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A REVIEW ON ENERGY EFFICIENCY IMPROVEMENTS IN CNC MACHINING

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Today, the manufacturing industry faces significant pressure to become more sustainable while maintaining competitiveness. In the spirit of the green manufacturing philosophy, numerous efforts have been undertaken to replace or reduce waste materials that burden the environment, and to promote environmentally friendly raw materials. Minimizing energy consumption in CNC machining is also crucial, since it offers significant potential to reduce environmental impact. This review focuses on recent developments in energy consumption monitoring and modelling, energy-efficient machining strategies, energy-saving solutions in CNC machine tools and controllers, and optimized tool path planning algorithms. The first step in implementing energy optimization is modelling the energy consumption of machine tools. Traditionally, the energy demand for cutting has been described using formulas that rely on the material removal rate and specific cutting energy. However, in recent years, data-driven techniques have become more popular, necessitating the development of data monitoring and acquisition techniques. After modelling energy consumption, optimizing cutting parameters is the most straightforward way to increase energy efficiency. However, the complex effect of machining parameters and the quality requirements pose significant challenges. As a result, soft computing methods such as heuristic algorithms and machine learning techniques have become essential and remain the subject of extensive research today. Energy-saving functions of modern CNC machine tools, such as standby mode, auto-shutdown features, and regenerative drives, also play an important role in reducing overall energy consumption. AI-supported tool path generation algorithms have significant potential to improve energy efficiency and sustainability, but this potential is currently underutilized. Future research will presumably focus on intelligent machining technologies using adaptive control and real-time monitoring with predictive optimization methods. These advancements are expected to reduce the environmental impact of CNC machining while enhancing its overall sustainability and productivity.

Keywords: CNC machining, energy efficiency, sustainability, tool path optimization

1. Introduction

The manufacturing industry has traditionally been a key sector of the economy; however, it is also known for its high energy consumption. The European Union's Energy Efficiency Directive (EU/2023/1791), which was initially introduced in 2012 and updated in 2023, also highlighted the potential for significant energy savings within the manufacturing sector [1]. To meet the ambitious energy efficiency goals, the directive mandates that intensive industrial energy consumers implement energy management systems and continuously monitor and optimize their energy usage. According to the directive, even small and medium-sized enterprises (SMEs) would have to carry out an energy audit where there is significant energy-saving potential. These requirements, which are set to be introduced as early as 2025, make it inevitable to review and improve the energy efficiency of manufacturing processes. Therefore, the manufacturing sector faces significant challenges in producing high-quality products economically while adhering to environmental regulations. To overcome these challenges, technology must be modernized and innovative solutions introduced. Fortunately, research shows significant potential to enhance the efficiency of CNC machining operations in terms of sustainability, productivity, and economic viability [2]. Beyond compliance with international regulations, improving energy efficiency can reduce production costs, enhance the competitiveness of companies, and contribute to sustainable development by reducing environmental impacts and improving social welfare.

Despite the rise of new production technologies, cutting processes are still indispensable in part and tool manufacturing. CNC machining plays a vital role in producing high-precision parts used across a wide range

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of sectors, including aerospace, automotive, medical technology, and general manufacturing. At the same time, the way CNC machine tools consume energy is quite complex.

Increasing the efficiency of cutting processes is considered a priority research area since, due to the high prevalence, an improvement of even a few per cent can lead to significant savings. In addition to increasing production efficiency, today's main challenge in manufacturing is to provide sustainability. Although it may sound surprising at first, the machine tools, which are fundamental in manufacturing, exhibit low energy efficiency. Due to the system's complexity, machine tools sometimes operate very inefficiently, with energy efficiency as low as 15-30% [3]. As a result, reducing cycle time is beneficial not only from an economic point of view but also because it improves energy efficiency. Therefore, increasing productivity can be regarded as a clear goal in part manufacturing, but for this requires in-depth knowledge and mathematical descriptions of production processes. In addition, it is important to model, understand, and reduce the energy consumption of machine tools.

