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REVIEW ARTICLE

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ChatEMT: large language model framework for energy-efficient machine tools – review, paradigm, and perspectives

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ABSTRACT

The increasing demand for sustainable manufacturing has intensified the need for energy-efficient machining solutions that support economic, environmental, and societal sustainability. While emerging large language models (LLMs) have been successfully applied to other manufacturing problems, their application to energy-efficient machine tool management remains limited, leaving significant gaps in integrating LLM intelligence with energy-oriented machining services. To address this challenge, this paper proposes a novel LLM-enabled framework for energy-efficient machine tools, termed ChatEMT. This framework provides explainable, user-friendly, and semantically grounded energy services (e.g. analysis, monitoring, and optimisation) for sustainable machining. First, recent studies on the energy consumption of machine tools are systematically reviewed. Then, the paradigm and architecture of ChatEMT are presented, in which LLMs serve as the core layer that bridges energy data, domain knowledge, and diverse models. Specifically, LLMs incorporate domain knowledge of machine tool energy, retrieve production information, perform semantic reasoning over machining processes, and orchestrate tool invocations to support a wide range of energy services. Finally, open challenges and future research directions are discussed to guide subsequent studies. This work highlights the critical role of LLMs in enabling explainable, flexible, and context-aware energy intelligence for machining systems.

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KEYWORDS
Machine tools; energy-efficient manufacturing; large language model; sustainable manufacturing; ChatEMT; energy-efficient machines

Nomenclature

Abbreviation	Full Name
ACO	Ant colony optimisation
AI	Artificial intelligence
BP	Backpropagation
CAD	Computer-aided design
CAM	Computer-aided manufacturing
CNC	Computer numerical control
CNN	Convolutional neural network
CPS	Cyber-physical system
CPU	Central processing unit
ChatEMT	Chat energy-efficient machine tools
DT	Digital twin
ECMT	Energy consumption of machine tools
GA	Genetic algorithm
GCN	Graph convolutional network
GPT	Generative pre-trained transformer
GRU	Gated recurrent unit
IIoT	Industrial internet of things
IoT	Internet of Things
ISO	International organisation for standardisation
LCA	Life cycle assessment
LLM	Large language model
LM	Language model
LSTM	Long short-term memory
MDP	Markov decision process
MILP	Mixed-integer linear programming
MOEA	Multi-objective evolutionary algorithm
NSGA-II	Non-dominated sorting genetic algorithm II
PaLM	Pathways language model
PLC	Programmable logic controller
PSO	Particle swarm optimisation
RAG	Retrieval augmented generation
REALM	Retrieval augmented language model
RETRO	Retrieval-enhanced transformer
RNN	Recurrent neural network
RotatE	Rotational embedding model
SA	Simulated annealing
SVM	Support vector machine

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T5	Text-to-text transfer transformer
TransE	Translating embeddings
WOA	Whale optimisation algorithm
XGBoost	Xtreme gradient boost

1. Introduction

Sustainable manufacturing has become a global priority as industries face increasing pressures to reduce energy consumption, curb carbon emissions, and improve resource efficiency (Song Xu et al. 2024). The manufacturing sector remains one of the major contributors to industrial energy consumption and environmental impacts (Miao Yang et al. 2025). Rising energy costs, stricter regulatory policies, and the urgent need for sustainable transformation have compelled enterprises to pursue smarter and more energy-efficient production strategies. In recent years, emerging technologies such as artificial intelligence (Miao Niu et al. 2025; Yang et al. 2024), industrial analytics (Qian Chen et al. 2024; Wei Gao et al. 2023), and cyber-physical systems (Miao Yang et al. 2023) have demonstrated significant potential in enhancing energy visibility and enabling energy optimisation in manufacturing scenarios. Among these technologies, LLMs have rapidly advanced as powerful tools capable of understanding ECMT semantics, analysing multimodal energy information, and supporting intelligent decisions for energy-related services (Dong et al. 2025; Shim et al. 2025; Xuan Gautam et al. 2025; Liu et al. 2025). Their abilities enable new opportunities for semantic-driven machining control, autonomous energy management, and flexible interface bridging natural language and various models. Modern manufacturing systems are evolving toward interconnected digital ecosystems, where machine tools interact with digital twins, AI-driven analytics, and multiple organisational roles across the production lifecycle. Integrating intelligent models with such ecosystems is therefore critical for enabling sustainable and resilient production systems (Fosso Wamba et al. 2024; Melo et al. 2025). Therefore, it is essential to explore LLM-enabled approaches for delivering explainable, intelligent, user-friendly, and semantically grounded energy services for machine tools (i.e. energy analysis, saving, modelling, statistics, prediction, evaluation, monitoring, optimisation, pricing, assessment, identification, and quoting).

In response to the challenges posed by sustainable manufacturing, many countries have initiated policies to promote sustainability and environmental friendliness. For example, the National Science and Technology Council of the U.S.A. released the National Strategy for Advanced Manufacturing, which identifies clean and sustainable manufacturing that supports decarbonisation as the first goal for the future development of the manufacturing sector (National Science and Technology Council 2022). The European Union launched the Green Deal Industrial Plan, allocating €250 billion to support industrial greening and offering tax incentives for enterprises investing in sustainable manufacturing (European Commission 2023). Similar initiatives can be found in China and the UK (The State Council of the P. R. China 2021; UK Parliament 2021). In addition, some organisations and enterprises focus on the operational sustainability of machine tools. The ISO has released the 14955 series of standards for machine tool environmental evaluation, providing standardised support for energy-efficient machining production. The CIRP has delivered and planned keynote speeches on energy efficiency research in discrete manufacturing systems (Denkena et al. 2020; Shokrani et al. 2024). The reputable machine tool manufacturer DMG MORI has reduced ECMT by 30% through green technologies, becoming one of the first companies in the global industrial sector to achieve carbon neutrality (DMG MORI 2025). This indicates that the sustainability of machine tools has been highly valued by practitioners.

To enhance energy services for machine tools, an emerging AI technology (i.e. LLMs) developed in recent years shows significant potential, as it enables advanced semantic understanding of energy services, integration of multimodal energy information, and intelligent reasoning for sustainable machining production. These LLM techniques have been successfully applied in many fields, such as the job shop scheduling problem (Tingting Yang et al. 2025; Wang, Wang, and Chu 2025) and the fault diagnosis problem (Lin et al. 2025; Yan et al. 2025). However, significant limitations and gaps remain between LLM techniques and ECMT. Traditional methods for analysing ECMT often struggle to generalise across diverse machines, process variations, and rapidly changing production environments. Meanwhile, there is a lack of human language–driven energy management for machine tools, which is much easier for practitioners to use. In contrast, LLMs possess powerful capabilities to bridge fragmented data sources and incorporate energy knowledge into the management of machining production. Leveraging these strengths, LLMs can support more flexible energy-aware services, including engineering document interpretation, anomaly diagnosis, and machining scheme optimisation. Therefore, combining LLM intelligence with CNC machining energy analysis offers a transformative pathway to build flexible, scalable, and intelligent solutions for sustainable manufacturing.

Motivated by the aforementioned issues, this paper conducts a comprehensive and perspective review of energy-efficient machine tools empowered by LLMs, and proposes a paradigm for promoting the sustainability of machine tools named ChatEMT. Firstly, the paper systematically surveys the state of the art in machining energy modelling, monitoring, prediction, and optimisation, and identifies how recent advancements in LLM technologies can be integrated into these domains. Then, this paper further constructs a hierarchical architecture for ChatEMT, analyzes the key enabling technologies that support its implementation, and discusses the limitations, challenges, and open issues that currently hinder its practical deployment. Finally, the paper outlines future research directions across application, system integration, and methodological levels, providing a roadmap for sustainable machining systems powered by LLMs. The main contributions and novelties of this paper can be summarised as follows.

(1) This paper conducts a systematic and structured survey of the review and research articles on ECMT across equipment, process, and system. It critically reveals the fundamental limitations of existing energy-efficient machining studies, namely their reliance on separated models, fragmented data usage, and lack of cognitive intelligence. Unlike prior surveys, this review explicitly identifies the absence of an energy service paradigm enabled by LLMs.
(2) This paper introduces a novel paradigm, ChatEMT, to bridge the gaps between ECMT management and LLMs. It redefines energy services for machine tools by introducing semantic understanding, multimodal reasoning, and human–machine interaction, thereby extending traditional rigid energy services toward intelligent, explainable, and semantically grounded energy management frameworks.
(3) A layered system architecture and an application framework for ChatEMT are proposed, integrating infrastructure, data, knowledge, model, workflow, and application layers into a coherent whole. The framework based on LLMs demonstrates how perception, reasoning, and tool invocation can be systematically embedded into advanced energy services for ECMT.
(4) The challenges, limitations, and open issues of ChatEMT are systematically analysed, including data reliability, model generalizability, hallucination risks, system updatability, and competitiveness with conventional algorithms. Also, the research directions at the application, system integration, and methodological levels are outlined to guide potential studies in the future.

The rest of this paper is as follows. Section 2 examines existing reviews on ECMT, while Section 3 provides a comprehensive analysis of relevant research articles. The paradigms and architecture of ChatEMT are developed in Section 4. The challenges and limitations are introduced in Section 5, and the future directions are given in Section 6. Section 7 illustrates the conclusions of this review paper. Here, Figure 1 is displayed to introduce the overall structure of this paper.

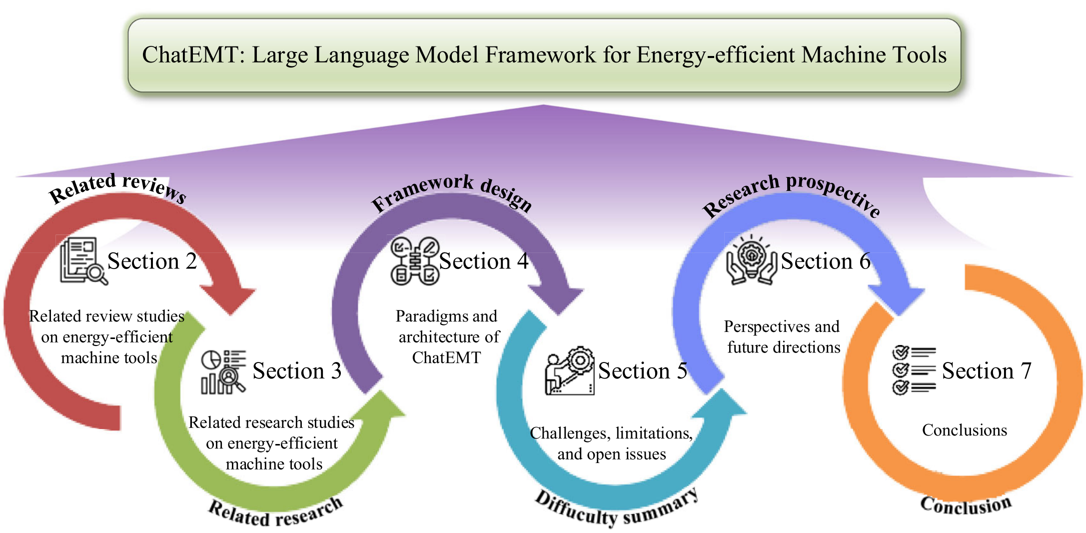

Figure 1. The overall structure of this paper.

2. Related review studies on energy-efficient machine tools

Motivated by the necessity of providing energy services for machine tools, many review articles have been published to summarise the recent studies from various perspectives. For example, a keynote paper was presented in CIRP Annals to analyse the energy-saving measures related to machine tools and cutting processes (Denkena et al. 2020). Related studies on energy consumption in machining operations were reviewed, and the challenges and trends for future research were provided (Pimenov et al. 2025). To support the evaluation and optimisation, the energy indices of machine tools were comprehensively reviewed and analysed (Xintao Hu et al. 2024). Here, Table 1 is provided to highlight the differences and novelties of this paper compared to the existing review studies, while the types, topics, motivations, and methodologies are included.

