Tool Wear Prediction in the End Milling Process of Ti-6Al-4V using Bayesian Learning

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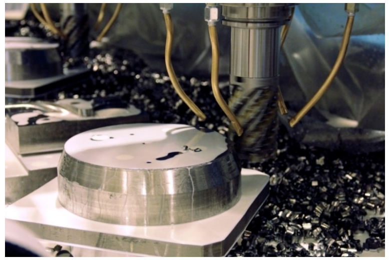
Contents

Abstract

- Titanium alloy is one of the most popularly used materials in various industries because of its desirable mechanical properties. However, it is also a difficult-to-cut material because of its low specific heat and thermal conductivity. This influences an end milling process of titanium alloy through tool wear that affects not only product quality but also productivity. Therefore, accurate tool wear prediction is required to improve titanium alloy quality and replace the tool at an appropriate time. Furthermore, since the effects of tool wear prediction on the overall machining process are significant in terms of cost and time, the uncertainty of tool wear prediction should be taken into account. In this work, a deep learning-based uncertainty-aware tool wear prediction model using Bayesian learning approach is proposed. The proposed probabilistic model could produce a predictive distribution over estimated tool wear with uncertainty awareness. Experiments with real-world end milling processes have proven the effectiveness of the proposed method. The results indicate that the proposed method outperforms existing comparative tool wear prediction models.

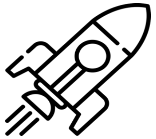
1. Introduction

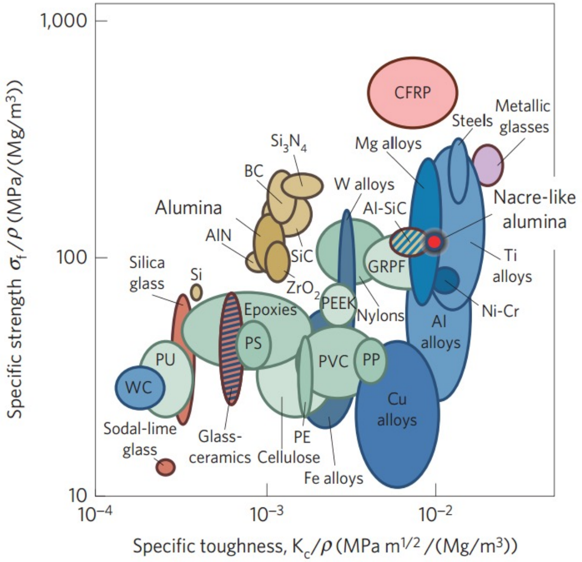
- Manufacturing process
  - Additive manufacturing (i.e., 3D printing)
    - Mass production, flexible design, eco-friendly
    - Inaccuracy and irregularity of precision, durability
    - Post-processing required
      - Relying on cutting/milling (e.g., surface milling)
  - Casting
    - Liquified material → solidification inside cavity (mold)
  - **Machining** (i.e., subtractive manufacturing)
    - High precision
    - Established theoretical analysis methods
    - Wide industrial applications (e.g., aerospace)

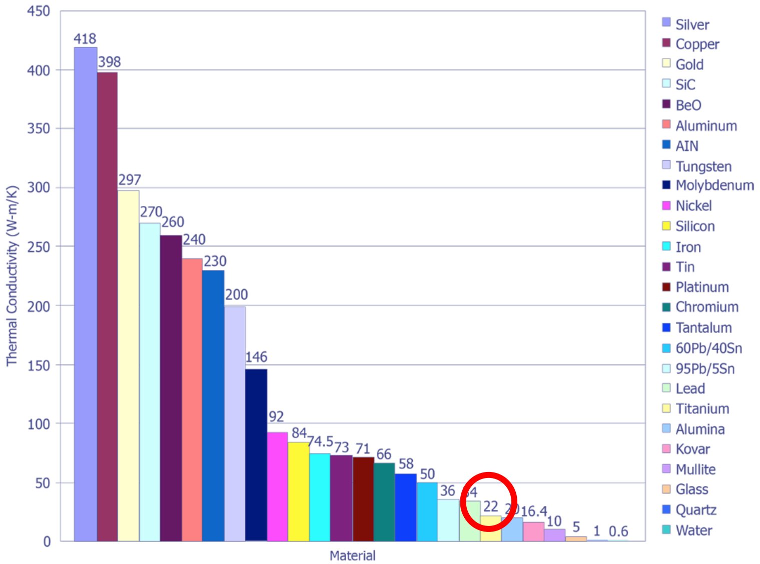


1. Introduction

- Titanium (Ti-6Al-4V)
  - Desirable mechanical properties
    - High strength-to-weight ratio
  - Use of titanium alloys
    - Various industries
      - e.g., aerospace, ocean engineering, automotive, medical, etc.



