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Physics-Informed Machine Learning in Machining Process Modeling

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ABSTRACT

Machining processes such as turning, milling, drilling, and grinding are complex manufacturing operations governed by nonlinear interactions among tool, workpiece, machine structure, and cutting environment. Accurate modeling of these processes is essential for improving productivity, surface integrity, tool life, and energy efficiency. Traditional physics-based models rely on analytical or numerical formulations derived from mechanics, thermodynamics, and material science, but they often suffer from simplifying assumptions and limited adaptability to real-world variations. On the other hand, purely data-driven machine learning (ML) models demonstrate strong predictive capability but lack physical interpretability and generalization outside the training domain. Physics-informed machine learning (PIML) has emerged as a promising paradigm that integrates domain knowledge in the form of physical laws, constraints, and governing equations with data-driven learning techniques. This paper presents a comprehensive review of physics-informed machine learning approaches applied to machining process modeling. The fundamental principles of machining physics are discussed, followed by an overview of conventional modeling techniques and data-driven methods. Various PIML frameworks, including physics-informed neural networks, hybrid modeling, and constrained learning, are analyzed with respect to cutting force prediction, tool wear estimation, chatter detection, temperature modeling, and surface quality prediction. Current challenges, practical implementation issues, and future research directions are also highlighted. The review indicates that *physics-informed machine learning provides a balanced approach, combining accuracy, robustness, and physical consistency, making it suitable for next-generation smart machining systems.*

KEYWORDS: *Physics-informed machine learning, machining process modeling, cutting forces, tool wear, hybrid models, smart manufacturing*

INTRODUCTION

Machining remains one of the most widely used manufacturing processes for producing precision components in aerospace, automotive, medical, and general engineering industries. Despite decades of research, machining processes continue to present challenges due to their highly nonlinear, multi-physics nature involving plastic deformation, friction, heat generation, vibration, and tool-workpiece interactions. Accurate modeling of machining behavior is critical for process planning, optimization, and real-time control.

Conventional machining models are largely based on physics and mechanics, such as Merchant's theory for orthogonal cutting, slip-line field theory, finite element simulations, and empirical force models. While these models provide valuable insight, they often require extensive calibration, high computational cost, or restrictive assumptions that limit their practical applicability. Moreover, real machining environments are influenced by uncertainties such as tool wear, material inhomogeneity, and machine dynamics, which are difficult to capture fully through analytical models.

In recent years, machine learning techniques have gained popularity in machining research due to the increasing availability of sensor data and computational power. Algorithms such as artificial neural networks, support vector machines, random forests, and deep learning models have been successfully applied for prediction of cutting forces, surface roughness, tool condition, and energy consumption. However, purely data-driven approaches often behave as "black boxes" and may violate known physical laws, leading to poor extrapolation and unreliable predictions under unseen conditions.

Physics-informed machine learning (PIML) addresses these limitations by embedding physical knowledge directly into the learning process. Instead of treating physics and data as competing approaches, PIML combines them to exploit their complementary strengths. This paper reviews recent developments in physics-informed machine learning for machining process modeling, highlighting methodologies, applications, and future prospects.

FUNDAMENTALS OF MACHINING PROCESS PHYSICS

Machining involves material removal through relative motion between a cutting tool and a workpiece. The fundamental physical phenomena governing machining include material deformation, friction, heat transfer, and dynamic interactions.

1. Cutting Mechanics

The cutting process is characterized by shear deformation along a primary shear zone and frictional interaction along the tool-chip interface. Cutting forces are typically resolved into tangential, radial, and axial components. These forces depend on cutting parameters such as feed rate, cutting speed, depth of cut, tool geometry, and workpiece material properties.

2. Thermal Effects

A significant portion of mechanical energy in machining is converted into heat due to plastic deformation and friction. The resulting temperature rise affects tool wear, workpiece microstructure, and dimensional accuracy. Thermal modeling often involves conduction, convection, and radiation, making it computationally intensive.

3. Tool Wear and Failure

Tool wear mechanisms include abrasion, adhesion, diffusion, and oxidation. Wear progression is influenced by cutting conditions, tool material, coating, and cooling strategy. Predicting tool life remains a challenging task due to complex interactions between thermal and mechanical loads.