This summary table underscores that the existing review studies are primarily focusing on the traditional energy services for machine tools (e.g. energy monitoring, evaluation, modelling, prediction, and optimisation) with heuristics, machine learning, physical modelling, deep learning, reinforcement learning, and other techniques. However, there remain limitations and gaps that need to be solved as follows.

(1) The existing reviews primarily summarise frontier research on ECMT from a perspective viewpoint, yet they lack a novel energy-oriented paradigm grounded in advanced intelligence technologies. Such a paradigm could serve as a valuable prototype framework for integrating emerging AI capabilities into energy-efficient machining, offering both theoretical significance and practical potential.
(2) Current reviews have paid limited attention to the emerging role of LLMs in the domain of ECMT. LLMs have abilities in constructing energy-oriented intelligent agents and large-scale models capable of understanding machining semantics, analysing energy data, and generating optimised decisions or strategies for energy services.
(3) Although several paradigms and LLM-based frameworks have recently been proposed for smart manufacturing, their development remains in an early stage. These existing efforts are still insufficient to fully exploit the potential of LLMs in practical manufacturing applications, necessitating further advancement, adaptation, and promotion of energy-oriented architectures.

Therefore, this paper aims to address the aforementioned research gaps by providing a comprehensive and prospective review of energy-efficient machine tools empowered by LLMs. Specifically, the paper summarises existing reviews and research studies on the energy efficiency of machine tools, and then proposes an energy-oriented paradigm named ChatEMT for a more advanced energy service driven by AI and LLM techniques.

These review papers have successfully summarised related research papers about the ECMT topics, and they have provided essential theoretical and technological foundations for the recent developments. A detailed retrospective of the related research works is provided in Section 3 of this paper.

3. Related research studies on energy-efficient machine tools

Related research works on machine tools are rich yet fragmented across hardware design, process planning, operations, and assessment. Machining systems should also be analysed within broader manufacturing ecosystems, including organisational structures, digital twin infrastructures, and role-based decision processes that coordinate machines, operators, and service platforms (Elnourani et al. 2026; Melo et al. 2025). As a result, a retrospective is needed. This section reviews the landscape of machine tools to ground the later LLM-enabled framework.

3.1. Energy efficiency of machine tools

To ensure a reliable service for the energy efficiency of machine tools, the specific definition should be provided first. Generally, the term efficiency refers to the ratio between the input and output for a certain system. Many researchers have used different indicators for the sustainability of machining production (Mishra, Pattipati, and Bollas 2024; Chao Li, Tian, and Zhang 2022; Lu et al. 2022). The ISO 14955 series of the environmental evaluation of machine tools defines energy efficiency as 'the ratio or another quantitative relationship between the output and input' (ISO 2017).

In CNC machining, the total electrical power drawn by the machine is distributed across spindle and feed drives, CNC/PLC controls and electronics, coolant and lubrication pumps, and other auxiliaries. Only a portion is converted into cutting power at the interface between cutting tools and workpieces. To anchor subsequent assessment and to keep a function-oriented boundary, this paper adopts the ratio of cutting power to total

Table 1. Summary of the related review papers about ECMT and this one.

Reference	Sources	Types	Topics	Motivations and objectives	Methodologies
(Denkena et al. 2020)	CIRP Ann Manuf Technol	Review article	Energy efficiency of machine tools, operational strategies, and component optimisation.	To provide a broad overview of current measures to improve the energy efficiency of machine tools and to identify design measures, operational methods, and future research needs.	Machine-component energy modelling, load decomposition, idle-state control, and operational optimisation.
(Sihag and Sangwan 2020)	J Clean Prod	Review article	Machine tool and energy consumption.	To categorise key aspects of machining energy includes classification, modelling, improvement strategies, and evaluation.	Energy modelling, process parameter optimisation, simulation-based estimation, and energy evaluation metrics.
(abdelaoui, Jabri, and Barkany 2023)	Int J Adv Manuf Technol	Review article	Machining processes, energy efficiency, and optimisation techniques.	To survey modelling techniques and optimisation methods used in machining processes for energy efficiency.	Response surface methodology, Taguchi method, heuristic algorithms, and machine learning.
(Pimenov et al. 2025)	Renew sust energ rev	Review article	Machining operations, energy consumption patterns, and influencing factors.	To provide a comprehensive review of energy consumption mechanisms, influencing factors, and emerging trends in machining.	Digital twin, IoT, real-time monitoring, and machine learning.
(Xintao Hu et al. 2024)	J Clean Prod	Review article	Energy performance, energy index, and machine tools.	To establish a framework for energy performance improvement and analyse methods across monitoring, evaluation, optimisation, and benchmarking phases.	Energy index modeling, life cycle assessment, and benchmarking models.
(Cai et al. 2022)	Renew sust energ rev	Review article	Machine tool, sustainable manufacturing, and energy services.	To propose an integrated four-phase framework that links energy data acquisition, evaluation, optimisation, and benchmarking for sustainable manufacturing.	Key performance indicators, benchmarking analysis, and evolutionary algorithms.
(Sarıkaya et al. 2022)	J Clean Prod	Review article	Machining operations, energy consumption, and sustainability assessment.	To critically evaluate how sustainability assessment and energy modelling methods contribute to resource savings and efficiency in machining.	Life cycle assessment, machine learning, and finite element simulation.
This study	Int J Prod Res	Review with a new paradigm	Energy efficiency, machine tools, LLMs, and ChatEMT.	To promote an AI-enabled intelligent management and control of ECMT.	LLMs, agents, RAG, domain fine-tuning, knowledge graphs, and tool invocation.

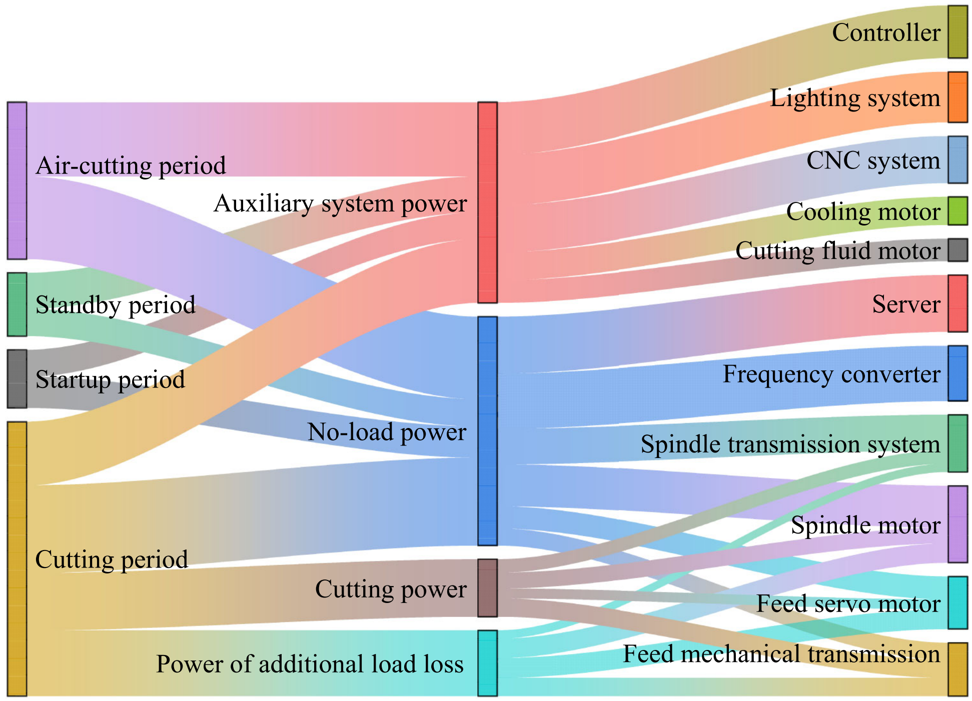

Figure 2. Coupling characteristics between energy consumption periods and components of CNC machine tools.

machine power as the working definition of energy efficiency. The details to calculate the energy efficiency are provided as follows.

$$\eta = \frac{E_{\text{cut}}}{E_{\text{total}}} = \frac{\int_0^t P_{\text{cut}}(t)\mathrm{d}t}{\int_0^t P_{\text{total}}(t)\mathrm{d}t} \tag{1}$$

where η is the energy efficiency. $E_{\text{cut}}/P_{\text{cut}}$ refers to the energy/power consumption of the cutting operation. $E_{\text{total}}/P_{\text{total}}$ denotes the total energy/power consumption. t represents the time. It is worth noting that energy efficiency is defined in accordance with ISO 14955, as it represents the ratio of output energy to input energy.

Apart from the energy efficiency, the authors' previous studies also reveal that there are coupling characteristics between energy consumption periods and components of CNC machine tools. As shown in Figure 2, there are periods during different working statuses, and energy-consuming components. Also, the current research mainly focuses on three major parts, including the energy efficiency within the levels of equipment, process, and system, as shown in Figure 3. Hence, the rest of this section comprehensively reviews the research articles on these topics.

3.2. Equipment-level energy efficiency

Equipment-level energy efficiency serves as the foundation for the optimisation efforts within machine tools. Aiming at the equipment level, the current studies on the assessment, design, and monitoring are reviewed as follows. There is a summary of the related research studies that can be found in Table 2.

3.2.1. Energy assessment and evaluation methods

Before effective optimisation strategies can be developed, it is essential to establish a clear and quantitative understanding of how energy is used, where losses occur, and how different operational conditions influence consumption (Cozzolino et al. 2023). Therefore, research on energy assessment and evaluation methods has emerged as a critical foundation for analysing machine tool performance and guiding subsequent energy-efficient design and operation.

An assessment aligned with ISO was connected to broader sustainability evaluation in mechanical manufacturing, with the selection of appropriate indicators clarified and the dominance of the operation phase (Cai and Lai 2021). Grading methods were introduced for energy efficiency of machine tools that translate assessed power into management decisions (Ma et al. 2021). Four machine tool process energy efficiency evaluation indicators were proposed: material cutting specific energy, cutting specific energy, effective energy utilisation rate, and machining process energy utilisation rate (Qiulian Wang, Liu, and Li 2013). A set of evaluation indicators of inherent energy performance was investigated for key process controls during the usage phase, aiming to support the design and selection of energy-efficient machine

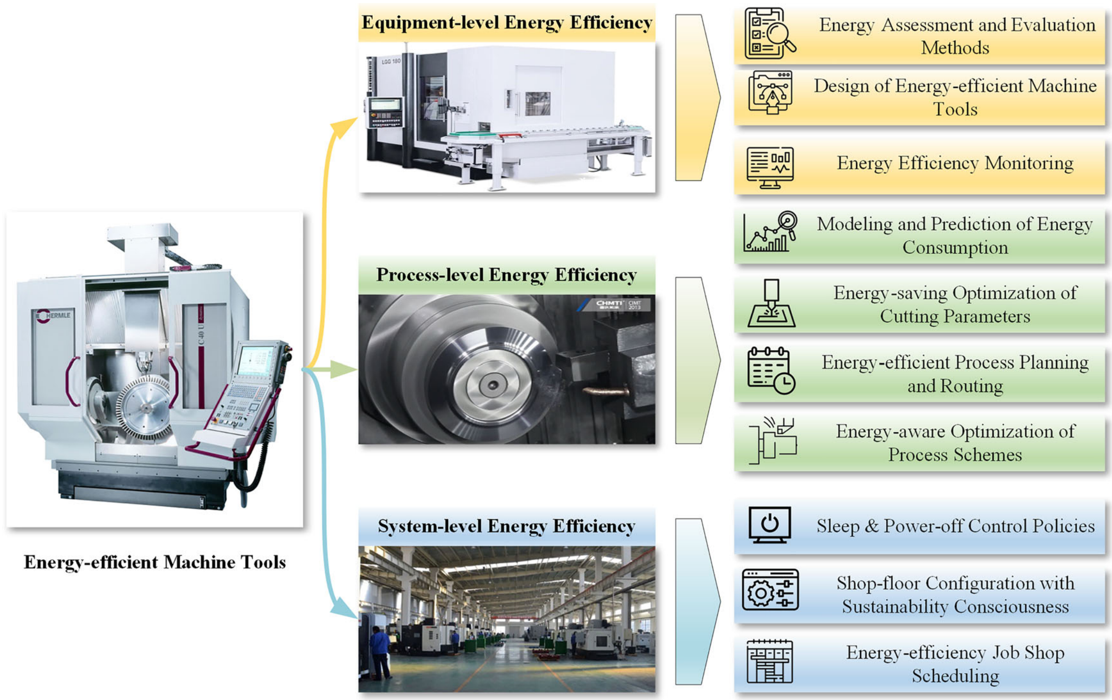

Figure 3. Related research studies on energy-efficient machine tools.