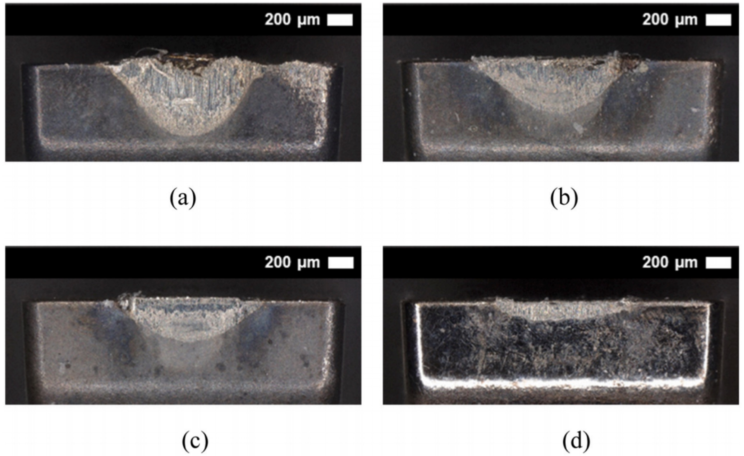




1. Introduction

- Machining of titanium
  - High precision required → complex 3D machining process
  - Milling process
    - High labor cost, tool cost required
    - End milling, slot milling, up/down milling, face milling
      - Rough machining, surface finish machining

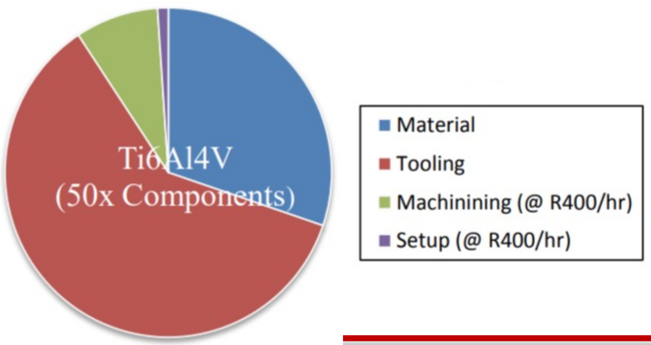
  - End milling using titanium
    - Tool wear → surface quality degradation
    - Rapid tool breakage
    - Tool wear replacement
      - Domain knowledge-based
      - Experience-based



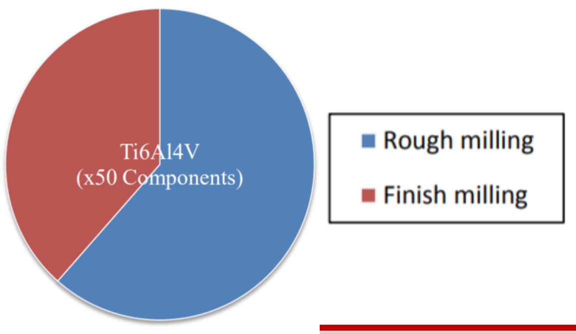
(a) (b) (c) (d)

1. Introduction

- Main strategy of machining process
  - Status: tooling costs account for more than 60% of titanium-based aviation parts machining
  - Purpose: increased productivity, reduced tooling cost via tool wear prediction!
  - Method:
    - Establishment of basic machining database for titanium milling process
    - Preprocessing of data for AI-based application
    - Development of tool wear prediction model using AI



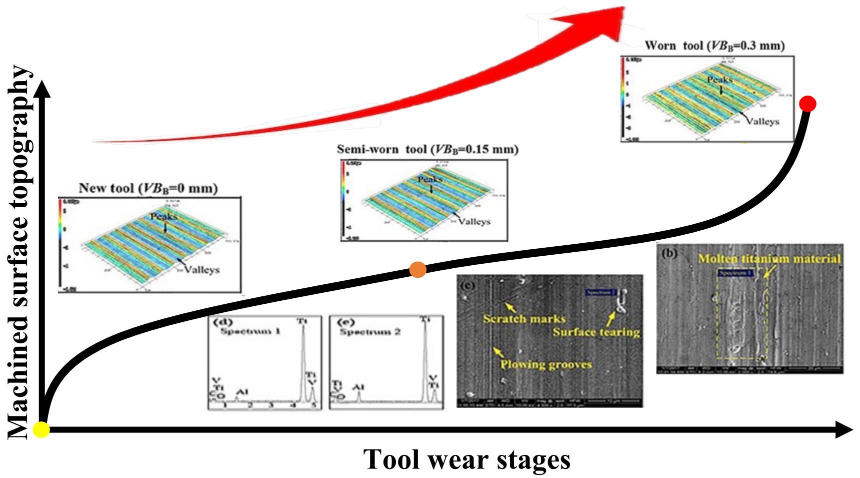
< Percentage of total process cost >



< Roughing/finishing ratio in the entire process >

1. Introduction

- Needs for automated tool wear prediction
  - Accurate prediction
  - For high-cost decision
    - Reliability, uncertainty-aware prediction



- Deep learning (DL)-based tool wear prediction

Conventional approaches

1. Complexity
2. Long running time and prediction time
3. Low accuracy

DL-based approaches

1. Flexibility
2. Raw inputs (e.g., force, vibration, etc.)
3. Real-time
4. High accuracy

2. Preliminaries and Literature Review

- Traditional tool wear prediction approaches
  - Machining process with highly non-linear and complex dynamics
    - Temperature, material properties, vibration

- Analytical methods
  - Empirical models
  - Numerical methods
    - Finite element method (FEM)
    - Finite differential method (FDM)

  - Limitations:
    - Difficult to use, low accessibility
    - High computational cost and time

2. Preliminaries and Literature Review

- Data-driven tool wear prediction approaches
  - Data obtained from multiple sensors (e.g., dynamometer, audio, etc.)
  - Multivariate time-series inputs → supervised regression task
  - Two-stage approaches;
    - 1) Feature extraction, selection (feature engineering)
    - 2) Regression using extracted features (tool wear prediction)

  - Conventional machine learning (ML) prediction algorithms
    - Feature extraction/data compression
      - PCA, SVD, etc.
    - Transformation techniques
      - FFT, WPD
    - Prediction algorithms (e.g., SVM, GBM, HMM)

2. Preliminaries and Literature Review

- DL-based tool wear prediction
  - High prediction performance, expressive power
  - Use of raw input signals without handcrafted feature extraction
  - Models capable of handling multivariate time-series sensor signals
    - Recurrent neural network (RNN), convolutional neural network (CNN), transformer, etc.

