
Energy saving (multiobjective optimization)	Bhushan [43]	Turning	7075 Al alloy	Carbide insert	Dry, wet and cryogenic	RSM and DFA	×	Cutting energy	Tool life	v_c	$v_c \downarrow, f \downarrow, a_p \downarrow$	N/A
	Yan and Li [44]	Face milling	medium-carbon steel (C45)	Carbide insert	Dry	RSM, GRA, and SQP	×	Cutting energy	MRR surface roughness	a_e	$v_c \downarrow, f \uparrow, a_p \uparrow, a_e \uparrow$	N/A
	Arriaza et al. [45]	Milling	Aluminum 7075	N/A	N/A	RSM and DFA	×	Cutting energy	Machining time	v_c	N/A	N/A
	Bagaber and Yusoff [46]	Turning	AISI 316 steel	Carbide insert	Dry	RSM and DFA	×	Cutting energy	Surface roughness, tool wear	f	$v_c \downarrow, f \uparrow, a_p \uparrow$	N/A
	Suneesh and Sivapragash [47]	Turning	Mg/Al_2O_3 hybrid composite	Carbide insert	Dry and MQL	Taguchi and GRA, Taguchi, and TOPSIS (for contrast)	×	Cutting energy	Surface roughness, cutting force, cutting temperature	f	$v_c \downarrow, f \downarrow, a_p \downarrow$	N/A

Note: $v_c \downarrow$, mainlining with a small cutting velocity; $f \rightarrow$, mainlining with a medium feed rate; $a_p \uparrow$, machining with a large cutting depth; $a_e \uparrow$, machining with a large cutting width; MQL, minimum quantity lubrication; GRA, gray relational analysis; PCA, principal component analysis; HSS, high-speed steel; DFA, desirability function analysis; RSM, response surface methodology; TOPSIS, technique for order of preference by similarity to ideal solution; SQP, sequential quadratic programming; MRR, material removal rate.

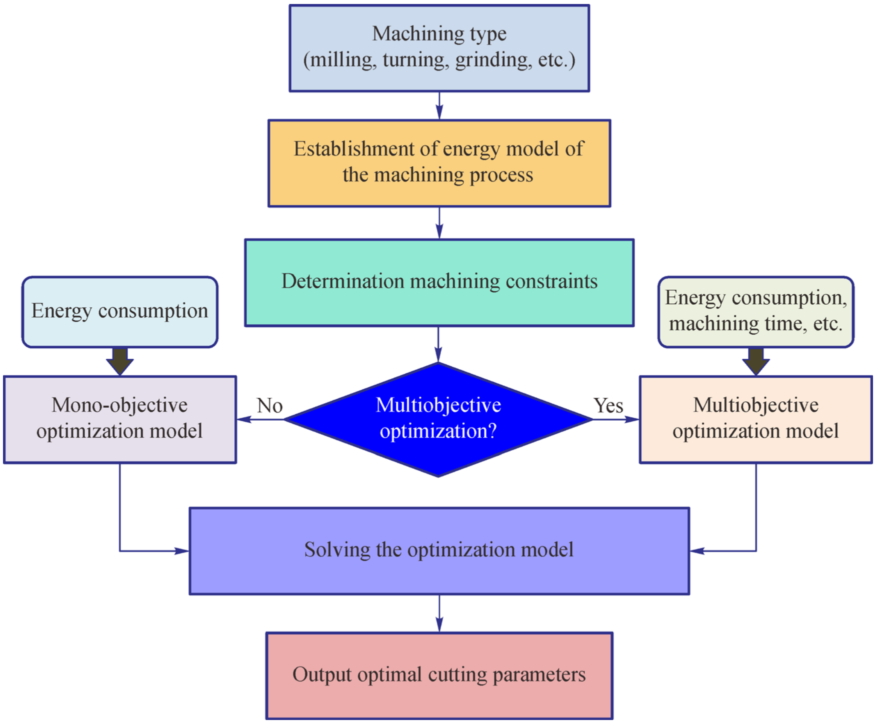

Fig. 4 Flowchart of cutting parameter optimization by using energy models.

Table 2 summarizes the recent studies about cutting parameter optimization based on energy models. The details of the main steps shown in Fig. 4 are given below to understand these studies in a comprehensive manner.

4.1 Modeling of energy consumption with respect to cutting parameters

The methods for modeling the relationship between energy consumption and cutting parameters can be mainly classified into two categories. The first category models energy consumption with respect to cutting parameters by using experimental design and mathematical models, such as artificial neural network (ANN) [48], response surface methodology (RSM) [14,35], and Kriging model [15]. The accuracy of these energy models can be extremely high because they are close to the specific machining conditions. The second category analyzes the energy characteristics of the machining process and then models the relationship between energy consumption and cutting parameters by using empirical models, such as cutting force and cutting power models. These energy models are general and can be used in many machining scenes if the main machining condition remains unchanged. As shown in Table 2, most of the existing studies about energy efficient cutting parameter optimization are conducted on the basis of empirical models. This section mainly focuses on the modeling process of these empirical models. Other models established using standard mathematical models, such as ANN, RSM, and Kriging model, can be found in Refs. [14,15,35,48]. The methods in Table 2 are classified into two categories, namely, energy modeling method based on machine tool component (EMMBMTC) and energy modeling method based on machining state (EMMBMS). EMMBMS is the most widely used, as mentioned in Section 2.

As shown in Fig. 1, the energy consumption of a machining process includes the electrical energy of machine tool and the embodied energy of consumable material. The electrical energy of a machine tool can be divided into standby energy E_{standby}, spindle acceleration energy E_{ac}, spindle deceleration energy E_{dc}, air cutting energy E_{air}, and cutting energy E_{cutting}. The embodied energy of consumable material is composed of the embodied energy of cutting tool $E_{\text{tool-embodied}}$ and the embodied energy of cutting fluid $E_{\text{fluid-embodied}}$. Consequently, the general expression of the energy consumption of a machining process can be expressed as follows:

$$\begin{aligned} E_{\text{footprint}} &= E_{\text{electrical}} + E_{\text{embodied}} \\ &= E_{\text{standby}} + E_{\text{ac}} + E_{\text{dc}} + E_{\text{air}} + E_{\text{cutting}} \\ &\quad + E_{\text{tool-embodied}} + E_{\text{fluid-embodied}}, \end{aligned} \tag{1}$$

where $E_{\text{electrical}}$ and E_{embodied} are the electrical energy of machine tool and the embodied energy of consumable material, respectively.

Table 2 Studies on energy efficient cutting parameter optimization by using energy models

Category	References	Machining/model type	Energy models	Multiobjective optimization with other objective(s)	Main conclusions
Cutting parameter optimization by using experimental design and mathematical models, such as ANN, RSM or Kriging model	Jang et al. [48]	Milling, ANN-based energy model	$\mathrm{SEC} = P_{\mathrm{cutting}}/\mathrm{MRR}$	N/A	PSO was used to find the optimal cutting parameters for minimizing specific cutting energy. Minimum energy consumption can be achieved with a large feed rate and cutting depth
	Li et al. [35]	Milling, RSM-based energy model	$\mathrm{SEC} = (E_{\mathrm{standby}} + E_{\mathrm{air}} + E_{\mathrm{cutting}} + E_{\mathrm{tool\text{-}changing}})/\mathrm{MRV} = 229.21 - 41.48v_{\mathrm{c}} - 48.58f - 61.30a_{\mathrm{p}} - 91.66a_{\mathrm{e}} + 27.82v_{\mathrm{c}}^2 + 35.17a_{\mathrm{e}}^2 + 31.06v_{\mathrm{c}}f + 22.48fa_{\mathrm{p}} + 24.01fa_{\mathrm{e}} + 25.52a_{\mathrm{p}}a_{\mathrm{e}}$	Machining time	A trade-off is found between SEC and machining time. Cutting width is observed to be the major factor affecting SEC, followed by cutting depth, feed rate, and cutting velocity. Minimum energy consumption can be achieved with a large cutting velocity, feed rate, cutting depth, and cutting width
	Moreira et al. [14]	Milling, RSM-based energy model	$\mathrm{SEC} = E_{\mathrm{cutting}}/\mathrm{MRV}$	MRR, power load	Feed rate is found to be the most significant factor on SEC. A large feed rate is recommended for energy efficient machining
	Nguyen [15]	Milling, Kriging-based energy model	$\mathrm{SEC} = F_{\mathrm{cutting}}/(fa_{\mathrm{p}})$	Surface roughness, production rate	Cutting depth is the most influential parameter on SEC. Large cutting parameters can decrease SEC
Cutting parameter optimization by using empirical models	Rajemi et al. [13]	Turning (EMMBMS)	$E_{\mathrm{footprint}} = E_{\mathrm{standby}} + E_{\mathrm{cutting}} + E_{\mathrm{tool\text{-}changing}} + E_{\mathrm{tool\text{-}embodied}}$	×	Optimal cutting parameters vary with energy boundaries. The optimal cutting parameters for minimum cost does not necessarily satisfy the minimum energy criterion
	Arif et al. [16]	Turning (EMMBMS)	$E_{\mathrm{footprint}} = E_{\mathrm{cutting}} + E_{\mathrm{standby}} + E_{\mathrm{tool\text{-}changing}} + E_{\mathrm{tool\text{-}embodied}}$	×	Influence of cutting parameters on energy consumption is different in roughing pass and finishing pass

(*Continued*)

