Towards a Probabilistic Fusion Approach for Robust Battery Prognostics

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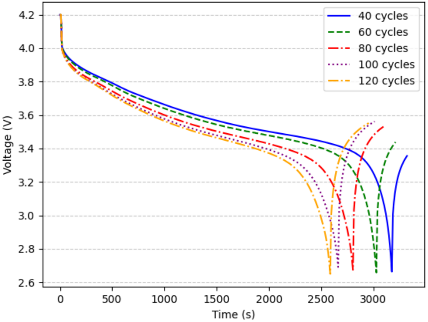
1. Motivation

Motivation

- **Batteries** are key components in the transition towards a sustainable carbon-free future
- **Accurate Remaining Useful Life (RUL)** prediction of batteries is a crucial activity
- Estimating the **state-of-health (SOH)** is **crucial for** designing **RUL** prognostic models



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2. Proposed Approach

Proposed Approach Overview

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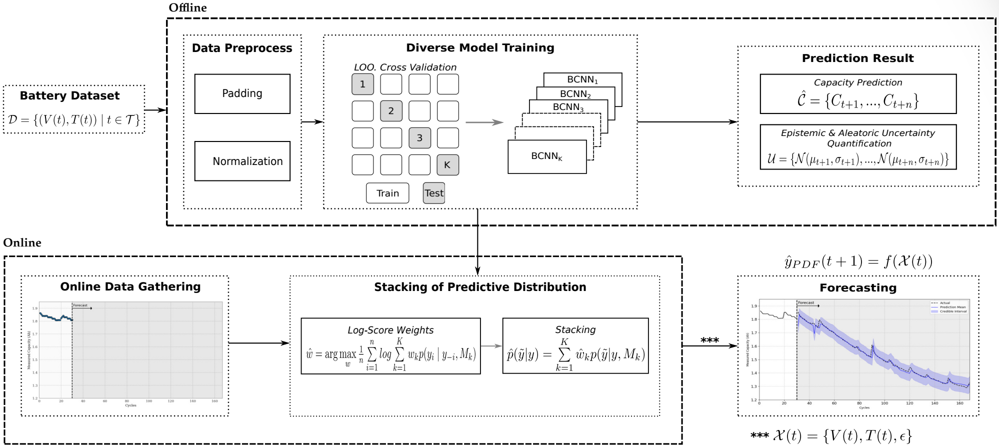
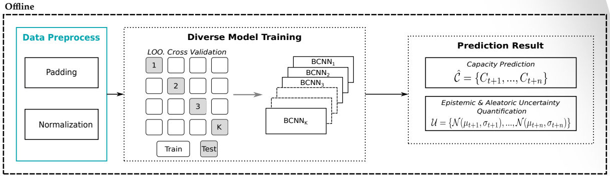
Probabilistic Ensemble of Bayesian Convolutional Neural Networks



Offline Phase



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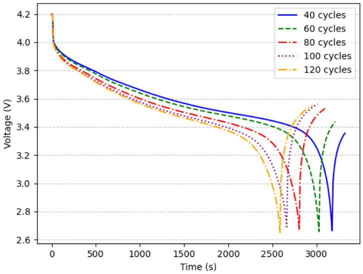
Data Preprocessing

- **Padding:** Ensures all battery discharge curves are of equal length by extending them with the last observed value
- **Normalization:** Scales data, improving neural network efficiency



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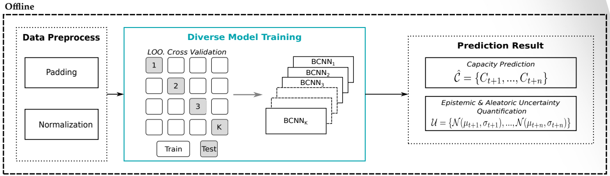
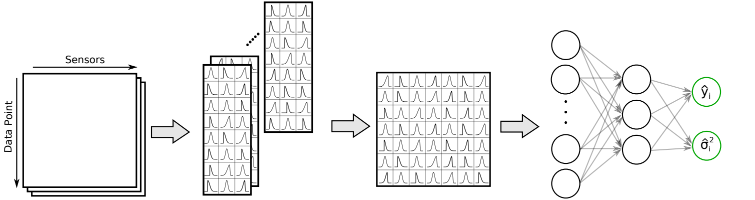


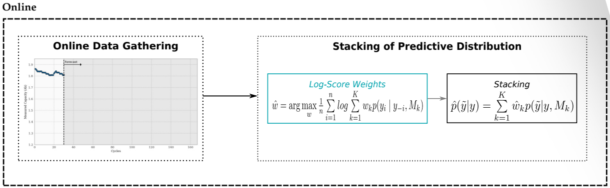
Diverse Model Training

Ensemble Base Models: Bayesian Convolutional Neural Networks (BCNNs)

- **Variational inference** to approximate posterior distributions
- **Epistemic** and **aleatoric uncertainty** quantification
- **LOOCV** strategy for diverse model training