  - Two categories of DL-based approaches
    - 1) Supervised regression
      - Feature extraction using a deep neural network (DNN) architecture
    - 2) Unsupervised anomaly detection
      - Reconstruction-based architecture
        - Autoencoder-based

2. Preliminaries and Literature Review

- Bayesian learning (for parameter estimation)
  - Given data *D*: (*x*, *y*), parameter *w*
  - v.s. Maximum likelihood estimation (MLE)
    - Maximize the likelihood $p(D|w)$
  - Bayes theorem (Bayes rule)

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)} = \frac{p(D|w)p(w)}{\int p(D|\hat{w})p(\hat{w})\,d\hat{w}}.$$

  - Inference

$$p(y|x,D) = \int p(y|x,w)p(w|D)\,dw.$$

    - Predictive distribution instead of point estimate (MLE)
  - Approximation (sampling-based, variational inference (VI), stochastic gradient descent (SGD)-based)

3. Proposed Method

- Tool wear prediction in the end milling process
  - Data collection is difficult (time/cost)
  - Lengthy multivariate time-series inputs

- Architecture
  - CNN (1-dimensional) > RNN-based algorithms (e.g., LSTM, GRU)
    - Faster speed, parallelization, adjustable receptive field
  - Multi-scale convolutional operation
    - Using multiple different-sized convolutional kernels in parallel

$$f * k(i) = \sum_{j=1}^{l} k(j)\, f(i - j + \frac{1}{2}).$$

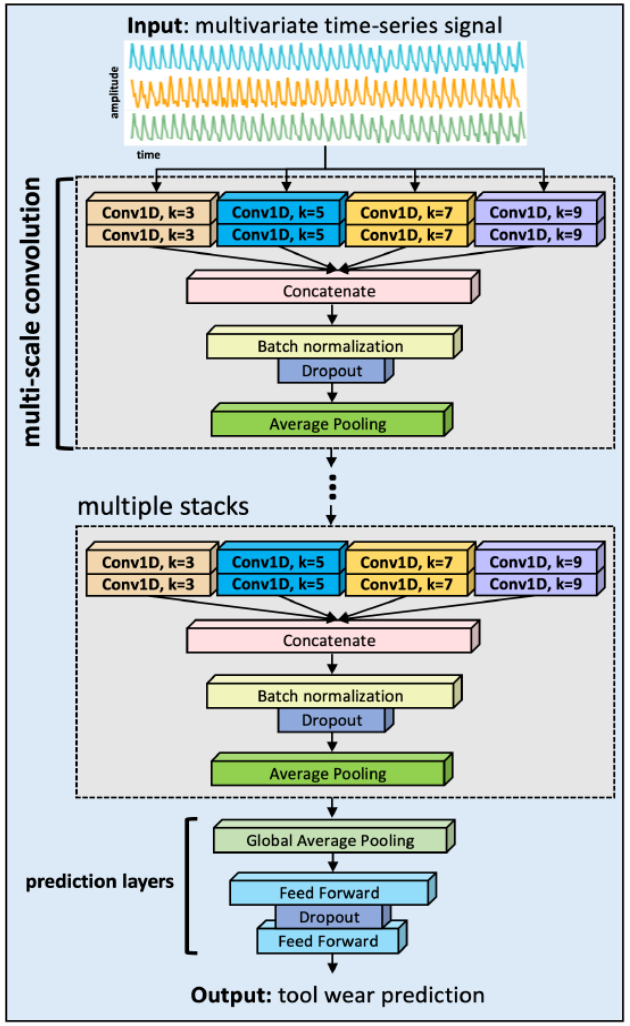
$$g = [g_1, ..., g_p] = [f * k^{l_1}, ..., f * k^{l_p}], \;\; where \; |k^{s_i}| = l_i.$$

3. Proposed Method

- Deep multi-scale CNN (DMSCNN)
  - Feature extraction
    - Multiple stacks of MS-Conv blocks
    - Adjustable, various size of receptive fields
    - Information fusion via concatenation

    - Batch normalization, dropout

  - Final tool wear prediction
    - Layers for regression
    - Global average pooling (GAP)



An architecture of the proposed deep multi-scale CNN (DMSCNN)

3. Proposed Method

- Bayesian DMSCNN
  - Finding a posterior distribution p(w|D)…
  - Variational inference (VI)
    - Variational distribution q(w|D)
    - Optimization of an evidence lower bound (ELBO)

$$\begin{aligned}
KLD &= D_{KL}(q(w|D)||p(w|D)) \\
&= \int q(w|D)\, log \frac{q(w|D)}{p(w|D)}\, dw \\
&= \int q(w|D)[log\, q(w|D) - log\, p(w|D)]\, dw \\
&= -\int q(w|D)[log\, \frac{p(D,w)}{p(D)} - log\, q(w|D)]\, dw \\
&= log\, p(D) - \int q(w|D)[log\, \frac{p(D,w)}{q(w|D)}]\, dw \\
&= log\, p(D) - \int q(w|D)[log\, \frac{p(w)p(D|w)}{q(w|D)}]\, dw \\
&= log\, p(D) - ELBO.
\end{aligned}$$

$$\begin{aligned}
p(D) &\simeq log\, p(D) \\
&= log \int p(D,w)\, dw \\
&= log \int p(D,w) \cdot \frac{q(w|D)}{q(w|D)}\, dw = log\, E_q[\frac{p(D,w)}{q(w|D)}] \\
&\geq E_q[log\, \frac{p(D,w)}{q(w|D)}] = \int q(w|D)\, log\, \frac{p(D,w)}{q(w|D)}\, dw \\
&= \int q(w|D)[log\, p(D,w) - log\, q(w|D)]\, dw \\
&= ELBO.
\end{aligned}$$