In the last two decades, the issue of energy efficiency has come to the fore in CNC machining, as it is associated with improving economic and environmental performance and increasing competitiveness. Although machine tools are not the only large industrial energy consumers, significant reserves are available in this area. As a result, improving the energy efficiency of machine tools has been a focal point of development for a long time, exemplified by initiatives such as the ISO 14955 standard [4] and the European Union's directive 2009/125/EC [5], which also prioritizes environmentally conscious design requirements for machine tools. However, high levels of energy efficiency also require energy-conscious operation.

This review examines the most recent literature on energy efficiency in CNC machining, providing a comprehensive overview of the state-of-the-art knowledge in the field. A comprehensive strategy was used to explore theoretical frameworks and practical studies on energy efficiency in CNC machining, utilizing major scientific databases, such as IEEE Xplore, ScienceDirect, SpringerLink, and MDPI journals. To enhance the reliability of the literature review, keyword searches were combined with citation tracking, which facilitated the collection of a wide range of papers and helped identify the most significant areas. The keywords were grouped in different ways, including terms like CNC machining, energy efficiency, tool optimization, cutting power consumption, spindle motor energy, indirect energy consumption, sustainable manufacturing, machine learning, and artificial intelligence. To keep the review focused, explicit inclusion and exclusion criteria were set. Papers were included only if they dealt with energy usage in CNC machining, reported measurable results on improving energy efficiency, discussed tool path optimization, or studied energy use at the system level. Also, studies that introduced new ways of measuring, modelling, or optimizing energy consumption were prioritized. Additionally, studies on energy use in areas outside machine tools were excluded. The analysis used both quantitative and qualitative approaches. Quantitative analysis examined energy improvement percentages, identified achievable savings, and explored links between optimization methods and energy demands. Qualitative analysis studied the research methods, highlighted key research in the literature, and helped understand the limitations of current knowledge.

The following chapters will explore various topics related to machine tools' energy consumption. Section 2 focuses on the methods for monitoring and modelling energy usage in machine tools. Section 3 examines the energy-efficient machining strategies. Section 4 reviews existing energy-efficient solutions for machine tools and their control systems. Section 5 details the optimized tool path generation methods. Section 6 addresses the challenges and future directions for reducing energy consumption. Finally, Section 7 concludes with a brief discussion.

2. Energy consumption monitoring and modelling

Studies on the energy efficiency of machining processes frequently focus solely on the material removal process, primarily in modelling and reducing the energy consumption of the spindle [6]. However, if the goal is to minimize the overall environmental impact, this approach can be misleading, because only a portion of the machine's total energy demand originates from the cutting process. In reality, a more significant part of the energy consumption comes from other units, such as feed drives, cooling systems, lubricant units, hydraulic systems, chip conveyors, tool changing mechanism, and various additional elements [7]. Therefore, the machine tool and its environment must be considered as a complex system to improve economic and environmental impacts [8].

CNC machining uses energy in a complex way, and identifying the most promising areas for savings can often be challenging. Fundamentally, the energy usage of machine tools can be classified into three main categories: (1) the energy required for cutting the material, (2) the energy consumed by the motors that move and rotate the axes, and (3) the energy needed for supporting systems such as cooling, lubrication, etc. [9]. To improve efficiency, it is essential to understand how each component functions and to explore methods for reducing their energy consumption separately. Fortunately, both internal data from CNC controls and measured data collected by external sensors can support the transparency of the energy consumption of machine tools. Furthermore, digital twin technology can also support real-time analysis of CNC machine tools' energy profiles [10].

Energy usage varies significantly depending on machine configuration, material type, tool choice, and the machining parameters set [11]. The relationships between energy consumption and key machining parameters (e.g., cutting speed, cutting feed, depth of cut) have been extensively deeply analyzed to support process planners in implementing energy-saving measures efficiently [12]. Algorithmic modelling of energy demand using STEP-NC (Standard for the Exchange of Product model data for Numerical Control) has also been developed, which can be used to optimize machining schemes, showing measurable improvements in energy efficiency [13].

