Development of a Bayesian-based Uncertainty-aware Tool Wear Prediction Model in the End Milling Process

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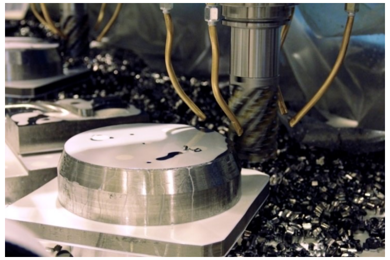
Contents

Abstract

- Titanium alloy is one of the most widely used materials in various industries, such as aerospace, medical, and automotive industry because of its desirable mechanical properties. However, titanium alloy is also a difficult-to-cut material due to the low thermal conductivity and low specific heat. In particular, in an end milling process using titanium alloy, tool wear influences not only the cutting force but also material removal volume per a single tool as well as the quality of the material surface. Therefore, accurate tool wear prediction is necessary during an end milling process to improve product quality and replace the tool at an appropriate time. Furthermore, because the effects of tool wear prediction on the overall process are significant both in terms of cost and time, uncertainty-aware tool wear prediction should be performed. In this work, a deep learning-based tool wear prediction model, which uses a Bayesian approach, is proposed. First, a CNN-based architecture that integrates multi-scale information extracted from raw sensor measurement data, named deep multi-scale CNN (DMSCNN) is proposed. Second, using a Bayesian approach, DMSCNN is transformed into a probabilistic model that outputs a predictive distribution with uncertainty awareness. Experiments with data collected from the real-world end milling process with three distinct setups have proven the effectiveness of the proposed DMSCNN in tool wear prediction. In addition, Bayesian DMSCNN has shown promising results, outperforming existing comparative deterministic methods, as well as probabilistic methods for tool wear prediction.

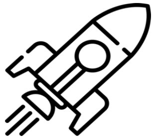
1. Introduction

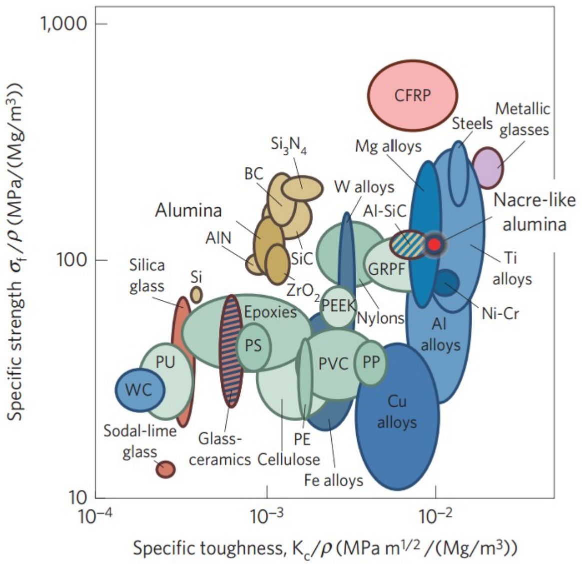
- Manufacturing process
  - Additive manufacturing (i.e., 3D printing)
    - Mass production, flexible design, eco-friendly
    - Inaccuracy and irregularity of precision, durability
    - Post-processing required
      - Relying on cutting/milling (e.g., surface milling)
  - Casting
    - Liquified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

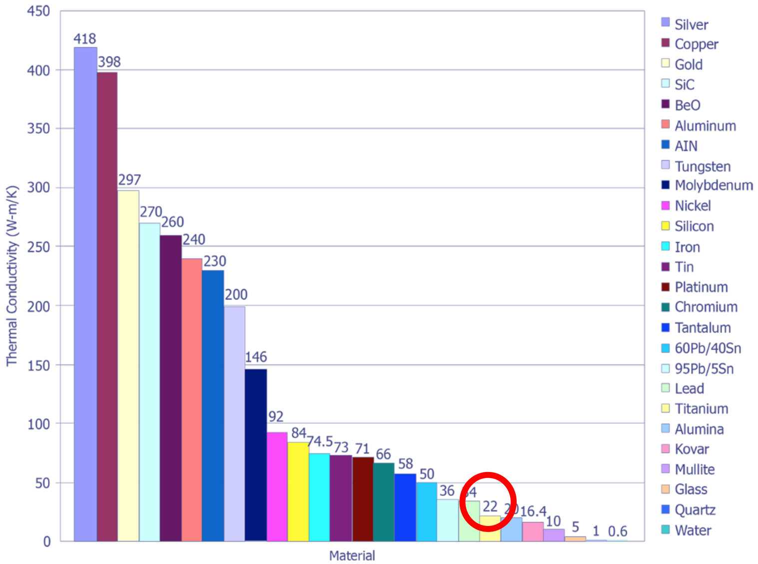


1. Introduction

- 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.