tools (Tuo, Liu, and Liu 2019). An exergy analysis method was studied to evaluate and visualise the thermal energy efficiency of the cutting space in dry cutting machine tools (Lai et al. 2025). A generalised modelling and evaluation method was investigated for the inherent energy efficiency of machine tools based on an analysis of their intrinsic characteristics (Peiji Liu et al. 2021). This study proposes a data-driven method for the quantitative analysis of product carbon footprints in discrete manufacturing based on an energy dataspace framework (Pulin Li, Cheng, and Jiang 2021). A multi-objective modelling and evaluation method was studied, addressing the limitations of conventional machining (Yanqi Li et al. 2024). The authors formulated two Chinese national standards for the evaluation and assessment of energy efficiency for machine tools (Chinese Technical Committee for Standardization of Metal Cutting Machine Tools 2021b, 2021a). Similar studies can be found in (Feng et al. 2024; Suwa and Samukawa 2022; Zheng et al. 2024; Peiji Liu et al. 2018).

3.2.2. Design of energy-efficient machine tools

This topic refers to the development of machine tool structures, components, and control systems with the goal of minimising energy consumption during their operation, particularly maintaining productivity and quality (Ullah et al. 2025).

Aiming at the design problem of energy-efficient machine tools, researchers have attempted to provide applicable approaches. A hybrid approach driven by model and data was proposed for the energy-saving design of the CNC machine tool feed system, while the energy consumption and deformation are considered as the two optimisation objectives (Wei Li et al. 2022). The lightweighting of a slide table was investigated in terms of its potential to reduce energy consumption (Triebe, Zhao, and Sutherland 2022). An integrated optimisation design model was developed for the machining unit of a hobbing machine tool to reduce energy consumption and tool displacement by jointly optimising motor and structural parameters (Lv et al. 2022). An energy-saving design method was proposed for gear hobbing machines based on the analytical target cascading method, which optimises the coupled design parameters of multiple energy-consuming subsystems (Shaoqing Wu et al. 2025). To simultaneously reduce energy consumption and dynamic performance, a structural design optimisation method was studied for machine tool moving components (Ji et al. 2020). A combining strategy was introduced for experimental tests, machine learning, and virtual reality for energy-efficient milling (Checa et al. 2022). To enhance machining performance, a component optimisation and lattice redesign approach was developed (Ullah, Chan, and Chang 2025). Similar studies on the design of energy-efficient machine tools can be found in (Triebe, Zhao, and Sutherland 2021; Uchiyama et al. 2015; Jinwen Zhang et al. 2024).

Table 2. Summary of the research studies on energy efficiency within machine tool equipment.

Topics	Representative studies	Main focus	Objectives and goals	Methodologies
Energy assessment and evaluation methods	(Cai and Lai 2021)	Sustainability assessment of mechanical manufacturing systems.	Sustainability of energy, economy, and the environment.	Sustainability index system and benchmark-based assessment models.
	(Ma et al. 2021)	Energy efficiency grading and inherent energy characteristics of machining systems.	Inherent energy efficiency.	Indicator system of inherent energy efficiency and quantitative grading method.
	(Peiji Liu et al. 2021)	Inherent energy performance modelling of machine tools for sustainable manufacturing.	Inherent energy consumption.	Generalised experimental design, automatic coding, and data processing.
	(Lai et al. 2025)	The evaluation of thermal energy efficiency for dry cutting machine tools.	Thermal energy efficiency.	Exergy balance and destruction modelling with time-varying graphical evaluation.
	(Yanqi Li et al. 2024)	Energy efficiency modelling and evaluation for multidirectional turning processes.	Energy, efficiency, cost, and quality.	Mathematical modelling and order preference evaluation.
Design of energy-efficient machine tools	(Wei Li et al. 2022)	Energy-saving design of CNC machine tool feed systems.	Feed system energy consumption and structural deformation.	Data–model hybrid optimisation with surrogate modelling and energy flow analysis.
	(Triebe, Zhao, and Sutherland 2022)	The lightweight design of machine tool tables aims to reduce operational energy consumption.	Energy consumption.	Mechanistic energy modelling and coupling between kinematics and dynamics.
	(Lv et al. 2022)	Energy-efficient optimisation design of hobbing machine tool machining units.	Energy consumption, tool displacement, and machining accuracy.	Surrogate models and integrated motor structure optimisation.
	(Shaoqing Wu et al. 2025)	Energy-saving design optimisation of gear hobbing machines with coupled subsystems.	Energy consumption.	Decomposition with surrogate modelling and adaptive sequential sampling optimisation.
	(Checa et al. 2022)	Energy optimisation of milling operations through cutting tool design.	Energy consumption.	Energy modelling based on machine learning and virtual reality design.
Energy efficiency monitoring	(Lee and Lee 2025)	Energy consumption monitoring of machine tools compliant with ISO 14955.	Standardised and real-time energy monitoring.	Integration of multiple sensors and CNC data with automatic state detection.
	(Selvaraj, Xu, and Min 2023)	Intelligent monitoring of CNC machine tools based on energy data.	Machine operation status and process variations using energy data.	Energy signal classification with hyperparameter optimisation based on CNN.
	(Kang and Lee 2024)	Energy monitoring and analysis for machine tools based on DT and CPS.	Visualisation and analysis of ECMT.	Digital twin modelling integrated with IoT-based CPS.
	(Mohammadi et al. 2017)	Energy flow monitoring and energy efficiency improvement of machine tools.	Real-time monitoring of energy flows.	Subsystem-based measurements and Sankey visualisation.
	(Gupta et al. 2024)	Machine learning-based real-time monitoring and classification of machining energy consumption.	Energy characteristics and energy efficiency.	Real-time energy measurement and random forest models.

3.2.3. *Energy efficiency monitoring*

Energy efficiency monitoring of machine tools refers to the real-time or periodic observation, measurement, and analysis of energy consumption. Energy efficiency monitoring aims to disaggregate energy flows, identify non-productive consumption, and quantify how much of the input energy is converted into value creation (Liang et al. 2022).

Focusing on the monitoring issues of energy efficiency on machine tools, a real-time compliant energy efficiency monitoring system was developed for machine tools by integrating CNC and sensor data to identify components with high energy consumption (Lee and Lee 2025). To identify operational status and feed rate from energy data, a 1D-CNN-based intelligent energy monitoring method was established for precise CNC machine tools (Selvaraj, Xu, and Min 2023). By developing a cyber-physical system based on digital twins, monitoring and analysing the energy consumption of machine tools were realised (Kang and Lee 2024). A real-time method was studied for monitoring and visualising the complete energy flows of CNC machine tools to support energy efficiency optimisation (Mohammadi et al. 2017). Motivated by the requirements on energy efficiency monitoring, an accurate handling approach was proposed for machining system energy efficiency (Jun Xie et al. 2021). Similar studies can be found in (Xingzheng Chen et al. 2018; Luoke Gupta et al. 2024; Hu et al. 2020).

3.3. *Process-level energy efficiency*

Energy efficiency within the process level focuses on improving the energy performance of machining operations at the process execution layer (Ge et al. 2022).

Recent research also considers lifecycle sustainability perspectives, linking machining parameters, tool wear, and part durability with broader circular manufacturing objectives (Elnourani et al. 2026; Rodriguez et al. 2026). The process-level energy efficiency includes not only predicting energy usage based on cutting dynamics and material behaviour but also optimising process parameters, operation sequences, and machining schemes (Lai et al. 2023). Table 3 is provided here to illustrate the research works on the energy efficiency of the machining process.

3.3.1. Modelling and prediction of energy consumption

This topic refers to the model development to estimate the energy required during machining operations based on various influencing factors. These models characterise energy behaviour across machining stages, enabling accurate prediction to support the latter energy services (Cheng Kai Huang et al. 2026).

Aiming at this topic, researchers have increasingly developed hybrid models that combine physical principles with machine learning approaches, allowing generalisation across materials, machines, and operating conditions. Driven by incomplete data, a CNC machining energy prediction framework using generative adversarial imputation nets was studied to handle incomplete workshop data, achieving accurate results even with up to 30% missing data (Pan et al. 2021). The machine learning techniques were investigated to predict the energy demand of CNC machining strategies, eliminating the need for dedicated experiments (Brillinger et al. 2021). An energy consumption model was studied for CNC turning that integrates both constant and variable material removal rate processes, enabling accurate prediction of total energy use (Pawanr, Garg, and Routroy 2022). To characterise and predict energy consumption in CNC machining and optimise toolpaths for improved energy efficiency, an automated design method of experiments toolset was developed (Pantazis et al. 2023). A spatial energy consumption field model was established to quantify the impact of motion position errors on machining energy and precision (Lin Zhang et al. 2024). A quantitative modelling approach was proposed to evaluate the energy consumption and carbon footprint of the grinding process by considering energy use, resource consumption, and waste generation (Hui Ding et al. 2014). To accurately predict the instantaneous energy consumption of five-axis machine tools, a deep learning model based on an attention mechanism was proposed (Zhicheng Xu, Selvaraj, and Min 2025). Similar studies can be found in (Dai et al. 2025; Chunxiao Li et al. 2022; Yang Xie et al. 2025; Zhicheng Xu, Selvaraj, and Min 2025).

3.3.2. Energy-saving optimisation of cutting parameters

This topic refers to the process of systematically selecting and adjusting cutting parameters (spindle speed, feeding rate, cutting depth, cutting width) with the objectives of minimising energy consumption. The cutting parameters can directly influence the material removal mechanism, cutting force, machine load, and thermal behaviour, all of which contribute to the energy profile of a machining operation. Moreover, other conditions (e.g. tool wear and product quality deterioration) are increasingly incorporated into machining optimisation models, enabling condition-based maintenance and more sustainable tool utilisation (Biao Lu and Luo 2024).

Aiming at this topic, an optimisation method was studied for milling cutting parameters to minimise machining cost and improve energy efficiency (Weiye Li et al. 2022). To address the cutting parameter optimisation problem, an optimisation method based on deep reinforcement learning was studied for flank milling (Fengyi Lu et al. 2023). Considering the energy characteristics with dynamic tool wear, an adaptive cutting parameter optimisation method based on reinforcement learning was studied to reduce energy consumption and production time (Congbo Li et al. 2023). A dynamic optimisation method for cutting parameters was proposed based on a reinforcement learning algorithm according to tool wear progression (Xikun Zhao et al. 2024). Motivated by the requirements of energy saving, a multi-objective cutting parameter optimisation method was studied (You Zhang et al. 2025). An integrated optimisation model was proposed for machining process plans and cutting parameters to minimise both electrical and embodied energy consumption (Xingzheng Chen et al. 2022). Similar studies can be found in (Hamıd et al. 2025; Luoke Hu et al. 2023; Shunhu et al. 2024; Liping Wang et al. 2024; Yau et al. 2024).

3.3.3. Energy-efficient process planning and routing

Process planning and routing determine the selection, sequence, and machine assignment of processes, as well as the material flow in the manufacturing system. The energy impacts at this level include not only the cutting energy but also setup changes, idle energy between operations, auxiliary energy, and transportation across machines or stations.