As mentioned before, CNC machines typically use 70-85% of their energy independently of the cutting process, so energy is consumed even when the machine is not actively cutting anything [2]. During these idle times, the spindle motor keeps the tool spinning, the feed drives move the axes between the cutting segments, and the system maintains the machine's cooling and lubrication. Other parts, such as the chip removal system, automatic tool changers, and the controller's electronics, also consume energy when the machine is not in use [14]. Among all these, the spindle and feed motors use the most energy, making up about 45% of the total during regular operation. Empirical data-driven energy modelling has shown significant reserves in idle times [15].

Energy models differ significantly in terms of structure and underlying assumptions, and there is currently no standard benchmarking framework. Real-time predictive models, such as V_MET and neural networks that analyze CNC programs, show considerable potential, but they still require wider validation across different machine types [6],[10].

3. Energy-efficient machining strategies

To find an energy-efficient machining strategy, it is crucial to determine the suitable environment, material removal plan, and machining parameters. According to the review by Pawanr et al., the following energy savings can be achieved through various strategies: energy-efficient design can reduce consumption by up to 45%, optimizing cutting parameters can lead to a reduction of up to 40%, improving tool paths can save up to 50%, optimizing non-cutting energy consumption and optimized sequencing can achieve up to 30% savings, and employing AI can result in a reduction of up to 20% [16].

The optimal selection of machining environment and material removal strategy requires exploring a discrete search space while considering sustainability factors. Along with selecting machine tools, machining methods, and tools, choosing the right cooling technology is also important. Flood coolant is becoming less prominent due to the environmental issues associated with its disposal. In addition to reducing hazardous waste, modern cooling technologies can also increase productivity and energy efficiency. The application of cryogenic cooling involves the use of extremely low temperatures, typically achieved by employing liquid nitrogen or other cryogenic fluids [17]. Minimum quantity lubrication (MQL) also provides a sustainable alternative with quantifiable energy benefits [18]. Advanced cooling methods such as cryogenic cooling and nanofluid-assisted lubrication have demonstrated measurable reductions in energy consumption and environmental impact [19]. Energy-aware scheduling strategies are increasingly adopted in smart factories. Pawar and Gupta [16] highlighted how energy-aware scheduling and smart factory technologies like IoT and AI can significantly reduce idle power usage, supporting real-time control and sustainable machining.

Finding the most effective machining parameters, which is also crucial in production process planning, often involves optimizing in a continuous search space [20]. Response surface methodology (RSM) is frequently used to minimize energy consumption [21]. However, due to the complexity of the problem, it is often necessary to use soft computing methods such as genetic algorithm (GA) or particle swarm optimization (PSO) [22].

Previous studies have proved that the choice of optimization method can lead to significantly different levels of energy reduction. These findings suggest that manufacturers should carefully evaluate and adopt the strategies most suited to their individual production environment and objectives [23]. Recent works have emphasized the growing importance of real-time energy monitoring, where IoT-based solutions can enable precise process data collection [24]. Digital twin technology is also increasingly used to analyze the operational behavior and energy demand of CNC machine tools [10]. Hybrid optimization algorithms have been shown to decrease energy usage considerably [25]. The multi-objective optimization approaches can provide a good balance to achieve a compromise between energy efficiency and machining performance [26]. Among these methods, meta-reinforcement learning has resulted in the most impressive energy savings so far. In some case studies, the energy consumption was reduced by up to 70% compared to traditional end milling processes [23]. These outstanding results indicate a significant step forward in improving the energy efficiency of CNC machining, helping manufacturers lower costs, enhance environmental sustainability, and maintain or even improve product quality. Notably, meta-reinforcement learning also shortens processing times by up to 68%, proving that energy efficiency improvements can go hand-in-hand with higher productivity [23].