3. Proposed Method

- Bayesian DMSCNN
  - Objective: $\mathcal{L}_{ELBO} = D_{KL}(q(w|D)||p(w)) - E_q[log\, p(D|w)]$.
  - Reparameterization trick (from Variational Bayes, Bayes by Backprop)

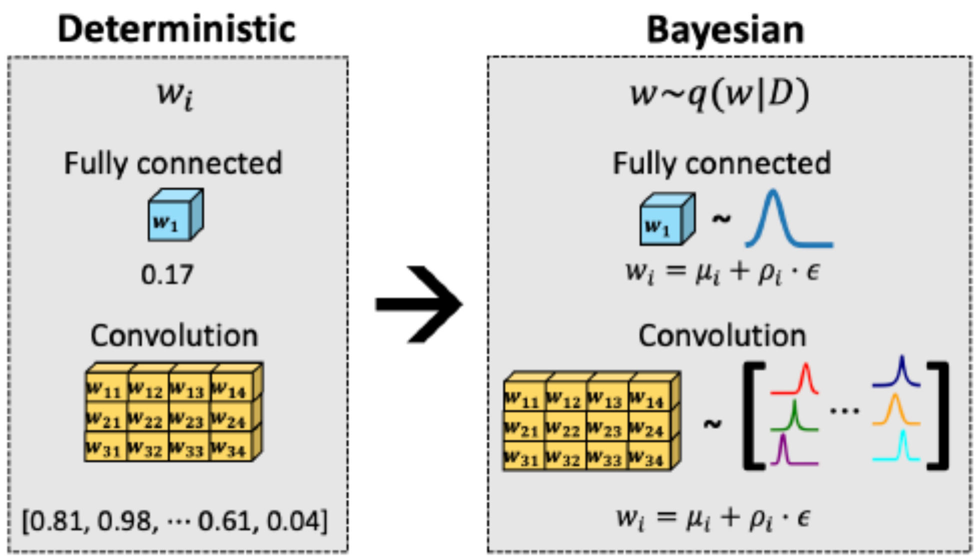
    $$w = \mu + \rho \cdot \epsilon \;\; where \;\; \epsilon \sim \mathcal{N}(0,1).$$

  - ELBO approximation using Monte Carlo sampling

    $$\tilde{\mathcal{L}}_{ELBO} = \frac{1}{n}\sum_{i=1}^{n}[log\; q(w_{(i)}|D) - log\; p(w_{(i)}) - log\; p(D|w_{(i)})].$$

  - Inference (i.e., prediction)

    $$p(y|x,D) = \int p(y|x,w)p(w|D)\,dw \approx \frac{1}{T}\sum_{t=1}^{T} p(y|x,w_{(t)}).$$



4. Experiments

- Data collection
  - End milling experimental setup
    - 5-axis CNC machine

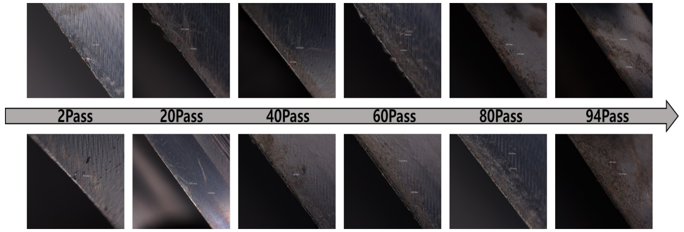
TABLE I
DETAILED PARAMETERS OF THE END MILLING CUTTING TOOL.

Parameter	Value
Cooling condition	Wet
Tool diameter	16 mm
Hone radius	0.012 mm
Nose radius	0.5 mm
Clearance angle	1^{st} 9°, 2^{nd} 20°
Rake angle	13°
Helix angle	44°

TABLE II
EXPERIMENT CONDITION.

Machining condition	Value
Cutting speed	60 mm/min
Feed per tooth	0.08 mm/rev
Axial depth	5 mm
Radial depth	1 mm
Machining distance	9400 mm

  - Dynamometer sensor measurement
  - Pass-wise tool wear measurement
    - Laser confocal scanning capability



Tool wear by machining length

4. Experiments

- Tool wear calculation
  - Tool flank wear estimated with the Levenberg-Marquardt (LM) method

$$VB = d(a + bT^c)^{-1}.$$

$$\mathbf{p}_{k+1} = \mathbf{p}_k - (J_{\mathbf{r}}^T J_{\mathbf{r}} + \mu_k \, diag(J_{\mathbf{r}}^T J_{\mathbf{r}}))^{-1} J_{\mathbf{r}}^T \mathbf{r}(\mathbf{p}_k), \;\; k \geq 0$$

$$J_{\mathbf{r}}(\mathbf{p}) = \begin{bmatrix} \frac{\partial r_1(\mathbf{p})}{\partial p_1} & \cdots & \frac{\partial r_1(\mathbf{p})}{\partial p_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial r_n(\mathbf{p})}{\partial p_1} & \cdots & \frac{\partial r_n(\mathbf{p})}{\partial p_m} \end{bmatrix}$$

$$\mathbf{r}(\mathbf{p}) = \begin{bmatrix} r_1(\mathbf{p}) \\ r_2(\mathbf{p}) \\ \vdots \\ r_n(\mathbf{p}) \end{bmatrix} = \begin{bmatrix} y_1 - f(x_1, \mathbf{p}) \\ y_2 - f(x_2, \mathbf{p}) \\ \vdots \\ y_n - f(x_n, \mathbf{p}) \end{bmatrix}$$