Category	References	Machining/model type	Energy models	Multiobjective optimization with other objective(s)	Main conclusions
	Li et al. [49]	Milling (EMMBMS)	$E_{\text{cutting}} = E_{\text{material}} + E_{\text{loss-motor}} + E_{\text{loss-moving}} + E_{\text{idle-auxiliary}}$	Surface roughness	Increasing feed rate but decreasing spindle speed can reduce energy consumption and improve production rate
	Velchev et al. [50]	Milling (EMMBMS)	$E_{\text{electrical}} = \text{SEC} \cdot \text{MRR} \cdot t_{\text{cutting}} + P_{\text{standby}} t_{\text{insert-changing}} z \dfrac{t_{\text{cutting}}}{T_{\text{tool}}}$	×	Low energy consumption can be achieved with maximum possible values of feed rate and cutting depth
	Wang et al. [33]	Turning (EMMBMS)	$E_{\text{footprint}} = E_{\text{startup}} + E_{\text{cutting}} + E_{\text{tool-changing}} + E_{\text{tool-embodied}} + E_{\text{fluid-embodied}}$	Machining cost, surface roughness	Cutting parameter optimization is significant to energy reduction but optimization effect on surface roughness is limited. Cutting parameters are ranged in relatively reasonable ranges before optimization
	Albertelli et al. [51]	Milling (EMMBMTC)	$E_{\text{electrical}} = E_{\text{functional-modules}} + E_{\text{standby}} + E_{\text{material}}$	×	The optimal cutting parameters for minimum energy consumption is different from that of minimum machining time. Proper selection of cutting parameters can reduce both energy consumption and the machining time
	Ma et al. [52]	Millling (EMMBMS)	$E_{\text{electrical}} = \int_0^{t_{\text{cutting}}} (P_{\text{material}} + P_{\text{air}}) \mathrm{d}t$	×	Increment of cutting velocity leads to a decrement of energy consumption
	Xiong et al. [53]	Milling (EMMBMS)	$E_{\text{cutting}} = \dfrac{\pi D_{\text{milling}} F_{\text{cutting}} \text{MRR}}{3.672 \times 10^6 f_z a_{\text{p}} a_{\text{e}} \eta_{\text{m}}} + 0.746 P_{\text{rated-compressed}} \gamma_{\text{compressed}}$	Milling dimensional accuracy, machining time, machining cost	Multiobjective cutting parameter optimization obtained a more reasonable results even each objective is not the absolute optimal

(*Continued*)

Category	References	Machining/model type	Energy models	Multiobjective optimization with other objective(s)	Main conclusions
	Deng et al. [54]	Milling (EMMBMS)	$E_{\text{cutting}} = \int_0^{t_{\text{cutting}}} (P_{\text{standby}} + P_{\text{unload-feed}} + P_{\text{unload-spindle}} + P_{\text{material}} + P_{\text{auxiliary}})\mathrm{d}t$	Machining time	Cutting specific energy consumption first decreased and then increased with the increase of cutting velocity, while it always decreased with the increase of feed rate, cutting depth and cutting width
	He et al. [55]	Milling and turning (EMMBMTC)	$E_{\text{electrical}} = \dfrac{\begin{pmatrix} P_{\text{standby}} t_{\text{standby-preparation}} + P_{\text{spraying-cooling}} t_{\text{spraying-cooling}} \\ + P_{\text{unload-spindle}} t_{\text{cutting}} + P_{\text{unload-feed}} t_{\text{cutting}} + P_{\text{feed-fast}} t_{\text{feed-fast}} + P_{\text{material}} t_{\text{cutting}} \end{pmatrix}}{60}$	Machining time, cutting force	Different algorithms can be selected for different machining conditions and demands of specific objective problem
	Li et al. [25]	Milling (EMMBMS)	$E_{\text{electrical}} = E_{\text{startup}} + E_{\text{standby}} + \sum_{i=1}^{m} (E_{\text{air}}^i + E_{\text{cutting}}^i) + E_{\text{tool-changing}}$	Machining cost	Specific energy consumption first decreases with the increase in cutting velocity and then increases. It always decreases with the increase in feed rate and cutting depth
	Lu et al. [17]	Turning (EMMBMS)	$E_{\text{footprint}} = E_{\text{standby}} + E_{\text{tool-changing}} + E_{\text{tool-embodied}} + E_{\text{fluid-embodied}} + E_{\text{cutting}}$	Machining precision	A balance is found between minimum energy consumption and maximum machining precision. MOBSA outperforms NSGA-II, MOPSO, multiobjective evolutionary algorithm based on decomposition (MOEA/D), and MOHS
	Zhang et al. [56]	Milling (EMMBMS)	$E_{\text{electrical}} = E_{\text{startup}} + \sum_{i=1}^{m} E_{\text{standby}}^i + \sum_{i=1}^{m} E_{\text{approaching}}^i + \sum_{i=1}^{m} E_{\text{cutting}}^i + E_{\text{tool-changing}}$	Machining time, carbon emission	Energy consumption can be reduced with a large cutting velocity, feed rate, cutting depth, and cutting width. The balance of machining time, energy consumption, and carbon emissions should be struck

(*Continued*)

Category	References	Machining/model type	Energy models	Multiobjective optimization with other objective(s)	Main conclusions
	Zhong et al. [57]	Turning (EMMBMS)	$\mathrm{SEC}=\frac{P_{\mathrm{standby}}+k_{\mathrm{spindle}}n+b_{\mathrm{spindle}}+\lambda v_{\mathrm{c}}^{\alpha_{\mathrm{F}}}f^{\beta_{\mathrm{F}}}a_{\mathrm{p}}^{\psi_{\mathrm{F}}}}{\mathrm{MRR}}$	×	The effect of feed rate on specific energy consumption is less than that of cutting velocity and cutting depth. A large feed rate can be used in energy efficient machining process
	Zhang et al. [58]	Turning (EMMBMS)	$E_{\mathrm{electrical}}=(P_{\mathrm{air}}+P_{\mathrm{material}}+P_{\mathrm{loss\text{-}spindle}})t_{\mathrm{cutting}}+P_{\mathrm{standby}}t_{\mathrm{standby\text{-}preparation}}+P_{\mathrm{air}}t_{\mathrm{air}}+P_{\mathrm{standby}}t_{\mathrm{tool\text{-}changing}}+P_{\mathrm{auxiliary}}(t_{\mathrm{standby\text{-}preparation}}+t_{\mathrm{air}}+t_{\mathrm{cutting}}+t_{\mathrm{tool\text{-}changing}})$	Noise emission, machining cost	A large feed rate and cutting depth minimize the energy consumption of the machining process. The influence of cutting speed on energy is insignificant. A conflict is found between minimizing energy consumption and noise emission
	Bagaber and Yusoff [59]	Turning (EMMBMS)	$E_{\mathrm{electrical\text{-}dry}}=P_{\mathrm{startup}}t_{\mathrm{startup}}+P_{\mathrm{standby}}t_{\mathrm{standby\text{-}preparation}}+P_{\mathrm{air}}t_{\mathrm{air}}+(P_{\mathrm{air}}+k_{\mathrm{m}}\mathrm{MRR})t_{\mathrm{cutting}}+P_{\mathrm{standby}}t_{\mathrm{tool\text{-}changing}}$, $E_{\mathrm{electrical\text{-}wet}}=P_{\mathrm{startup}}t_{\mathrm{startup}}+P_{\mathrm{standby}}t_{\mathrm{standby\text{-}preparation}}+P_{\mathrm{air}}t_{\mathrm{air}}+(P_{\mathrm{air}}+k_{\mathrm{m}}\mathrm{MRR})t_{\mathrm{cutting}}+P_{\mathrm{standby}}t_{\mathrm{tool\text{-}changing}}+E_{\mathrm{fluid\text{-}embodied}}$	Machining cost, surface roughness	Minimum energy consumption can be achieved with the highest value of feed rate and lowest value of cutting depth. Feed rate is the most significant factor affecting energy consumption
	Hu et al. [60]	Turning (EMMBMS)	$E_{\mathrm{electrical}}=(P_{\mathrm{material}}+P_{\mathrm{unload\text{-}feed}}+P_{\mathrm{unload\text{-}spindle}}+P_{\mathrm{spraying\text{-}cooling}}+P_{\mathrm{standby}})t_{\mathrm{cutting}}+E_{\mathrm{approaching}}+E_{\mathrm{rotation\text{-}changing}}$	×	Simulated annealing (SA) outperforms expectation–maximization (EM) because it requires less computation time with minimal sacrifice in solution quality compared with EM
	Li et al. [61]	Milling (EMMBMS)	$E_{\mathrm{electrical}}=E_{\mathrm{standby}}+E_{\mathrm{air}}+E_{\mathrm{cutting}}+E_{\mathrm{tool\text{-}changing}}$	Machining time	Cutting depth and width are the most influential factors for specific energy consumption. A trade-off is found between specific energy consumption and machining time

(*Continued*)

Category	References	Machining/model type	Energy models	Multiobjective optimization with other objective(s)	Main conclusions
	Wang et al. [62]	Milling (EMMBMS)	$E_{\text{electrical}} = E_{\text{standby}} + E_{\text{approaching}} + E_{\text{leaving}} + E_{\text{cutting}}$	×	The range of cutting parameters increases with cutting tool diameter. Accordingly, a large MRR can be used to reduce energy consumption
	Chen et al. [32]	Milling (EMMBMS)	$E_{\text{footprint}} = E_{\text{standby}} + E_{\text{air}} + E_{\text{cutting}} + E_{\text{tool-changing}} + E_{\text{tool-embodied}}$	Machining time	Multiobjective optimization strikes a balance between minimum energy consumption and minimum machining time

