

Optimizing Cutting Tool Price Prediction using Artificial Intelligence for Enhanced Cost and Time Efficiency: A Survey

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ABSTRACT

Efficient cutting tool selection and precise cost estimation play a vital role in modern manufacturing, significantly influencing productivity, energy efficiency, and overall process sustainability. This study proposes an artificial intelligence driven framework for predicting cutting tool costs while optimizing machining parameters to reduce processing time and material waste. The methodology integrates key machining performance indicators, including tool wear, energy consumption, and surface quality, with advanced machine learning models such as Random Forest, XGBoost, and Decision Trees.

To enhance model transparency and interpretability, explainable AI techniques, particularly SHAP, are utilized to analyze predictions and identify the most influential factors affecting tool cost and performance. The results demonstrate that the proposed framework not only achieves high accuracy in cost prediction but also provides actionable insights for optimizing machining conditions, extending tool life, and lowering operational costs.

Overall, the study highlights the effectiveness of combining data driven predictive modeling with sustainable manufacturing principles to enable cost efficient, high performance, and environmentally responsible machining operations.

Keywords

Artificial intelligence, cutting tool cost prediction, machine learning, Random Forest, tool wear, sustainable manufacturing, SHAP, machining optimization, Industry 4.0.

1. INTRODUCTION

In modern manufacturing, efficient machining and effective cost management are essential for maintaining competitiveness and achieving high productivity. Cutting tools represent a substantial portion of operational expenses, and their performance significantly influences machining efficiency, surface quality, and energy consumption [6], [7]. Conventional approaches to tool selection and cost estimation primarily rely on historical data, operator expertise, or empirical guidelines, which often result in suboptimal decisions and increased operational costs [10], [12].

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has facilitated the development of predictive, data-driven solutions for manufacturing optimization.

AI-based models enable accurate prediction of tool wear, machining performance, and associated costs, thereby supporting proactive maintenance strategies and efficient

resource allocation [7],[15],[19]. In particular, ensemble learning techniques.

Random Forest and XGBoost have demonstrated strong predictive performance in complex machining environments by effectively capturing nonlinear relationships between input variables and machining responses [9], [18], [19].

Sustainable manufacturing has become a critical focus, emphasizing energy efficiency, waste minimization, and environmental responsibility.

Advanced machining approaches, including cryogenic machining and optimized cutting strategies, have been shown to improve tool life, reduce energy consumption, and enhance surface quality, especially for difficult-to-machine materials such as Inconel 718 [6].

The integration of these process improvements with AI-driven predictive models enables a comprehensive approach to achieving cost efficiency, process optimization, and environmental sustainability.

Furthermore, explainable AI techniques, particularly SHAP, enhance the interpretability of complex ML models by quantifying the contribution of individual machining parameters to tool performance and cost outcomes [8].

This level of transparency supports informed decision-making in industrial settings, ensuring that predictive insights can be effectively translated into practical actions.

This study proposes an AI-based framework for predicting cutting tool costs and optimizing machining parameters to minimize operational time, tool wear, and energy consumption.

By integrating predictive modeling, feature-driven cost estimation, and interpretability techniques, the proposed approach aims to deliver accurate cost predictions while providing actionable insights for sustainable and efficient manufacturing practices [4], [19], [20].

2. RELATED WORK

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in manufacturing has significantly advanced predictive maintenance, cost estimation, and process optimization. Tool wear is a critical factor affecting machining efficiency, surface quality, and operational cost. Khanna et al. [6] demonstrated that cryogenic machining of Inconel 718 improves tool life by 133% while reducing energy consumption and surface roughness, highlighting the importance of thermal management.

AI-based approaches have been widely used for tool wear prediction. Munaro et al. [7] reviewed techniques such as Support Vector Machines and Convolutional Neural Networks

for real-time monitoring, while Srivastava et al. [15] reported 97.3% accuracy using Random Forest models. Bhowmik et al. [19] further showed that Gene Expression Programming outperforms other models in predicting machining responses in superalloy milling.