Online Phase



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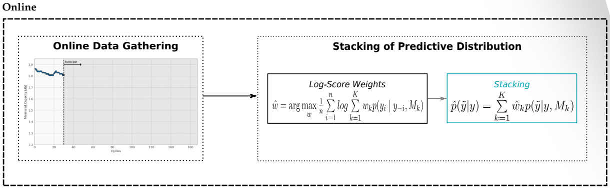
Log-score Weights

- **Proper scoring rule** used to **evaluate** the accuracy of **probabilistic forecasts**
- Optimal method to combine **posterior predictive distributions**
- **Regularization** term λ_{reg} is added to the likelihood function, **penalizing large weights**

$$\hat{w} = \arg\max_{w} \frac{1}{N} \sum_{i=1}^{N} log \sum_{k=1}^{K} w_k p(y_i \mid y_{-i}, M_k) + \lambda_{reg} \sum_{k=1}^{K} w_k^2 \quad (1)$$

Online Phase



Stacking

- Stacking to **average Bayesian predictive distributions** instead of point predictions
- The stacking of the predictive distribution enables the **fusion of uncertainties** from various models into a unified predictive framework
- The fusion of predictive distributions is done by **sampling** from the **weighted distribution**

$$\hat{p}(\tilde{y}|y) = \sum_{k=1}^{K} \hat{w}_k p(\tilde{y}|y, M_k) \quad (2)$$

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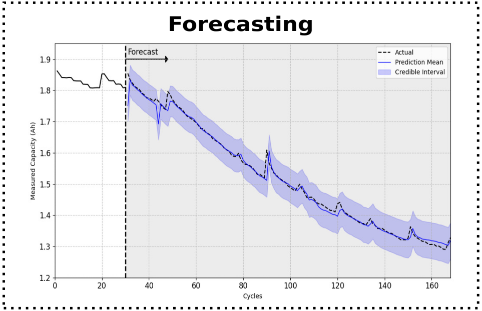
Forecasting

- **One-step-ahead** capacity distribution prediction

$$\hat{y}_{PDF}(t+1) = f(\mathcal{X}(t)) \quad (3)$$

- Previous data until the instant t is used, plus an uncertainty factor expressed as noise

$$\mathcal{X}(t) = \{V(t), T(t), \epsilon\} \quad (4)$$



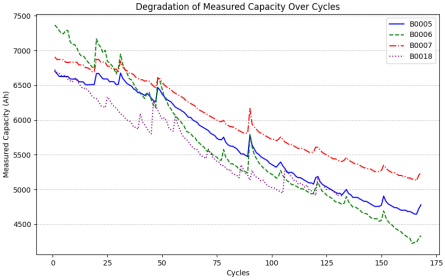
3. Case Study

Case Study

Dataset Description

The proposed approach tested with a battery dataset from `NASA Ames Prognostics Center`

- Li-ion batteries with maximum capacity of 2Ah; batteries #5, #6, #7 and #18
- **Discharge** cycles involved a **constant load** at 2A
- Variations in capacity degradation rates for identical batteries. This is an indicator of **uncertainty** inherent in the **manufacturing process**



Case Study

Benchmarking

- Leave-one-out **mean squared error** as scoring rule to determine stacking weights
- L_2 regularization term (λ_{reg})

$$\hat{w} = \arg\min_{w} \sum_{i=1}^{n} \left(y_i - \sum_{k=1}^{K} w_k \hat{f}_K^{(-i)}(x_i) \right)^2 + \lambda_{reg} \sum_{k=1}^{K} w_k^2 \tag{5}$$

Stacking of point prediction

$$\hat{y} = \sum_{k=1}^{K} \hat{w}_k f_k(x|\theta_k) \tag{6}$$

4. Results

Results

Probabilistic Ensemble Strategies

- **Comparative analysis** in terms of accuracy and probabilistic metrics
- Batteries #5 and #6 exhibited superior outcomes in probabilistic metrics (NLL and CRPS) for the proposed approach
- For batteries #7 and #18 the same based model minimizes the MSE and maximizes the likelihood at the same time.

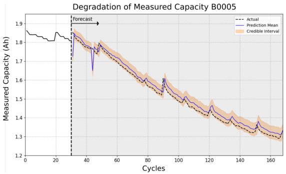
	Baseline Model			Benchmarking Ensemble			Proposed Ensemble		
	$MSE(\downarrow)$	$NLL(\downarrow)$	$CRPS(\downarrow)$	$MSE(\downarrow)$	$NLL(\downarrow)$	$CRPS(\downarrow)$	$MSE(\downarrow)$	$NLL(\downarrow)$	$CRPS(\downarrow)$
B0005	0.0007	2.3397	0.0183	**0.0002**	-1.9523	0.0145	0.0003	**-2.1001**	**0.0131**
B0006	0.0013	8.0947	0.0213	**0.0009**	-1.8222	0.0183	0.0009	**-1.9358**	**0.0178**
B0007	0.0005	-0.0409	0.0149	**0.0003**	**-1.9755**	**0.0145**	**0.0004**	**-1.9769**	**0.0145**
B0018	0.0013	9.0342	0.0223	**0.0010**	**-1.9478**	**0.0174**	**0.0010**	**-1.9312**	**0.0178**

Table 1: Comparison of different ensemble strategies for different batteries used as test.