Note: ANN, artificial neural network; PSO, particle swarm optimization; SEC, specific cutting energy, the amount of energy required to cut a unit volume of a workpiece; MRR, material removal rate; RSM, response surface methodology; EMMBMTC, energy modeling method based on machine tool component; EMMBMS, energy modeling method based on machining state; MOBSA, multiobjective backtracking search algorithm; NSGA-II, nondominated sorting genetic algorithm II; MOPSO, multiobjective particle swarm optimization; MOHS, multiobjective harmony search; P_{cutting}, cutting power; E_{standby}, standby energy; E_{air}, air cutting energy; E_{cutting}, cutting energy; $E_{\text{tool-changing}}$, standby energy used for changing the worn cutting tool; v_c, cutting velocity; f, feed rate; a_p, cutting depth; a_e, cutting width; F_{cutting}, cutting force; $E_{\text{footprint}}$, energy footprint of the machining process; P_{standby}, standby power; $E_{\text{tool-embodied}}$, embodied energy consumption of cutting tool; E_{material}, material removal energy; $E_{\text{loss-moving}}$, inertia energy loss of moving components; $E_{\text{loss-motor}}$, additional load loss energy of main motor; $E_{\text{idle-auxiliary}}$, idle energy of auxiliary system; $E_{\text{electrical}}$, electrical energy of the machining process; t_{cutting}, cutting time; $t_{\text{insert-changing}}$, time for changing an insert; T_{tool}, tool life; z, number of cutting inserts; $E_{\text{fluid-embodied}}$, embodied energy consumption of cutting fluid; $E_{\text{functional-modules}}$, energy consumption by main machine tool functional modules; E_{startup}, startup energy; P_{material}, material removal power; P_{air}, air cutting power; D_{milling}, diameter of milling tool; f_z, feed rate per tooth; η_m, overall efficiency of spindle motor; $P_{\text{rated-compressed}}$, rated power of compressed air motor; $\gamma_{\text{compressed}}$, load factor of compressed air motor; $P_{\text{unload-feed}}$, unload power of feed system; $P_{\text{unload-spindle}}$, unload power of spindle system; $P_{\text{auxiliary}}$, power of auxiliary system; $t_{\text{standby-preparation}}$, standby time used to bring the workpiece and cutting tool to the about-to cut position and to set up the numerical control program before machining; $P_{\text{spraying-cooling}}$, power for spraying cooling fluid; $P_{\text{feed-fast}}$, power for fast feeding; $t_{\text{feed-fast}}$, time for fast feeding; E^i_{air}, air cutting energy of the ith pass; E^i_{cutting}, cutting energy of the ith pass; E^i_{standby}, standby energy of the ith pass; $E^i_{\text{approaching}}$, energy consumption for tool approaching of the ith pass; k_{spindle}, unload power coefficient of spindle system; b_{spindle}, unload power coefficient of spindle system; n, spindle speed; m, number of machining passes; λ, coefficient of cutting force; α_F, coefficient of cutting force; β_F, coefficient of cutting force; ψ_F, coefficient of cutting force; $P_{\text{loss-spindle}}$, additional load loss power of spindle system; $E_{\text{electrical-dry}}$, electrical energy of the machining process under dry condition; $E_{\text{electrical-wet}}$, electrical energy of the machining process under wet condition; P_{startup}, startup power; t_{startup}, startup time; k_m, constant for material removal power; $E_{\text{rotation-changing}}$, energy consumption for spindle rotation changing (non-cutting); E_{leaving}, energy consumption for tool leaving.

4.1.1 Modeling of standby energy E_{standby}

As mentioned in Section 2.1.1, the standby energy is composed of two parts, namely, the standby energy used for the preparation of workpiece, cutting tool, and NC program before machining, $E_{\text{standby-preparation}}$, and the energy used for changing worn cutting tool, $E_{\text{tool-changing}}$:

$$E_{\text{standby}} = E_{\text{standby-preparation}} + E_{\text{tool-changing}}. \tag{2}$$

1) Standby energy used for the preparation of workpiece, cutting tool, and NC program, $E_{\text{standby-preparation}}$

During the standby state for the preparation of workpiece, cutting tool, and NC program, the activated components of the machine tool are the inverters, servos, and computer NC system [63]. The rated power consumption of each component is usually fixed in the standby state. The energy consumption during standby state is only dependent on standby time $t_{\text{standby-preparation}}$ and total power P_{standby} of these machine tool components and is usually modeled, as shown in Eq. (3):

$$E_{\text{standby-preparation}} = P_{\text{standby}} t_{\text{standby-preparation}}, \tag{3}$$

where $t_{\text{standby-preparation}}$ is the standby time related to the operating skills of workers.

2) Standby energy used for changing worn cutting tool, $E_{\text{tool-changing}}$

During a machining process, the worn cutting tool is replaced with a sharp tool in standby state. However, the tool changing operation may not occur in each machining process because a sharp tool can be usually used for machining several parts [32]. Hence, the standby energy used for changing worn cutting tool of each part is evaluated in terms of the actual cutting time per tool life multiplied by standby power, which is expressed as shown in Eqs. (4) and (5):

$$E_{\text{tool-changing}} = P_{\text{standby}} t_{\text{tool-changing}}, \tag{4}$$

$$t_{\text{tool-changing}} = t_{\text{insert-changing}} z \frac{t_{\text{cutting}}}{T_{\text{tool}}}, \tag{5}$$

where $t_{\text{tool-changing}}$ is the tool changing time, $t_{\text{insert-changing}}$ is the time to change each cutting insert, z is the total inserts in a cutting tool, and T_{tool} is the tool life. Taking the cylindrical turning process as an example, t_{cutting} and T_{tool} are calculated as shown in Eqs. (6) and (7) [64]:

$$t_{\text{cutting}} = \frac{\pi D_{\text{avg}} l}{f v_{\text{c}}}, \tag{6}$$

$$T_{\text{tool}} = \frac{C_{\text{T}}}{v_{\text{c}}^{\alpha_{\text{T}}} f^{\beta_{\text{T}}} a_{\text{p}}^{\gamma_{\text{T}}}}, \tag{7}$$

where D_{avg} is the average diameter of workpiece, l is the cutting length of workpiece, α_{T}, β_{T}, γ_{T} and C_{T} are tool life coefficients, and α_{p} is cutting depth.

4.1.2 Modeling of spindle acceleration energy E_{ac} and spindle deceleration energy E_{dc}

Spindle acceleration energy E_{ac} is related to spindle speed. In the work presented by Huang et al. [65], they modeled spindle acceleration energy E_{ac} with respect to spindle speed, as shown in Eq. (8):

$$E_{\text{ac}} = E_{\text{loss-motor}} + E_{\text{m}} + 2\pi M_{\text{om}}(n_{\text{s}}) \int_{t_{\text{st}}}^{t_{\text{end}}} n(t)\text{d}t + 4\pi^2 B(n_{\text{s}}) \int_{t_{\text{st}}}^{t_{\text{end}}} n^2(t)\text{d}t + 2\pi^2 J_{\text{m}}(n_{\text{s}}) n^2(t) + P_{\text{standby}} t_{\text{ac}}, \tag{8}$$

where $E_{\text{loss-motor}}$ is the additional load loss energy of main motor, E_{m} is the changed energy of electromagnetic field, $M_{\text{om}}(n_{\text{s}})$ represents the load torque of electric motor in the main transmission system, $B(n_{\text{s}})$ represents the viscous damping coefficient of main transmission system equivalently transformed to motor shaft, $J_{\text{m}}(n_{\text{s}})$ is the rotational inertia of main transmission system equivalently transformed to motor shaft, $n(t)$ denotes the spindle speed varying with time, t_{st} represents the spindle acceleration starting at this time point and ending at t_{end}, and t_{ac} is the time duration of spindle acceleration.

Similar to the work reported by Huang et al. [65], Hu et al. [26] studied spindle acceleration energy E_{ac} and modeled it, as shown in Eqs. (9) and (10):

$$E_{\text{ac}} = \int_0^{t_{\text{c}j}^{pq}} (P_{\text{standby}} + P_{\text{c}j}^{pq})\text{d}t, \tag{9}$$

$$P_{\text{c}j}^{pq} = B_{\text{SA}} \left(n_{\text{S}j}^{pq} + \frac{30\alpha_{\text{A}} t}{\pi} \right) + C_{\text{SA}} + T_{\text{SA}} \left(\frac{\pi n_{\text{S}j}^{pq}}{30} + \alpha_{\text{A}} t \right), \tag{10}$$

where $P_{\text{c}j}^{pq}$ and $t_{\text{c}j}^{pq}$ are the power consumptions of spindle system and time duration during the jth speed change of the spindle rotation in noncutting operations from feature F_p to feature F_q, $n_{\text{S}j}^{pq}$ is the initial spindle speed for the jth speed change in spindle rotation, and B_{SA}, C_{SA}, α_{A}, and T_{SA} are the coefficients of the spindle system.

For spindle deceleration energy E_{dc}, Hu et al. [26] found that $P_{\text{c}j}^{pq}$ was zero when no energy recycling device was installed on the machine tool, and the power consumption during deceleration equaled to the standby power of the machine tool. Otherwise, the power consumption during deceleration is negative because the energy was recovered with energy recycling devices. P_{cj}^{pq} is modeled as shown in Eq. (11):

$$P_{cj}^{pq} = B_{SRD}(n_{Ej}^{pq} - n_{Sj}^{pq}) + C_{SRD}, \tag{11}$$

where n_{Ej}^{pq} is the final spindle speed for the jth speed change in spindle rotation, and B_{SRD} and C_{SRD} are the coefficients of the spindle system.

4.1.3 Modeling of air cutting energy E_{air}

During air cutting state, the spindle and feed systems are powered on, and the cutting-related auxiliary systems, such as chip conveyor and coolant system, are simultaneously activated to ensure the operational readiness. Consequently, the energy consumption during air cutting state is related to three types of machine tool components. The first two types are the machine tool components activated in standby state and the cutting-related auxiliary system powered on in air cutting state. The power consumption of these components is fixed. The third type is the spindle and feed systems, and their power consumption varies with different spindle speeds and feed rates. Air cutting energy E_{air} is usually modeled as follows [25]:

$$E_{air} = (P_{standby} + P_{auxiliary} + P_{unload}) t_{air}, \tag{12}$$

where t_{air} is the air cutting time related to air cutting length and cutting parameters, $P_{auxiliary}$ is the power consumption of cutting-related auxiliary system activated in air cutting state, and P_{unload} is the power consumption of the spindle and feed systems during air cutting state. It is usually defined as unload power because the spindle and feed systems are running without load. P_{unload} is usually composed of the unload power of spindle and feed systems, which can be expressed as shown in Eq. (13):

$$P_{unload} = P_{unload\text{-}spindle} + P_{unload\text{-}feed}, \tag{13}$$

where $P_{unload\text{-}spindle}$ and $P_{unload\text{-}feed}$ are the unload power of spindle and feed systems, respectively.

As shown in Eq. (14), Mativenga and Rajemi [66] found that the unload power of spindle system follows a linear relationship with spindle speed n:

$$P_{unload\text{-}spindle} = k_{spindle} n + b_{spindle}, \tag{14}$$

where $k_{spindle}$ and $b_{spindle}$ are the coefficients that can be measured through experiments.

In the work presented by Li et al. [61], they improved the unload power model of spindle system and approximated it with a quadratic function in terms of spindle speed n:

$$P_{unload\text{-}spindle} = \alpha_{spindle} + \beta_{spindle} n + \gamma_{spindle} n^2, \tag{15}$$

where $\alpha_{spindle}$, $\beta_{spindle}$, and $\gamma_{spindle}$ are the unload power coefficients of spindle system.