Machine learning is also increasingly applied to cost estimation. Lin and Shaw [10] and Chwastyk and Kołosowski [12] proposed feature-based and structured approaches for early-stage cost prediction, while Bodendorf and Franke [20] achieved high accuracy ($R^2 = 0.960$) in automotive cost modeling. Hennebold et al. [4] emphasized the role of ML in improving resource efficiency.

For machining time prediction and CNC optimization, Denkena et al. [3] introduced a grey-box model combining physical and data-driven approaches, while Sun et al. [5] and Musca et al. [16] utilized neural networks and simulation frameworks to enhance production planning and cost efficiency.

Algorithm selection plays a vital role in predictive performance. Decision Trees [17], Random Forests [18], and XGBoost [9] have shown strong capabilities in capturing complex machining relationships, supported by tools such as Scikit-learn [14]. Additionally, hybrid approaches integrating physics-based models with ML have improved prediction accuracy and reliability [2], [1]. XGBoost act as a benchmark for high-performance gradient boosting, influencing both academic research and industrial applications across diverse domains.

3. LITERATURE REVIEW

The field of predictive modeling and optimization in machining and product development has advanced significantly in recent decades. This review explores developments in tool wear prediction, machining cost estimation, and process optimization, with a focus on the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques.

3.1 Early Work

Early research in machining and cost estimation relied predominantly on empirical models and direct observation. Quinlan [17] contributed to predictive modeling through decision tree induction, enabling interpretable, rule-based predictions for industrial applications. Traditional methods for tool wear monitoring and process optimization were largely dependent on manual inspection and operator expertise, often resulting in inconsistencies and inefficiencies [6].

Similarly, The cost estimation in product development and shipbuilding was primarily based on heuristic and feature based approaches. Lin and Shaw [10] introduced early feature-based techniques for preliminary cost estimation, Chwastyk and Kołosowski [12] emphasized structured methodologies for cost evaluation during new product development.

These foundational studies highlighted the need for more advanced predictive approaches to effectively manage tool wear, optimize machining processes, and improve early-stage cost estimation.

3.2 Evolution of Tool Wear Prediction and Machining Optimization

With advances in sensing technologies and computational power, researchers began integrating AI and ML for predictive maintenance and machining optimization. Khanna et al. [6] demonstrated the impact of thermal management on tool wear and surface finish in Inconel 718, showing that cryogenic

machining significantly extends tool life and reduces energy consumption. This study marked a shift from purely empirical approaches to data-informed process optimization. Subsequent research expanded AI applications to predictive modeling of tool wear.

Munaro et al. [7] reviewed AI methods for tool wear monitoring, highlighting machine learning techniques such as Support Vector Machines (SVM), neural networks, and convolutional neural networks (CNNs). Srivastava et al. [15] validated the efficacy of ensemble ML models like Random Forests for predicting lathe tool wear, achieving high predictive accuracy. Bhowmik et al. [19] explored multiple ML algorithms—including Gene Expression Programming (GEP), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Artificial Neural Networks (ANN) for superalloy milling, confirming the superiority of GEP in modeling nonlinear machining responses such as surface roughness, cutting force, and temperature. Parallel to tool wear studies, cost estimation techniques evolved to incorporate ML for early-stage product design. Bodendorf and Franke [20] demonstrated that predictive ML models can forecast automotive component costs with high accuracy ($R^2 = 0.960$) using a limited set of design features. Hennebold et al. [4] applied similar approaches in mechanical engineering, showing that ML-based cost predictions enhance resource allocation and process efficiency. In CNC machining, Musca et al. [16] and Denkena et al. [3] proposed simulation-based and grey-box modeling techniques to optimize machining strategies, cycle times, and operational costs. Sun et al. [5] further employed neural networks to model machine tool feed-rate behaviour, enabling accurate prediction of machining cycle times.

3.3 Recent Advances

The most recent studies emphasize hybrid and physics-informed approaches. Pashmforoush et al. [2] integrated a thermo-mechanical wear model with ML, demonstrating enhanced prediction accuracy for turning processes. This reflects the growing trend of combining first principle models with data-driven methods to improve reliability.

