Bayesian Recurrent Neural Networks for Monitoring Rotorcraft Icing from Aeroacoustics Time-Series Data

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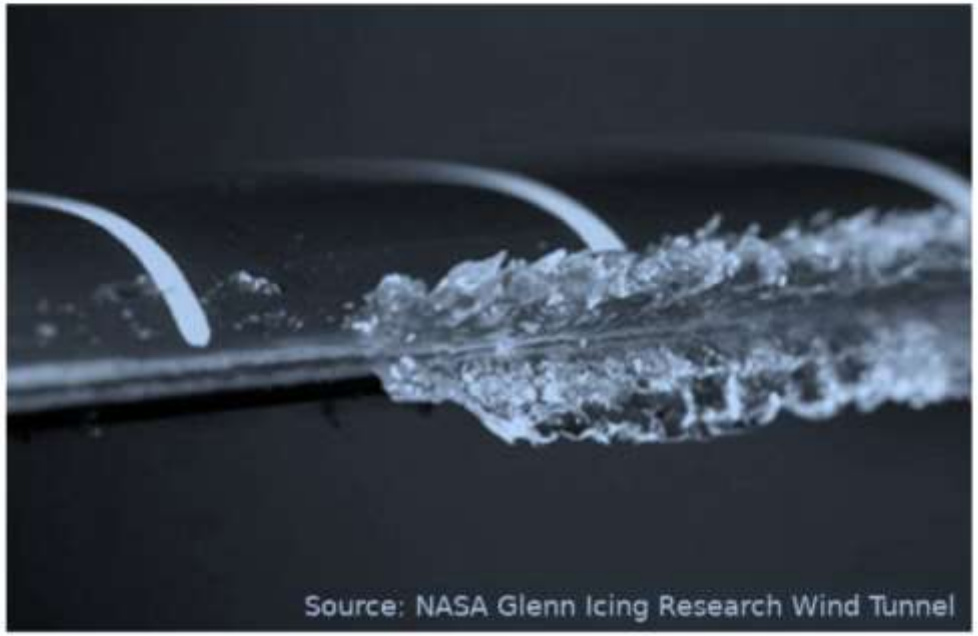
AIAA SciTech Forum
January 6, 2021, San Diego, CA

TECHNISCHE UNIVERSITÄT KAISERSLAUTERN

Rotorcraft icing

Source: BBC NEWS, Mar 2nd 2006



Source: NASA Glenn Icing Research Wind Tunnel

In-flight rotorcraft icing is extremely dangerous:

- alters leading-edge shape of rotor blades
- severely degrades aerodynamic performance
- is difficult to escape from/recover

Many icing-induced fatal accidents in recent years

Real-time in-flight ice detection system is of paramount importance

Icing detection from acoustics, machine learning model

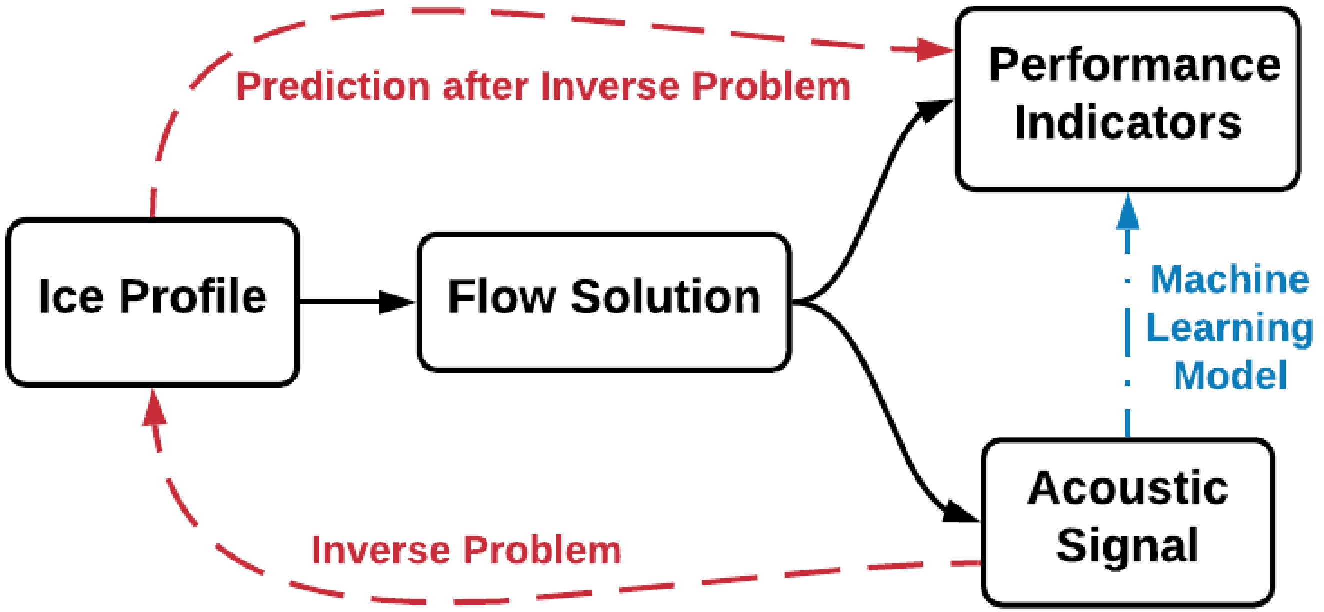
In-flight visual inspection nearly impossible due to high rotor RPM