Similar to the unload power of spindle system, the unload power of feed system is modeled by researchers in a linear [67] or in a quadratic function [68] with respect to feed rate f:

$$P_{unload\text{-}feed} = \alpha_{feed} f + \beta_{feed}, \tag{16}$$

$$P_{unload\text{-}feed} = \gamma_{feed} f + \mu_{feed} f^2, \tag{17}$$

where α_{feed}, β_{feed}, γ_{feed} and μ_{feed} are the unload power coefficients of feed system.

4.1.4 Modeling of cutting energy $E_{cutting}$

Generally, there is no extra machine tool component activated in cutting state because the needed machine tool components are activated in standby state or air cutting state. However, the power profile in cutting state increases obviously compared with that in air cutting state, as shown in Fig. 2. This condition is because the tool tip needs more energy to remove the material from the workpiece and to overcome the additional friction of the transmission system generated by cutting load. To this end, cutting energy $E_{cutting}$ is composed of more than three parts compared with air cutting energy, which is calculated as shown in Eq. (18):

$$E_{cutting} = (P_{standby} + P_{auxiliary} + P_{unload} + P_{material} + P_{loss}) \cdot t_{cutting}, \tag{18}$$

where $P_{material}$ and P_{loss} are the material removal power and additional load loss power.

1) Material removal power $P_{material}$

The material removal power is highly dependent on cutting parameters, workpiece material, cutting tool, and machining conditions. Over the past 10 years, many researchers have proposed a variety of methods to model the material removal power. In the work presented by Gutowski et al. [69,70], they found that there was a linear relationship between material removal power $P_{removal}$ and MRR, which can be expressed in Eq. (19):

$$P_{material} = k_m \text{MRR}, \tag{19}$$

where k_m is a constant, and MRR is calculated on the basis of different machining types. In a milling process, MRR = $n f_z a_p a_e$, where f_z is the feed rate per tooth and a_e is the cutting width.

The cutting force reflects the deformation of workpiece material. Some researchers established material removal power models in terms of on cutting force. Albertelli et al. [51] modeled the material removal power of a milling process, as shown in Eq. (20):

$$P_{material} = K h a_p n_{teeth} v_c, \tag{20}$$

where n_{teeth} is the average number of engaged tool teeth, h

is the deformed chip thickness, and K is the cutting pressure. This model can be calculated considering the effects of chip thickness on specific cutting pressure [71].

In a machining process, empirical modeling is a widely used method to model the material removal power with respect to cutting parameters. The established models can be found in Refs. [72–76]. A typical material removal power model of a milling process is expressed as shown in Eq. (21):

$$P_{\text{material}} = C_{\text{F}} a_{\text{p}}^{x_{\text{F}}} f_{\text{z}}^{y_{\text{F}}} a_{\text{e}}^{z_{\text{F}}} v_{\text{c}}^{1+\mu_{\text{F}}}, \tag{21}$$

where C_{F}, x_{F}, y_{F}, z_{F}, and μ_{F} are the coefficients that can be obtained through cutting experiments.

2) Additional load loss power P_{loss}

During the cutting state, cutting load increases the friction of transmission systems and causes additional power consumption of the machine tool. In the work presented by Hu et al. [77], they defined the additional power consumption of machine tool as additional load loss power P_{loss} and modeled it with a quadratic function of material removal power, which can be expressed as Eq. (22):

$$P_{\text{loss}} = \lambda_{\text{loss}} P_{\text{material}} + \xi_{\text{loss}} P_{\text{material}}^2, \tag{22}$$

where λ_{loss} and ξ_{loss} are the additional load loss coefficients.

4.1.5 Modeling of embodied energy of cutting tool $E_{\text{tool-embodied}}$

As mentioned in Section 4.1.1, a worn cutting tool is replaced with a sharp one when the tool wear reaches the preset criterion. Accordingly, the embodied energy of the cutting tool is consumed. A new cutting tool usually can be used for machining more than one part. The needed embodied energy of a cutting tool in a machining process is calculated on the basis of the unit embodied energy of cutting tool, tool life, and actual cutting time [32].

$$E_{\text{tool-embodied}} = \frac{t_{\text{cutting}}}{T_{\text{tool}}} U_{\text{tool}}, \tag{23}$$

where U_{tool} is the unit embodied energy of cutting tool.

$$U_{\text{tool}} = \frac{E_{\text{insert}} V_{\text{insert}} z}{N}, \tag{24}$$

where E_{insert} is the energy to fabricate the cutting insert material, V_{insert} is the volume of one insert, N is the number of cutting edges of each insert.

4.1.6 Modeling of embodied energy of cutting fluid $E_{\text{fluid-embodied}}$

As reported by Yi et al. [19], the cutting fluid used in the machining process is composed of two categories. The first category is the water-based cutting fluid, and the second category is the oil-based cutting fluid. The energy used to produce cutting fluid varies with different categories. In a machining process, the needed embodied energy of cutting fluid is dependent on the unit embodied energy of cutting fluid U_{fluid}, replacement cycle of cutting fluid T_{fluid}, and cutting time t_{cutting}, which is expressed as Eq. (25):

$$E_{\text{fluid-embodied}} = \frac{t_{\text{cutting}}}{T_{\text{fluid}}} U_{\text{fluid}}, \tag{25}$$

$$U_{\text{fluid}} = E_{\text{fluid-material}} (V_{\text{initial}} + V_{\text{additional}}) \rho \delta, \tag{26}$$

where V_{initial} and $V_{\text{additional}}$ are initial and additional volumes of cutting fluid, ρ is the density of the cutting fluid, $E_{\text{fluid-material}}$ is the energy used to fabricate the material of cutting fluid, and δ is the concentration of cutting fluid. Note that the energy from water generation is negligible [29].

4.2 Machining constraints

In a machining process, all cutting parameters must be set within a permitted region to ensure the safety of the machine and cutting tools and to satisfy the machining quality and economic requirements. Therefore, some machining constraints should be satisfied in energy efficient cutting parameter optimization. The typical constraints for a milling process are expressed as follows:

$$v_{\text{c,min}} \leqslant v_{\text{c}} \leqslant v_{\text{c,max}}, \tag{27}$$

$$a_{\text{p,min}} \leqslant a_{\text{p}} \leqslant a_{\text{p,max}}, \tag{28}$$

$$f_{\text{min}} \leqslant f \leqslant f_{\text{max}}, \tag{29}$$

$$P_{\text{unload}} + P_{\text{material}} + P_{\text{loss}} \leqslant \eta_{\text{m}} P_{\text{m}}, \tag{30}$$

$$Ra = 318 \frac{f_z^2}{\tan a_{\text{l}} + \cot a_{\text{c}}} \leqslant Ra_{\text{max}}, \tag{31}$$

$$T_{\text{tool}} \geqslant T_{\text{e}}. \tag{32}$$

Equations (27)–(29) ensure the cutting velocity, feed rate, and cutting depth to be within their feasible ranges for avoiding quick tool wear and machine tool damage [78], where $v_{\text{c,max}}/v_{\text{c,min}}$, $a_{\text{p,max}}/a_{\text{p,min}}$, and $f_{\text{max}}/f_{\text{min}}$ are the maximum/minimum cutting velocity, cutting depth, and feed rate. Equation (30) controls the required power to be less than the output power of the spindle motor, where P_{m} and η_{m} are nominal motor power and overall efficiency of the spindle. Equation (31) ensures the final surface roughness Ra to be less than the permitted Ra_{max}, where a_{l} and a_{c} are the lead and clearance angles of the tool tip, respectively. Similarly, Eq. (32) controls the tool life to be longer than the economic one, T_{e}.

The abovementioned constraints are typically used in cutting parameter optimization. For a specific machining case, other constraints are needed to be satisfied. In a multipass machining process, the summation of all cutting widths should be equal to the total machining stock [79–81]. In a drilling process, the stability of the drill should be focused because a deviation of the drill may lead to a failure of the machine tool and drill [82].

4.3 Optimization solution via evolutionary or metaheuristic algorithms

Energy efficient cutting parameter optimization is a highly nonlinear, multidimensional, and ill-behaved engineering problem with multiple constraints and multiple conflicting objectives [83]. Two methods are mainly used to solve this problem. Traditional methods include the conventional nonlinear programming-based algorithms, such as quasi-Newton and steepest descent methods [84]. With the development of optimization algorithms, many nonconventional methods, such as evolutionary or metaheuristic algorithms, have been proposed by researchers in recent years [85]. These methods include backtracking search algorithm (BSA) [17], PSO [86], and artificial bee colony (ABC) [87]. Particularly, for energy efficient cutting parameter optimization with multiple conflicting objectives, Pareto multiobjective optimization methods used to search comprise solutions are proposed by researchers on the basis of these algorithms. These methods include multiobjective backtracking search algorithm (MOBSA), multiobjective PSO (MOPSO), and multiobjective ABC. These algorithms are inspired by nature or animal's behavior, and their performance is different from each another due to their unique solution searching mechanism. The performance of each algorithm varies with different optimization problems. Lu et al. [17] compared the performance of different algorithms in solving the multi-pass energy efficient cutting parameter optimization problem. They found that MOBSA outperforms nondominated sorting genetic algorithm II (NSGA-II), MOPSO, multiobjective evolutionary algorithm based on decomposition (MOEA/D), and multiobjective harmony search (MOHS) from the perspectives of the extent of spread in the Pareto fronts, generational distance, and inverse generational distance. In the work reported by He et al. [55], they concluded that the convergence speed of NSGA-II is faster than MOEA/D. However, the solutions obtained by MOEA/D are found to be more efficient for engineering use due to the diversity and good performance.