4. Dynamic Behavior and Chatter

Machining systems are prone to self-excited vibrations known as chatter, which degrade surface quality and reduce tool life. Chatter is governed by machine-tool dynamics, cutting force coefficients, and regenerative effects.

CONVENTIONAL MACHINING PROCESS MODELING

Traditional machining models can be broadly classified into analytical, numerical, and empirical models.

1. Analytical Models

Analytical models are based on simplifying assumptions to derive closed-form equations for cutting forces, chip thickness, and shear angles. Although computationally efficient, these models often fail to capture complex material behavior and 3D effects.

2. Numerical Models

Finite element (FE) models provide detailed insight into stress, strain, and temperature distribution during machining. However, FE simulations require accurate material models and are computationally expensive, limiting their use for real-time applications.

3. Empirical and Regression Models

Empirical models use experimental data to fit regression equations for predicting outputs such as surface roughness or cutting force. Their applicability is limited to the range of experimental conditions.

MACHINE LEARNING IN MACHINING MODELING

Machine learning methods learn patterns directly from data without explicit physical equations. Common applications include tool condition monitoring, surface roughness prediction, and fault diagnosis.

1. Supervised Learning Approaches

Artificial neural networks and support vector machines have been widely used for regression and classification tasks in machining. Deep learning models, particularly convolutional and recurrent neural networks, have shown success in processing sensor signals.

2. Limitations of Purely Data-Driven Models

Despite high prediction accuracy, ML models often lack interpretability and may generate physically inconsistent results. They also require large datasets and may perform poorly when extrapolating beyond trained conditions.

PHYSICS-INFORMED MACHINE LEARNING: CONCEPT AND FRAMEWORKS

Physics-Informed Machine Learning (PIML) represents a paradigm that tightly couples data-driven learning with established physical principles. Unlike conventional machine learning approaches that rely purely on large datasets, PIML integrates domain knowledge in the form of governing equations, physical constraints, or simplified analytical models. This integration enhances model interpretability, reduces data requirements, and ensures physically consistent predictions, which is especially important in complex and safety-critical machining processes.

In machining, physical knowledge such as cutting mechanics, heat transfer, material behavior, and machine tool dynamics is well understood at a fundamental level but difficult to model completely due to nonlinearities and uncertainties. PIML frameworks leverage this partial knowledge and use ML to capture the remaining unknown or unmodeled phenomena.

1. Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks are one of the most widely adopted PIML frameworks. In PINNs, governing differential equations are embedded directly into the loss function of a neural network. During training, the network is optimized not only to fit experimental or simulation data but also to satisfy the underlying physical laws.

In machining applications, PINNs have been used to enforce heat conduction equations for predicting cutting temperature distributions, where the network outputs temperature fields while minimizing the residuals of the heat transfer partial differential equations. Similarly, force balance equations and dynamic equilibrium constraints can be imposed to improve cutting force and vibration predictions.

An important advantage of PINNs is their ability to work with sparse or noisy data, which is common in machining environments. By constraining the learning process with physics, PINNs prevent non-physical solutions and improve extrapolation performance beyond the training domain. However, challenges remain in terms of computational cost and tuning of loss function weights, particularly for complex multi-physics machining problems.

2. Hybrid Physics–Data Models

Hybrid physics–data models combine conventional physics-based models with machine learning components in a modular manner. In this framework, the physics-based model captures the dominant behavior of the machining process, while the ML model learns the residual errors or compensates for effects that are difficult to model analytically.

For example, a mechanistic cutting force model may be used to estimate baseline cutting forces based on chip geometry and material properties. A neural network or regression model is then trained to correct these predictions by accounting for unmodeled factors such as progressive tool wear, material inhomogeneity, or changes in lubrication conditions. This approach retains the transparency and reliability of physics-based models while significantly improving accuracy.

Hybrid models are relatively easy to implement and integrate into existing machining simulations and control systems. They are particularly suitable for industrial applications, as they balance physical interpretability with the flexibility of data-driven learning and typically require less data than fully data-driven models.

