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Optimization of Machine Tool Downtime Using Predictive Approaches Based on Minimalist Data

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***Abstract*—Minimizing machine tool downtime is crucial in manufacturing due to its impact on production efficiency, profitability, and maintenance costs. Unplanned equipment failures result in production halts, high repair expenses, and prolonged downtime. This study investigates predictive maintenance strategies based on minimalist data (e.g., tool wear, temperature, and vibration) to forecast breakdowns, thereby reducing the reliance on complex and costly monitoring systems. Current AI and ML techniques often capture only correlations rather than true causal relationships, and they struggle with uncertainties in small datasets. To overcome these limitations, our approach employs a probabilistic framework that is rigorously tested to accurately reflect industrial conditions, enhancing both prediction accuracy and risk estimation. The ultimate goal is to develop a cost-effective and reliable solution for small and medium-sized enterprises, improving equipment management, reducing unplanned downtime, and optimizing maintenance planning.**

***Index Terms*—Machine tool downtime, Predictive maintenance, Manufacturing industry, Minimalist data, Artificial Intelligence (AI), Machine Learning (ML), Probabilistic approach**

I. Introduction

In the manufacturing industry, the availability and reliability of machine tools are essential for ensuring efficient and profitable production. Unplanned equipment downtime not only causes significant economic losses but also reduced productivity and high maintenance costs. Predictive maintenance has emerged as an innovative solution to anticipate failures and optimize interventions, thereby minimizing unplanned interruptions.

Traditional maintenance approaches whether preventive or corrective face limitations in terms of cost and effectiveness. Additionally, the advent of Industry 4.0 technologies, particularly Artificial Intelligence (AI) and Machine Learning (ML), has enabled the development of new methods that utilize sensor data to enhance fault diagnosis reliability. However, these solutions often depend on complex and expensive infrastructures, which can hinder their adoption, especially among small and medium-sized enterprises (SMEs).

This study proposes an alternative approach based on the use of minimalist data such as vibrations, temperature, and tool wear to predict equipment failures while reducing the complexity and costs of monitoring systems. By integrating a probabilistic framework with traditional predictive maintenance techniques, our goal is to improve diagnostic accuracy and better assess the risks associated with equipment failures.

The following sections will review the state-of-the-art in predictive maintenance strategies and probabilistic methods in this field, as well as outline the methodology for developing a predictive model tailored to industrial requirements.

II. Concepts and Evolutions

A. Design of Predictive Maintenance

Predictive maintenance relies on the analysis of data collected in real time by sensors integrated into industrial equipment, enabling the anticipation of failures before they occur. Unlike traditional approaches, such as corrective maintenance, which intervenes after a breakdown, or preventive maintenance, scheduled at fixed intervals, this proactive method minimizes unexpected downtime, optimizes resource utilization, and improves profitability.

Advanced sensors measure parameters such as vibrations, temperature, or acoustic emissions, providing valuable indicators to detect anomalies and prevent malfunctions.

B. Technological Evolutions and Advancements

Thanks to the emergence of the Industrial Internet of Things (IIoT) and artificial intelligence (AI), predictive maintenance has reached a new level of performance. AI analyzes massive datasets, identifies complex patterns, and enhances predictions, while tools like Fast Fourier Transform (FFT) enable the early detection of defects such as misalignments or wear. The integration of technologies like infrared thermography and acoustic sensors strengthens the reliability of diagnostics. Finally, self-learning systems based on machine learning offer increased adaptability, solidifying predictive maintenance as a strategic pillar of Industry 4.0.

III. IoT Technologies for Real-Time Monitoring

Predictive maintenance for CNC machines leverages IoT for real-time vibration monitoring. Accelerometers measure vibrations and transmit data for analysis using FFT to detect anomalies and assess machine conditions. A graphical interface compliant with ISO 10816 displays equipment status for informed maintenance decisions. IoT enables predictive maintenance that prevents, consequently monitoring machine conditions via databases like Firebase to prevent unexpected failures. Monitoring four CNC machines showed CNC 2 and 3 in good condition (0.55 and 0.33 mm/s), CNC 1 satisfactory (1.39 mm/s), and CNC 4 requiring intervention (2.08 mm/s). IoT-ML synergy enhances diagnostics, fault detection, and predictive maintenance, reducing downtime and improving efficiency. [1]

IV. Predictive Maintenance and Machine Learning in Industry 4.0

Predictive maintenance in Industry 4.0 integrates IoT, machine learning, and deep learning to anticipate equipment failures. LSTM networks excel in real-time sequential data analysis, while XGBoost efficiently classifies faults. Combining signal processing techniques like wavelet decomposition with deep learning enhances prediction accuracy, reducing downtime and optimizing resources for greater industrial competitiveness. [2]

V. Deep Learning-Based Approach for Estimating the Remaining Useful Life of Machine Tools

Predictive maintenance in CNC milling uses RTF data and AI models to estimate tool wear and RUL, enabling proactive maintenance. Deep learning techniques excel in handling complex data, ensuring accurate predictions and minimizing unexpected failures.

A. Examples of Promising Models

LSTM-Autoencoder networks excel in time-series analysis and anomaly detection through precise signal reconstruction. Hybrid approaches, combining signal processing (FFT, wavelet) with machine learning (Random Forest, Gradient Boosting), enhance detection accuracy under varying conditions.