As shown in Fig. 5, the flowchart of a popularly used NSGA-II [88–90] is taken as an example to demonstrate the basic logic of nonconventional optimization methods. From Fig. 5, four main steps are used in the algorithm, which are initialization, determination, selection, and reproduction. The initialization step is composed of solution representation and solution initialization. It is used to code the cutting parameters and generate the initial cutting parameter solutions. The initialization solutions are

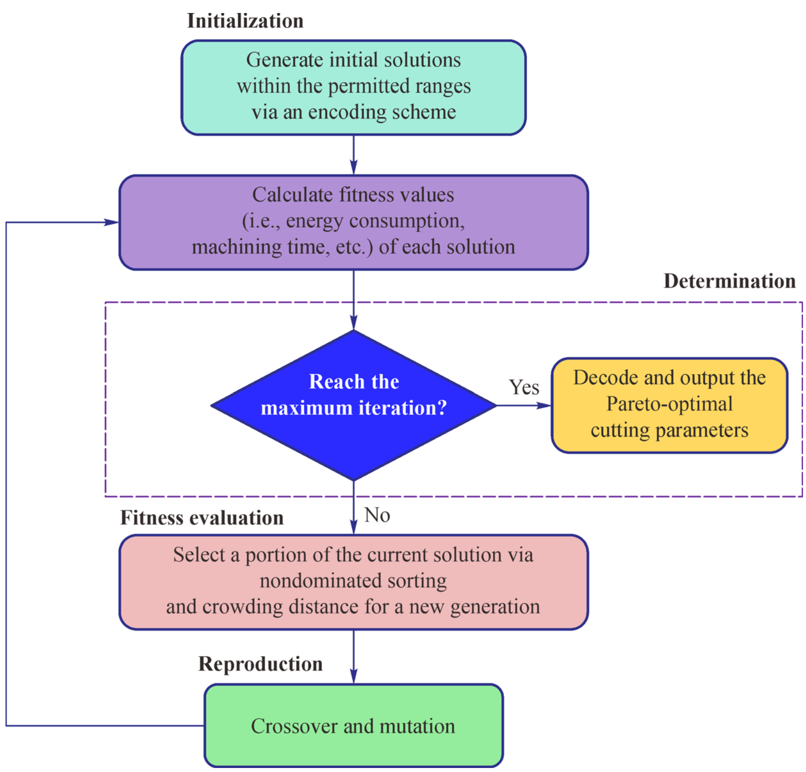

Fig. 5 Flowchart of an exemplary nondominated sorting genetic algorithm II.

generated randomly within the cutting parameter ranges. The determination step is set to calculate the fitness values (i.e., energy consumption, machining time, etc.) of each cutting parameter solutions and identify the termination of the algorithm. The selection step is used to choose a portion of the existing solution for a new generation. Each optimization algorithm has its unique mechanism for solution selection. For the NSGA-II, nondominated sorting and crowding distance are usually used. The reproduction step is used to produce new generations and varies with different algorithm. In NSGA-II, crossover and mutation are adopted to realize the production of new generation.

4.4 Remarks

The following remarks based on the reviewed studies are summarized:

- The established energy models involve many parameters, such as coefficients of unload power, material removal power, and tool changing power. These coefficients are usually determined by a variety of machining conditions, including machining type, machine tool specification, material of workpiece, and cutting tool. This condition indicates that although the established energy models are general, they should not be directly used for a specific machining case before identifying these coefficients.
- The results of the studies listed in Table 2 are relatively similar to that shown in Table 1. The most influential cutting parameter on energy consumption differs with machining conditions. The optimal cutting parameters for energy saving should be selected under restriction of these machining conditions. A minor change in the machining conditions may cause the entire optimization process to start all over again.
- The optimal cutting parameters vary with different energy boundaries of the machining system. Current research is concentrated on reducing the electrical energy consumption of the machine tool because it can be easily measured with a power meter. Only a few studies extend their focus to the embodied energy of cutting tool and cutting fluid. This condition is mainly because the production process of the material is extremely complicated, and an effective method to obtain the energy consumption is lacking for producing the material [91]. However, from the machining system point of view, cutting parameter optimization with a comprehensive consideration of all energy consumption reduces the total energy consumption. A reasonable estimation of the embodied energy of material is better rather than disregarding it.
- The optimal cutting parameters for minimizing energy consumption should be within the permitted region restricted by machining constraints. Setting up reasonable constraints is usually a difficult task. This is because these constraints are affected by many machining conditions, and obtaining the parameters in these constraints may be extremely difficult. Furthermore, insufficient constraint may lead to impractical cutting parameters, whereas excessive constraints may result in a few limited solutions or no solution.

5 Recommendations

On the basis of the above review of current studies about energy efficient cutting parameter optimization, the authors provide some recommendations on this topic for future research.

1) The energy consumption of the machining process includes the electrical energy consumption of machine tool and the embodied energy of cutting tool and cutting fluid. Energy efficient cutting parameter optimization should start with the definition of the system boundary because the optimal cutting parameters vary with different energy boundaries. Current studies are concentrated on reducing the electrical energy consumption of the machine tool. Only a few studies extend their focus to the embodied energy of cutting tool and cutting fluid. Future work can be concentrated on cutting parameter optimization with a comprehensive consideration of electrical energy and embodied energy.

2) For a specific energy efficient cutting parameter optimization problem, researchers exert their best effort to find the most suitable method to solve it or modify some existing algorithms to make them applicable for the optimization cases. However, a method or guideline is lacking for the proper selection of suitable method in solving energy efficient cutting parameter optimization problem. Furthermore, for some optimization problems with multiple conflicting objectives, the optimal cutting parameter schemes for minimizing energy consumption do not necessarily satisfy the optimization criteria of minimizing surface roughness, maximizing tool life, and MRR. Multiobjective optimization is an effective method used to solve this problem. However, the decision rules for selecting the Pareto-optimal solutions should be further studied to strike a balance between these objectives and meet various engineering applications.

3) Although the influence of cutting parameters on energy consumption varies with different machining conditions, it shows similarities under some machining conditions. For example, Yan and Li [44] found that the energy consumption of milling process can be reduced with a large MRR. Li et al. [49] and Moreira et al. [14] found that machining with a large feed rate can reduce the energy consumption of their milling process. This is because the main machining conditions of these studies are relatively similar, and the main conclusions are consistent. It gives us an inspiration that we can conduct energy

efficient cutting parameter optimization by mining the knowledge included in the machining data [92], which are easy to acquire by monitoring [4] the cutting parameters, machining conditions, and the corresponding energy consumption. In our prior work, we analyzed the machining data to find the optimal cutting parameters for energy saving in a turning process, as shown in Fig. 6 [93]. However, this is only a beginning of this research direction and deserves further study.

4) Most of the existing studies about energy efficient cutting parameter optimization are completed before machining, and the obtained cutting parameters are inserted into the numerical codes. In recent years, with the development of measurement technology, monitoring the machining signals, such as torque, cutting power, vibration, and temperature of the spindle system or the whole machine tool, is convenient. As shown in Fig. 7, on-board cutting parameter optimization by considering

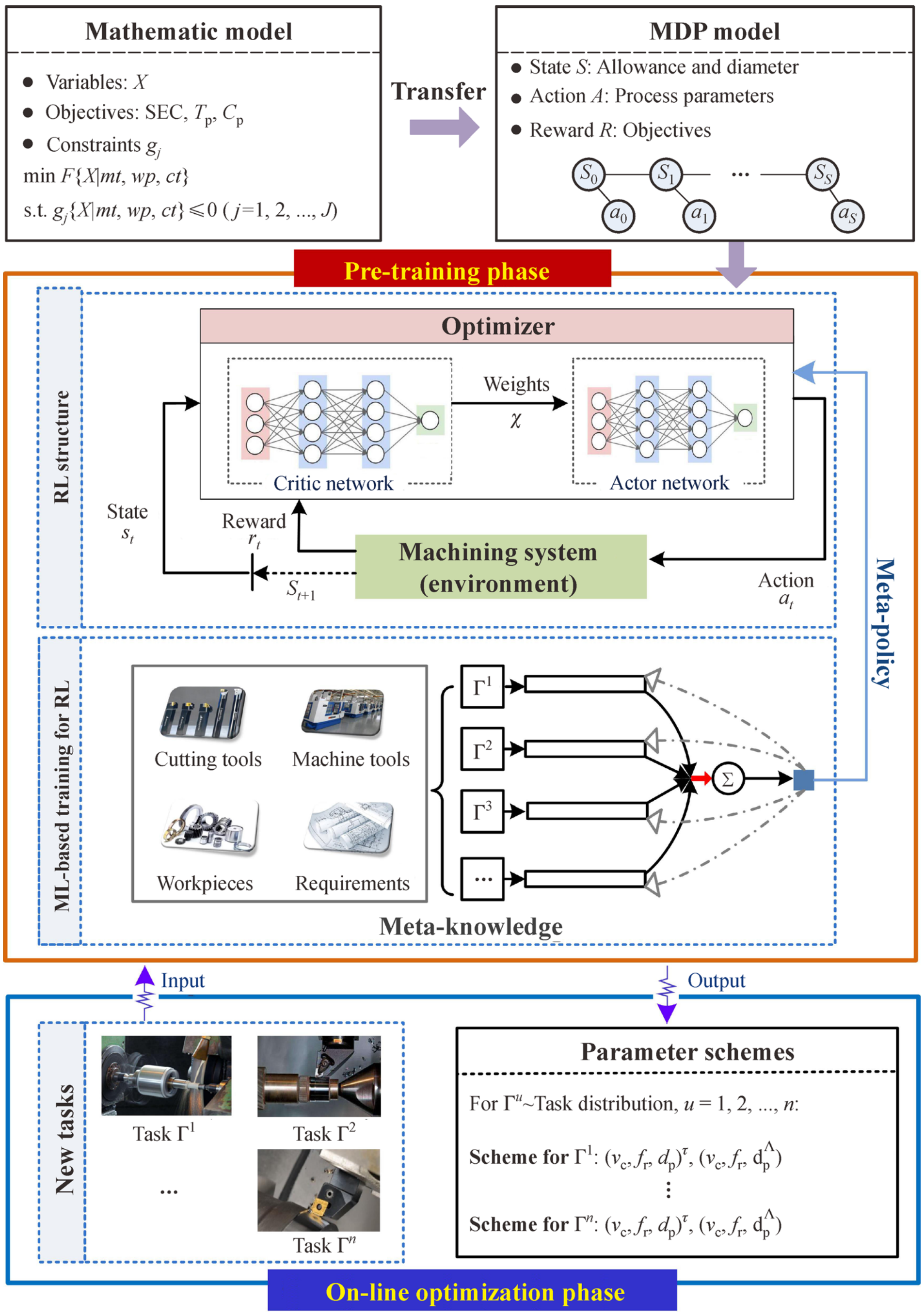

Fig. 6 Schematic representation of metareinforcement learning of cutting parameter optimization [93].

