FSM Online Internship Completion Report
on

ML03- PREDICTING TOOL WEAR AND SURFACE ROUGHNESS FOR A LATHE MACHINE

In

Machine Learning in Manufacturing

Submitted by

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Predicting Tool Wear and Surface Roughness for a Lathe Machine

Abstract:
In the realm of modern manufacturing, the optimisation of tool usage, enhancement of product quality, and elevation of overall operational efficiency stand as paramount objectives. This study presents a pioneering approach to achieving these goals through the development and implementation of an advanced machine learning model. This model harnesses the power of data analytics, drawing insights from various process parameters, tool characteristics, and historical records. By employing sophisticated algorithms, the model predicts tool wear and surface roughness in workpieces generated by a lathe machine across diverse machining operations. Through its intricate analysis, the model accurately estimates the progression of tool wear and the resulting surface roughness, thereby offering manufacturers the ability to make informed decisions about maintenance and process adjustments. By embracing this innovation, the manufacturing industry gains a transformative tool to optimise operations, ensure superior product quality, and drive unparalleled efficiency, underscoring a new era of data-driven manufacturing excellence. This project report presents a study and implementation on the application of machine learning algorithms for Predicting tool wear and surface roughness for a lathe machine. The primary objective is to develop an intelligent and autonomous system capable of predicting tool wear and surface roughness. The proposed methodology using the Extra-Trees Regressor model has shown a Root Mean Squared Error (RMSE) of 0.4716%. Additional experiments will be performed to confirm the repetitiveness of the results and also extend the measurement range to improve accuracy of the measurement system.

Keywords: Predictive maintenance, Extra-Trees Regressor, Tool Wear, Lathe Machine, Surface Roughness

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1. *Introduction*

In the dynamic landscape of modern manufacturing, where efficiency, precision, and product quality are paramount, the development of innovative solutions has become imperative. One such compelling avenue is the integration of machine learning techniques into traditional machining processes. This report delves into the conceptualisation, implementation, and implications of a predictive machine learning model designed to revolutionise the prediction of tool wear and surface roughness in lathe machining operations.

Manufacturing industries worldwide face the constant challenge of achieving optimal production outcomes while minimising costs and maximising resource utilisation. The process of lathe machining, a cornerstone of manufacturing, involves shaping workpieces with rotational symmetry, making it fundamental to various sectors, from automotive to aerospace. However, despite its ubiquity, lathe machining is not devoid of complexities. Two critical factors that significantly influence machining operations are tool wear and surface roughness.

Tool wear, the gradual deterioration of the tool's cutting edges due to friction and heat, and surface roughness, which directly impacts product quality, pose considerable challenges. Traditional methods for estimating tool wear and surface roughness often rely on periodic inspections or rule-based systems, resulting in inefficiencies, inconsistent product quality, and increased downtime. As machining processes become more intricate and diverse, the need for real-time, data-driven insights to inform decision-making has become indispensable.

The advancement of machine learning techniques offers a transformative solution to these challenges. By harnessing the power of data analysis, pattern recognition, and predictive modelling, a machine learning model can predict tool wear progression and surface roughness during machining operations in real time. By analysing a plethora of process parameters, tool characteristics, and historical data, the model can yield insights that enable optimised tool usage, improved product quality, and enhanced overall manufacturing efficiency. The average surface roughness (Ra) can be predicted with the use of the parameters like the rotation speed at which a lathe machine is turning (rpm), how far the cutting spindle travels across the metal part during one full rotation of the tool (feed), and depth of the cut (depth).

The subsequent sections of this report delve into the finer details of this project. We will explore the physical equipment on which the model is implemented, the unique challenges encountered, the key objectives guiding the development, and the step-by-step methodology employed. The report will also illuminate the intricate process of data collection, preprocessing, and visualisation, as well as the selection and development of machine learning models. Additionally, the implementation process, the innovative utilisation of Online Learning for continuous model improvement, and the model's scalability to solve industrial challenges will be elaborated upon.

This report focuses to transform the manufacturing landscape by seamlessly integrating cutting-edge machine learning techniques with traditional machining processes. The subsequent sections will delve into the details of this transformative endeavour, elucidating the technical nuances and implications that underscore the development of a predictive model for tool wear and surface roughness in lathe machining operations.