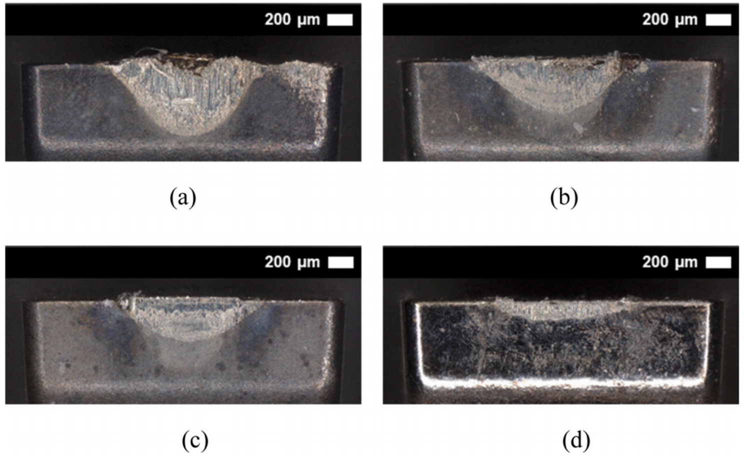






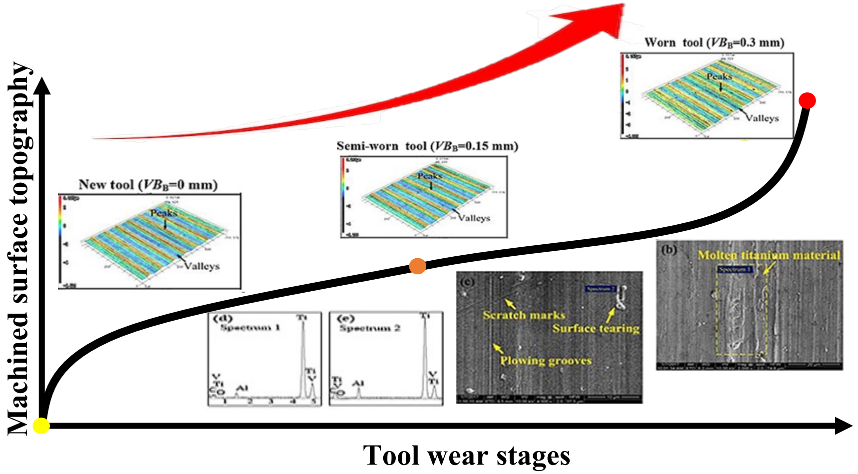
1. Introduction

- 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



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
  - Analytical methods
    - Tool wear models, equations
    - e.g., finite element method (FEM), simulation-based methods

- 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
  - Conventional machine learning (ML) prediction algorithms

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

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

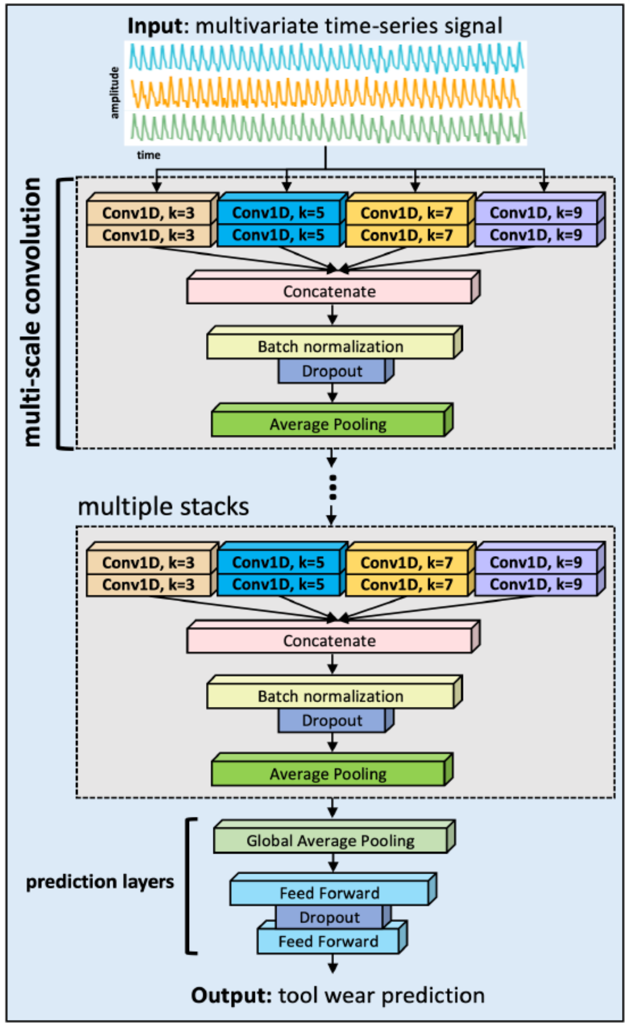
$$g = [g_1, \ldots, g_p] = [f * k^{l_1}, \ldots, f * k^{l_p}], \quad where\ |k^{s_i}| = l_i.$$

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)