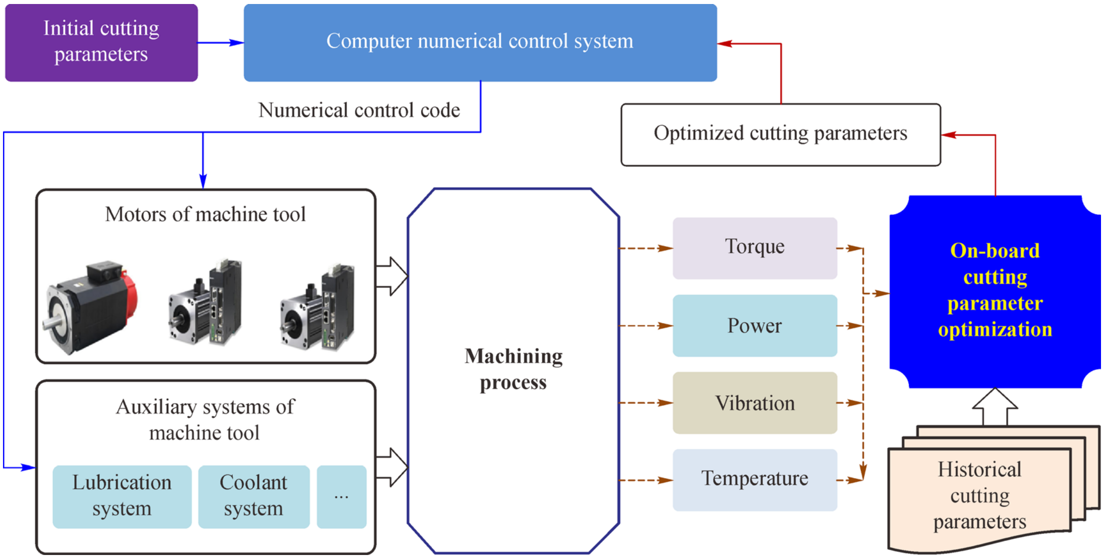

Fig. 7 On-board cutting parameter optimization.

the real-time machining signals may be a future research area because the optimal cutting parameter can be adjusted in accordance with the real-time machining conditions [94].

6 Conclusions

Energy efficient cutting parameter optimization has attracted wide attention from the academic community and industry practitioners because it is a vital method toward energy saving in a machining process. In this paper, an overview of the state-of-the-art energy efficient cutting parameter optimization is presented. The energy consumption characteristics of machining process are analyzed by decomposing the total energy consumption into electrical energy consumption of machine tool and the embodied energy of cutting tool and cutting fluid. Current literature about cutting parameter optimization for energy saving is reviewed by classifying them into two categories, namely, energy efficient cutting parameter optimization by using experimental design methods and energy models. On the basis of the reviewed studies, the advances and limitations of the existing studies are analyzed. Some future research recommendations are provided, including cutting parameter optimization with a comprehensive consideration of the electrical energy and embodied energy of cutting tool and cutting fluid, development of decision rules for selecting Pareto-optimal cutting parameter solutions, energy efficient cutting parameter optimization by mining the knowledge included in the machining data, and on-board energy efficient cutting parameter optimization. This work can be a good help for researchers in this research area.

Nomenclature

Variables

a_c	Clearance angle of the tool tip
a_e	Cutting width
a_l	Lead angle of the tool tip
a_p	Cutting depth
$a_{p,max}$	Maximum cutting depth
$a_{p,min}$	Minimum cutting depth
$b_{spindle}$	Unload power coefficient of spindle system
$B(n_s)$	Viscous damping coefficient of main transmission system equivalently transformed to motor shaft
B_{SA}	Coefficient of the spindle acceleration energy
B_{SRD}	Coefficient of the spindle deceleration energy
C_F	Coefficient of cutting force
C_{SA}	Coefficient of the spindle acceleration energy
C_{SRD}	Coefficient of the spindle deceleration energy
C_T	Coefficient of tool life
D_{avg}	Average diameter of workpiece
$D_{milling}$	Diameter of milling tool
E_{ac}	Spindle acceleration energy
E_{air}	Air cutting energy
E^i_{air}	Air cutting energy of the *i*th pass
$E^i_{approaching}$	Energy consumption for tool approaching of the *i*th pass
$E_{cutting}$	Cutting energy
$E^i_{cutting}$	Cutting energy of the *i*th pass
E_{dc}	Spindle deceleration energy
$E_{electrical}$	Electrical energy of the machining process

$E_{\mathrm{electrical\text{-}dry}}$	Electrical energy of the machining process under dry condition
$E_{\mathrm{electrical\text{-}wet}}$	Electrical energy of the machining process under wet condition
E_{embodied}	Electrical energy of machine tool and the embodied energy of consumable material
$E_{\mathrm{fluid\text{-}embodied}}$	Embodied energy consumption of cutting fluid
$E_{\mathrm{fluid\text{-}material}}$	Energy used to fabricate the material of cutting fluid
$E_{\mathrm{footprint}}$	Energy footprint of the machining process
$E_{\mathrm{functional\text{-}modules}}$	Energy consumption by main machine tool functional modules
$E_{\mathrm{idle\text{-}auxiliary}}$	Idle energy of auxiliary system
E_{insert}	Energy to fabricate the cutting insert material
E_{leaving}	Energy consumption for tool leaving
$E_{\mathrm{loss\text{-}motor}}$	Additional load loss energy of main motor
$E_{\mathrm{loss\text{-}moving}}$	Inertia energy loss of moving components
E_{m}	Changed energy of electromagnetic field
E_{material}	Material removal energy
$E_{\mathrm{rotation\text{-}changing}}$	Energy consumption for spindle rotation changing (non-cutting)
E_{standby}	Standby energy
E^{i}_{standby}	Standby energy of the *i*th pass
$E_{\mathrm{standby\text{-}preparation}}$	Standby energy used to bring the workpiece and cutting tool to the about-to cut position and to set up the numerical control program before machining
E_{startup}	Startup energy
$E_{\mathrm{tool\text{-}changing}}$	Standby energy used for changing the worn cutting tool
$E_{\mathrm{tool\text{-}embodied}}$	Embodied energy consumption of cutting tool
f	Feed rate
$f_{\max}$	Maximum feed rate
$f_{\min}$	Minimum feed rate
f_{z}	Feed rate per tooth
F_{cutting}	Cutting force
h	Deformed chip thickness
$J_{\mathrm{m}}(n_{\mathrm{s}})$	Rotational inertia of main transmission system equivalently transformed to motor shaft
k_{m}	Constant for material removal power
k_{spindle}	Unload power coefficient of spindle system
K	Cutting pressure
l	Cutting length of workpiece
m	Number of machining passes
$M_{\mathrm{om}}(n_{\mathrm{s}})$	Load torque of electric motor in the main transmission system
n	Spindle speed
n_{teeth}	Average number of engaged tool teeth
$n^{pq}_{\mathrm{E}j}$	Final spindle speed for the *j*th speed change in spindle rotation
$n^{pq}_{\mathrm{S}j}$	Initial spindle speed for the *j*th speed change in spindle rotation
$n(t)$	Spindle speed varying with time
N	Number of cutting edges of each insert
P_{air}	Air cutting power
$P_{\mathrm{auxiliary}}$	Power of auxiliary system
$P^{pq}_{\mathrm{c}j}$	Power consumption of spindle system during the *j*th speed change of the spindle rotation in noncutting operations from feature F_p to feature F_q
P_{cutting}	Cutting power
$P_{\mathrm{feed\text{-}fast}}$	Power for fast feeding
$P_{\mathrm{idle\text{-}auxiliary}}$	Idle power of auxiliary system
P_{loss}	Additional load loss power of spindle system and feed systems
$P_{\mathrm{loss\text{-}spindle}}$	Additional load loss power of spindle system
P_{m}	Nominal motor power of spindle
P_{material}	Material removal power
$P_{\mathrm{rated\text{-}compressed}}$	Rated power of compressed air motor
P_{removal}	Material removal power
$P_{\mathrm{spraying\text{-}cooling}}$	Power for spraying cooling fluid
P_{standby}	Standby power
P_{startup}	Startup power
P_{unload}	Unload power of spindle and feed systems
$P_{\mathrm{unload\text{-}feed}}$	Unload power of feed system
$P_{\mathrm{unload\text{-}spindle}}$	Unload power of spindle system
Ra	Surface roughness
$Ra_{\max}$	Permitted maximum surface roughness
t_{ac}	Time duration of spindle acceleration
t_{air}	Air cutting time
t_{cutting}	Cutting time
$t^{pq}_{\mathrm{c}j}$	Time duration during the *j*th speed change of the spindle rotation in noncutting operations from feature F_p to feature F_q
t_{end}	Spindle acceleration ending at this time point
$t_{\mathrm{feed\text{-}fast}}$	Time for fast feeding
$t_{\mathrm{insert\text{-}changing}}$	Time for changing an insert
$t_{\mathrm{spraying\text{-}cooling}}$	Time for spraying cooling fluid
t_{st}	Spindle acceleration starting at this time point
$t_{\mathrm{standby\text{-}preparation}}$	Standby time used to bring the workpiece and cutting tool to the about-to cut position and to set up the numerical control program before machining
t_{startup}	Startup time
$t_{\mathrm{tool\text{-}changing}}$	Tool changing time
T_{fluid}	Replacement cycle of cutting fluid
T_{e}	Economic tool life
T_{SA}	Coefficient of the spindle acceleration energy
T_{tool}	Tool life
U_{fluid}	Unit embodied energy of cutting fluid
U_{tool}	Unit embodied energy of cutting tool
$V_{\mathrm{additional}}$	Additional volume of cutting fluid

v_c	Cutting velocity
$v_{c,max}$	Maximum cutting velocity
$v_{c,min}$	Minimum cutting velocity
$V_{initial}$	Initial volume of cutting fluid
V_{insert}	Volume of one insert
x_F	Coefficient of cutting force
y_F	Coefficient of cutting force
z	Number of cutting inserts
z_F	Coefficient of cutting force
α_A	Coefficient of the spindle system
α_F	Coefficient of cutting force
α_{feed}	Unload power coefficient of feed system
$\alpha_{spindle}$	Unload power coefficient of spindle system
α_T	Coefficient of tool life
β_F	Coefficient of cutting force
β_{feed}	Unload power coefficient of feed system
$\beta_{spindle}$	Unload power coefficient of spindle system
β_T	Coefficient of tool life
$\gamma_{compressed}$	Load factor of compressed air motor
γ_{feed}	Unload power coefficient of feed system
$\gamma_{spindle}$	Unload power coefficient of spindle system
γ_T	Coefficient of tool life
δ	Concentration of cutting fluid
ξ_{loss}	Additional load loss coefficient
η_m	Overall efficiency of spindle motor
λ	Coefficient of cutting force
λ_{loss}	Additional load loss coefficient
μ_F	Coefficient of cutting force
μ_{feed}	Unload power coefficient of feed system
ρ	Density of the cutting fluid
ψ_F	Coefficient of cutting force