TABLE III
ESTIMATED LEARNABLE PARAMETER VALUES OF THE VB EQUATION.

a	b	c	d
-1.186	982.4	-0.8471	306.9

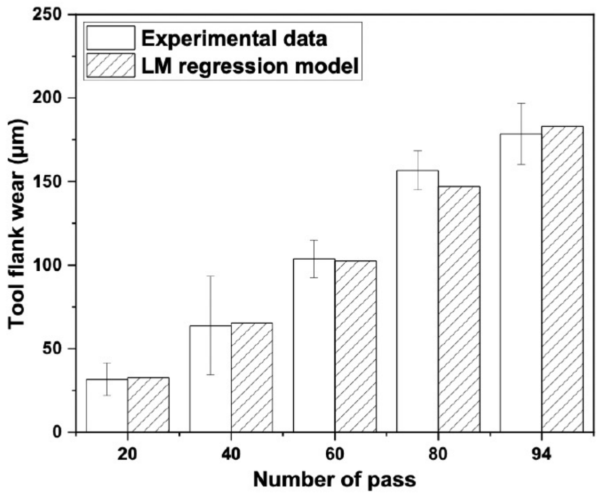
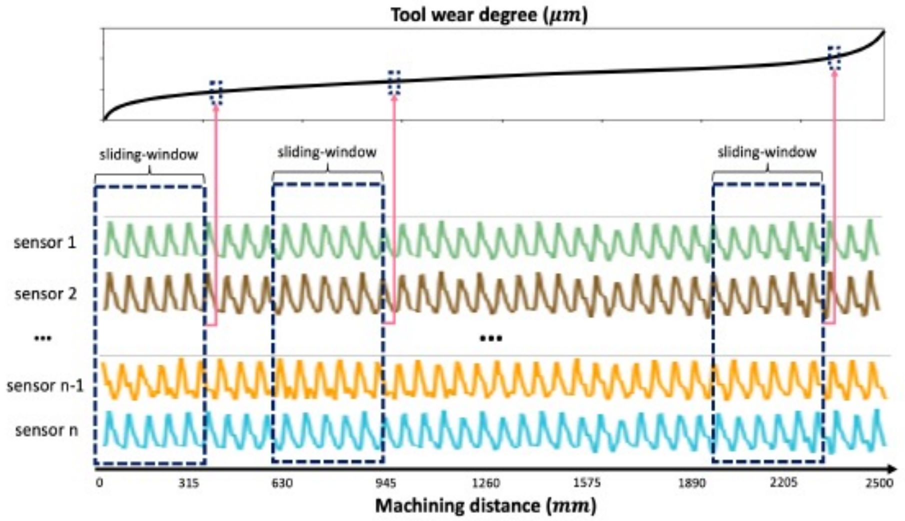


Fig. 3. LM regression model and experimental data plot

4. Experiments

- Data preprocessing
  - Normalization (standardization) $x_{scaled} = \frac{x - \bar{x}}{s}.$
  - Sliding-window preprocessing



Sliding-window preprocessing

- Evaluation metrics
  - MAE, RMSE, MAPE, R squared

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|.$$

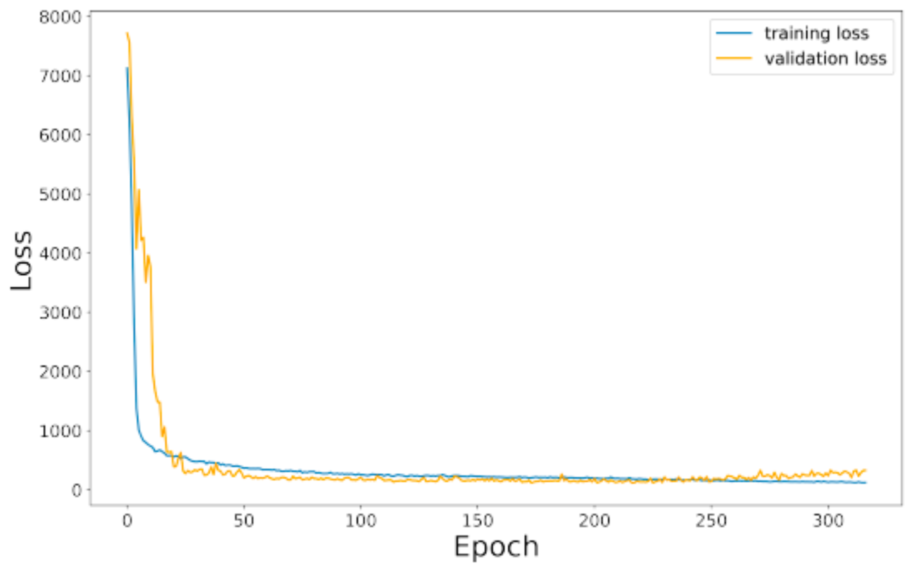
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}.$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{|y_i|}.$$