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

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

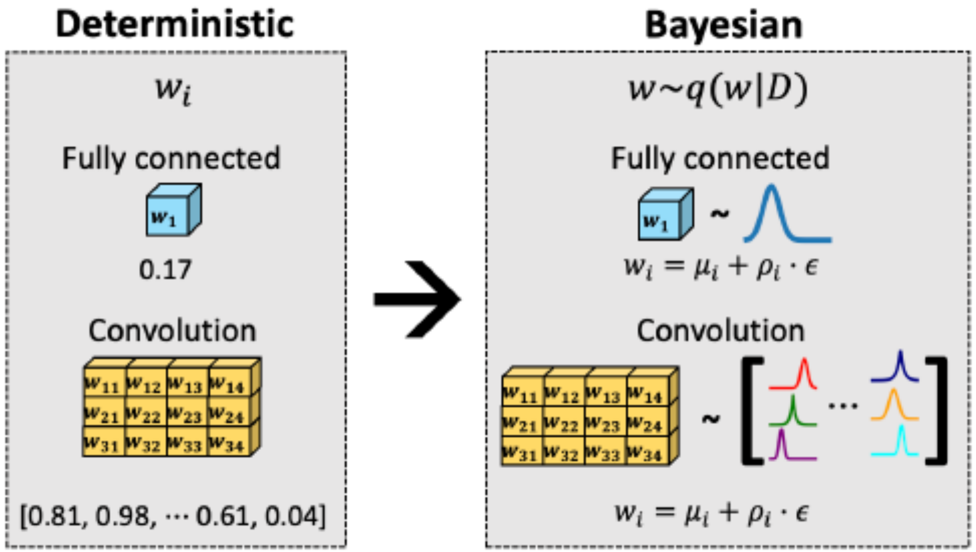
3. Proposed Method

- 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

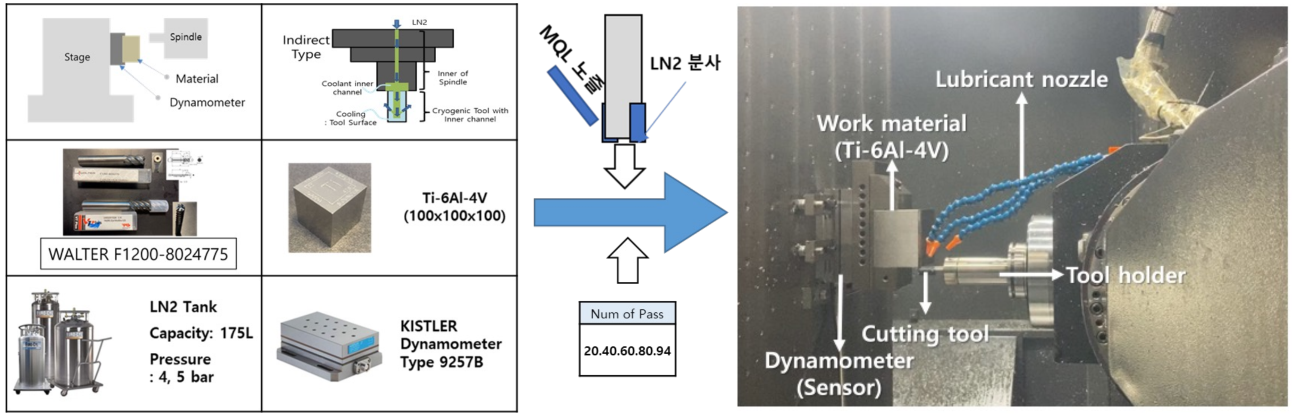
    $$\tilde{\mathcal{L}}_{ELBO} = \frac{1}{n}\sum_{i=1}^{n}[log\ q(w_{(i)}|D) - log\ p(w_{(i)}) - log\ p(D|w_{(i)})].$$
  - Inference (i.e., prediction)

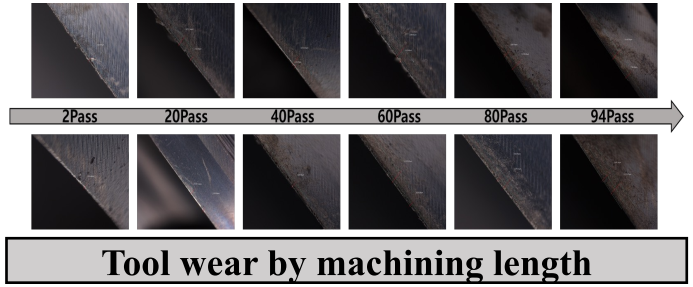
    $$p(y|x,D) = \int p(y|x,w)p(w|D)\,dw \approx \frac{1}{T}\sum_{t=1}^{T} p(y|x,w_{(t)}).$$



4. Experiments

- Data collection
  - End milling experimental setup





SETUP OF CUTTING TOOL PARAMETERS.

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°

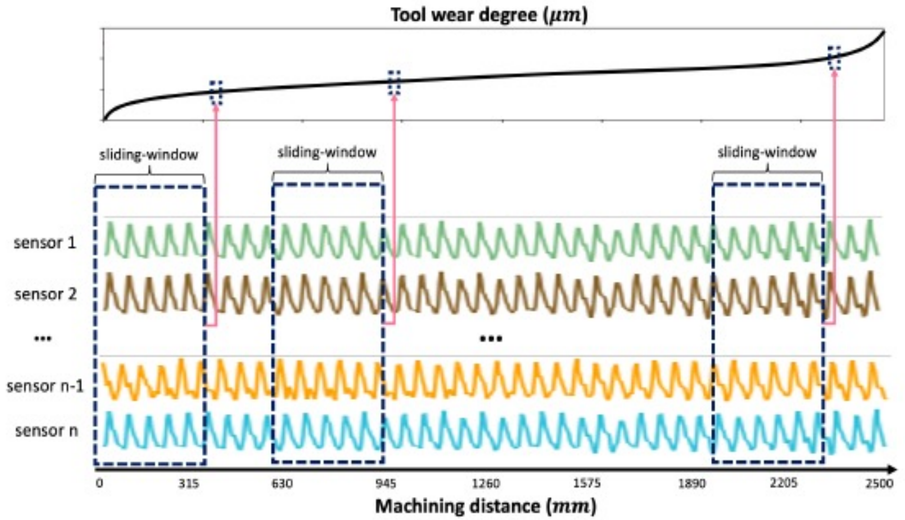
- Dynamometer sensor measurement
- Pass-wise tool wear measurement
  - Tool wear calculation: Levenberg-Marquardt algorithm