Aiming at the problems of planning and routing, a MILP model was studied, and a hybrid evolutionary algorithm was proposed to improve algorithm flexibility (Qihao Liu, Li, and Gao 2021). To automatically generate efficient machining process routes, graph neural networks were studied to improve the planning efficiency (Hang Zhang et al. 2024). To minimise machining energy

Table 3. Summary of the research studies on the energy efficiency of the machining process.

Topics	Representative studies	Main focus	Objectives and goals	Methodologies
Modelling and prediction of energy consumption	(Zhicheng Xu, Selvaraj, and Min 2025)	Energy prediction of ultra-precision machine tools for sustainable machining.	Prediction of instantaneous power consumption.	1DCNN-LSTM-Attention model.
	(Dai et al. 2025)	Energy consumption prediction of CNC machine tools is based on limited experimental data.	Prediction accuracy of ECMT.	Time-generative adversarial networks.
	(Yang Xie et al. 2025)	Energy prediction and state recognition of CNC machine tools.	Clarification of dynamic energy behaviour and accurate prediction of energy consumption.	LSTM and XGBoost.
	(Pantazis et al. 2023)	Modelling and optimisation of ECMT.	Energy consumption.	CPS integration and Hidden Markov Model.
	(Pawanr, Garg, and Routroy 2022)	Energy consumption modelling for cylindrical turning processes.	Energy consumption.	Modular energy modelling with experimental calibration.
Energy-saving optimisation of cutting parameters	(Weiye Li et al. 2022)	Energy-efficient and cost-oriented milling parameter optimisation.	Energy consumption and production cost.	Back propagation neural network, deep reinforcement learning, and Markov decision process.
	(Fengyi Lu et al. 2023)	Energy-efficient multi-pass flank milling with deformation-aware cutting parameter optimisation.	Energy efficiency and variable deformation.	Deep reinforcement learning, Markov decision processes, and surrogate models.
	(You Zhang et al. 2025)	Modelling and optimisation for energy consumption of internal gear power honing.	Energy consumption and machining time.	Mechanistic model and atomic orbital search algorithm.
	(Xikun Zhao et al. 2024)	Dynamic cutting parameter optimisation considering tool wear for energy-efficient machining.	Energy consumption, cutting time, and production costs.	Reinforcement learning with a Markov decision process.
	(Hamıd et al. 2025)	Effects of cooling conditions and cutting parameters on energy, emissions, and quality in milling Inconel 718.	Energy consumption, carbon emissions, surface roughness, cutting temperature, tool wear, and vibration.	Machine learning algorithm.
Energy-efficient process planning and routing	(Xiaocheng Tian et al. 2024)	Joint energy-efficient optimisation of feature processing sequence and toolpath strategy.	Energy consumption and processing time.	Dual-objective modelling and NSGA-II.
	(Feng et al. 2022)	Energy-efficient CNC machining via feature sequencing and parameter optimisation.	Energy consumption, machining quality, and processing time.	Mechanistic modelling and NSGA-II.
	(Xiao et al. 2023)	Energy-aware process planning under dynamic perturbations.	Energy consumption and processing time.	Graph convolutional reinforcement learning.
	(Lv et al. 2022)	Energy-efficient rescheduling with process planning.	Energy consumption and makespan.	Mechanistic modelling and simulated annealing algorithms.
	(Changle Tian et al. 2020)	Integrated optimisation of process routes and cutting parameters for low-carbon CNC machining.	Carbon emissions and processing time.	Mechanistic modelling and NSGA-II.
Energy-aware optimisation of process schemes	(Han Ding et al. 2023)	LCA-driven power dry cutting optimisation for sustainable face-hobbing hypoid gear production.	Sustainability and accuracy.	Kinematic modelling, sensitivity analysis, and GA.
	(Fengyi Lu et al. 2025)	Energy-efficient tool path optimisation for five-axis flank milling.	Energy consumption and processing time.	Meta-reinforcement learning and Markov decision process.
	(Yang Xie, Mei, and Zhang 2025)	Energy-efficient process parameter optimisation for CNC milling.	Energy consumption and specific cutting energy.	WOA-BP and NSGA-II.
	(Dhouib and Zouari 2023)	Tool path optimisation for reducing non-productive movements in CNC drilling operations.	Production time, cost, and energy consumption.	The Adaptive Dhouib Matrix and many heuristics.
	(Lai et al. 2025)	Thermal error modelling of motorised spindles in high-speed dry hobbing machines.	Thermal error and energy balance.	Semi-mechanical modelling and PSO–GA.

and processing time, a joint optimisation approach for feature processing sequence and toolpath strategy was investigated (Xiaocheng Tian et al. 2024). A cutting parameter selection was studied to reduce both cutting and non-cutting energy consumption (Feng et al. 2022). A graph convolutional reinforcement learning method was investigated for proper planning of a sustainable process (Xiao et al. 2023). Aiming at the dynamic events such as job arrivals and machine breakdowns, a decision-making mechanism was introduced for the integrated problem of rescheduling and process planning (Lv et al. 2022). Similar studies can be found in (Changle Tian et al. 2020; Wen et al. 2022; Changle Tian et al. 2021).

3.3.4. Energy-aware optimisation of process schemes

Process scheme optimisation involves evaluating the combinations of process options that fundamentally shape the energy behaviour of the machining system. These schemes determine not only the power intensity of each operation but also the duration, auxiliary system usage, and transition energy between processes.

Aiming at the process scheme optimisation problems, a collaborative optimisation model of face-hobbing hypoid gears was developed based on LCA, which is hoped to enhance energy efficiency and sustainability (Han Ding et al. 2023). A tool path optimisation method was studied using meta-reinforcement learning to reduce energy consumption and processing time (Fengyi Lu et al. 2025). Considering the influences caused by the variable diameters of cutting tools, the machining parameters are accordingly adjusted and optimised to minimise energy consumption (Yang Xie, Mei, and Zhang 2025). Aiming at the peripheral milling with variable curvature, a composite optimisation approach was studied with the objective of reducing energy consumption (Chunxiao Li et al. 2024). Similar studies can be found in (Dhouib and Zouari 2023; Lai et al. 2025; Shi et al. 2025).

3.4. System-level energy efficiency

Energy efficiency at the system level extends the scope of optimisation from individual machines and machining processes to the holistic operation of the workshop. It emphasises how production organisation, resource coordination, and systematic policies influence overall energy performance. In this subsection, the three parts, including sleep & power-off control policies, shop-floor configuration, and energy-efficient scheduling, are reviewed. An overall review of system-level energy efficiency can be found in Table 4.

3.4.1. Sleep & power-off control policies

In modern CNC machining environments, machines often spend a significant portion of their operational time

Table 4. Summary of the research studies on the energy efficiency of mechanical manufacturing systems.

Topics	Representative studies	Main focus	Objectives and goals	Methodologies
Sleep & power-off control policies	(Zixuan Huang et al. 2024)	Energy-saving control of machine tools with multisleep states.	Energy consumption.	Multisleep control is solved by an improved whale optimisation algorithm.
	(Jia et al. 2024)	Energy saving in CNC machine tools during no-load spindle operations.	Energy waste.	Spindle deceleration strategy with energy modelling.
	(Frigerio, Tan, and Matta 2024)	Energy-efficient on/off control of multiple machines in serial production lines.	Energy consumption and production rate.	Threshold control based on buffers.
	(Gong et al. 2021)	Energy-efficient production scheduling with integrated machine on/off control and maintenance.	Makespan, machine restarts, and energy consumption.	On/off control and fast heuristics for maintenance insertion and block movement.
	(Tan, Karabağ, and Khayyati 2024)	Energy-efficient production control via dynamic machine on/off policies.	Energy, inventory, and backlog costs.	Markov decision process, phase-type modelling, and matrix-geometric analysis.
Shop-floor configuration with sustainability consciousness	(Ferretti, Zanoni, and Zavanella 2023)	Energy-aware facility layout design considering auxiliary electrical systems.	Layout cost and energy efficiency.	Mechanistic modelling and commercial solvers.
	(Zhongwei Zhang et al. 2022)	Energy-efficient facility layout optimisation for sustainable manufacturing systems.	Energy consumption.	Facility layout modelling and PSO algorithm.
	(Forghani, Fatemi Ghomi, and Kia 2022)	Integrated cell formation and group layout optimisation with energy-aware manufacturing.	Material handling cost and energy consumption.	Mixed-integer programming with a hybrid GA–SA algorithm.
	(Cai Xia Zhang et al. 2021)	Energy-efficient layout design of mixed-flow parallel production lines.	Idle energy consumption.	Energy consumption modelling and GA algorithm.
	(Iqbal and Al-Ghamdi 2018)	Energy-efficient machine shop layout and process assignment optimisation.	Energy consumption of machining and transportation.	Nonlinear energy model and SA algorithm.
Energy-efficient job shop scheduling	(Zhiqiang Tian et al. 2025)	Energy-efficient scheduling for flexible job shops under uncertainty and deterioration.	Production cost, makespan, and energy consumption.	Mechanistic modelling and hybrid heuristics.
	(Zhiqiang Tian et al. 2025)	Job shop lot-streaming scheduling for multiple resource constraints.	Energy consumption, makespan, and processing cost.	Mechanistic modelling with lot splitting and MOEA algorithm.
	(Lv et al. 2022)	Energy-efficient rescheduling with process plan flexibility in dynamic flexible job shops.	Energy consumption and makespan.	Mechanistic modelling and SA algorithms.
	(Guo et al. 2023)	Dynamic job-shop scheduling integrates machines, logistics, and energy awareness.	Energy consumption and makespan.	Mechanistic modelling, GA algorithm, and digital twin.
	(Füchtenhans and Glock 2024)	Energy-aware job-shop scheduling under power demand flexibility.	Energy consumption and weighted tardiness.	Mechanistic modelling and GA algorithm.

in idle states, during which energy is greatly wasted. By intelligently controlling when and how to switch machine states, manufacturers can significantly reduce standby energy losses.

Aiming at this area, energy control policies were investigated for reducing consumption during idle periods (Frigerio and Matta 2021). A similar study was also conducted to adaptively switch machine tools to save energy (Frigerio, Cornaggia, and Matta 2021). To further reduce makespan and energy consumption, a machine switch approach was proposed with maintenance planning (Gong et al. 2021). By considering component startup priorities and optimising control parameters, an effective control strategy with multi-sleep states was introduced (Zixuan Huang et al. 2024). In order to reduce idle time and carbon emissions, theoretical models that intend to switch machine status were developed (Tridech and Cheng 2011). To minimise energy waste, a spindle deceleration strategy during idle stages of CNC machine tools was proposed to reduce energy waste (Jia et al. 2024). Similar studies can be found in (Frigerio, Tan, and Matta 2024; Tan, Karabağ, and Khayyati 2023, 2024).

3.4.2. Shop-floor configuration with sustainability consciousness

This topic seeks to minimise energy waste, reduce transportation and idle time, enhance equipment utilisation, and support the adoption of sustainability.

To improve energy efficiency through machine configuration, a facility layout design approach was studied to optimise machine placement and electrical system configuration (Ferretti, Zanoni, and Zavanella 2023). A nonlinear optimisation model using simulated annealing was proposed by optimising machine assignments and cell layouts (Iqbal and Al-Ghamdi 2018). Aiming at promoting the sustainability of manufacturing workshops, a facility layout model was investigated (Zhongwei Zhang et al. 2022). An integrated cell formation and group layout optimisation model that jointly determines machine cells, layout, process routes, and operation speeds was developed (Forghani, Fatemi Ghomi, and Kia 2022). An energy-efficient layout design method was proposed for parallel production lines to reduce idle energy consumption and improve equipment utilisation (Cai Xia Zhang et al. 2021).