1.1. *Methodology*

In machining applications, spindle rotational speed, feed rate, depth of cut, and acceleration of mechanical vibration are crucial factors closely tied to tool design geometry. Monitoring and measuring these parameters yield valuable information for wear identification, cutting parameter selection, and tool choice. To create a comprehensive dataset, a series of experiments were conducted. Each test involved capturing the acceleration of the tool along the x, y, and z axes (vibration data). This dataset, derived from the experiments, serves as the input for training a regression model capable of recognising tool and workpiece behaviour. Once trained, the model exhibits remarkable accuracy in predicting wear.

2. *Problem Definition*

The challenge is to develop a cutting-edge machine learning model capable of accurately predicting tool wear and surface roughness in workpieces produced by a lathe machine. By harnessing the power of data and analysing various process parameters, tool characteristics, and historical data, the model must provide precise estimates of tool wear progression and surface roughness across diverse machining operations. The ultimate goal of this project is to optimize tool usage, elevate product quality, and enhance overall manufacturing efficiency.

The problem is centered around the uncertainty and inefficiency associated with tool wear and surface roughness in lathe machine operations. The main challenges include:

1. Lack of accurate real-time estimation of tool wear and surface roughness during machining.
2. Inefficient tool usage leading to increased downtime and costs.
3. Variability in product quality due to unpredictable tool wear and surface roughness.

3. *Existing Solution*

The existing traditional methods that are currently used or have been historically employed have grappled with the challenge of predicting tool wear and surface roughness. These solutions, while serving as a foundation, often fall short in providing the real-time insights and adaptability required to navigate the complexities of modern manufacturing.

1. **Manual Inspection:** Historically, manual inspection has been a common method for assessing tool wear and surface roughness. Skilled technicians periodically halt machining operations to visually examine tools and workpieces. However, this approach is subjective, time-consuming, and prone to human error. The intermittent nature of inspections means that emerging wear patterns or surface irregularities might go unnoticed until the next scheduled assessment, leading to potential discrepancies in product quality and operational

efficiency.

2. **Rule-Based Systems:** Rule-based systems attempt to address the challenge by establishing predetermined thresholds for tool replacement or adjustment based on specific conditions. While these systems provide a degree of automation, they often lack the flexibility to adapt to evolving machining conditions and nuanced relationships between variables. As machining processes become more intricate, rule-based systems struggle to capture the dynamic interactions that govern tool wear and surface roughness accurately.

3. **Offline Measurement and Analysis:** Another approach involves measuring and analysing tools and workpieces after machining operations are completed. This post-mortem analysis can offer valuable insights into tool wear and surface roughness, but it falls short in real-time decision-making. Delays in identifying issues and making adjustments can lead to significant downtimes, affecting production schedules and overall operational efficiency.

4. **Historical Data Analysis:** Historical data analysis entails studying past machining operations to infer patterns and trends in tool wear and surface roughness. While this approach can provide valuable hindsight, it is limited by its inability to capture real-time variations and adapt to the ever-changing conditions of modern machining environments.

In essence, the existing solutions, while serving as valuable starting points, suffer from limitations in accuracy, real-time adaptability, and comprehensive understanding of the intricate relationships underlying tool wear and surface roughness. It is within this context that the innovative integration of machine learning techniques emerges as a transformative avenue, promising to bridge the gap between traditional methods and the demands of contemporary manufacturing. This report delves into the novel approach proposed to overcome these limitations, leveraging the power of data-driven predictive modelling to revolutionise tool wear and surface roughness prediction in lathe machining operations.