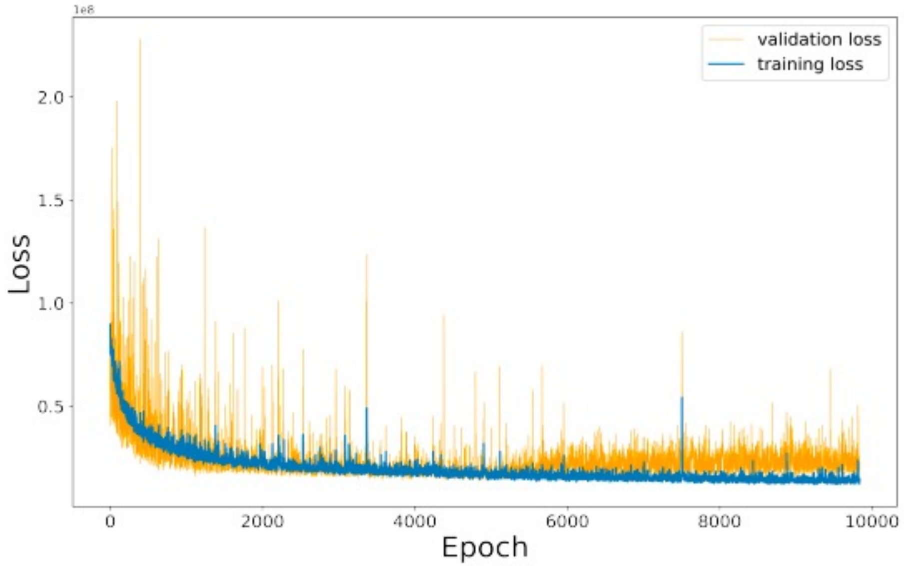
$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}.$$

5. Results and Discussion

- Training convergence analysis



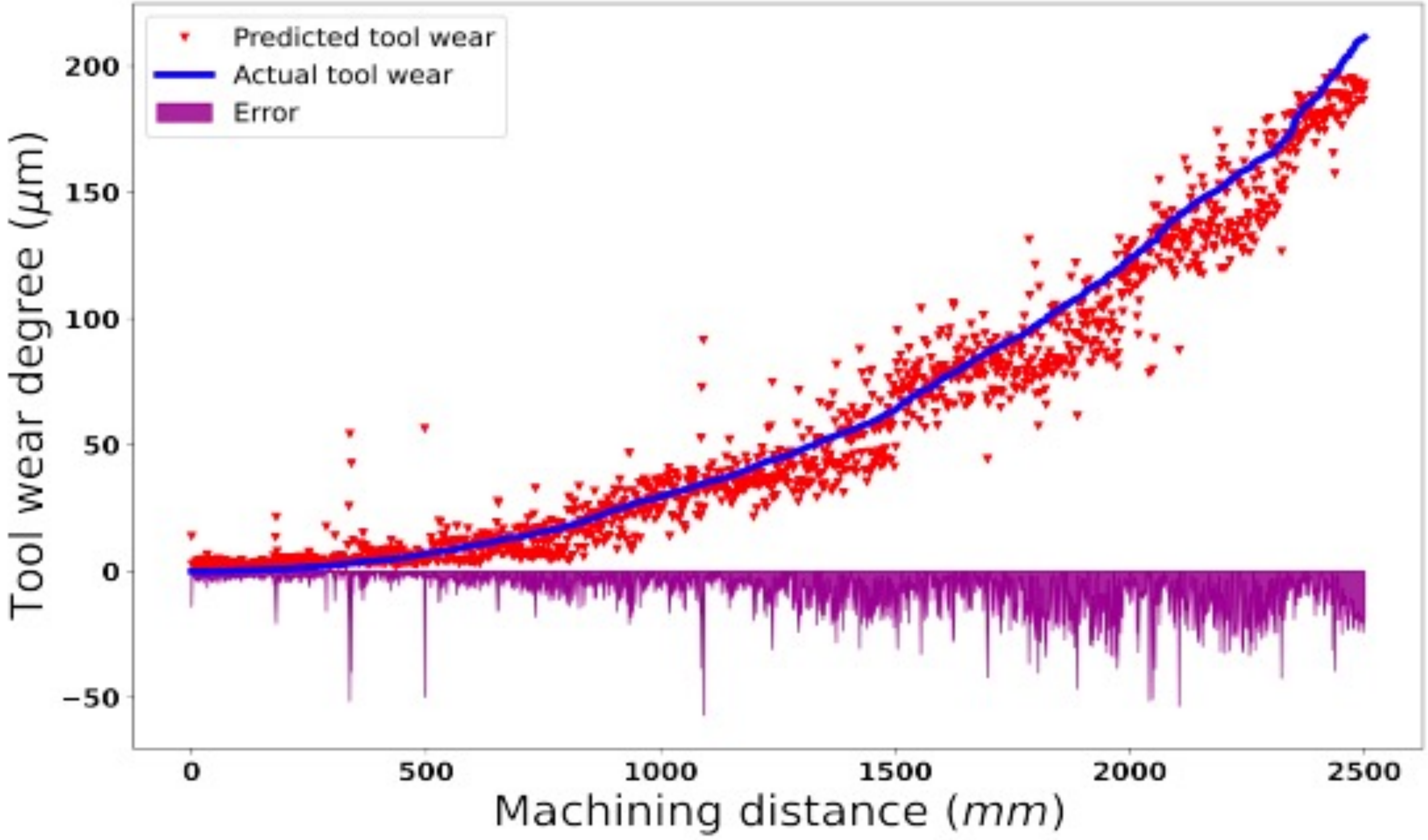
Convergence analysis of the training of the DMCSNN