3.4.3. Energy-efficient job shop scheduling

Energy-efficient scheduling refers to the strategic allocation and sequencing of machining tasks, resources, and time slots across the shop floor with the explicit goal of minimising energy consumption. Aiming at shop scheduling problems, an energy-efficient rescheduling mechanism was studied for flexible job shops by integrating alternative process plans (Lv et al. 2022). To minimise energy consumption and makespan, a multi-objective optimisation model that integrates parameter settings, process planning, and shop floor scheduling problem was studied (Lingling Li et al. 2019). Enabled by digital twin data, a dynamic job shop scheduling method that integrates machine and logistics scheduling was studied (Guo et al. 2023). A scheduling optimisation method was studied for flexible job shops with machine deterioration and maintenance (Zhiqiang Tian et al. 2025). A scheduling optimisation method based on simulation was proposed to analyse the relationships among production workflow, energy consumption, and product quality to improve energy efficiency (Katchasuwanmanee, Cheng, and Bateman 2016). To minimise energy consumption, makespan, and processing cost, a hybrid optimisation approach using lot splitting was proposed (Zhiqiang Tian et al. 2025). Under power constraints, a scheduling model for machine shop manufacturing that minimises makespan was studied, aiming to reduce peak power consumption (Carlucci, Renna, and Materi 2023). Similar studies can be found in (Füchtenhans and Glock 2024; Rui Li et al. 2023; Yao, Li, and Gao 2024; Fuqing Zhao, Di, and Wang 2023; Fuqing Zhao, Jiang, and Wang 2023).

3.5. Research gaps and challenges

According to the aforementioned reviews on ECMT, existing studies have achieved substantial progress across the equipment, process, and system levels. It covers energy assessment, modelling, monitoring, optimisation, and scheduling with a wide range of physical models, data-driven methods, and optimisation algorithms. These efforts have significantly deepened the machining energy mechanisms and enabled various energy-saving strategies in practical manufacturing scenarios.

However, the current research still predominantly relies on traditional modelling paradigms and conventional algorithms, where energy analysis and optimisation are often treated as isolated problems with limited semantic understanding and weak cross-level integration. In particular, despite the rapid advancement of artificial intelligence techniques, most existing studies focus on conventional machine learning, deep learning, or heuristic optimisation methods, while the potential of LLMs for energy-efficient machining remains largely unexplored. There is a clear lack of research that leverages LLMs to unify heterogeneous energy data, machining knowledge, and human intent through semantic reasoning, interactive decision-making, and intelligent energy

Table 5. Potentials and capabilities of LLMs for ECMT.

Levels	Research directions	LLM-enabled capabilities
Equipment	Energy assessment and evaluation methods	Automatic extraction of energy assessment knowledge from technical documents, and reasoning over heterogeneous energy data to support explainable energy evaluation.
	Design of energy-efficient machine tools	The integration of design knowledge, component energy models, and engineering experiences assists in the energy-efficient design of machine tools through simulation and optimisation tools.
	Energy efficiency monitoring	Semantic analysis through real-time sensor data and energy models to identify machine states, explain abnormal energy consumption patterns, and support intelligent energy efficiency monitoring.
Process	Modelling and prediction of energy consumption	Knowledge-enhanced modelling involves integrating machining knowledge, process parameters, and historical data to assist in constructing or selecting appropriate prediction models for energy consumption.
	Energy-saving optimisation of cutting parameters	LLM-guided decision support for selecting cutting parameters by interpreting user intentions and optimisation tools.
	Energy-efficient process planning and routing	The semantic understanding of machining features, process knowledge, and routing constraints supports the intelligent generation and adjustment of energy-efficient process plans.
	Energy-aware optimisation of process schemes	Integration of toolpath generation through modelling and optimisation algorithms, and trajectory verification by simulation to assist decision-making.
System	Sleep & power-off control policies	Semantic and/or autonomous status control of machine tools with interfaces assists in determining appropriate sleep or shutdown strategies.
	Shop-floor configuration with sustainability consciousness	Knowledge-driven analysis of machine layout and tool-assist resource allocation to support sustainable shop-floor configuration and facility planning.
	Energy-efficient job shop scheduling	LLM-enabled coordination of scheduling algorithms, production constraints, and energy objectives to support intelligent energy-aware scheduling decisions.

services, leaving significant research gaps between current ECMT studies and emerging LLM-enabled intelligent manufacturing paradigms.

3.6. Discussion on LLMs' abilities for energy management of machine tools

The emergence of LLMs provides new opportunities to address the aforementioned limitations. Benefiting from their strong capabilities in semantic understanding, knowledge reasoning, and multimodal information integration, LLMs can act as an intelligent coordination layer that bridges heterogeneous energy data, machining knowledge, and analytical models. In particular, LLMs can interpret engineering documents, analyse operational information from machine tools, and orchestrate different computational tools to support energy-related services.

Therefore, the integration of LLMs into ECMT research has the potential to enhance the flexibility and intelligence of energy-efficient manufacturing systems. Table 5 summarises how the LLM-enabled framework can support the major research directions reviewed in this section, highlighting the corresponding semantic analysis and intelligent capabilities provided by LLM technologies.

4. Paradigms and architecture of ChatEMT

The aforementioned reviews highlight a critical gap between the growing complexity of energy-efficient machining tasks and the capabilities of traditional computational approaches. Hence, this section introduces ChatEMT, an energy service paradigm driven by LLM for machine tools that leverages recent advances in natural language intelligence, multimodal fusion, and semantic reasoning.

4.1. Large language model: the core enabling foundation of ChatEMT

4.1.1. The emergence and evolution of LLMs

The evolutionary development of LLMs has been characterised by a continuous shift from symbolic reasoning toward large-scale and general intelligent agents with strong domain adaptability. Figure 4 illustrates this trajectory, highlighting six representative stages of development.

In the 1950s, early LMs relied on manually crafted grammatical and logical rules, enabling simple text manipulation but lacking scalability and semantic depth. In the 1990s, the rise of statistical LMs introduced probabilistic approaches such as n-gram and Hidden Markov Models, which learned word occurrence patterns from large corpora but were still limited by short context windows (Renhai Chen et al. 2022). Since 2013, with the advent of deep learning, neural LMs adopted distributed word embeddings and recurrent networks (RNNs, LSTMs) to capture contextual and semantic relationships automatically (Fang et al. 2022). Around 2017, a breakthrough occurred with the pretrained LMs based

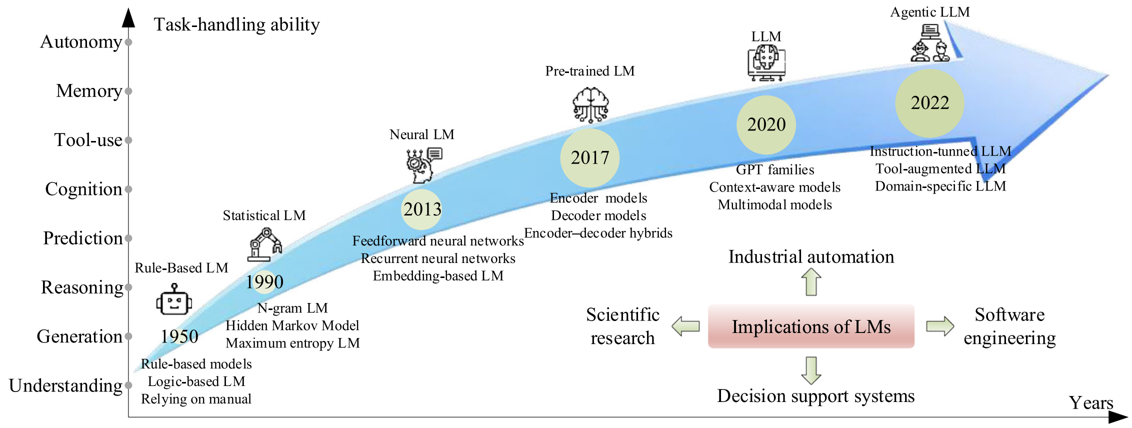

Figure 4. The emergence and evolution of LLMs.

on Transformers, where attention mechanisms and large-scale pretraining enabled parallel computation and transfer learning across diverse tasks (Berdyugina and Cavallucci 2023). After 2020, building on this foundation, large autoregressive LLMs, exemplified by GPT-3, T5, and PaLM, demonstrated emergent abilities (Sheng Gao et al. 2025). Starting in 2022, agentic LLMs have integrated instruction following, human alignment, and external tool use, enabling them to work autonomously across different domains (Zhen Zhao et al. 2026). Collectively, these advances have transformed LMs from handcrafted symbolic systems into cognitive agents capable of supporting complex decision-making.

The rapid evolution of LLM technology signifies a paradigm shift in artificial intelligence, namely, from passive language understanding to active reasoning and interaction. Their emergence not only advances natural language processing but also redefines how humans interact with intelligent systems. Ultimately, the progression of LLMs marks a critical step toward general artificial intelligence that can reason, collaborate, and act meaningfully in complex environments.

4.1.2. Foundation architecture of LLM

LLMs rely on a unified foundation architecture that integrates Transformers to support advanced language understanding and reasoning. The overall architecture of LLM can be found in Figure 5. Conceptually, an LLM can be regarded as a parametric knowledge system that encodes linguistic, semantic, and patterns into billions of model parameters. This foundational architecture provides the core intelligence for ChatEMT, enabling advanced services for ECMT that rely on natural language interaction and domain knowledge grounding.

4.1.3. The current agentic LLM in manufacturing

Recent studies have demonstrated that LLM-based agents can serve as intelligent coordinators within complex manufacturing systems. By integrating the reasoning capability of LLMs with data access, simulation tools, and optimisation methods, these agents can perceive operational states, plan sequences of actions, and autonomously make decisions based on context.

There are already successful cases that have developed specific agents based on LLMs for manufacturing problems. For instance, a review on industrial applications of LLM techniques was reported (Raza et al. 2025). A knowledge graph vector RAG framework was proposed to enhance the accuracy, contextual relevance, and efficiency of LLM applications in the smart manufacturing industry (Wan et al. 2025). A language interface system was studied for data integration in a smart factory (Garcia et al. 2024). Aiming at the digital inexperience of workers and rigid user interfaces, a conversational monitoring framework was proposed to enable natural language interaction with machine data, improving human–machine collaboration and digital literacy (Jeon et al. 2025). To achieve adaptive and flexible scheduling in customised workshops, a digital twin system oriented to carbon emission enhanced by LLMs was studied (Tao Wu et al. 2025). An adaptive process management framework based on LLMs was introduced to transform user descriptions into structured manufacturing workflows (Ni et al. 2025). A hybrid framework that combines LLMs with information retrieval techniques was studied to improve software defect localisation accuracy in flexible manufacturing systems (Haiyang Yang et al. 2025). Similar studies can be found in (Du et al. 2025; Gkournelos, Konstantinou, and Makris 2024; Changchun Liu and Nie 2025; Tian Wang, Fan, and Zheng 2024; Bo Wang et al. 2025; Yiwei Wang et al. 2026; Yuan et al. 2025). These studies demonstrate that LLM techniques

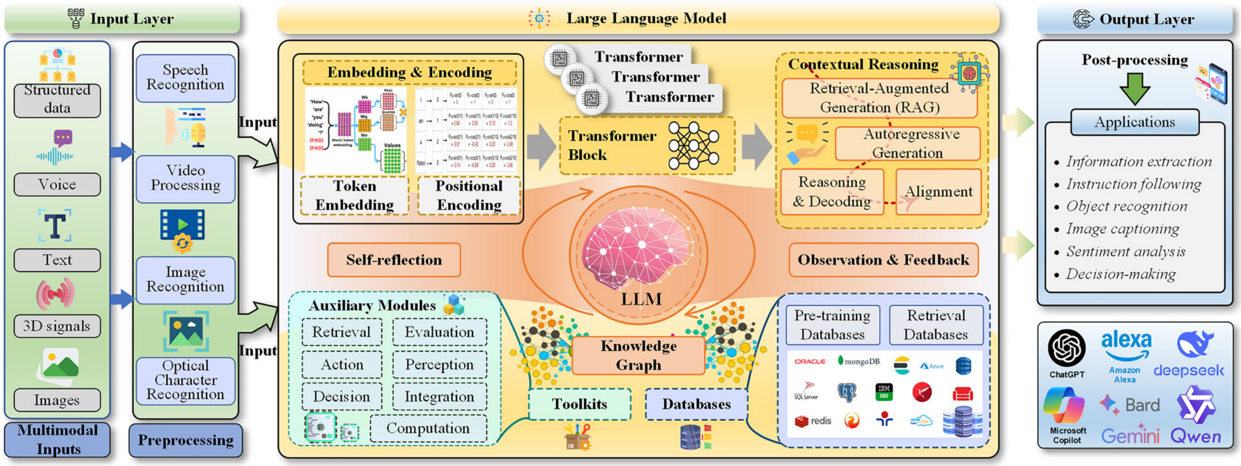

Figure 5. The foundation architecture of LLM.

have been successfully applied to various manufacturing problems. However, LLM-based research on ECMT remains scarce. Accordingly, this paper aims to bridge the identified gaps in the existing literature.