Promising route: detection using **acoustic signals** enabled by simulations

- computational fluid dynamics (CFD)
- computational aeroacoustics (CAA)

But: physics-based solutions very expensive (min/hours)

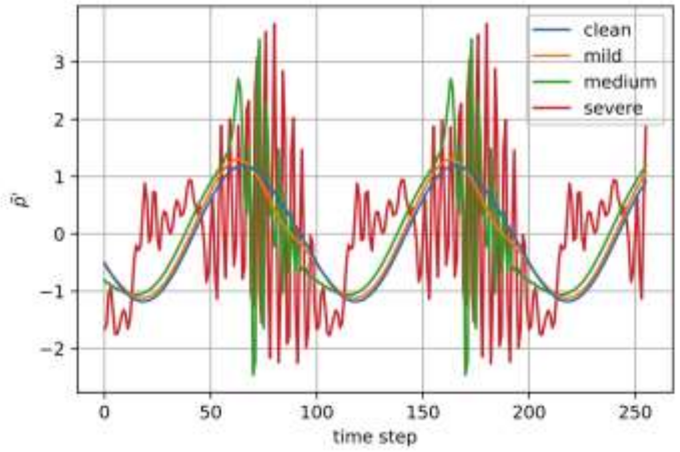
$\Rightarrow$ accelerate via **machine-learning (ML)** models



Data generated from physics-based simulations

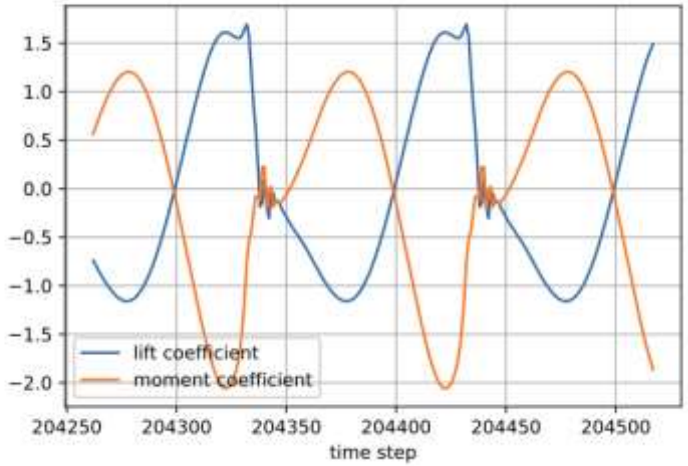
Key components:

- PoliDrop, PoliMIce—ice seeding and accretion
- URANS/DES—turbulent flow solve for near field
- FW-H (Ffowcs Williams-Hawking)—acoustics solver propagate signals to far field
- Coupled through open-source software SU2



Input feature
(acoustic signal time-series)