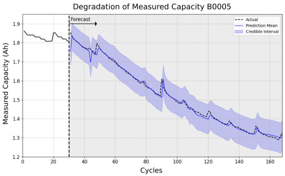
Results

Probabilistic Ensemble Strategies

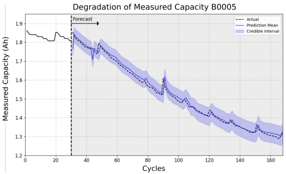
- Comparative analysis of baseline, benchmarking ens. and proposed ens. of battery #5
- Ensemble models enhance baseline model in terms of accuracy and uncertainty
- Stacking of predictive distribution shows an improvement in prediction uncertainty



(a) Baseline model.



(b) Stacked point prediction.



(c) Stacked predictive distribution.

Results

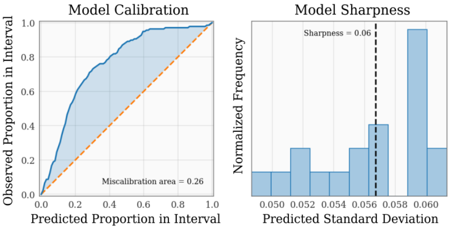
Calibration and Sharpness of Probability Distribution Function (PDF)

Calibration plot #5

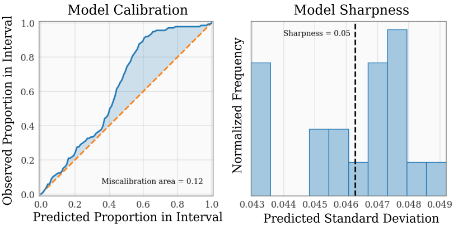
- The proposed ensemble model has a **miscalibration area** of **0.12**, showing better calibration compared to point prediction model with **0.26**

Sharpness plot #5

- The proposed ensemble model has a **sharpness** of **0.05**, showing more confident predictions compared to point prediction model with **0.06**



(a) Stacked point prediction method.



(b) Stacked predictive distribution method.

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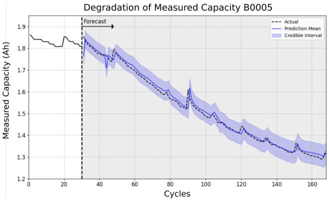
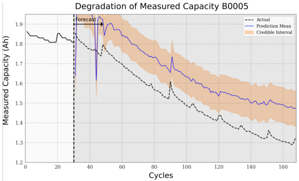
Results

Sensitivity of the Ensemble Strategy with Base-Models

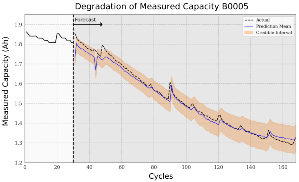
Individual components contribute as follows: $w_1 = 0.0058$, $w_2 = 0.5811$ and $w_3 = 0.4131$



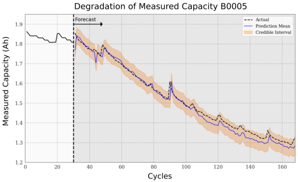
(a) Ensemble Forecast



(b) Forecast from first base-model



(c) Forecast from second base-model



(d) Forecast from third base-model

5. Conclusions

Conclusions

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Framework Validation

- Developed a **probabilistic stacking** method using BCNNs
- Tested on NASA's battery dataset, showing improved accuracy and uncertainty quantification.

Research Contributions

- **Logarithmic score** for the stacking of BNN
- Demonstrated the importance of probabilistic and ensemble methods in **addressing manufacturing and operational uncertainties**

Implications

- **Robust** tool for improving the reliability and safety of battery systems
- Supports **enhanced decision-making** in battery management and operational strategies

6. Future Lines

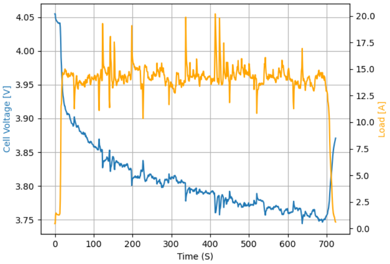
Future Lines

Expanding Dataset Diversity and Scope

- Increase the diversity of battery dataset
- Include **dynamic discharge profiles** to replace static discharge conditions

Advanced Comparative Analysis of Fusion Strategies

- **Comparative analysis** of fusion strategies such as *Bayesian Model Averaging (BMA)*, *Pseudo Bayesian Model Averaging (PBMA)*, and *Bayesian Mixture Models*.



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