4.2. Overall design philosophy and functional analysis

As shown in Figure 6, the overall design philosophy of ChatEMT constructs a cognitive framework centred on the LLM technique that seamlessly connects perception, understanding, reasoning, and energy services for CNC machine tools. As illustrated in the design blueprint, ChatEMT positions the LLM as the cognitive engine, supported by multimodal comprehension, knowledge retrieval, and human–machine collaboration. This design emphasises an integrated cognitive cycle consisting of perception, analysis, reasoning, optimisation, and iterative learning, enabling ChatEMT to achieve comprehensive and intelligent energy services.

Functionally, ChatEMT organises advanced services for ECMT into a hierarchical set of capabilities, including energy analysis, saving, modelling, statistics, prediction, evaluation, monitoring, optimisation, pricing, assessment, identification, and quoting. Each function is mapped to the cognitive modules. Reasoning enables the generation of optimised schemes using LLM logic enhanced by machine learning, deep learning, reinforcement learning, heuristics, and knowledge graphs, and reasoning algorithms. By connecting language interaction with engineering operations, the overall design philosophy ensures that ChatEMT can interpret human instructions, synthesise domain knowledge, reason about complex energy behaviours, and autonomously deliver reliable, explainable, and adaptive solutions for modern machining environments.

To clarify the exceptional role of LLMs in the construction of ChatEMT, Table 6 is provided to identify the key functions of the twelve energy-oriented services mentioned in Figure 6. It reveals that LLMs have the distinct abilities (e.g. domain knowledge, RAG, semantic reasoning, and tool invocation) that can realise advanced and intelligent services for ECMT. It will be hopeful to realise lower energy consumption and easier energy management with ChatEMT.

4.3. Layered system architecture of ChatEMT

To further illustrate the components of ChatEMT, the layered system architecture is constructed as shown in Figure 7. It starts from the energy-oriented infrastructure layer, which provides the foundational hardware and software environment necessary for sustainable machining. This layer encompasses machine tools, cutting tools, workpieces, power sensors, CNC systems, and industrial communication protocols, together with network facilities such as routers and data transmission formats.

Built upon this foundation, the energy-oriented database and knowledge layers serve as the core repositories and semantic backbone of ChatEMT. The database layer supports the full lifecycle of data transmission, caching, cleaning, aggregation, annotation, compression, and tiered storage, enabling data sharing, backup, and recovery for reliable and stable operation. The knowledge layer organises process knowledge, machine knowledge, and energy knowledge into structured forms, such as process routing, cutting constraints, and equipment structures. These knowledge elements allow ChatEMT to reason about machining processes and energy behaviours in an interpretable manner, providing domain semantics that guide subsequent model construction and intelligent decisions.

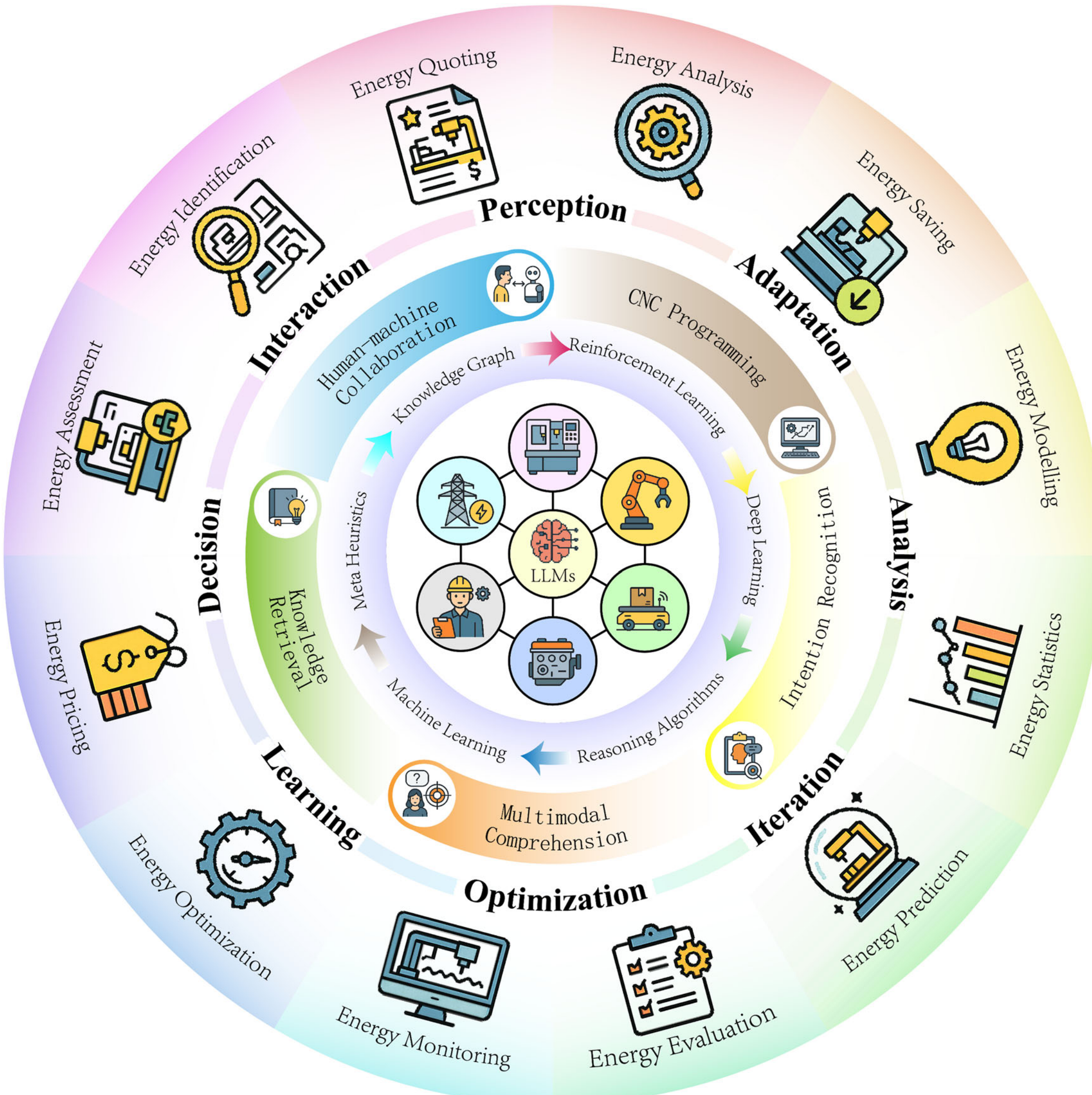

Figure 6. The overall design philosophy of ChatEMT.

The energy-oriented model layer and workflow layer convert domain knowledge into computational intelligence and executable actions. The model layer includes energy consumption and efficiency models, prediction models, evaluation models, and optimisation models implemented through advanced algorithms (e.g. machine learning, heuristics, pretraining, and adaptation). The workflow layer integrates these models into operational procedures through event listening and dynamic matching, ensuring that data, models, and decisions are orchestrated coherently to support stable and adaptive operations.

At the top of the architecture, the energy-oriented application layer delivers intelligent management and control services to machine shops. This includes energy services for achieving a sustainable machining production, such as energy statistics of equipment, energy monitoring, and energy efficiency evaluation. These applications directly support production management, manufacturing control, and decision support, enabling manufacturers to achieve comprehensive machining operations.

By chaining the infrastructure, data, knowledge, model, workflow, and application layers into a coherent hierarchy, ChatEMT provides a scalable, interpretable, and intelligent architecture for promoting the sustainability of CNC machining systems. Such an architecture also facilitates the integration of machine tools with broader manufacturing ecosystems, enabling interactions with digital twins, maintenance services, and organisational decision roles across the production lifecycle.

Table 6. ChatEMT capabilities and the core functions of LLMs.

Energy-related services	Core questions	Key role, importance, and benefits of LLMs
Energy analysis	Why does energy behave this way?	Through semantic reasoning with energy information, the energy consumption behaviours and mechanisms of machine tools can be revealed by LLMs with the help of equipment states and historical patterns.
Energy saving	What actions can reduce energy consumption?	The LLM techniques serve as the translator from human intention and analytical results insights into actionable and context-aware energy-saving solutions for operators and decision-makers.
Energy modelling	How can energy consumption be formally represented?	With the domain knowledge after fine-tuning, LLMs can be used as a large-scale model using the influencing factors to obtain the specific energy consumption and efficiency of machine tools.
Energy statistics	How much energy is consumed?	Using the tool invocation, LLMs can organise, summarise, and aggregate statistical energy data.
Energy prediction	What will happen to energy consumption in the future?	Based on the real-time data and energy trends, LLMs can be used as an interface to forecast the future ECMT under varying process and scheduling conditions.
Energy evaluation	How good is the current energy performance?	Driven by the evaluation model and the historical energy data, LLMs can accordingly interpret evaluation indicators and benchmarks, providing explainable assessments rather than isolated numerical scores.
Energy monitoring	What is the current energy state?	By providing interpretation of energy signals, LLMs can enhance real-time monitoring with flexible image generations according to human instructions.
Energy optimisation	How can optimal energy performance be achieved?	Through incorporating process semantics and practical constraints, LLMs act as intelligent coordinators that select, configure, and guide optimisation tools.
Energy pricing	How much does energy cost under different conditions?	With retrieval and generation based on external pricing information with operational data, LLMs can provide proper reasoning and calculation for the price of ECMT.
Energy assessment	Which option performs better in terms of energy?	By reasoning across multiple scenarios and criteria, LLMs can integrate outputs from simulation and evaluation tools to support comparative assessment for ECMT.
Energy identification	Where does energy consumption occur?	Equipped with fine-tuned domain knowledge, LLMs can map heterogeneous data sources to specific machines, states, and operations.
Energy quoting	How much energy will a specific task or order cost?	Using the retrieval-augment generation from across historical cases, process plans, and pricing information, LLMs can accordingly provide an energy quota for machining production to achieve the sustainability of production.

4.4. Application framework of ChatEMT

To clearly illustrate the workflow of ChatEMT, its application framework is provided as shown in Figure 8. It begins with a multimodal input layer, which collects human, data, and multimodal file inputs. The human-input interface accepts requests such as machine diagnosis queries, optimisation requests, and comparison demands. Similarly, the data-input interface ingests machine tool data, sensor data, and PLC data. Additionally, a file input channel allows ChatEMT to process structured documents (e.g. programmes, CNC code files, figures, and videos).

Based on these inputs, ChatEMT conducts internal cognitive processing through an integrated mechanism that combines RAG, memory, fine-tuning, and tool invocation. Specifically, RAG enables ChatEMT to dynamically retrieve relevant machining knowledge, energy models, and historical records to support context-aware reasoning. The memory module accumulates interaction histories and operational states to ensure continuity and consistency in decision-making. Fine-tuning further aligns the underlying large language model with machining and energy-efficiency tasks. Tool invocation allows ChatEMT to interact with external computational modules, simulation tools, and databases, enabling actionable outputs rather than purely textual interaction.