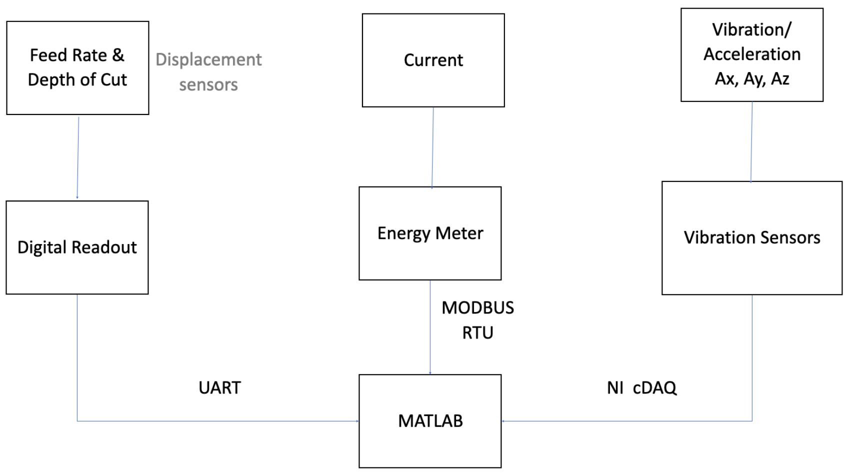
4. Proposed Development

The proposed development represents a groundbreaking leap towards addressing the challenges of predicting tool wear and surface roughness in lathe machining. By integrating cutting-edge machine learning techniques, this project aims to transform the manufacturing landscape and usher in a new era of precision and efficiency.

Central to the proposed development is the creation of a predictive model fueled by data-driven insights. This model will analyze a rich repository of process parameters, tool characteristics, and historical data to uncover intricate relationships governing tool wear and surface roughness. Through sophisticated feature engineering, the model will grasp the nuanced interactions among rotation speed, feed rate, depth of cut, and tool properties, enabling accurate real-time predictions.

An innovative addition is the incorporation of Online Learning, enabling the model to adapt continuously as new data streams in from the lathe machine's sensors. This dynamic learning process ensures that the model remains effective amidst evolving machining conditions, enhancing its accuracy and relevance.

By seamlessly integrating with the lathe machine's control system, the predictive model will provide timely insights, optimizing tool usage, improving product quality, and enhancing overall manufacturing efficiency. This holistic approach, underpinned by continuous improvement and real-time adaptability, promises to redefine the dynamics of lathe machining and catalyze a paradigm shift in the manufacturing realm. The diagram below shows the proposed development and how the data was collected during experiments.



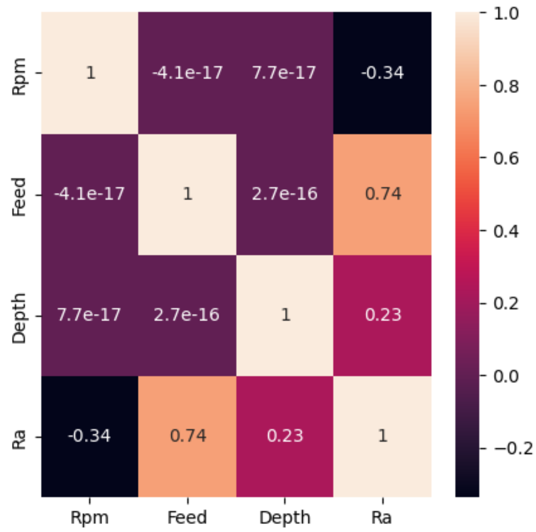
5. *Functional Implementation*

The functional implementation of the predictive model for tool wear and surface roughness in lathe machining is a meticulously orchestrated process that encompasses data collection, preprocessing, model development, validation, and real-time integration. Each stage is meticulously designed to ensure seamless operation, accurate predictions, and tangible benefits for manufacturing processes.

Data Collection: The functional implementation begins with the collection of real-time data directly from the lathe machine. Sensors strategically placed on the machine capture essential process parameters, including rotation speed (rpm), feed rate, depth of cut, and average surface roughness (Ra). This stream of data forms the bedrock upon which the predictive model's training and predictions are built.

Data Preprocessing: Raw data collected from the sensors undergoes a rigorous preprocessing phase. This involves cleaning, normalisation, and transformation to ensure consistency and compatibility. Techniques such as StandardScaler are employed to normalize the data, enhancing model convergence and performance. Preprocessing also involves addressing missing values and outliers that might distort the model's learning process.

Feature Engineering: The processed data is then subjected to feature engineering, a critical step that extracts meaningful insights from the raw parameters. Feature engineering entails the creation of relevant features that encapsulate the intricate relationships among rotation speed, feed rate, depth of cut, and tool characteristics. This step enables the model to capture complex interactions that govern tool wear and surface roughness accurately. The figure below denotes Pearson's Correlation matrix. It shows the pairwise correlations between all the variables in a dataset. It is used to measure the linear relationship between two continuous variables. Each cell in the matrix represents the correlation coefficient between two variables.