ML
Model

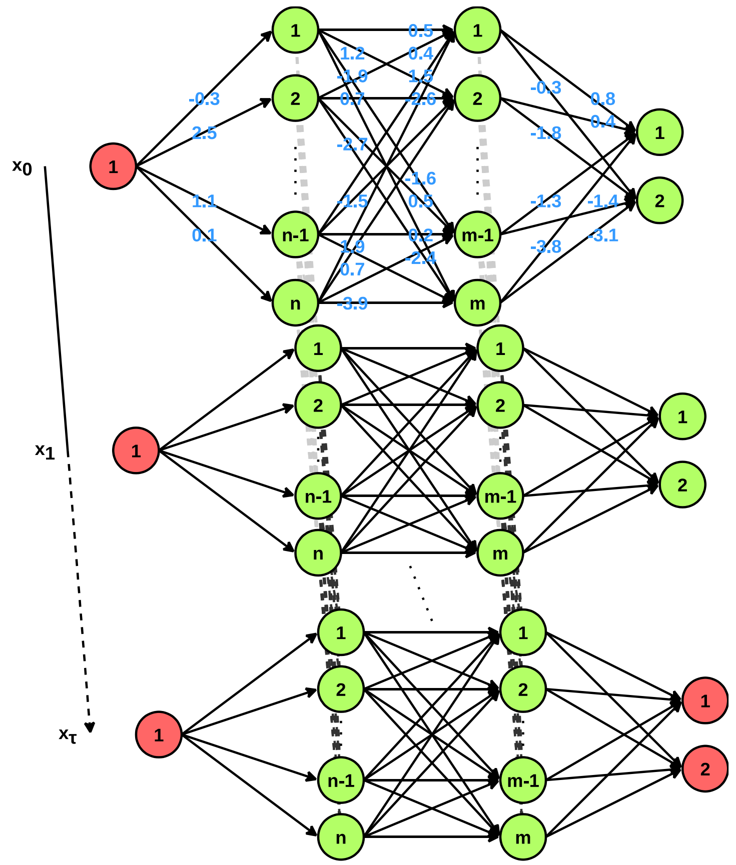


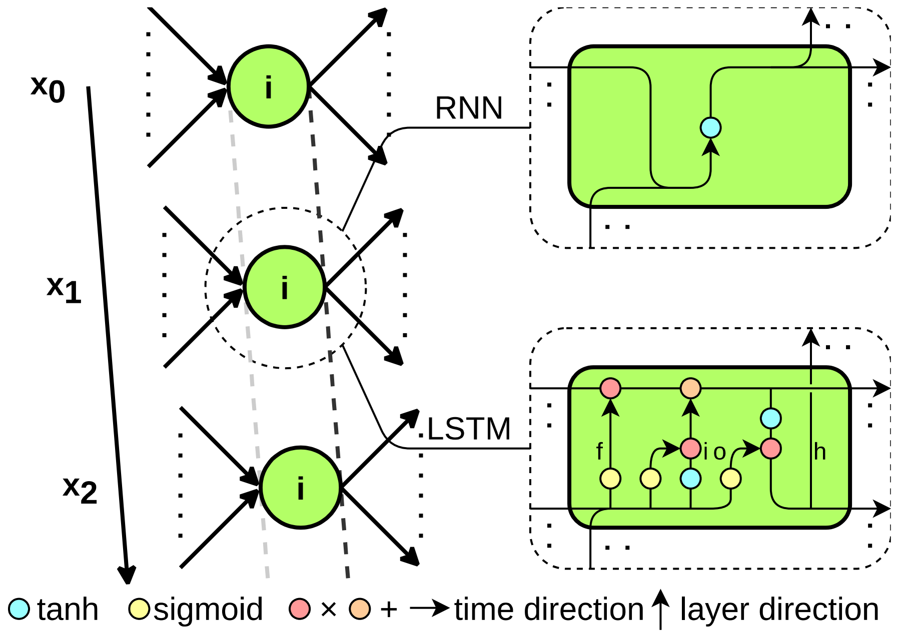
Output prediction
(C_L, C_M time-series)

Long short-term memory (LSTM) recurrent neural network

Recurrent neural networks (RNNs)

- Similar to dense DNNs, also use information from previous time steps
- LSTM adds a cell chain to memorize long-term information