At the bottom of the framework, ChatEMT delivers a comprehensive suite of energy-oriented services for CNC machine tools, directly mapped from the functional modules shown in the application diagram. To support practical manufacturing operations, ChatEMT also provides strategy reports, optimisation recommendations, and parameter generation for machining processes. By integrating cognitive reasoning with engineering actions, the application framework ensures that ChatEMT can transform heterogeneous inputs into actionable and accurate decision-making.

4.5. Key enabling technologies of ChatEMT

To realise the full potential of ChatEMT in promoting the sustainability of machining production, a series of key enabling technologies is presented in this subsection.

4.5.1. Large language model foundations

LLMs constitute the foundational intelligence core of ChatEMT, enabling natural language understanding, reasoning, and adaptive interaction across machining

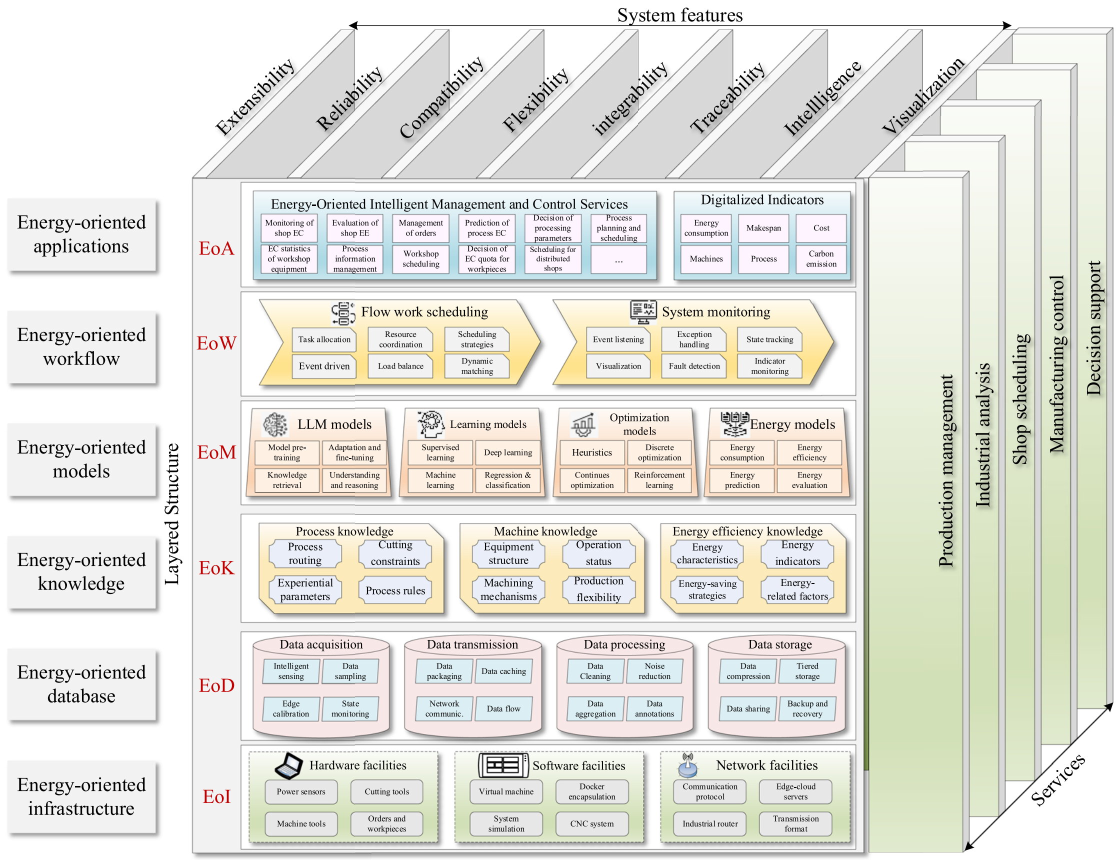

Figure 7. The layered system architecture of ChatEMT.

energy-efficiency tasks. Modern LLMs (such as ChatGPT, Claude, and Gemini, as shown in Figure 9) leverage Transformer-based architectures with billions of parameters trained on massive multimodal corpora. Their training on diverse textual and code datasets allows them to generalise linguistic patterns, infer latent knowledge, and generate context-aware responses with remarkable fluency. In the ChatEMT paradigm, LLM foundations provide the semantic and cognitive substrate upon which downstream modules are constructed, serving as the interface between human intent, domain knowledge, and autonomous decision-making in sustainable manufacturing systems.

4.5.2. Domain knowledge integration and retrieval-augmented generation

Effective deployment of ChatEMT in energy-efficient machining relies on the seamless integration of domain-specific knowledge with LLM reasoning. Traditional LLMs often lack the precision and factual grounding required for industrial applications. Thus, knowledge graph (e.g. TransE, RotatE, and GCN) and RAG (e.g. REALM and RETRO) approaches have become key enabling techniques (Lou et al. 2025; Ye and Wang 2026). RAG enhances model responses by retrieving information from multimodal manufacturing knowledge bases before generation, ensuring both accuracy and interpretability. Meanwhile, modelling and semantic embedding enable alignment between machining terminology, process parameters, and energy efficiency principles.

4.5.3. Multimodal data and sensor fusion for energy services

To enable better management for ECMT with ChatEMT, it is crucial to obtain the multimodal data related to machining production and raised energy consumption. Modern energy-efficient manufacturing systems generate massive data streams and textual logs from controller records. Hence, it is necessary to use advanced fusion algorithms (e.g. Kalman filtering, Bayesian inference, and graph neural representations) to enable the model to align and correlate these heterogeneous modalities in a shared semantic space (McKinney et al. 2025). Through this integration, ChatEMT can perceive real-time machine states and understand contextual dependencies between energy consumption and machining parameters.

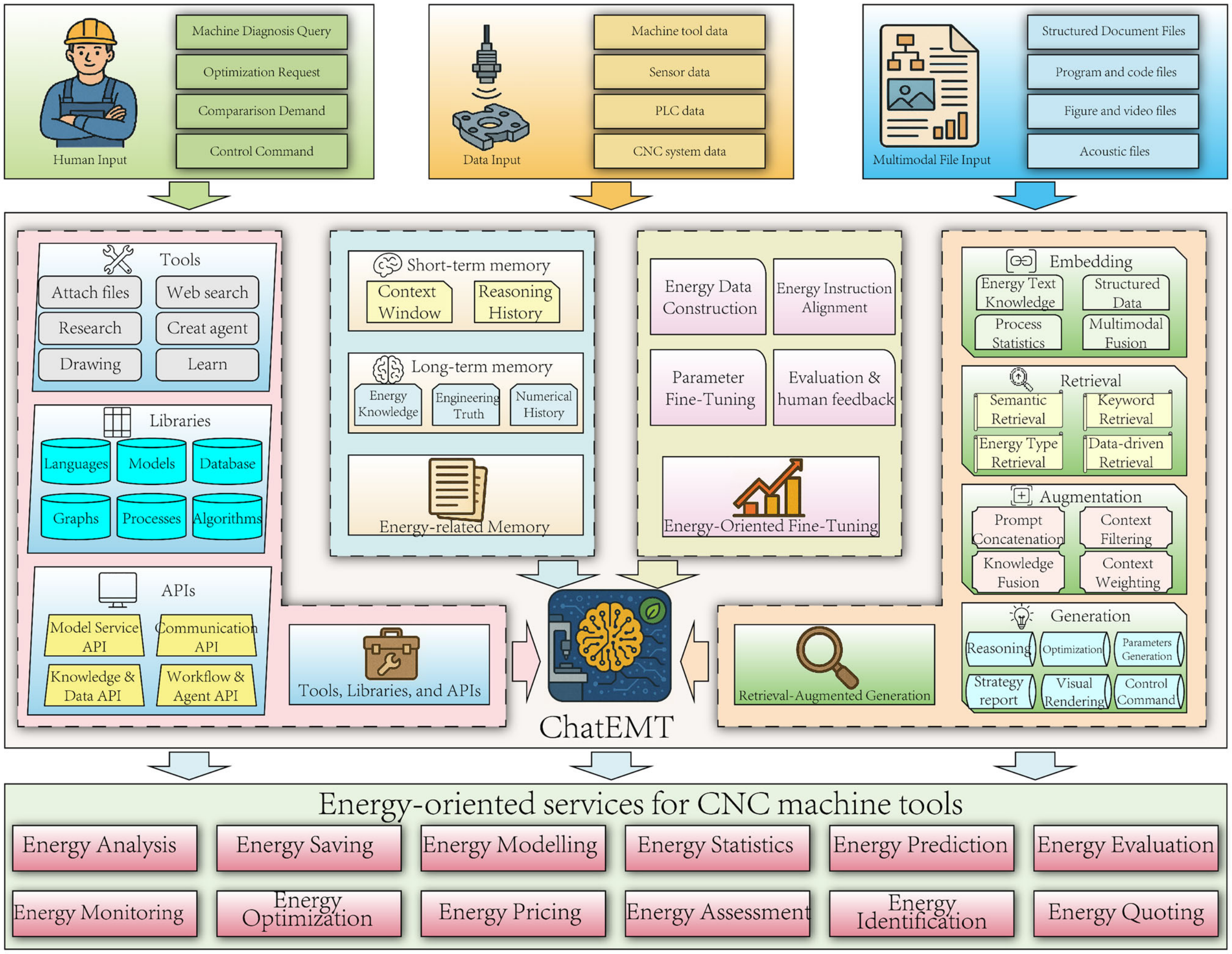

Figure 8. The application framework of ChatEMT.

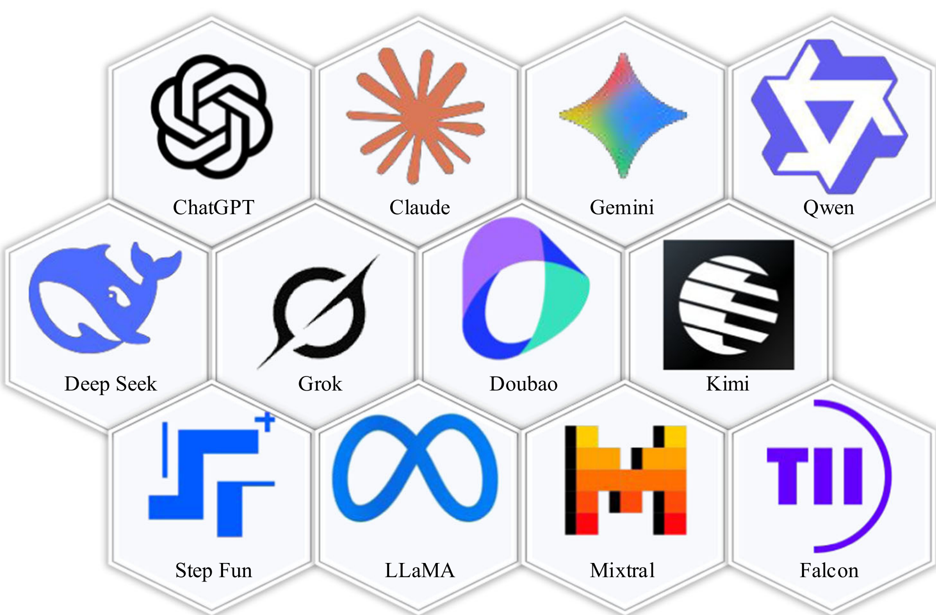

Figure 9. Typical LLMs for the foundations of ChatEMT.