Abbreviations

ABC	Artificial bee colony
ANN	Artificial neural network
ANOVA	Analysis of variance
BSA	Backtracking search algorithm
DFA	Desirability function analysis
EMMBMS	Energy modeling method based on machining state
EMMBMTC	Energy modeling method based on machine tool component
GA	Genetic algorithm
GRA	Gray relational analysis
GRG	Gray relational grade
HSS	High-speed steel
MOBSA	Multiobjective backtracking search algorithm
MOEA/D	Multiobjective evolutionary algorithm based on decomposition
MOHS	Multiobjective harmony search
MOPSO	Multiobjective particle swarm optimization
MQL	Minimum quantity lubrication
MRR	Material removal rate
MRV	Material removal volume
NC	Numerical control
NSGA-II	Nondominated sorting genetic algorithm II
RSM	Response surface methodology
PCA	Principal component analysis
PSO	Particle swarm optimization
SEC	Specific cutting energy, the amount of energy required to cut a unit volume of a workpiece
SQP	Sequential quadratic programming
S/N	Signal-to-noise ratio
TOPSIS	Technique for order of preference by similarity to ideal solution

Acknowledgements This work was supported in part by the National Natural Science Foundation of China (Grant No. 51905448), the Fundamental Research Funds for the Central Universities of China (Grant No. SWU119060), the Natural Science Foundation of Chongqing, China (Grant No. cstc2018jcyjAX0579), and the Technological Innovation and Application Development of Chongqing, China (Grant No. cstc2019jscx-mbdx0118).

References

1. IEA. Key energy statistics. Available at IEA website. 2020-08-20
2. Cai W, Liu C, Lai K, et al. Energy performance certification in mechanical manufacturing industry: A review and analysis. Energy Conversion and Management, 2019, 186: 415–432
3. Cai W, Liu F, Zhou X, et al. Fine energy consumption allowance of workpieces in the mechanical manufacturing industry. Energy, 2016, 114: 623–633
4. Chen X, Li C, Tang Y, et al. An Internet of Things based energy efficiency monitoring and management system for machining workshop. Journal of Cleaner Production, 2018, 199: 957–968
5. Liu P, Liu F, Qiu H. A novel approach for acquiring the real-time energy efficiency of machine tools. Energy, 2017, 121: 524–532

6. ISO. Machine tools—Environmental evaluation of machine tools—Part 1: Design methodology for energy-efficient machine tools. 2017. Available at ISO website. 2020-08-20
7. Newman S T, Nassehi A, Imani-Asrai R, et al. Energy efficient process planning for CNC machining. CIRP Journal of Manufacturing Science and Technology, 2012, 5(2): 127–136
8. Yoon H S, Kim E S, Kim M S, et al. Towards greener machine tools—A review on energy saving strategies and technologies. Renewable & Sustainable Energy Reviews, 2015, 48: 870–891
9. Camposeco-Negrete C. Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA. Journal of Cleaner Production, 2013, 53: 195–203
10. Aslani M, Mesgari M S, Wiering M. Adaptive traffic signal control with actor-critic methods in a real-world traffic network with different traffic disruption events. Transportation Research Part C, Emerging Technologies, 2017, 85: 732–752
11. Kumar R, Bilga P S, Singh S. Multi objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation. Journal of Cleaner Production, 2017, 164: 45–57
12. Dahmus J B, Gutowski T G. An environmental analysis of machining. In: Proceedings of 2004 ASME International Mechanical Engineering Congress and RD&D Expo. Anaheim: ASME, 2004, 643–652
13. Rajemi M F, Mativenga P T, Aramcharoen A. Sustainable machining: Selection of optimum turning conditions based on minimum energy considerations. Journal of Cleaner Production, 2010, 18(10–11): 1059–1065
14. Moreira L C, Li W, Lu X, et al. Energy-efficient machining process analysis and optimisation based on BS EN24T alloy steel as case studies. Robotics and Computer-Integrated Manufacturing, 2019, 58: 1–12
15. Nguyen T T. Prediction and optimization of machining energy, surface roughness, and production rate in SKD61 milling. Measurement, 2019, 136: 525–544
16. Arif M, Stroud I A, Akten O. A model to determine the optimal parameters for sustainable-energy machining in a multi-pass turning operation. Proceedings of the Institution of Mechanical Engineers. Part B, Journal of Engineering Manufacture, 2014, 228(6): 866–877
17. Lu C, Gao L, Li X, et al. Energy-efficient multi-pass turning operation using multi-objective backtracking search algorithm. Journal of Cleaner Production, 2016, 137: 1516–1531
18. Li C, Tang Y, Cui L, et al. A quantitative approach to analyze carbon emissions of CNC-based machining systems. Journal of Intelligent Manufacturing, 2015, 26(5): 911–922
19. Yi Q, Li C, Tang Y, et al. Multi-objective parameter optimization of CNC machining for low carbon manufacturing. Journal of Cleaner Production, 2015, 95: 256–264
20. Priarone P C, Robiglio M, Settineri L, et al. Modelling of specific energy requirements in machining as a function of tool and lubricoolant usage. CIRP Annals-Manufacturing Technology, 2016, 65(1): 25–28
21. Li W, Zein A, Kara S, et al. An investigation into fixed energy consumption of machine tools. In: Hesselbach J, Herrmann C, eds. Glocalized Solutions for Sustainability in Manufacturing. Berlin: Springer, 2011, 268–273
22. Zhou L, Li J, Li F, et al. Energy consumption model and energy efficiency of machine tools: A comprehensive literature review. Journal of Cleaner Production, 2016, 112: 3721–3734
23. Zhao G Y, Liu Z Y, He Y, et al. Energy consumption in machining: Classification, prediction, and reduction strategy. Energy, 2017, 133: 142–157
24. Renna P. Energy saving by switch-off policy in a pull-controlled production line. Sustainable Production and Consumption, 2018, 16: 25–32
25. Li C, Chen X, Tang Y, et al. Selection of optimum parameters in multi-pass face milling for maximum energy efficiency and minimum production cost. Journal of Cleaner Production, 2017, 140: 1805–1818
26. Hu L, Liu Y, Lohse N, et al. Sequencing the features to minimise the non-cutting energy consumption in machining considering the change of spindle rotation speed. Energy, 2017, 139: 935–946
27. Emami M, Sadeghi M H, Sarhan A D, et al. Investigating the minimum quantity lubrication in grinding of Al_2O_3 engineering ceramic. Journal of Cleaner Production, 2014, 66: 632–643
28. Hanafi I, Khamlichi A, Cabrera F M, et al. Optimization of cutting conditions for sustainable machining of PEEK-CF30 using TiN tools. Journal of Cleaner Production, 2012, 33: 1–9
29. Chen X, Li C, Jin Y, et al. Optimization of cutting parameters with a sustainable consideration of electrical energy and embodied energy of materials. International Journal of Advanced Manufacturing Technology, 2018, 96(1–4): 775–788
30. Ullah A M M S, Kitajima K, Akamatsu T, et al. On some eco-indicators of cutting tools. In: Proceedings of ASME 2011 International Manufacturing Science and Engineering Conference. Corvallis: ASME, 2011, 105–110
31. Arif M, Stroud I A, Akten O. A model to determine the optimal parameters in a machining process for the most profitable utilization of machining energy. Proceedings of the Institution of Mechanical Engineers. Part B, Journal of Engineering Manufacture, 2015, 229(2): 266–274
32. Chen X, Li C, Tang Y, et al. Integrated optimization of cutting tool and cutting parameters in face milling for minimizing energy footprint and production time. Energy, 2019, 175: 1021–1037
33. Wang Q, Liu F, Wang X. Multi-objective optimization of machining parameters considering energy consumption. International Journal of Advanced Manufacturing Technology, 2014, 71(5–8): 1133–1142
34. Fratila D, Caizar C. Application of Taguchi method to selection of optimal lubrication and cutting conditions in face milling of $AlMg_3$. Journal of Cleaner Production, 2011, 19(6–7): 640–645
35. Li C, Xiao Q, Tang Y, et al. A method integrating Taguchi, RSM and MOPSO to CNC machining parameters optimization for energy saving. Journal of Cleaner Production, 2016, 135: 263–275
36. Campatelli G, Lorenzini L, Scippa A. Optimization of process parameters using a response surface method for minimizing power consumption in the milling of carbon steel. Journal of Cleaner Production, 2014, 66: 309–316
37. Bhattacharya A, Das S, Majumder P, et al. Estimating the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel using Taguchi design and