Convergence analysis of the training of the Bayesian DMSCNN

5. Results and Discussion

- DMSCNN's deterministic tool wear prediction results



Prediction results of DMSCNN

5. Results and Discussion

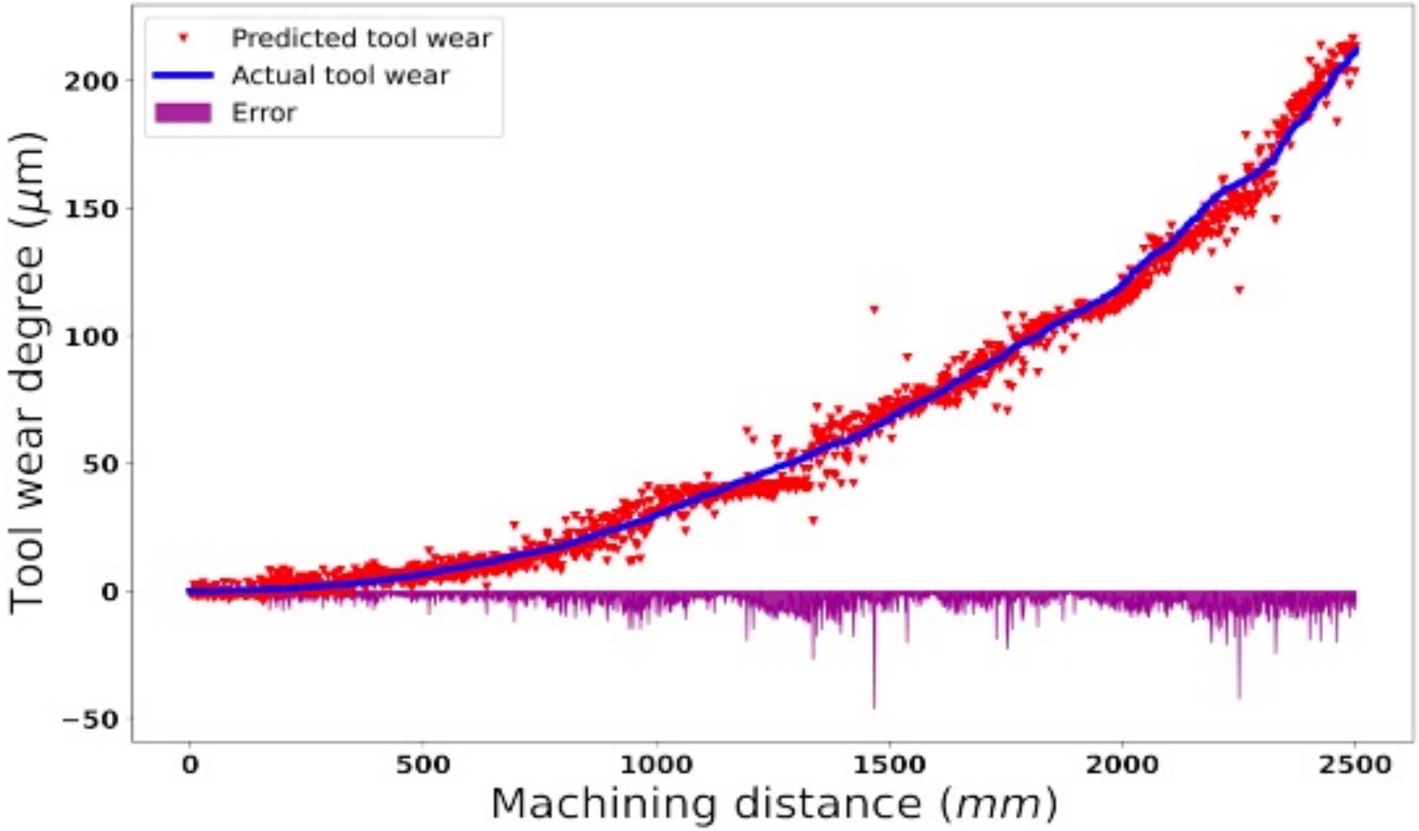
- DMSCNN v.s. deterministic tool wear prediction models

TABLE IV
PERFORMANCE COMPARISON OF DETERMINISTIC TOOL WEAR PREDICTION MODELS.

Model	MAE	RMSE	MAPE	R^2
TSF	13.1047 ($\pm$0.2720)	22.8500 ($\pm$0.7443)	229.7708 ($\pm$305.1545)	0.8513 ($\pm$0.0100)
GRU	6.5810 ($\pm$0.4025)	10.2392 ($\pm$0.4280)	283.6626 ($\pm$116.6763)	0.9698 ($\pm$0.0025)
LSTM	6.5340 ($\pm$0.7912)	10.1571 ($\pm$1.0522)	500.1723 ($\pm$318.6876)	0.9703 ($\pm$0.0062)
1D-CNN	7.0196 ($\pm$1.2387)	10.3567 ($\pm$1.4657)	124.3978 ($\pm$170.0191)	0.9685 ($\pm$0.0089)
DMSCNN (**proposed**)	**5.9349** ($\pm$1.2047)	**8.8442** ($\pm$1.5927)	**41.2545** ($\pm$30.9068)	**0.9766** ($\pm$0.0094)