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

4. Experiments

- Data preprocessing
  - Normalization (standardization)
  - Sliding-window preprocessing

$$x_{scaled} = \frac{x - \bar{x}}{s}.$$



Sliding-window preprocessing

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

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

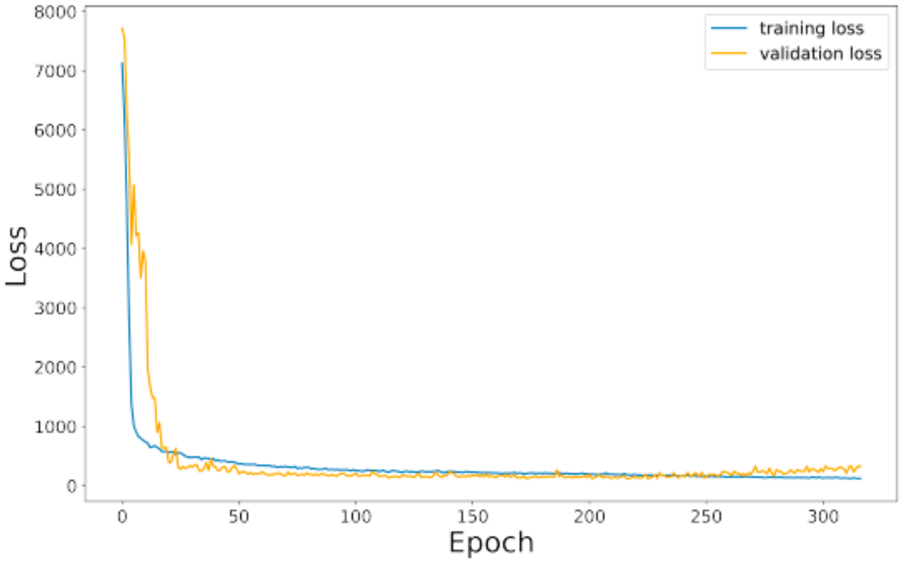
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}.$$

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

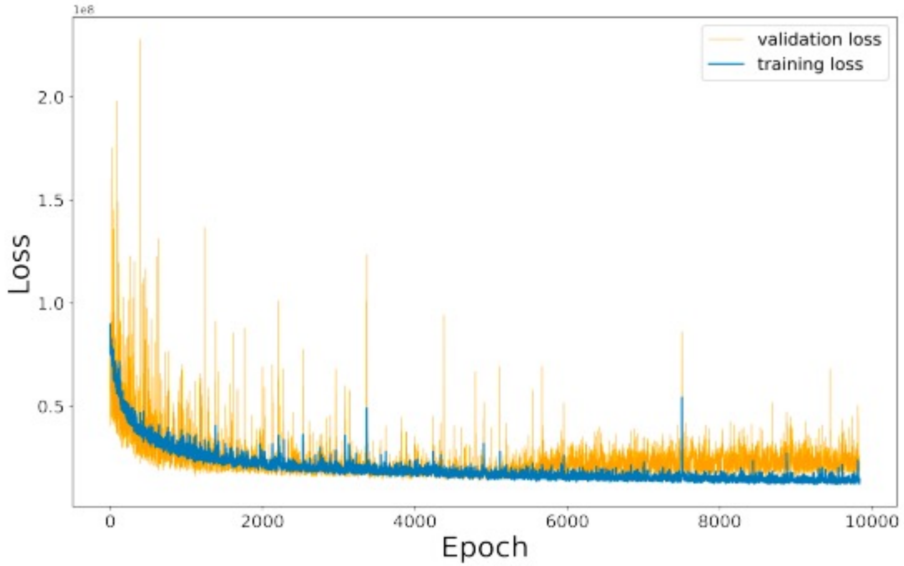
$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}.$$

5. Results and Discussion

- Training convergence analysis



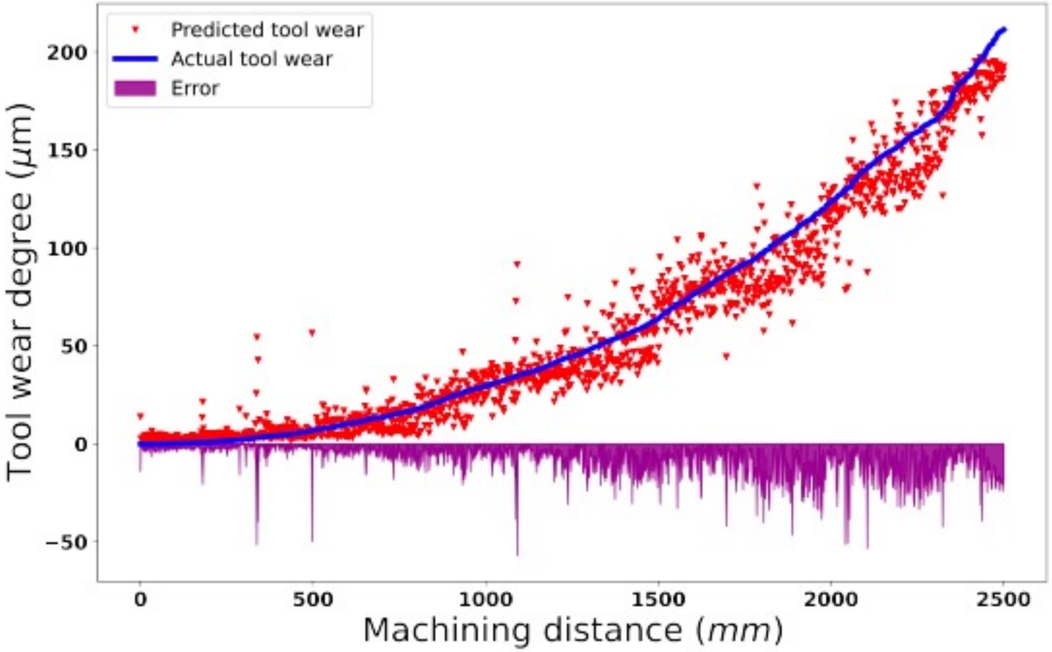
Convergence analysis of the training of the DMCSNN



