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Research Paper

Review of Energy Consumption Optimization in CNC Milling Processes

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I. Introduction

The rapid advancement of modern manufacturing technologies has significantly increased the application of Computer Numerical Control (CNC) machining systems in industrial production. CNC milling processes are extensively utilized in aerospace, automotive, mold manufacturing, medical engineering, and heavy industries due to their high productivity, machining accuracy, flexibility, and automation capability. However, the increasing use of CNC machine tools has also resulted in substantial energy consumption and environmental impacts, leading researchers and industries to focus on sustainable and energy-efficient manufacturing strategies [1].

Manufacturing industries are responsible for a considerable proportion of global electricity consumption, and machining operations account for a significant share of industrial energy usage because of the extensive utilization of machine tools and automated production systems [2]. Unlike conventional manufacturing studies that mainly focused on machining quality and productivity, recent investigations have increasingly emphasized energy efficiency, carbon emission reduction, and environmental sustainability. Consequently, energy optimization in CNC machining has become one of the most important research topics in green manufacturing and sustainable production systems [3].

In CNC milling operations, electrical energy is consumed not only during material removal but also by spindle drives, feed drive systems, cooling systems, lubrication units, hydraulic components, and control systems. Studies have shown that actual cutting energy represents only a small proportion of the total energy consumed by CNC machine tools, while a substantial amount of electrical power is wasted during idle operation and non-productive machining stages [4]. Therefore, optimizing energy consumption requires a comprehensive understanding of machine tool characteristics, machining parameters, cutting mechanics, and control strategies.
Recent developments in this field have focused on:

- energy consumption modeling,
- cutting parameter optimization,
- intelligent toolpath planning,
- AI-based machining optimization,
- Digital Twin technologies,
- sustainable machining strategies,
- real-time adaptive control systems.

These advancements have transformed energy-efficient machining into an interdisciplinary research area involving manufacturing engineering, machine dynamics, artificial intelligence, optimization theory, and sustainable production technologies [5].

II. Energy Consumption Characteristics of CNC Milling Machines

Energy consumption in CNC milling machines originates from multiple interacting subsystems operating simultaneously during machining processes. These subsystems include spindle motors, feed drive motors, coolant pumps, lubrication systems, controllers, and auxiliary equipment. According to Zhou et al. [6], idle energy consumption constitutes one of the largest contributors to total machine power usage, especially during low material removal rate operations.
Several researchers have categorized machine tool energy consumption into three primary groups:

1. constant energy consumption,
2. load-dependent energy consumption,
3. material-removal energy consumption.

Constant energy consumption includes electrical power required by controllers, lubrication systems, and standby components that continuously operate regardless of machining conditions. Load-dependent energy consumption is mainly associated with spindle rotation and feed drive motion, while material-removal energy directly corresponds to the cutting process itself [7].

Table 1. Typical energy distribution in CNC milling machines

Machine Subsystem	Typical Energy Ratio (%)	Characteristics
Idle systems	30–50	Constant consumption
Spindle system	20–40	Speed-dependent
Feed drive system	10–20	Motion-dependent
Cutting process	15–30	Load-dependent
Auxiliary systems	5–15	Semi-constant

The results presented in Table 1 indicate that non-cutting energy consumption can account for more than half of the total machine energy usage. Moradnazhad and Unver [4] reported that idle power alone may reach up to 80% of total power consumption under certain machining conditions. This observation highlights the importance of minimizing non-productive machining operations to improve energy efficiency.
Another important indicator used in sustainable machining studies is Specific Energy Consumption (SEC), which represents the energy required to remove a unit volume of material. Lower SEC values generally indicate more efficient machining operations [8].

III. Energy Consumption Modeling Approaches

Energy modeling is considered a fundamental step in analyzing and optimizing machining power consumption. Existing studies mainly classify energy models into empirical models, physics-based models, and data-driven models.

Empirical models are commonly developed using experimental measurements and regression analysis techniques. These models establish relationships between machining parameters and energy consumption. Researchers frequently employ Response Surface Methodology (RSM), Taguchi methods, and Analysis of Variance (ANOVA) to determine parameter sensitivity and identify optimal machining conditions [9].

Physics-based models are established based on cutting mechanics, machining dynamics, and thermal analysis. These models enable detailed investigations of cutting force generation, friction mechanisms, chip formation, and vibration behavior during machining operations [10]. Although physics-based models provide good interpretability, they often require extensive computational effort and accurate knowledge of material properties and machining conditions.

In recent years, artificial intelligence and machine learning methods have emerged as highly effective approaches for predicting machining energy consumption. AI-based models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Deep Learning algorithms can accurately capture nonlinear relationships among machining variables and energy characteristics [11].

Table 2. Comparison of energy modeling methods

Modeling Method	Advantages	Limitations	Typical Applications
Empirical models	Simple and practical	Strongly data-dependent	Parameter optimization
Physics-based models	Mechanism-oriented	Complex implementation	Cutting analysis
AI-based models	High prediction accuracy	Requires large datasets	Real-time prediction
Digital Twin models	Online monitoring capability	High computational cost	Smart manufacturing

Pawar and Gupta [11] emphasized that AI-driven machining optimization is becoming one of the fastest-growing research directions in sustainable manufacturing due to its capability for adaptive control and online optimization.