4.5.4. Industrial IoT integration and cyber-physical fusion

The integration of IIoT technologies and CPS forms the operational backbone of ChatEMT, enabling real-time perception, communication, and interaction between physical machine tools and the digital ones. Through standardised industrial protocols, entities (e.g. heterogeneous sensors, controllers, and machine tools) can be interconnected to collect multi-source energy and process data. The CPS frameworks further support data processing and bidirectional synchronisation between the physical and digital spaces. With these technologies, ChatEMT can then obtain trustworthy data and accordingly provide services for sustainable machining.

4.5.5. Intelligent agent formulation and collaboration

The intelligent agent architecture of ChatEMT plays a crucial role in enabling autonomous and collaborative energy management across CNC machine tools and workshops. Recent developments in agent developers (e.g. LangChain, Coze, and Dify) provide modular infrastructures for orchestrating multi-agent interactions, tool integration, and context reasoning (Kundu et al. 2025). These frameworks allow ChatEMT models to operate as specialised components capable of perception, reasoning, and generation.

4.5.6. Advanced AI algorithms for learning and optimisation

ChatEMT is anticipated to have the generality to handle many kinds of energy services, which require the help of advanced AI algorithms. They can provide the computational backbone for ChatEMT to achieve adaptive learning and intelligent optimisation in energy-efficient machining. Hence, many kinds of algorithms are required to equip the ChatEMT model with heuristic algorithms (e.g. GA, PSO, and ACO), machine learning (e.g. SVM, linear regression, and decision tree), deep learning (e.g. CNN, RNN, and GRU), and reinforcement learning (e.g. deep Q-learning). ChatEMT can then be endowed with intelligence capabilities for energy management of machine tools. The integration of these algorithms with LLM reasoning further enhances the ability to explore the potential of energy savings, accelerate convergence, and optimise machining solutions.

5. Challenges, limitations, and open issues

5.1. Ensuring access to reliable and representative energy data of machine tools

The effectiveness of ChatEMT fundamentally relies on the availability of reliable and representative datasets describing the energy behaviour of machine tools. However, current industrial environments often suffer from fragmented data sources, inconsistent acquisition standards, and limited accessibility. ChatEMT also requires a reliable dataset to equip itself with sufficient knowledge of energy consumption and machining production. Moreover, the diversity of machining processes, materials, and operational conditions makes it challenging to build unified benchmarks for training and evaluation. As a result, providing reliable and representative energy data of machine tools is crucial and difficult to support the development, adjustment, and validation of ChatEMT models.

5.2. Guaranteeing the generalizability of energy services across diverse machine tool types

One of the major challenges for ChatEMT lies in ensuring the generalizability of its energy services across heterogeneous machine tools and manufacturing environments. Machine tools differ significantly in structure, control logic, spindle dynamics, auxiliary systems, and power behaviour, leading to variations in energy consumption patterns and characteristics. Models trained on a specific type or brand of machine often fail to transfer effectively to others due to differences in data formats, control parameters, and energy feature distributions. To achieve generalizability, ChatEMT requires mechanisms such as domain adaptation, meta-learning, and knowledge distillation. Furthermore, establishing unified energy modelling standards and interoperable communication protocols is essential to enable scalable and general ChatEMT deployment in machining production.

5.3. Enabling continuous updatability of ChatEMT across functions, data, and knowledge

Another challenge for sustaining the effectiveness of ChatEMT lies in maintaining continuous updates across its functional modules, data repositories, and domain knowledge base. In dynamic manufacturing environments, the static systems based on LLMs might get outdated along with sustained services. Achieving updatability requires mechanisms for incremental learning, online fine-tuning, and automated knowledge injection from newly collected operational data and expert feedback. However, it would be challenging for practitioners to provide additional materials with updating mechanisms to renew the ChatEMT.

5.4. Mitigating hallucination and inaccurate responses in energy knowledge of machine tools

Since ChatEMT is the extension and fine-tuned version of LLMs, there would be risks of hallucination and factual inaccuracy when generating energy knowledge or optimisation suggestions for machine tools. LLMs are primarily trained on general textual corpora rather than verified industrial datasets, and so their responses may contain plausible but incorrect technical information, misleading parameter recommendations, or inconsistent interpretations of energy mechanisms. Such errors can compromise decision reliability and even cause unintended operational risks on the shop floor. Hence, there would be limitations for ChatEMT to mitigate hallucination and inaccurate responses during the energy services.

5.5. Enhancing domain-specific competitiveness against conventional algorithms

Although LLMs exhibit strong general reasoning and semantic understanding, they might underperform compared to conventional algorithms when dealing with highly specialised machining problems. In optimisation tasks (e.g. production scheduling, cutting parameter tuning, and process routing), traditional heuristic algorithms (e.g. GA, PSO, and NSGA-II) might have satisfying convergence and solution quality. Likewise, in predictive modelling tasks such as energy consumption prediction, machine learning and deep learning models might already have satisfying performance in numerical accuracy and computational efficiency. Hence, it is an open issue to enhance the domain-specific competitiveness against conventional algorithms.

6. Perspectives and future directions

The aforementioned challenges highlight that ChatEMT is still in its primary stage of development, with multiple gaps remaining between conceptual design and practical deployment. To facilitate a better energy service for machine tools, future directions of related research within application, system integration, and methodology levels are provided in this section as follows.

6.1. Perspectives and future directions at the application level

6.1.1. Autonomous ChatEMT for machining production and energy management

The biggest advance of the ChatEMT is that it can read and respond to the requirements with semantics and languages. Naturally, realising autonomous management for machine tools becomes greatly valuable for manufacturers to reduce manual labour and improve the autonomy. By integrating LLMs with real-time production data, ChatEMT could autonomously interpret order information, assess delivery priorities, and optimise machine utilisation while minimising energy consumption. Such autonomy requires combining natural language understanding to ensure that decision outputs align with both operational efficiency and sustainability goals.

6.1.2. Resilience and adaptation of ChatEMT under disturbances and process variations

In real manufacturing environments, machining processes are subject to various disturbances (e.g. tool wear, equipment degradation, order fluctuation, and environmental variation), which can significantly affect energy performance and production stability. Future ChatEMT systems should therefore possess resilience and adaptive capabilities to respond dynamically to these uncertainties. By integrating real-time monitoring data with adaptive reasoning and feedback learning, ChatEMT can continuously adjust energy solutions in response to deviations. Furthermore, coupling ChatEMT with digital twins and edge intelligence can ensure stable, efficient, and sustainable machining operations in fluctuating industrial conditions.

6.1.3. Balancing multiple optimisation objectives in sustainable machining

Sustainable machining inherently involves complex contradictions among multiple optimisation objectives, such as minimising energy consumption, reducing production cost, shortening makespan, and maintaining product quality. Future ChatEMT frameworks should be capable of understanding these competing objectives to achieve a systematic optimisation for machining production.

6.2. Perspectives and future directions at the system integration level

6.2.1. Multi-agent collaboration and coordination in ChatEMT ecosystems

ChatEMT systems are expected to realise multi-agent collaboration and coordination, where diverse intelligent agents collaborate to handle energy services in an integrated and comprehensive manner. Each agent (e.g. perceptive, diagnostic, predictive, decisive, and cognitive ChatEMT) can specialise in different aspects of sustainable machining while communicating through shared memory and coordinated reasoning. This architecture would enable distributed intelligence, parallel task execution, and dynamic resource allocation across machine shops. Achieving effective collaboration among agents requires standardised communication protocols, task allocation strategies, and coordination mechanisms to ensure coherent behaviours.

6.2.2. Integration of ChatEMT with digital twin technology for closed-loop optimisation

Integrating ChatEMT with DT technology represents a crucial step toward achieving closed-loop optimisation in sustainable machining. By coupling the reasoning and generative capabilities of LLMs with the interaction between the physical and virtual entities, ChatEMT can continuously perceive, analyse, and optimise machining operations in both virtual and physical spaces. This integration enables bidirectional data flow, where sensor data from the physical workshop updates the virtual model, while ChatEMT provides adaptive optimisation strategies, anomaly interpretation, and decision recommendations back to the shop floor. Through this closed-loop interaction, machining systems can dynamically adjust process parameters, improve energy utilisation efficiency, and prevent potential energy wastage or process deviations.

6.3. Perspectives and future directions at the methodology level

6.3.1. Lightweight design and energy-aware construction of ChatEMT

Future studies related to ChatEMT frameworks should emphasise lightweight and energy-aware model construction to achieve sustainable deployment in real industrial environments. Current LLMs require substantial computational resources for training and inference, which can consume a large amount of electricity and CPU time. To address this, techniques (e.g. model pruning, quantisation, and knowledge distillation) can be employed and specially designed for ECMT to reduce model size and inference latency without compromising reasoning performance. Moreover, the lightweights of ChatEMT have benefits for the response time and scalable deployment across diverse machine tools and workshops. It can enable a more sustainable and practical intelligent manufacturing ecosystem.

6.3.2. ChatEMT with tool augmentation for sustainable machining

To enhance the practical applicability of ChatEMT in practical machining environments, future research should focus on developing tool-augmented frameworks that endow the system with specialised capabilities for machining production with lower energy consumption. Beyond natural language reasoning, ChatEMT can be equipped with dedicated tools such as engineering drawing interpreters for extracting machining features from CAD/CAM files and energy consumption analyzers. In addition, route planners and simulation tools could enable ChatEMT to validate energy solutions before execution.

6.4. Managerial insights for practitioners

For a better implementation of industrial practices, the managerial insights are given in this subsection as follows.

First, the ChatEMT can significantly lower the technical barriers for energy analysis and optimisation. In many manufacturing workshops, energy management often relies on specialised engineering experience, which limits the participation of operational staff in energy-related decision-making. By enabling natural-language interaction and automated orchestration of analytical models, the proposed framework allows engineers and managers without deep expertise in optimisation algorithms to access energy analysis, diagnosis, and optimisation services more conveniently.

Second, the ChatEMT enhances the transparency and explainability of energy-related decisions. Industrial practitioners often require understandable explanations of optimisation results and operational recommendations before adopting them in real production environments. By leveraging the reasoning and knowledge integration capabilities of large language models, the framework can provide interpretable insights into energy consumption patterns and recommended actions.

Finally, the proposed framework provides a pathway toward intelligent energy service platforms in manufacturing enterprises. By integrating data resources, domain knowledge, and analytical models through LLM-based orchestration, the proposed paradigm can serve as a foundation for future intelligent energy management systems of machine tools.

7. Conclusions

To bridge the gaps between the emerging AI technique LLM and ECMT to unlock the application potential for sustainable machining production, this paper comprehensively reviews the existing reviews and research studies on ECMT and proposes a new paradigm for energy-efficient machine tools enabled by LLMs, ChatEMT. This paradigm can provide explainable, user-friendly, and semantically grounded energy services for energy-efficient machining. The conclusions of this study can be summarised as follows.

(1) This paper reviews the latest survey papers and recent research studies on ECMT, synthesising findings across the multiple levels of equipment, process, and system. It is concluded that the existing works remain fragmented and lack a systematic and intelligent paradigm based on LLMs to enable intelligent energy services for machine tools.
(2) A novel paradigm named ChatEMT is proposed based on the LLM technique, and the analysis concludes that LLMs offer new potential for understanding machining semantics, integrating energy knowledge, and supporting energy services for sustainable machine tools.
(3) A layered system architecture and application framework for ChatEMT are established, which can provide explainable, intelligent, user-friendly, and semantically grounded energy services for energy-efficient machining production.
(4) Critical challenges, limitations, and future research directions are proposed, concluding that advancements in data quality, model generalisation, hallucination mitigation, hybrid algorithm design, and adaptive ecosystem construction are essential for realising sustainable machining.

Author contributions

CRediT: **Miao Yang:** Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Wei Wu:** Formal analysis, Supervision, Writing – original draft, Writing – review & editing; **Congbo Li:** Formal analysis, Supervision, Writing – original draft; **George Q. Huang:** Funding acquisition, Supervision, Writing – original draft, Writing – review & editing

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Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that ChatGPT (versions 5.1 and 5.2) was used to improve English writing and language clarity for better reader comprehension.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon request.

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