Model Selection and Development: Leveraging a rich repository of preprocessed features, various machine learning models are explored and evaluated. These include Extra Trees Regressor, Random Forest Regressor, AdaBoost Regressor, Gradient Boosting Regressor, and Linear Regression. The chosen model is meticulously trained on a subset of the data, learning the underlying patterns and correlations. The models were evaluated on basis of MSE, RMSE, and R^2 and out of all the models, Extra Trees Regressor outperformed all. The evaluation metrics of all the models are mentioned in the *Table 1*.

Model Validation: Rigorous validation ensures the model's effectiveness and generalisation ability. The dataset is split into training and testing sets, with the model trained on one portion and tested on the other. Performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2) are computed to assess the model's predictive accuracy and reliability.

Real-Time Integration: The culmination of the functional implementation involves integrating the trained predictive model into the lathe machine's control system. This seamless integration enables the model to receive real-time data streams during machining operations and deliver instantaneous predictions of tool wear progression and surface roughness. As the lathe machine operates, the model's predictions guide decision-making, optimising tool usage and enhancing product quality in real time.

The functional implementation of the predictive model harmoniously weaves together data collection, preprocessing, feature engineering, model development, validation, and real-time integration. This carefully orchestrated process empowers manufacturing processes with the ability to make informed decisions, streamline operations, and achieve unprecedented levels of precision and efficiency in lathe machining.

MODEL	MSE	RMSE	R^2
Extra Trees Regressor	0.4716	0.6867	0.8792
Random Forest Regressor	0.9331	0.9659	0.7611
AdaBoost Regressor	1.2409	1.1139	0.6824
Gradient Boosting Regressor	0.8608	0.8608	0.7866
Linear Regressor	1.4008	1.1201	0.6489

Table:1 Comparison of evaluation metrics of all the models

6. *Final Deliverable*

The culmination of this transformative endeavour yields a powerful and dynamic final deliverable poised to reshape the landscape of lathe machining. The core of this deliverable is a fully functional and seamlessly integrated predictive model for tool wear and surface roughness, meticulously designed to enhance manufacturing processes in unprecedented ways. At the heart of the final deliverable lies the predictive model itself—a sophisticated culmination of data-driven insights, intricate feature engineering, and advanced machine learning algorithms. This model stands as a testament to the fusion of cutting-edge technology and traditional manufacturing, offering real-time predictions of tool wear progression and surface roughness during machining operations.

The deliverable encompasses a user-friendly interface that seamlessly integrates with the lathe machine's control system. This intuitive interface provides real-time visualisations and insights, enabling operators and technicians to monitor tool wear and surface roughness dynamically. Leveraging the predictive model's capabilities, operators can make informed decisions, optimising tool usage, adjusting parameters, and enhancing product quality on the fly. Continuous improvement lies at the core of the final deliverable. The model's adaptive nature, driven by Online Learning, ensures that it evolves and refines itself with each new data point. As the lathe machine operates and data streams in, the model updates its predictions in real-time, aligning with the ever-changing dynamics of the machining process.
In essence, the final deliverable transcends mere prediction; it catalyzes a paradigm shift in manufacturing. It empowers operators and manufacturers with a potent tool to enhance operational efficiency, reduce downtime, and elevate product quality. It unites the precision

of machine learning with the craftsmanship of lathe machining, ushering in an era where technology and tradition converge to shape the future of manufacturing.