B. Context and Importance

Predictive maintenance, particularly for CNC milling machines, relies heavily on RTF data to estimate tool wear and predict the RUL. AI-based models have become essential due to their ability to provide accurate predictions and analyze complex data.

C. Process and Innovations

The innovation lies in the use of deep neural networks to model and predict tool wear. Key elements of this process include:

- **Multidomain Feature Extraction:** Relevant features such as entropy and interquartile range (IQR) are extracted from sensor data, which are strongly correlated with tool wear.
- **LSTM-AE Model Training:** The hybrid LSTM-AE model combines an LSTM network to capture temporal dynamics and an Auto-Encoder to model nonlinear relationships between variables.
- **Tool Wear Prediction:** The model is trained on datasets such as PHM10 to predict wear and estimate the RUL.

D. Experiments Conducted and Observations

- **Feature Extraction:** Indicators such as IQR and entropy are identified as strongly correlated with tool wear through Pearson correlation coefficient (PCC) analysis.
- **Construction of the Feature Map:** This map serves as input for the LSTM model to predict target wear.
- **Performance Improvement:** Using wear thresholds and degradation curves allows the generation of accurate RUL estimates, showing significant improvements in MAE and RMSE metrics.

E. Key Results

The model demonstrates exceptional accuracy of 98% in wear prediction, with reduced absolute errors (MAE: $2.6 \pm 0.3222 \times 10^{-3}$; RMSE: $3.1 \pm 0.6146 \times 10^{-3}$). Though the RUL values are slightly underestimated, this approach ensures proactive maintenance planning, thus minimizing unexpected failures.

F. Tool Condition Monitoring (TCM)

The main steps of monitoring include:

1) Fault detection.
2) Identification of fault types.
3) Estimation of the RUL (Remaining Useful Life).

These steps enable the prediction of failures before they occur, ensuring proactive and reliable maintenance.

G. AI-Based Predictive Maintenance Techniques

Approaches integrating AI include:

- **Machine Learning (ML):** Algorithms such as Support Vector Machines (SVM) and Random Forest (RF) are effective in fault classification.
- **Deep Learning (DL):** Advanced deep learning techniques can handle complex scenarios, particularly through sophisticated feature extraction methods.

In specific cases, algorithms like Random Forest have been used to predict tool wear, while XGBoost has been applied to optimize RUL estimation metrics.

VI. Mathematical Formulation for Predictive Maintenance

Either
$$\mathbf{X} = [x_1, x_2, \dots, x_n]^T \in \mathbb{R}^n,$$
the characteristic vector of a machine tool, and $Y \in \mathbb{R}^+$ the time before a failure. The objective is to estimate the conditional density $f_{Y|X}(y)$ in order to obtain the conditional expectation $E[Y \mid X]$.

A. Conditional Expectation

The mathematical definition is:
$$E[Y \mid X] = \int_0^\infty y\, f_{Y|X}(y)\, dy.$$

For a numerical resolution, we discretize the integral:
$$E[Y \mid X] \approx \sum_{i=1}^{k} y_i\, f_{Y|X}(y_i)\, \Delta y_i,$$
where y_i represents discrete values and Δy the discretization step.

B. Estimate of $f_{Y|X}(y)$

We use a Machine Learning model, noted M, trained on the whole $\{(X(j), y(j))\}_{j=1}^N$ to approximate:
$$M : X \mapsto \{y_1, \dots, y_k\},$$
with
$$p_i \approx \Delta y\, f_{Y|X}(y_i).$$

In the presence of unbalanced data, an oversampling method such as SMOTE is applied to balance the classes.

C. Attention Mechanism via Transformer

To model more finely $f_{Y|X}(y)$, we can use a Transformer model. We first define:
$$\mathbf{Q} = \phi(X) \in \mathbb{R}^d,$$
where ϕ is an encoding function. For each y_i discretized, we associate:
$$\mathbf{K}_i = \phi(y_i), \quad \mathbf{V}_i = \chi(y_i).$$

Or ψ and χ are key and value encoding functions. The attention score is then calculated by:
$$\alpha_i = \frac{\exp\left(\frac{\mathbf{Q}\cdot\mathbf{K}_i}{\sqrt{d}}\right)}{\sum_{j=1}^{k} \exp\left(\frac{\mathbf{Q}\cdot\mathbf{K}_j}{\sqrt{d}}\right)}.$$

The conditional density is modeled by:
$$f_{Y|X}(y_i) \propto \alpha_i,$$
standardized to satisfy:
$$\sum_{i=1}^{k} f_{Y|X}(y_i)\, \Delta y_i = 1.$$

This mathematical approach combines classical probabilistic techniques with advanced machine learning models (Random Forest and Transformers) to estimate the time before a machine fails, based on conditional expectation and the attention mechanism.

VII. Conclusion

This study highlights the potential of predictive maintenance using minimalist data to enhance failure diagnostics and risk assessment while reducing reliance on costly monitoring systems. By integrating traditional predictive techniques with a probabilistic framework, the approach improves accuracy and cost-effectiveness, making it accessible to a wider range of industries.

However, challenges remain in addressing data uncertainty and optimizing model adaptability across different industrial settings. Future work should focus on refining methodologies, conducting comparative analyses, and strengthening empirical validation. Additionally, incorporating high-impact references and ensuring a clearer demonstration of novelty will enhance the study's scientific contribution and practical relevance.

All cited bib entries are printed at the end of this article: [1]–[4].

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