ANOVA. Production Engineering, 2009, 3(1): 31–40
38. Kant G, Sangwan K S. Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining. Journal of Cleaner Production, 2014, 83: 151–164
39. Zhang Y, Zou P, Li B, et al. Study on optimized principles of process parameters for environmentally friendly machining austenitic stainless steel with high efficiency and little energy consumption. International Journal of Advanced Manufacturing Technology, 2015, 79(1–4): 89–99
40. Camposeco-Negrete C, de Dios Calderón Nájera J, Miranda-Valenzuela J C. Optimization of cutting parameters to minimize energy consumption during turning of AISI 1018 steel at constant material removal rate using robust design. International Journal of Advanced Manufacturing Technology, 2016, 83(5–8): 1341–1347
41. Bilga P S, Singh S, Kumar R. Optimization of energy consumption response parameters for turning operation using Taguchi method. Journal of Cleaner Production, 2016, 137: 1406–1417
42. Altıntaş R S, Kahya M, Ünver H Ö. Modelling and optimization of energy consumption for feature based milling. International Journal of Advanced Manufacturing Technology, 2016, 86(9–12): 3345–3363
43. Bhushan R K. Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites. Journal of Cleaner Production, 2013, 39(1): 242–254
44. Yan J, Li L. Multi-objective optimization of milling parameters: The trade-offs between energy, production rate and cutting quality. Journal of Cleaner Production, 2013, 52: 462–471
45. Arriaza O V, Kim D, Lee D, et al. Trade-off analysis between machining time and energy consumption in impeller NC machining. Robotics and Computer-Integrated Manufacturing, 2017, 43: 164–170
46. Bagaber S A, Yusoff A R. Multi-objective optimization of cutting parameters to minimize power consumption in dry turning of stainless steel 316. Journal of Cleaner Production, 2017, 157: 30–46
47. Suneesh E, Sivapragash M. Parameter optimisation to combine low energy consumption with high surface integrity in turning Mg/Al_2O_3 hybrid composites under dry and MQL conditions. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 2019, 41(2): 89
48. Jang D Y, Jung J, Seok J. Modeling and parameter optimization for cutting energy reduction in MQL milling process. International Journal of Precision Engineering and Manufacturing—Green Technology, 2016, 3(1): 5–12
49. Li J, Lu Y, Zhao H, et al. Optimization of cutting parameters for energy saving. International Journal of Advanced Manufacturing Technology, 2014, 70(1–4): 117–124
50. Velchev S, Kolev I, Ivanov K, et al. Empirical models for specific energy consumption and optimization of cutting parameters for minimizing energy consumption during turning. Journal of Cleaner Production, 2014, 80: 139–149
51. Albertelli P, Keshari A, Matta A. Energy oriented multi cutting parameter optimization in face milling. Journal of Cleaner Production, 2016, 137: 1602–1618
52. Ma F, Zhang H, Cao H, et al. An energy consumption optimization strategy for CNC milling. International Journal of Advanced Manufacturing Technology, 2017, 90(5–8): 1715–1726
53. Xiong Y, Wu J, Deng C, et al. Machining process parameters optimization for heavy-duty CNC machine tools in sustainable manufacturing. International Journal of Advanced Manufacturing Technology, 2016, 87(4): 1237–1246
54. Deng Z, Zhang H, Fu Y, et al. Optimization of process parameters for minimum energy consumption based on cutting specific energy consumption. Journal of Cleaner Production, 2017, 166: 1407–1414
55. He K, Tang R, Jin M. Pareto fronts of machining parameters for trade-off among energy consumption, cutting force and processing time. International Journal of Production Economics, 2017, 185: 113–127
56. Zhang H, Deng Z, Fu Y, et al. A process parameters optimization method of multi-pass dry milling for high efficiency, low energy and low carbon emissions. Journal of Cleaner Production, 2017, 148: 174–184
57. Zhong Q, Tang R, Peng T. Decision rules for energy consumption minimization during material removal process in turning. Journal of Cleaner Production, 2017, 140: 1819–1827
58. Zhang L, Zhang B, Bao H, et al. Optimization of cutting parameters for minimizing environmental impact: Considering energy efficiency, noise emission and economic dimension. International Journal of Precision Engineering and Manufacturing, 2018, 19(4): 613–624
59. Bagaber S A, Yusoff A R. Energy and cost integration for multi-objective optimisation in a sustainable turning process. Measurement, 2019, 136: 795–810
60. Hu L, Tang R, Cai W, et al. Optimisation of cutting parameters for improving energy efficiency in machining process. Robotics and Computer-Integrated Manufacturing, 2019, 59: 406–416
61. Li C, Li L, Tang Y, et al. A comprehensive approach to parameters optimization of energy-aware CNC milling. Journal of Intelligent Manufacturing, 2019, 30(1): 123–138
62. Wang H, Zhong R Y, Liu G, et al. An optimization model for energy-efficient machining for sustainable production. Journal of Cleaner Production, 2019, 232: 1121–1133
63. Li W, Kara S. An empirical model for predicting energy consumption of manufacturing processes: A case of turning process. Proceedings of the Institution of Mechanical Engineers. Part B, Journal of Engineering Manufacture, 2011, 225(9): 1636–1646
64. Chauhan P, Pant M, Deep K. Parameter optimization of multi-pass turning using chaotic PSO. International Journal of Machine Learning and Cybernetics, 2015, 6(2): 319–337
65. Huang J, Liu F, Xie J. A method for determining the energy consumption of machine tools in the spindle start-up process before machining. Proceedings of the Institution of Mechanical Engineers. Part B, Journal of Engineering Manufacture, 2015, 230(9): 1639–1649
66. Mativenga P T, Rajemi M F. Calculation of optimum cutting parameters based on minimum energy footprint. CIRP Annals-Manufactuing Technology, 2011, 60(1): 149–152
67. Li L, Yan J, Xing Z. Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modelling. Journal of Cleaner Production, 2013, 52: 113–121

68. Lv J, Tang R, Jia S. Therblig-based energy supply modeling of computer numerical control machine tools. Journal of Cleaner Production, 2014, 65: 168–177
69. Gutowski T, Branham M, Dahmus J, et al. Thermodynamic analysis of resources used in manufacturing processes. Environmental Science & Technology, 2009, 43(5): 1584–1590
70. Gutowski T, Dahmus J, Thiriez A. Electrical energy requirements for manufacturing processes. In: Proceedings of the 13th CIRP International Conference on Life Cycle Engineering. Leuven, 2006, 623–628
71. Altintas Y. Manufacturing Automation. Cambridge: Cambridge University Press, 2012
72. Diaz N, Choi S, Helu M, et al. Machine tool design and operation strategies for green manufacturing. In: Proceedings of the 4th CIRP International Conference on High Performance Cutting (HPC2010). Gifu, 2010, 271–276
73. Sealy M P, Liu Z, Zhang D, et al. Energy consumption and modeling in precision hard milling. Journal of Cleaner Production, 2016, 135: 1591–1601
74. Lv J, Tang R, Jia S, et al. Experimental study on energy consumption of computer numerical control machine tools. Journal of Cleaner Production, 2016, 112: 3864–3874
75. Hu L, Peng C, Evans S, et al. Minimising the machining energy consumption of a machine tool by sequencing the features of a part. Energy, 2017, 121: 292–305
76. Han F, Li L, Cai W, et al. Parameters optimization considering the trade-off between cutting power and MRR based on linear decreasing particle swarm algorithm in milling. Journal of Cleaner Production, 2020, 262: 121388
77. Hu S, Liu F, He Y, et al. Characteristics of additional load losses of spindle system of machine tools. Journal of Advanced Mechanical Design, Systems and Manufacturing, 2010, 4(7): 1221–1233
78. Xu H, Jiang Q, Cao T. Milling Processing Manual. Beijing: China Machine Press, 2012
79. Yang W A, Guo Y, Liao W H. Optimization of multi-pass face milling using a fuzzy particle swarm optimization algorithm. International Journal of Advanced Manufacturing Technology, 2011, 54(1–4): 45–57
80. Yildiz A R. Optimization of cutting parameters in multi-pass turning using artificial bee colony-based approach. Information Science, 2013, 220: 399–407
81. Gao L, Huang J, Li X. An effective cellular particle swarm optimization for parameters optimization of a multi-pass milling process. Applied Soft Computing, 2012, 12(11): 3490–3499
82. Shunmugam M S, Reddy S V B, Narendran T T. Optimal selection of parameters in multi-tool drilling. Journal of Materials Processing Technology, 2000, 103(2): 318–323
83. Li L, Li C, Tang Y, et al. An integrated approach of process planning and cutting parameter optimization for energy-aware CNC machining. Journal of Cleaner Production, 2017, 162: 458–473
84. Yusup N, Zain A M, Hashim S Z M. Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007–2011). Expert Systems with Applications, 2012, 39(10): 9909–9927
85. Resat H G, Unsal B. A novel multi-objective optimization approach for sustainable supply chain: A case study in packaging industry. Sustainable Production and Consumption, 2019, 20: 29–39
86. Peng H, Wang H, Chen D. Optimization of remanufacturing process routes oriented toward eco-efficiency. Frontiers of Mechanical Engineering, 2019, 14(4): 422–433
87. Duan X, Wu B, Hu Y, et al. An improved artificial bee colony algorithm with MaxTF heuristic rule for two-sided assembly line balancing problem. Frontiers of Mechanical Engineering, 2019, 14(2): 241–253
88. Gholami M H, Azizi M R. Constrained grinding optimization for time, cost, and surface roughness using NSGA-II. International Journal of Advanced Manufacturing Technology, 2014, 73(5–8): 981–988
89. Zhu S, Zhang H, Jiang Z, et al. A carbon efficiency upgrading method for mechanical machining based on scheduling optimization strategy. Frontiers of Mechanical Engineering, 2020, 15(2): 338–350
90. Tian C, Zhou G, Lu F, et al. An integrated multi-objective optimization approach to determine the optimal feature processing sequence and cutting parameters for carbon emissions savings of CNC machining. International Journal of Computer Integrated Manufacturing, 2020, 33(6): 609–625
91. Kirsch B, Effgen C, Büchel M, et al. Comparison of the embodied energy of a grinding wheel and an end mill. Procedia CIRP, 2014, 15: 74–79
92. Shin S J, Woo J, Rachuri S. Energy efficiency of milling machining: Component modeling and online optimization of cutting parameters. Journal of Cleaner Production, 2017, 161: 12–29
93. Xiao Q, Li C, Tang Y, et al. Meta-reinforcement learning of machining parameters for energy-efficient process control of flexible turning operation. IEEE Transactions on Automation Science and Engineering, 2021, 18(1): 5–18
94. Tapoglou N, Mehnen J, Butans J, et al. Online on-board optimization of cutting parameter for energy efficient CNC milling. Procedia CIRP, 2016, 40: 384–389