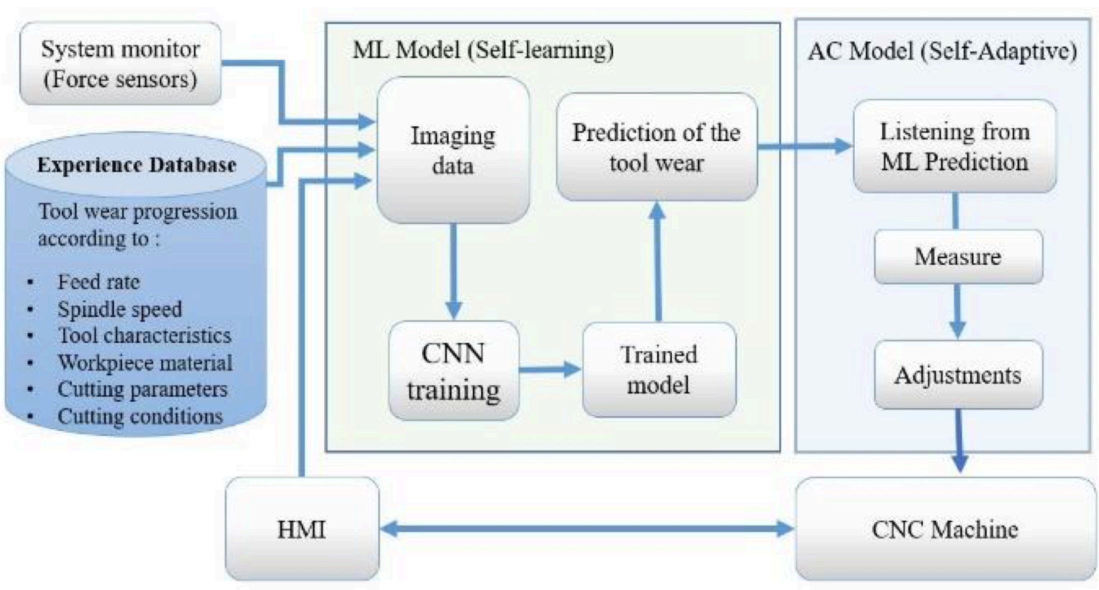
7. Innovation in Implementation

The innovative essence of this project lies not only in the predictive model's capabilities but also in the unique ways it transforms the landscape of lathe machining through its implementation. At its core, the innovation is driven by the integration of Online Learning—an adaptive, real-time learning technique that revolutionises the traditional approach to model development and utilisation.

Unlike static models, the implementation embraces the concept of continuous learning. The predictive model remains in a state of perpetual evolution, dynamically updating itself as new data streams in from the lathe machine's sensors. This real-time adaptation empowers the model to swiftly respond to shifting machining conditions, emerging wear patterns, and evolving tool characteristics.

The implementation of Online Learning also fuels a feedback loop that enhances the model's accuracy and relevance. As the model generates predictions, the actual outcomes are observed and used to recalibrate its parameters in real-time. This dynamic process of learning and updating ensures that the model remains attuned to the intricacies of the machining process, resulting in predictions that reflect the most current and accurate insights.

This innovative approach not only enhances the accuracy of tool wear and surface roughness predictions but also empowers manufacturing processes with an unparalleled degree of adaptability and responsiveness. It aligns seamlessly with the dynamic nature of modern machining operations, bridging the gap between technology and craftsmanship, and paving the way for a new era of precision, efficiency, and data-powered manufacturing. The Online Learning implementation is shown in the diagram below:



8. *Scalability to Solve Industrial Problem*

The scalability of the proposed predictive model for tool wear and surface roughness presents a transformative solution to a pervasive industrial challenge. This innovation extends beyond the confines of a single lathe machine, envisioning a scalable framework that can revolutionize machining processes across industries.

The core strength lies in the model's adaptability and generalization. As the model learns from data streams and refines its predictions in real-time, it becomes adept at accommodating diverse machining operations and varying tool wear characteristics. This adaptability lends itself seamlessly to different manufacturing setups, enabling its integration into a multitude of lathe machines without compromising accuracy.

Furthermore, the scalable implementation can be customised to cater to distinct industrial contexts. Whether it is automotive, aerospace, electronics, or any other manufacturing sector, the predictive model's framework remains flexible, capable of absorbing the unique nuances and demands of each industry. This adaptability holds the potential to streamline operations, enhance product quality, and reduce operational costs across the industrial spectrum.

In envisioning a future where the predictive model's impact transcends the boundaries of a single machine, this project champions a scalable approach that addresses the broader industrial problem of tool wear and surface roughness prediction. By imparting manufacturers with a versatile and scalable tool, the innovation not only optimizes machining processes on a granular level but also sets the stage for a far-reaching transformation of the manufacturing landscape.

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