3. Constraint-Based Learning

Constraint-based learning focuses on embedding physical constraints directly into the learning process to ensure realistic and feasible predictions. Instead of explicitly solving governing equations, constraints such as energy conservation, non-negativity of physical quantities, monotonic relationships, or bounded parameter ranges are enforced during training.

In machining, constraint-based learning has been applied to ensure monotonic tool wear progression with cutting time, non-negative cutting forces and temperatures, and stable system responses under bounded cutting conditions. These constraints help avoid physically implausible predictions that can arise from unconstrained ML models, especially when operating outside the range of training data.

This framework is computationally less intensive than PINNs and more flexible than fully physics-based models. Constraint-based learning is particularly effective when full governing equations are difficult to define or computationally expensive, but qualitative physical behavior is well understood. As a result, it serves as a practical and robust PIML strategy for real-time machining monitoring and optimization.

APPLICATIONS OF PHYSICS-INFORMED MACHINE LEARNING IN MACHINING

Physics-Informed Machine Learning (PIML) has emerged as a powerful framework for addressing long-standing challenges in machining process modeling. By embedding governing physical laws into learning architectures, PIML improves prediction accuracy, robustness, and interpretability compared to purely data-driven models. This section discusses key application areas where PIML has shown significant impact.

1. Cutting Force Prediction

Accurate cutting force prediction is essential for process planning, tool design, machine tool selection, and surface quality control. Conventional mechanistic models estimate cutting forces based on chip load, shear plane mechanics, and empirical force coefficients. However, these models often struggle to capture nonlinear effects arising from tool wear, material heterogeneity, and complex tool geometries.

Physics-informed machine learning models enhance cutting force prediction by integrating mechanistic force equations directly into the learning process. Instead of learning force behavior solely from experimental data, the ML model is constrained to satisfy known physical relationships, such as the proportionality between cutting force and uncut chip thickness or the dependence on rake and clearance angles. This hybrid formulation significantly reduces overfitting and improves generalization across different cutting conditions.

Furthermore, PIML approaches require fewer training samples compared to purely data-driven methods, as the embedded physics provides prior knowledge. Studies have demonstrated that PIML models maintain high prediction accuracy even under unseen spindle speeds, feed rates, or depth of cut. This makes them particularly suitable for adaptive machining and real-time force monitoring applications.

2. Tool Wear and Tool Life Estimation

Tool wear is a major factor affecting dimensional accuracy, surface integrity, and production cost in machining operations. Traditional tool wear models, such as Taylor’s tool life equation or Archard’s wear law, rely on simplified assumptions and often lack adaptability to varying process conditions. On the other hand, data-driven ML models can capture complex wear patterns but may produce physically unrealistic predictions when extrapolated.

Physics-informed machine learning bridges this gap by embedding wear evolution laws, thermal constraints, and contact mechanics into the learning framework. For instance, wear rate predictions can be constrained to remain non-negative and monotonic with cutting time, consistent with physical wear mechanisms. Temperature-dependent wear behavior can also be incorporated using physics-based relationships between cutting temperature and diffusion or oxidation wear.

As a result, PIML models offer more reliable tool wear progression and tool life estimation under changing cutting parameters. These models are particularly valuable for condition-based monitoring systems, enabling timely tool replacement and reducing unexpected tool failures. The improved interpretability of PIML also allows process engineers to understand the influence of individual parameters on wear behavior.

3. Temperature Modeling

Temperature in the cutting zone plays a critical role in tool wear, chip formation, residual stresses, and surface integrity. Direct temperature measurement in machining is challenging due to the harsh environment, high speeds, and limited sensor accessibility. Classical analytical and numerical models based on heat transfer equations can estimate temperature but often require precise knowledge of material properties and boundary conditions.

Physics-informed machine learning offers an effective alternative by embedding heat conduction and convection equations within neural networks. These models learn temperature distributions while respecting fundamental energy conservation laws. By incorporating physics constraints, the dependence on extensive experimental temperature data is significantly reduced.

PIML-based temperature models have demonstrated improved robustness under varying cutting speeds and cooling conditions. They also enable spatial and temporal temperature predictions, which are difficult to obtain experimentally. This capability is highly beneficial for optimizing cutting parameters, selecting cooling strategies, and preventing thermal damage to both tool and workpiece.