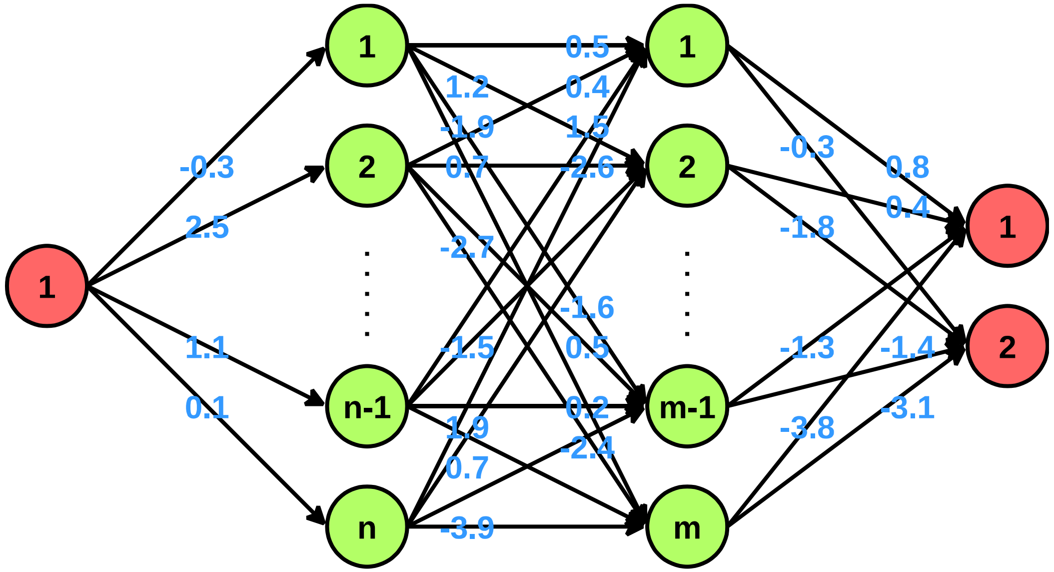


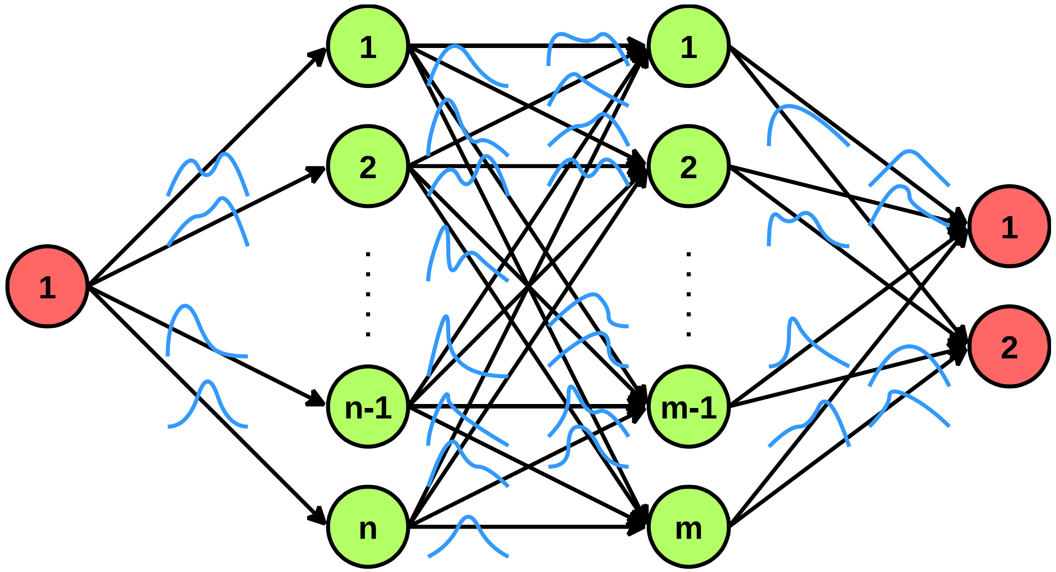


Bayesian neural networks

A Bayesian treatment

- computes *distribution* of weights
- captures **uncertainty** of weight parameters