In CNC machining, machine learning and other AI applications can be used for predictive modelling, dynamic parameter optimization, and energy-aware process control for sustainable manufacturing [27]. Integrated multi-objective optimization models for rough and finish milling parameters can significantly improve energy efficiency, machining time, and surface quality. This demonstrates that joint parameter tuning across stages can lead to more sustainable outcomes than isolated approaches [27]. Combining the optimization of feature processing sequences with tool path planning strategies can also offer moderate but significant gains, reducing energy use by 15% compared to empirical methods and by 11% relative to approaches that optimize

Table 1: Reported energy savings from selected strategies

Strategy / Method	Reported savings (%)	Conditions / Notes	Source
Toolpath Optimization (RL-based)	Up to 70%	5-axis flank milling, meta-reinforcement learning	[23]
Toolpath Strategy (zigzag vs contour)	~12%	Milling aluminum, smoother transitions reduce energy	[38]
Multi-objective Optimization (GA/ANN)	20–30%	Milling AISI 304L and 2017A alloys	[21],[22]
Cryogenic Cooling	10–25%	Depends on alloy and cutting speed	[17]
MQL (vs flood cooling)	15–20%	Sustainable machining of steels and aluminum	[18]
Hybrid Cooling (nanofluid + MQL)	Up to 30%	Advanced cooling in difficult-to-machine alloys	[19]

parameters separately [28]. These findings highlight how crucial it is to use integrated optimization methods that account for interactions among various parameters, rather than focusing on optimizing each separately.

Cryogenic and hybrid cooling methods are still challenging to implement on a large scale, and AI-driven parameter tuning has yet to prove broadly generalizable across different machines and materials [16],[17],[19].

Table 1 presents the energy savings achieved from selected strategies, along with the conditions under which these savings were measured.

4. Energy-saving solutions in CNC machine tools and controllers

Nowadays, the design of machine tools with an energy-conscious approach covers almost all components, supported by both comprehensive design studies and detailed energy consumption analyses [14],[29]. Recent design-focused studies have shown that the structural configuration of CNC machines can significantly influence the baseline energy consumption [30]. Recognizing how critical energy efficiency has become, the International Organization for Standardization also issued standards such as ISO 14955-1:2017 for design methodology and ISO 14955-2:2018 for energy measurement in machine tools [4],[31]. These standards set out a clear framework for evaluating the environmental impact of machine tools and provides design principles for making machines more energy-efficient.

The leading manufacturers of machine tools and CNC controls consider increasing energy efficiency a priority development goal and are continuously developing software and hardware solutions to achieve this goal. FANUC's sustainability initiatives [32] emphasize energy-saving features in CNC systems, such as efficient motors and servo systems, regenerative feed drives, reducing weight, auto sleep functions, which align with ISO 14955 and reinforce the industry's shift toward low-carbon, eco-efficient manufacturing. Okuma's "Green-Smart Machine" Declaration [33] aims to achieve higher productivity and reduced carbon emissions at the same time. Shortening warm-up, setup, machining and idle times, and stopping the unnecessary equipment play key roles in their concept. Furthermore, thermo-neutral machine tool design and intelligent thermal expansion compensation can maintain excellent accuracy without relying on excessive ambient temperature control from machine cooling systems or factory air conditioners. Mazak's energy-saving technology [34] also involves versatile monitoring of power consumption, usage of regenerative electric power systems, optimal control of coolant and stand-by mode.

Despite the advancements made by machine tool manufacturers, minimizing energy consumption can only be achieved through optimal operation. Users must strive for energy saving by choosing the appropriate machine tool [35], performing adequate maintenance [36], and conducting accurate process planning and scheduling [37].

Although regulatory frameworks such as ISO 14955 and EU 2019/1784 exist, the implementation of energy-saving features remains inconsistent [4],[5].