IV. Influence of Machining Parameters on Energy Consumption

Machining parameters significantly influence energy consumption because they directly determine cutting force, spindle load, machining time, and material removal rate. The primary machining parameters include spindle speed, feed rate, axial depth of cut, and radial depth of cut [12].

Increasing spindle speed generally increases spindle motor power due to higher rotational losses and friction. However, higher cutting speeds may also reduce machining time, which can lower overall energy consumption under optimized conditions.

Feed rate is widely recognized as one of the most influential factors affecting machining energy efficiency. Feng et al. [13] demonstrated that increasing feed rate within appropriate limits could substantially reduce Specific Energy Consumption because the increase in material removal rate exceeds the increase in electrical power demand.

Similarly, increasing axial and radial depths of cut can improve productivity by increasing material removal rates. Nevertheless, excessive cutting loads may lead to higher vibration levels, thermal deformation, and accelerated tool wear [14].

Table 3. Influence of machining parameters on energy consumption

Parameter	Energy Consumption Trend	Secondary Effects
Spindle speed	Increases spindle losses	Thermal rise
Feed rate	Reduces SEC under optimized conditions	Possible vibration increase
Axial depth of cut	Increases cutting force	Higher tool wear
Radial depth of cut	Raises spindle load	Increased cutting temperature

Tool condition also plays a significant role in energy consumption. Worn cutting tools increase friction and cutting resistance, thereby increasing spindle power demand and machining temperature [15].

V. Toolpath Optimization and Sustainable Machining

Toolpath planning has a considerable impact on machining energy consumption because it influences machine acceleration, feed motion smoothness, non-cutting movement, and cutter engagement conditions.

Conventional zig-zag toolpaths often generate abrupt directional changes, leading to large servo accelerations and unstable cutting loads. In contrast, advanced toolpath strategies such as spiral milling, trochoidal milling, and adaptive clearing provide smoother machine motion and more stable cutter engagement [16].

Table 4. Comparison of toolpath strategies

Toolpath Strategy	Energy Efficiency	Cutting Stability	Tool Life
Zig-zag	Moderate	Unstable	Moderate
Spiral	Improved	Stable	Improved
Trochoidal	High	Highly stable	High
Adaptive clearing	Very high	Optimized	Excellent

Li et al. [16] proposed an exergy-based toolpath evaluation method and demonstrated that optimized toolpaths could significantly reduce machine energy consumption while improving machining stability and tool life.

Sustainable machining research has also focused on environmentally friendly cooling and lubrication techniques such as dry machining and Minimum Quantity Lubrication (MQL). Compared with conventional flood cooling systems, MQL significantly reduces lubricant usage and auxiliary power consumption [17].

VI. Optimization Techniques in Energy-Efficient CNC Milling

Numerous optimization methods have been developed to minimize machining energy consumption while maintaining productivity and machining quality. Traditional statistical methods such as Taguchi design and Response Surface Methodology remain widely used because of their simplicity and low experimental cost [18]. However, modern machining systems involve highly nonlinear and multi-objective optimization problems. Consequently, metaheuristic optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer, and NSGA-II have gained increasing attention [19].

Table 5. Comparison of optimization methods

Optimization Method	Main Advantages	Main Limitations
Taguchi	Low experimental cost	Limited nonlinear capability
RSM	Good regression accuracy	Model-dependent
GA	Strong global optimization	Long computational time
PSO	Fast convergence	Local optimum risk
NSGA-II	Excellent multi-objective capability	High implementation complexity

Among these methods, NSGA-II has become one of the most popular approaches for sustainable machining optimization because it can simultaneously optimize energy consumption, machining time, surface roughness, and tool wear [20].

VII. Artificial Intelligence and Future Research Trends

Artificial intelligence has become one of the most promising technologies for future intelligent machining systems. AI techniques enable:

- real-time energy prediction,
- adaptive feed control,
- predictive maintenance,

- intelligent process optimization.

Machine learning models can predict machining power consumption using data collected from spindle motors, feed drives, vibration sensors, and cutting force measurement systems [11].

Digital Twin technology is another emerging trend in smart manufacturing. Digital Twins provide virtual representations of physical machine tools and continuously update system conditions using real-time operational data [5]. These technologies enable:

- online energy monitoring,
- adaptive process optimization,
- predictive maintenance,
- intelligent manufacturing management.

Table 6. Emerging technologies in sustainable CNC machining

Technology	Main Function	Expected Benefits
Artificial Intelligence	Real-time prediction	Improved optimization
Digital Twin	Virtual machine representation	Online monitoring
IoT systems	Data acquisition	Smart manufacturing
Adaptive control	Automatic parameter adjustment	Energy reduction

Future research is expected to focus on:

- AI-integrated machining systems,
- carbon-neutral manufacturing,
- vibration-energy integrated optimization,
- Digital Twin-based machining control,
- sustainable high-speed machining technologies.

The integration of machine dynamics, vibration analysis, and energy optimization may provide substantial improvements in machining performance and manufacturing sustainability.

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