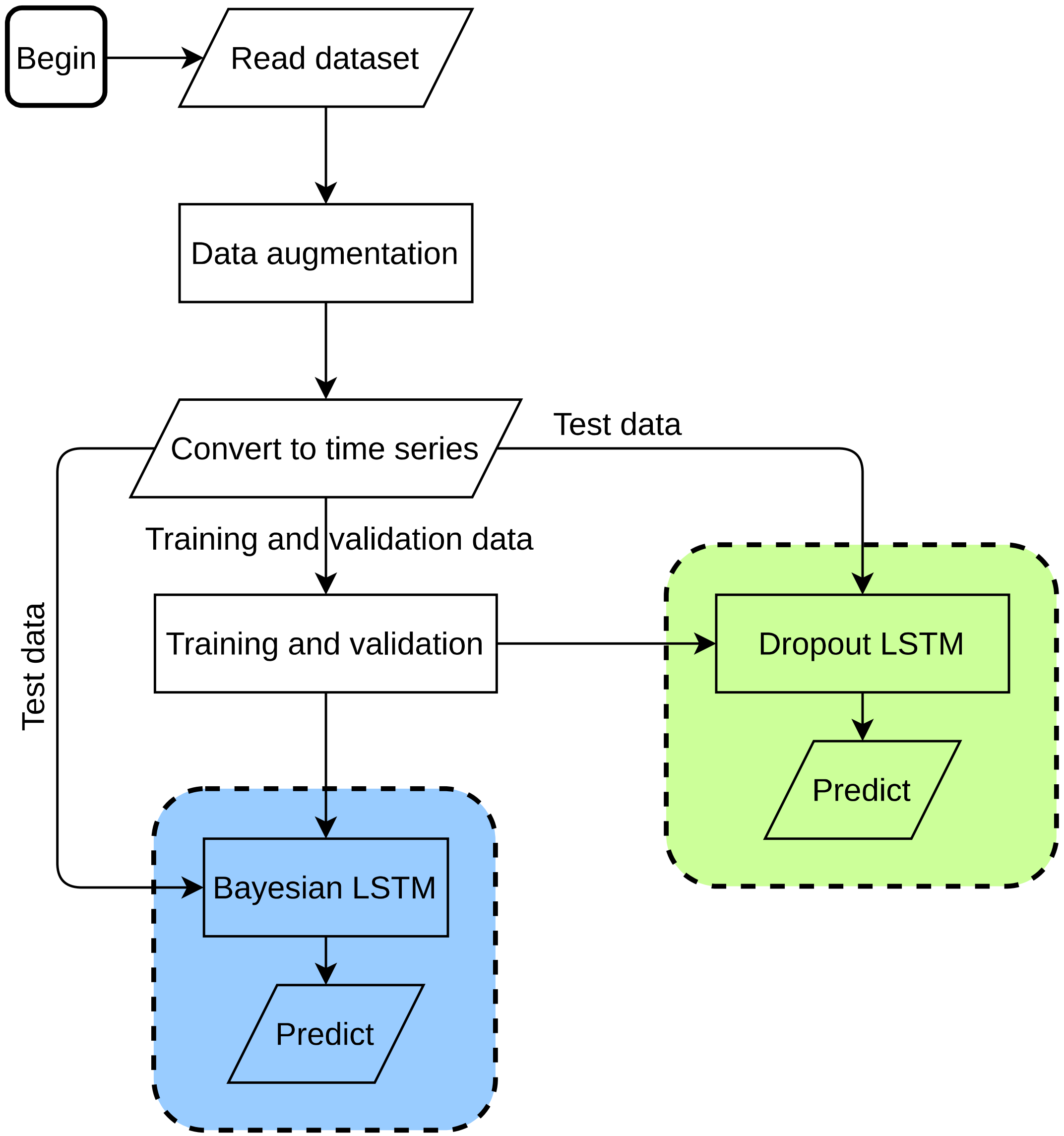




$$w^* = \underset{w}{\operatorname{argmin}} \mathcal{L}\left[f(x_T; w), y_T\right]$$