4. Chatter Detection and Stability Analysis

Chatter is a self-excited vibration phenomenon that limits productivity, degrades surface finish, and accelerates tool wear. Traditional chatter prediction relies on stability lobe diagrams derived from dynamic models of the machine–tool–workpiece system. While effective, these models often require accurate system parameters that are difficult to identify and may vary over time.

Physics-informed machine learning improves chatter detection and stability analysis by combining dynamic equations of motion with data-driven classifiers or regressors. The ML component learns complex nonlinear interactions and uncertainties, while the physics constraints ensure consistency with underlying vibration dynamics. This hybrid approach enhances prediction accuracy under varying cutting conditions and machine configurations.

PIML-based chatter models have shown improved early detection capabilities using limited sensor data, such as acceleration or acoustic emission signals. They are well-suited for real-time implementation in smart CNC systems, enabling adaptive control strategies to suppress chatter and expand stable machining regions.

Table 1: Comparison of Modeling Approaches in Machining

Approach	Accuracy	Interpretability	Data Requirement	Computational Cost
Physics-based models	Moderate	High	Low	High
Data-driven ML models	High	Low	High	Moderate
Physics-informed ML	High	Moderate to High	Moderate	Moderate

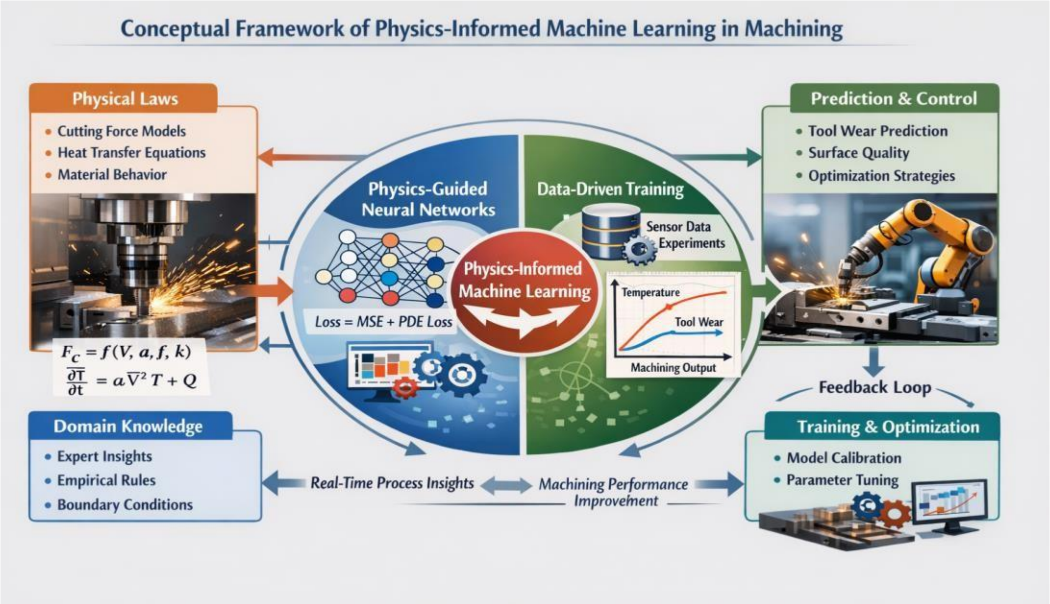

Figure 1: Conceptual Framework of Physics-Informed Machine Learning in Machining

CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite its promise, physics-informed machine learning faces challenges such as formulation of appropriate physical constraints, scalability to complex 3D processes, and integration with real-time control systems. Future research may focus on adaptive PIML models, digital twin integration, and standardization of benchmarking datasets.

CONCLUSION

Physics-informed machine learning represents a significant advancement in machining process modeling by bridging the gap between traditional physics-based approaches and modern data-driven techniques. By embedding physical knowledge into machine learning frameworks, PIML models achieve improved accuracy, robustness, and interpretability. This review has highlighted key methodologies, applications, and challenges associated with PIML in machining. As smart manufacturing continues to evolve, physics-informed machine learning is expected to play a crucial role in enabling reliable, efficient, and intelligent machining systems.

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