Li et al. [1] highlighted indicator-prioritized performance evaluation techniques for precision manufacturing systems, further underscoring the importance of integrating multiple performance metrics into predictive frameworks. AI frameworks for interpretability have also matured. Lundberg and Lee [8] introduced SHAP (Shapley Additive explanations), providing a theoretically grounded method to interpret model predictions, which is essential for industrial adoption where transparency and explainability are critical.

In terms of algorithmic advancements, XGBoost [9] has become a standard for high-performance predictive modeling, providing scalability, efficiency, and robustness for regression and classification tasks in machining and cost prediction applications. Scikit-learn [14] has enabled broad accessibility to ML algorithms, facilitating rapid experimentation and model deployment in industrial contexts.

3.4 Machine Learning Approaches for Tool Wear Prediction

Machine learning (ML) has emerged as a transformative approach for predicting tool wear in machining operations, addressing limitations of traditional empirical and experience-driven methods.

Supervised algorithms, such as Random Forests, Decision Trees, k-Nearest Neighbors (k-NN), AdaBoost, and Artificial

Neural Networks (ANNs), have been extensively employed to model the complex relationships between cutting parameters and tool degradation [15], [19]. Ensemble learning techniques, which combine multiple predictive models, have demonstrated superior accuracy and robustness in capturing nonlinear wear behaviors, outperforming single-model approaches [19].

Moreover, the integration of real-time sensor data, including vibration, acoustic emissions, cutting force, and temperature measurements enables continuous monitoring of tool conditions, supporting predictive maintenance and reducing unexpected machine downtime[7].

Recent advances have also introduced physics-informed ML models that incorporate mechanistic understanding of wear phenomena into data-driven predictions, enhancing both reliability and interpretability by bridging theoretical models and empirical observations [2]. These methods collectively facilitate proactive tool management, improved surface quality, and optimized machining efficiency.

AI Based Cost and Time Prediction in Manufacturing. Artificial intelligence has increasingly been applied to estimate machining costs and cycle times, particularly in early stage design and process planning.

ML based predictive frameworks allow accurate forecasting of product costs by analysing historical data and process-specific features, as demonstrated in automotive and mechanical engineering contexts [4], [20].

The effectiveness of these models often depends on careful feature selection, hyperparameter tuning, and the choice of regression algorithms to minimize prediction errors and enhance model generalization[20]. In addition to cost estimation, AI has been employed to predict machining cycle times, leveraging neural networks, grey-box modelling, and data-driven simulations of machine tool behavior [3],[5]. These approaches enable manufacturers to identify bottlenecks, optimize scheduling, and improve resource allocation. Nevertheless, challenges persist, particularly when applying ML models to heterogeneous datasets or integrating multiple objectives, such as cost, tool wear, and energy consumption, within a single predictive framework. Addressing these challenges is essential to ensure the practical applicability of AI in complex manufacturing environments.

Recent advancements in hybrid and explainable AI techniques are helping to overcome many of these limitations by combining the predictive capabilities of machine learning with the interpretability of physics-based and rule-based manufacturing models. Techniques such as ensemble learning, transfer learning, and digital twin integration allow predictive systems to adapt to varying machining conditions while maintaining robustness across different production environments. Furthermore, the incorporation of real-time sensor data from Industrial Internet of Things (IIoT) platforms has enhanced the ability of AI systems to perform continuous monitoring and adaptive optimization during machining operations. Explainable AI (XAI) methods are also gaining importance, as they provide insights into the influence of machining parameters on predicted outcomes, thereby increasing user trust and supporting informed decision-making. As a result, AI-driven manufacturing systems are gradually evolving from isolated prediction tools into intelligent, autonomous frameworks capable of improving productivity, sustainability, and operational efficiency simultaneously.