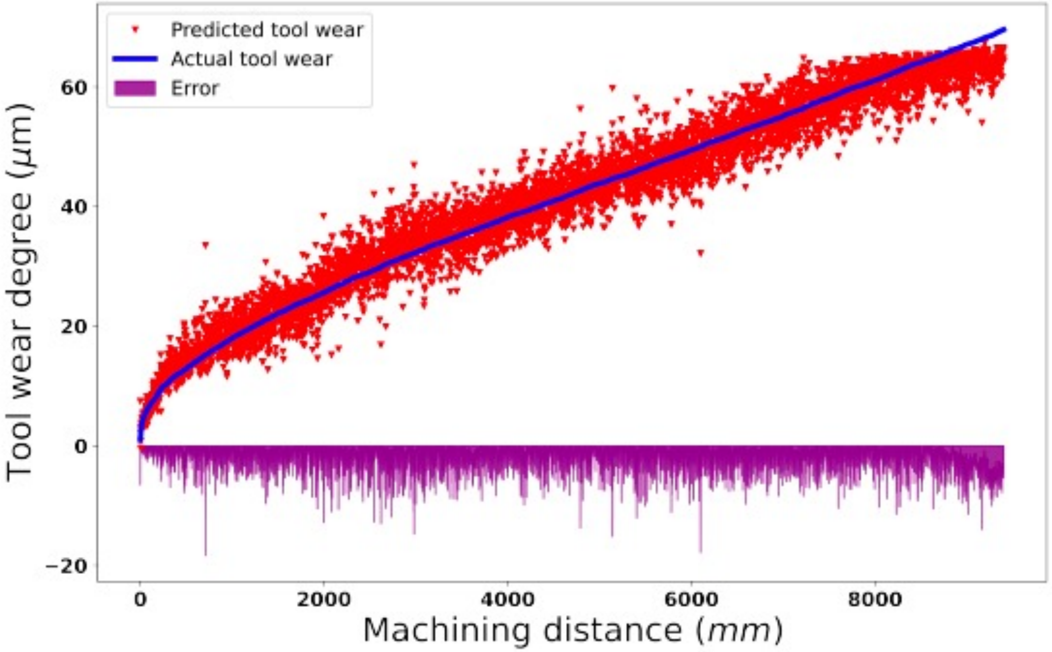
Convergence analysis of the training of the Bayesian DMSCNN

5. Results and Discussion

- DMSCNN v.s. deterministic tool wear prediction models



Prediction results of DMSCNN on dataset 1.



Prediction results of DMSCNN on dataset 2.

5. Results and Discussion

- DMSCNN v.s. deterministic tool wear prediction models

PERFORMANCE COMPARISON OF DETERMINISTIC TOOL WEAR PREDICTION MODELS ON DATASET 1.

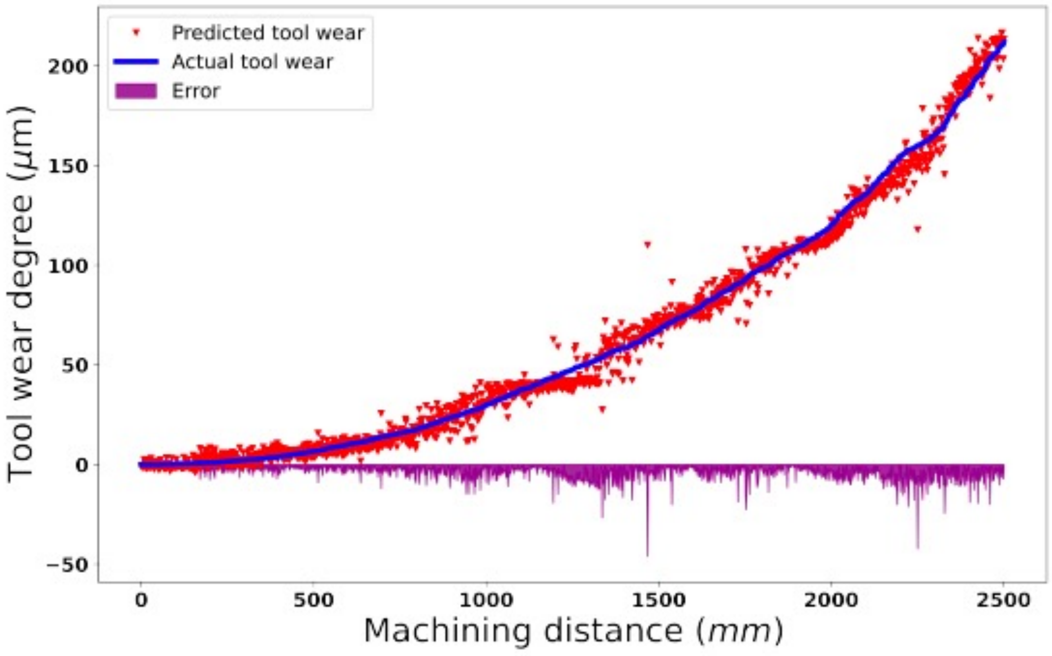
Model	Metric			
	MAE	RMSE	MAPE	R^2
TSF	13.1047 (±0.2720)	22.8500 (±0.7443)	229.7708 (±305.1545)	0.8513 (±0.0100)
GRU	6.5810 (±0.4025)	10.2392 (±0.4280)	283.6626 (±116.6763)	0.9698 (±0.0025)
LSTM	6.5340 (±0.7912)	10.1571 (±1.0522)	500.1723 (±318.6876)	0.9703 (±0.0062)
1D-CNN (kernel_size=3)	8.3762 (±1.3030)	12.1755 (±1.5131)	157.6921 (±160.2621)	0.9572 (±0.0105)
1D-CNN (kernel_size=5)	7.0196 (±1.2387)	10.3567 (±1.4657)	124.3978 (±170.0191)	0.9685 (±0.0089)
1D-CNN (kernel_size=7)	7.2237 (±0.8353)	10.3698 (±1.0951)	118.9289 (±133.1617)	0.9682 (±0.0057)
1D-CNN (kernel_size=9)	6.8805 (±1.0069)	9.9445 (±0.9736)	72.3878 (±33.8884)	0.9694 (±0.0102)
DMSCNN **(proposed)**	**5.9349** (±1.2047)	**8.8442** (±1.5927)	**41.2545** (±30.9068)	**0.9766** (±0.0094)