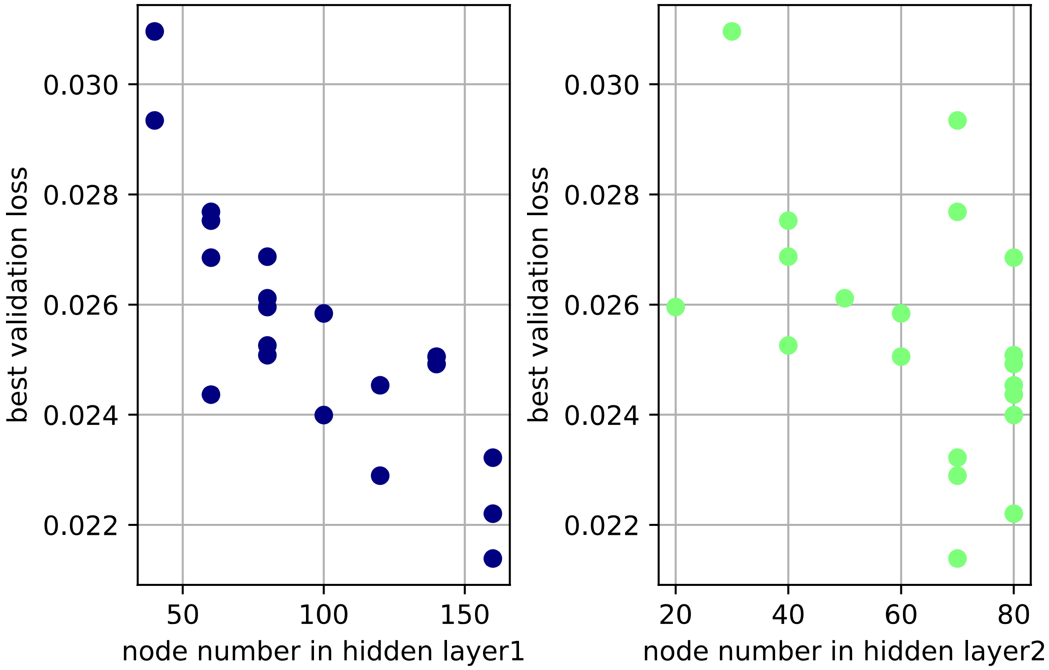
$$p(w|x_T, y_T) = \frac{p(y_T|x_T, w)p(w|x_T)}{p(y_T|x_T)}$$

Overall procedure workflow



- **Data augmentation:** added noise to clean data to simulate real-life measurement error
- **Validation:** hyperparameter optimization for # neurons
- **Comparison:** dropout Monte Carlo LSTM

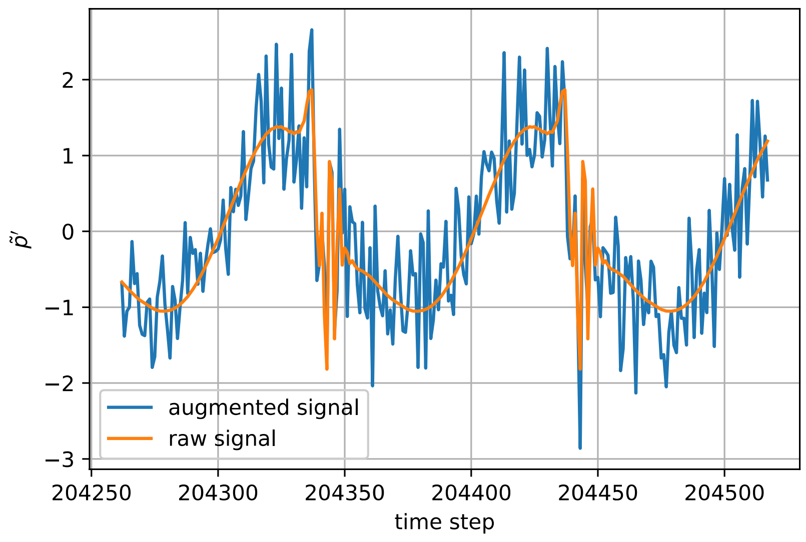
Hyperparameter optimization, test predictions