5. Optimized tool path planning strategies

It is well-known that the shape of the tool path shape significantly affects energy consumption [38]. In a case study, Campatelli et al. showed that even using the same tool path in different orientations, more than a 20% difference in the power consumption of feed drives can occur [39]. Guo et al. investigated a simple turning task, where splitting the allowance shape into radial and axial turning segments in four different ways showed an 80% difference in energy consumption between the best and worst cases [40]. However, the literature usually deals only with simple tasks, such as face milling [41] or pocket machining with rectangular areas [42]. Moreover, the tool path planning method is also limited to basic strategies. Mainly, only the examination of contour-parallel and direction-parallel strategies can be found [43]-[45], and usually, only a few different solutions are compared using the previously mentioned simple geometries [28]. Therefore, instead of mathematical optimization, only a comparison is made, where the tool paths are even obsolete considering the advanced cycles of CAM systems. In other words, optimizing the tool path according to energy consumption is still in its initial stage despite the significant consumption reduction possibilities. Unit-process-level energy modeling and systematic analysis are essential for machining optimization [46]. True optimization is encountered in five-axis finishing of free-form surfaces when the optimal cutting direction has to be found while ensuring a desired scallop height [47],[48]. As another example, Gao et al. [47] proposed a discrete energy consumption path model for multi-axis milling, optimizing tool orientation sequences to balance cutting efficiency and energy use, demonstrating that geometric-aware path planning can significantly reduce machining energy.

Tool path planning is usually considered a complex, time-consuming, and error-prone problem since the search space offers an infinite number of alternatives, and the optimization constraints are also challenging to formalize [49]. In such cases, only suboptimal results can be achieved with traditional search methods. Artificial intelligence-based methods are widely used to optimize the movement of self-driving vehicles [50] and robot arms [51]. However, the generation of cutting tool paths is a more complicated task since, in addition to the geometrical boundary conditions, cutting conditions must also be considered during the tool path planning procedure. In optimizing the cutting tool paths, many opportunities remain to be exploited. Applying heuristic and machine learning based algorithms have shown promising results, but still requires further research [52].

A comprehensive review of optimization strategies highlighted the effectiveness of hybrid and multi-objective approaches in reducing machining energy usage [53]. Hybrid optimization algorithms have shown promise in reducing energy use during CNC milling [54]. Li's empirical model [54] demonstrated a 20% improvement in energy efficiency, highlighting the effectiveness of multi-objective parameter optimization in conventional CNC milling. AI-driven predictive modelling enhanced energy efficiency in CNC turning operations [55]. Reinforcement learning can also help with complex tool path generation tasks such as pocket milling [42], while energy modeling frameworks provide a basis for evaluating machining energy consumption [56]. The application of Symbolic Discrete Control Synthesis to multi-pocket milling, modelling tool path planning as a TSP and achieving energy-efficient, formally correct machining can outperform traditional metaheuristics in precision-critical scenarios [44]. Energy-efficient machining parameters can be optimized using response surface methodology [57].

A significant breakthrough was the introduction of meta-reinforcement learning to tool path planning. In their method [23], Lu et al. used multiple Markov Decision Processes (MDPs) and a meta-learning approach integrated with the Soft Actor-Critic (MSAC) for five-axis machining. The algorithm uses numerous decision-making tools to determine the best movement direction and cutting depth values to shorten the tool path and reduce energy usage. As a result, in some cases, the energy consumption can drop by almost 70% compared to normal milling strategies. Kukreja and Pande [49] also developed a machine learning framework that predicts optimal tool path strategies based on part geometry and machining parameters, enabling automated energy-efficient planning and reducing idle movements. Significant reductions in energy consumption can be achieved in machining by optimizing cutting parameters and process conditions [58].

Even small changes in Tool path strategy can have a noticeable impact on energy use. For instance, Mario et al. [38] compared zigzag and contour-parallel paths when milling aluminum and found that the contour-parallel path reduced energy use by approximately 2%. The savings came mainly from smoother tool engagement and fewer sudden changes in direction. In another study, Lu et al. [23] applied a meta-reinforcement learning-based Tool path to five-axis flank milling and reported energy reductions of up to 70%, along with a 68% shorter machining time compared to traditional strategies. These results clearly show how much intelligent path planning can contribute to more sustainable machining.

Despite this potential, Tool path planning for complex geometries and multi-axis setups is still far from fully developed. Approaches like reinforcement learning and symbolic planning look promising, but their use in industry remains limited because of gaps in CAM integration and the need for thorough validation [23],[44],[48].