5. Results and Discussion

- Bayesian DMSCNN’s probabilistic tool wear prediction results



Prediction results of Bayesian DMSCNN

5. Results and Discussion

- Bayesian DMSCNN v.s. probabilistic tool wear prediction models

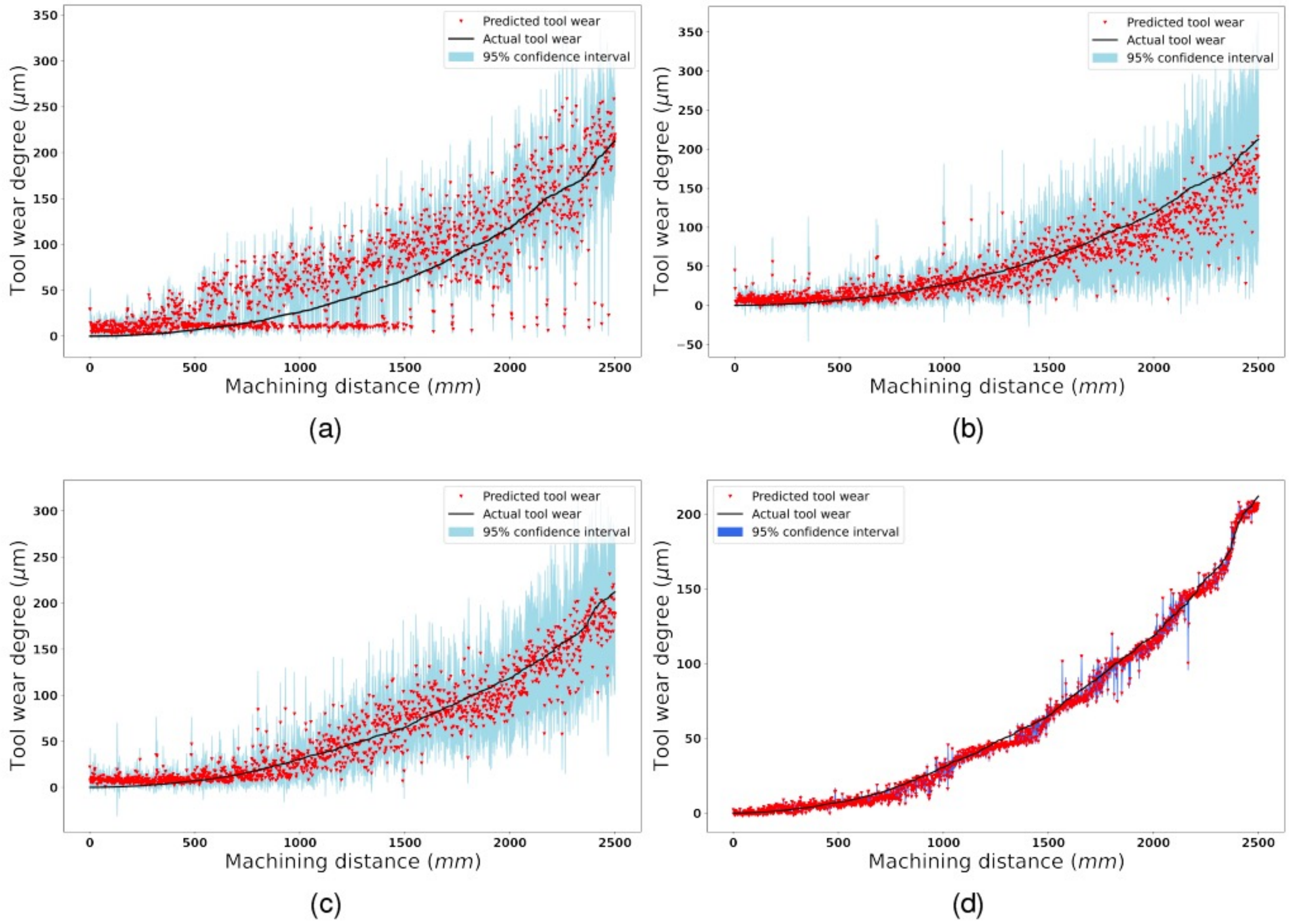
TABLE V
PERFORMANCE COMPARISON OF PROBABILISTIC TOOL WEAR PREDICTION MODELS.

Model	MAE	RMSE	MAPE	R^2
BNN	23.1017 ($\pm$2.0104)	31.8812 ($\pm$2.5667)	272.6718 ($\pm$202.3328)	0.7139 ($\pm$0.0476)
MC-dropout LSTM	20.0668 ($\pm$8.1623)	28.0024 ($\pm$9.5189)	210.5684 ($\pm$264.9961)	0.8225 ($\pm$0.0369)
MC-dropout CNN	12.2674 ($\pm$1.3735)	17.3275 ($\pm$2.2475)	250.3129 ($\pm$219.4896)	0.9137 ($\pm$0.0250)
Bayesian DMSCNN **(proposed)**	**5.3151** ($\pm$0.5271)	**7.8672** ($\pm$0.7653)	**29.8444** ($\pm$32.9993)	**0.9839** ($\pm$0.0037)

- c.f. performance of DMSCNN:

DMSCNN **(proposed)**	**5.9349** ($\pm$1.2047)	**8.8442** ($\pm$1.5927)	**41.2545** ($\pm$30.9068)	**0.9766** ($\pm$0.0094)

5. Results and Discussion



Visualization of 95% prediction intervals of: (a) BNN, (b) MC dropout LSTM, (c) MC dropout CNN, and (d) Proposed Bayesian DMSCNN

6. Conclusion and Future Works

- Summary: Bayesian-based uncertainty-aware tool wear prediction model – Bayesian deep multi-scale CNN
- Main points:
  - DL-based tool wear prediction using raw sensor measurement data
  - Multi-scale convolutional neural network architecture (DMSCNN)
  - Bayesian treatment of DMSCNN → Bayesian DMSCNN
    - Superior performance on tool wear prediction
    - Uncertainty-awareness, predictive distribution with confidence intervals
    - Diversity of network weights
- Future works:
  - Robust predictions, physics-informed tool wear prediction, active learning-based methods

Thank you for listening!

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