PERFORMANCE COMPARISON OF DETERMINISTIC TOOL WEAR PREDICTION MODELS ON DATASET 2.

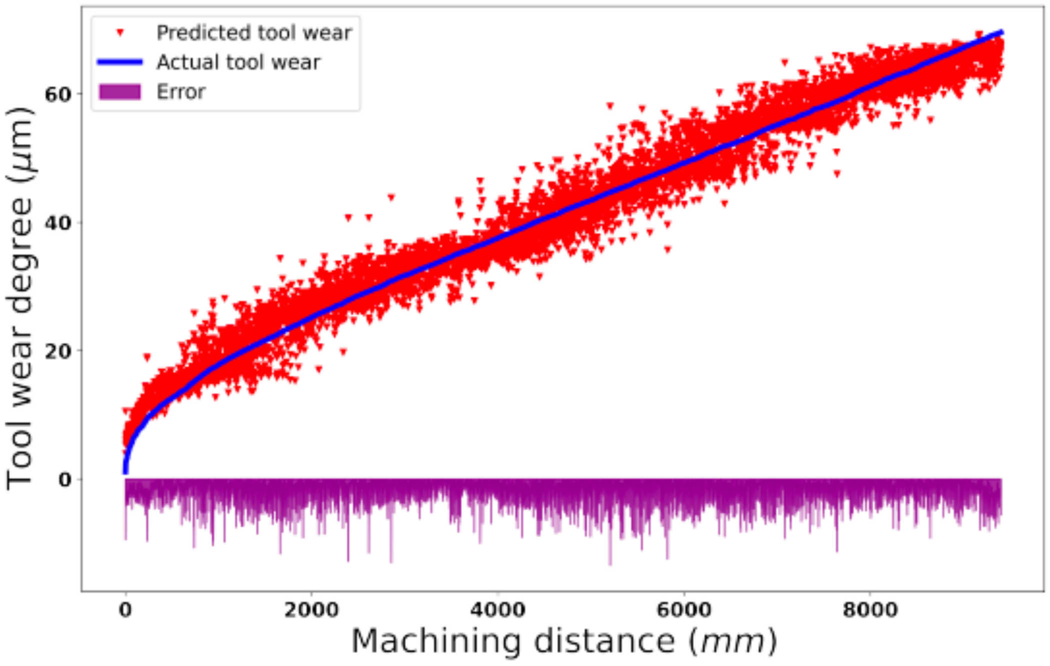
Model	Metric			
	MAE	RMSE	MAPE	R^2
TSF	7.7813 (±0.0101)	11.7798 (±0.0111)	0.3043 (±0.0016)	0.5255 (±0.0008)
GRU	3.6248 (±0.7324)	4.6265 (±0.8914)	0.1077 (±0.0189)	0.9229 (±0.0279)
LSTM	3.9679 (±0.2120)	5.0976 (±0.2693)	0.1246 (±0.0200)	0.9090 (±0.0097)
1D-CNN (kernel_size=3)	3.7913 (±0.3624)	4.8126 (±0.4432)	0.1219 (±0.0146)	0.9182 (±0.0146)
1D-CNN (kernel_size=5)	3.6828 (±0.7401)	4.6403 (±0.8424)	0.1137 (±0.0192)	0.9222 (±0.0292)
1D-CNN (kernel_size=7)	3.6379 (±0.4657)	4.5613 (±0.6206)	0.1121 (±0.0166)	0.9257 (±0.0196)
1D-CNN (kernel_size=9)	3.4687 (±0.6429)	4.2148 (±0.7455)	0.1089 (±0.0262)	0.9342 (±0.0264)
DMSCNN **(proposed)**	**3.1394** (±0.3892)	**3.9776** (±0.4681)	**0.1002** (±0.0091)	**0.9442** (±0.0137)

5. Results and Discussion

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



Prediction results of Bayesian DMSCNN on dataset 1.