6. Challenges and future directions

Despite the progress in developing energy-efficient machining solutions, several obstacles continue to hold back their industrial uptake. One of the most pressing issues is the lack of clear and unified standards that can be applied directly to machining practices. Policy instruments such as the EU Energy Efficiency Directive [1] and Commission Regulation (EU) 2019/1784 [5] set important targets, but they may not be implemented evenly across various operations. Standards like ISO 14955 [4] are moving in the right direction, offering structured guidelines for energy-efficient machine tool use, but their full implementation is still questionable.

Another area that continues to create difficulties is accurately modelling energy consumption. Although a wide range of approaches exists, including empirical models [16], data-driven methods [17], and coupling models [15], the reality of various industrial conditions makes it hard to guarantee reliable predictions. More advanced tools, such as digital twins and virtual machining [16],[42], are promising but come with high demands in terms of computation and calibration, which limit their immediate use in everyday production.

On the optimization side, manufacturers must balance energy savings, productivity, cost, and product quality. Research into multi-objective optimization [40],[45],[53], and hybrid methods that combine reinforcement learning and metaheuristics [27],[41] has yielded strong results in experimental and pilot studies. Even so, rolling out these solutions in real plants is far from straightforward, given the costs of integration, resistance from operators, and the uncertainty of real-time decision-making. The same can be said for tool path optimization, which has been studied in depth [27],[28], but still faces hurdles when applied to highly complex parts or low-volume, high-mix production.

Cooling and lubrication remain another challenge. Flood coolant is still widespread, mainly because it is reliable and easy to use. However, its environmental drawbacks are significant. Alternatives such as cryogenic cooling [11], minimum quantity lubrication (MQL) [12] and hybrid cooling approaches [14] have shown promising changes in both reducing energy demand and lowering resource use. The difficulty lies in making these methods work consistently when machining hard-to-cut alloys and in scaling them up to match industrial production requirements.

There is also little doubt that machine learning and other AI methods will shape the subsequent phases of development. Several recent reviews [23],[31][54] highlight their role in predictive modelling, adaptive tool path planning and maintenance scheduling, but there are still serious challenges remaining. Data quality and availability are often insufficient, platforms are not always interoperable, and trust in AI-driven decisions is still low when production depends on critical reliability.

Looking forward, future work is likely to concentrate on the following key areas:

1) Stronger adoption of ISO 14955, and closer alignment between broad regulations and industrial realities, are needed.
2) The use of digital twins and AI must move from research pilots to robust, real-time applications.
3) Optimization frameworks have to expand to cover energy, cost, and quality together, while reinforcement learning methods may help manage changing shop-floor conditions.
4) Sustainable cooling and lubrication systems need to prove their worth in cutting advanced alloys at scale.
5) IoT and predictive maintenance strategies should be used more systematically to monitor and optimize energy at the workshop level
6) Sustainability must be approached in a holistic way, looking beyond the machine itself to supply chains, equipment selection, and lifecycle-based assessments.
7) Finally, the way forward for energy-efficient machining will depend on the combined effort of researchers, machine tool builders, and policymakers.

Progress will not only require technical innovation but also the ability to align those innovations with industrial practice and economic reality. Sustainability goals can only be achieved in a practical, scalable, and competitive way.

7. Conclusion

Currently, CNC machine tools usually utilize only about 15–30% of the invested energy for material removal. This review highlights the vast potential for increasing energy efficiency in CNC machining through the use of advanced machine tools, energy-efficient machining strategies, and novel optimization methods. The research results show that achieving significant energy savings requires focusing on improving all parts of the system, not just the cutting process. The most challenging area, but also one that offers significant opportunities, is optimizing the energy efficiency of tool paths. Hybrid optimization methods, machine learning algorithms, and AI-driven predictive models can consistently improve energy efficiency across various machining scenarios.

In the future, the integration of artificial intelligence, digital twins, and cyber-physical systems can further enhance energy efficiency in smart manufacturing. Additionally, there are promising opportunities to develop explainable AI tools, use advanced materials, and implement sustainable manufacturing practices, leading to substantial improvements in machining quality and productivity while also advancing broader environmental and sustainability objectives.

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