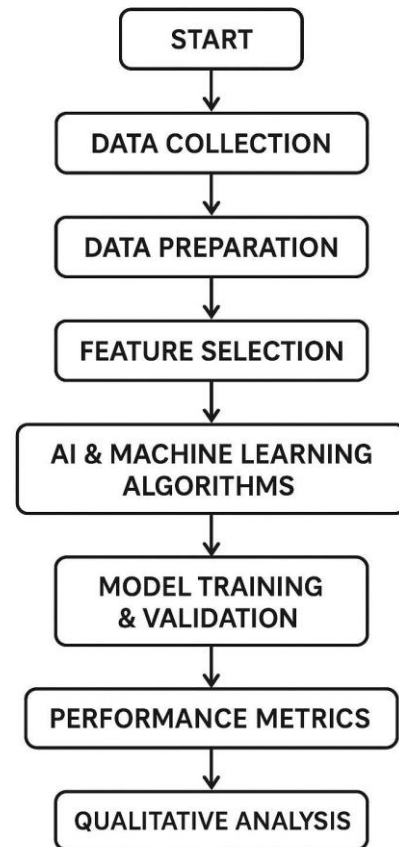


Fig-1: Workflow Diagram

3.5 Research Gaps

Despite significant progress, several research gaps remain. First, while numerous studies focus on tool wear prediction [6], [7], [15], few integrate tool wear, machining cost, and process time into a unified framework. Most models address single objectives, limiting their applicability for holistic process optimization. Second, although hybrid and physics-informed models [2] show promise, real-time implementation for adaptive process control remains underexplored. Third, early-stage cost prediction using ML has demonstrated high accuracy in limited domains [12],[20][22], but generalizability across diverse manufacturing sectors and complex product types is still a challenge. Finally, interpretability and explainability in predictive models are critical for industrial adoption, yet many ML-based studies focus primarily on accuracy without addressing decision transparency [8]. Addressing these gaps is crucial for developing an AI-driven framework that simultaneously optimizes tool life, process efficiency, and cost while ensuring interpretability and scalability. Such a framework would facilitate intelligent decision-making, improve sustainability, and reduce operational risks in high-precision manufacturing environments.

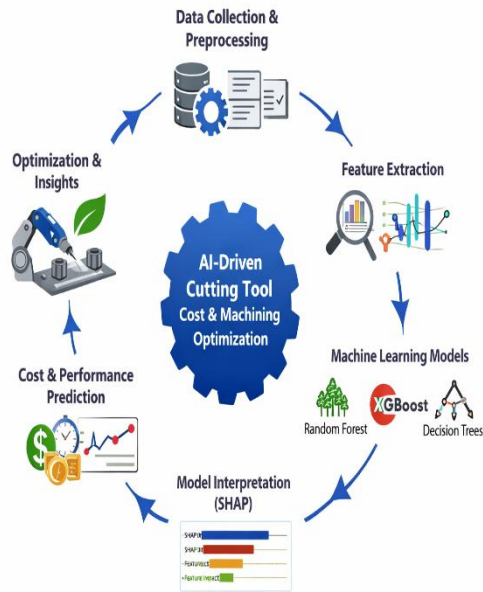


Fig-2: Flowchart for Optimizing Cutting Tools

4. CONCLUSION

Despite significant advancements, several research gaps persist. First, while many studies focus on tool wear prediction [6], [7], [15], only a few integrate tool wear, machining cost, and process time within a unified framework, limiting holistic optimization. Second, although hybrid and physics-informed models [2] show strong potential, their real-time application for adaptive process control remains limited. Third, while ML-based early-stage cost prediction has demonstrated high accuracy in specific domains [12], [20], [22], its generalizability across diverse manufacturing sectors and complex products is still a challenge.

Finally, model interpretability is essential for industrial adoption; however, many ML-based approaches prioritize accuracy over transparency [8]. Addressing these gaps is crucial for developing an AI-driven framework that simultaneously optimizes tool life, process efficiency, and cost while ensuring interpretability and scalability. Such a framework can support intelligent decision-making, enhance sustainability, and reduce operational risks in advanced manufacturing environments.

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