Prediction results of Bayesian DMSCNN on dataset 2.

5. Results and Discussion

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

PERFORMANCE COMPARISON OF PROBABILISTIC TOOL WEAR PREDICTION MODELS ON DATASET 1.

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

PERFORMANCE COMPARISON OF PROBABILISTIC TOOL WEAR PREDICTION MODELS ON DATASET 2.

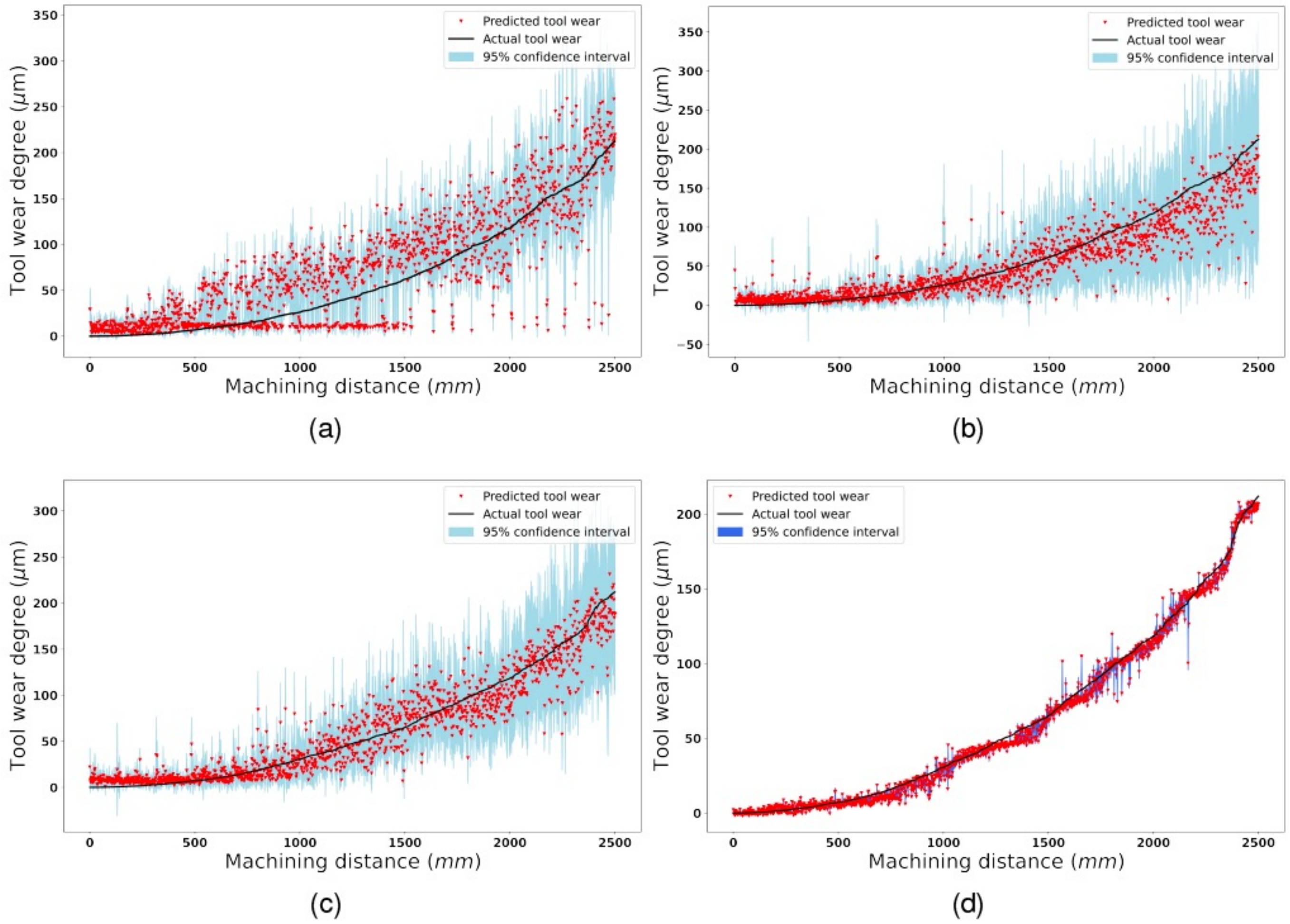
Model	Metric			
	MAE	RMSE	MAPE	R^2
BNN	6.7235 (±0.3380)	8.4677 (±0.4005)	0.2113 (±0.0131)	0.7482 (±0.0235)
MC-dropout LSTM	6.7012 (±0.3741)	8.6475 (±0.4824)	0.1748 (±0.0067)	0.7390 (±0.0274)
MC-dropout CNN	4.7723 (±0.1949)	6.0033 (±0.2224)	0.1585 (±0.0111)	0.8742 (±0.0094)
Bayesian DMSCNN (proposed)	**2.3398** (±0.1945)	**2.9862** (±0.2430)	**0.0796** (±0.0072)	**0.9737** (±0.0069)

- c.f. performance of DMSCNN:

DMSCNN (proposed)	**5.9349** (±1.2047)	**8.8442** (±1.5927)	**41.2545** (±30.9068)	**0.9766** (±0.0094)