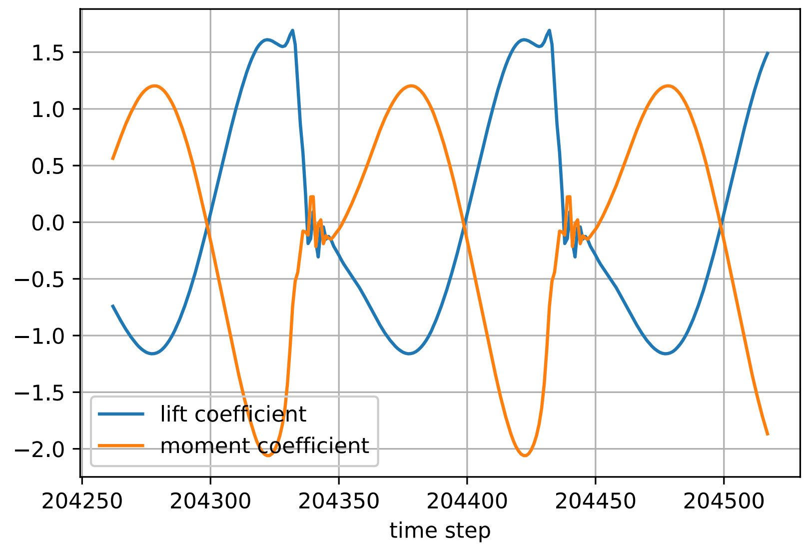


Model	C_L MSE Loss	C_M MSE Loss	Prediction time [s]
Bayesian LSTM	0.001516	0.0001307	721
Monte-Carlo Dropout LSTM	0.01168	0.001152	560

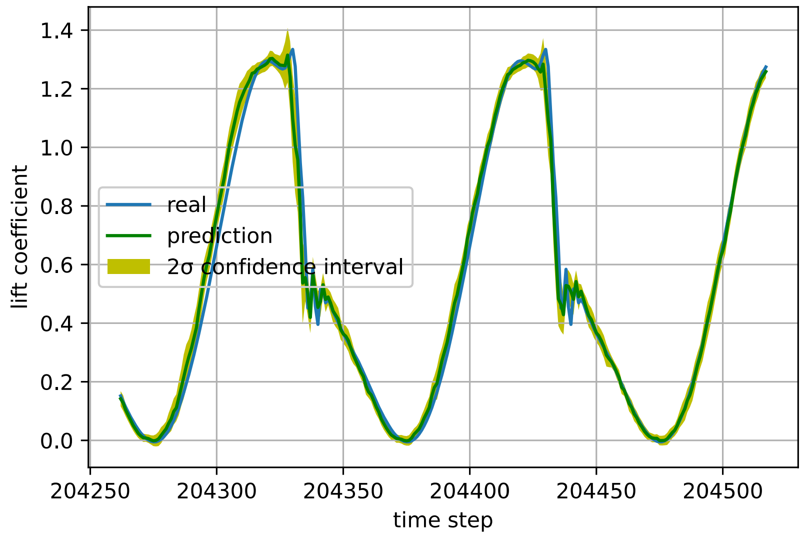
Sample model predictions from Bayesian LSTM

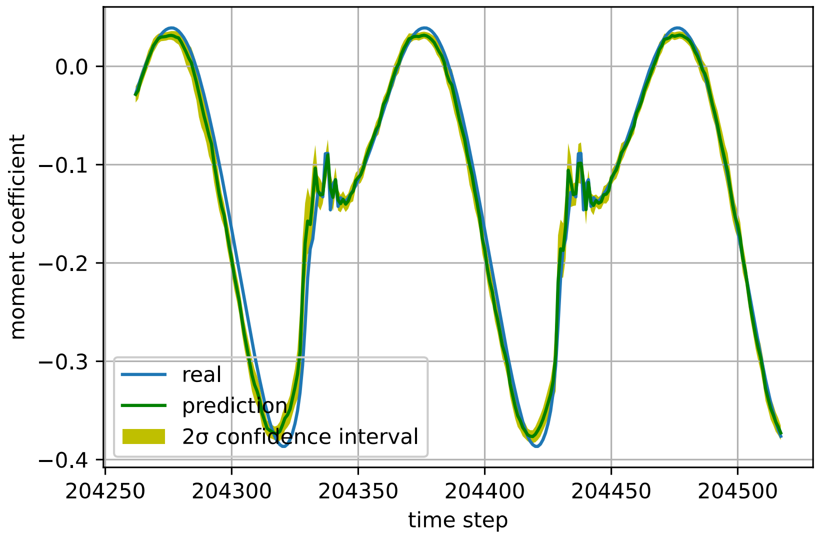
Simulation input and output





Bayesian LSTM prediction of C_L and C_M





Summary:

- Presented a Bayesian LSTM model
- Enabled time-series inputs and prediction quantities
- Employed Bayesian formulation for quantified uncertainty
- Illustrated promising preliminary performance

Future work:

- More simulation data with high-fidelity models
- Improve robustness under additional icing and flight conditions

Acknowledgement

This work is supported in part by:

- RHRK high performance computing center via the ‘Elwetritsch’ high performance cluster at the TU Kaiserslautern
- European Union’s H2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 721920