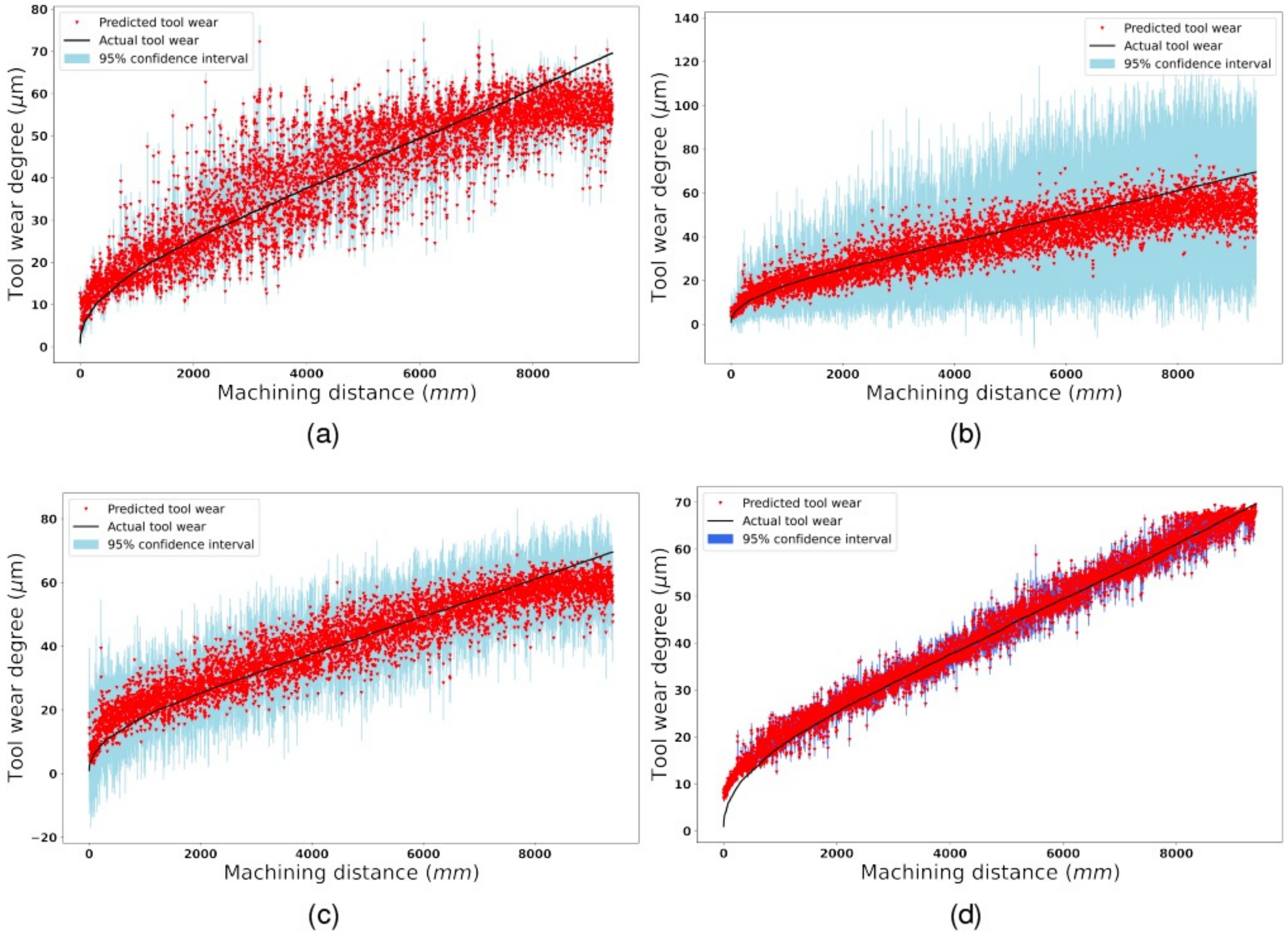
DMSCNN (proposed)	**3.1394** (±0.3892)	**3.9776** (±0.4681)	**0.1002** (±0.0091)	**0.9442** (±0.0137)

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, on dataset 1.

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, on dataset 2.

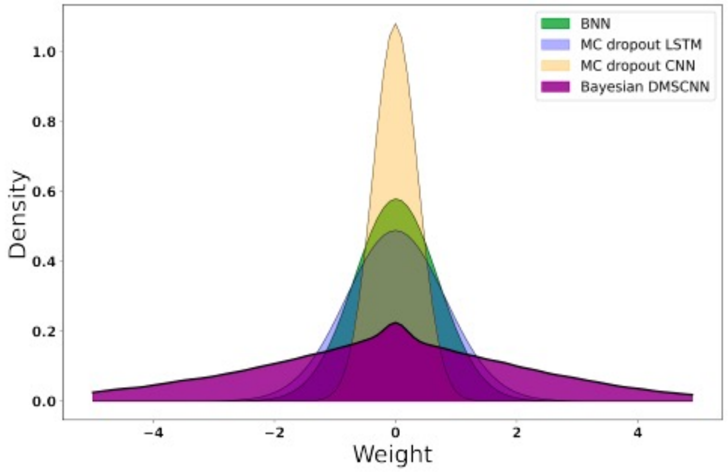
5. Results and Discussion

- Inference time

COMPARISON OF THE INFERENCE TIME OF PROBABILISTIC MODELS.

Model	Inference time (sec)
BNN	0.1059 ± 0.0157
MC-dropout LSTM	5.2091 ± 0.2294
MC-dropout CNN	0.1697 ± 0.0676
Bayesian DMSCNN (proposed)	0.3586 ± 0.2340

- Network weight distribution



Histogram of trained weights from probabilistic models.

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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