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Using artificial neural networks to predict synthetic fuel sprays from limited experimental data

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Introduction

Confidence intervals for neural network predictions (rather than a conventional validation exercise)

- ❖ Improve the usefulness neural networks as **engineering tools**
- ❖ Especially useful in cases with **limited training data** (limited experiment, cannot be augmented with CFD)
- ❖ In these cases conventional neural network training fails because:
 - ❖ The neural network is too simple to reflect the true physics (not enough nodes / connections) OR
 - ❖ The neural network is undertrained and unpredictable (too many variables to fix using the available data)

What is our approach?

- ❖ We accomodate **uncertainty** into confidence intervals. Two sources of uncertainty:
 - ❖ Uncertainty arising from experimental data (sample error)
 - ❖ Uncertainty arising from the neural network model (trained with a limited data set)

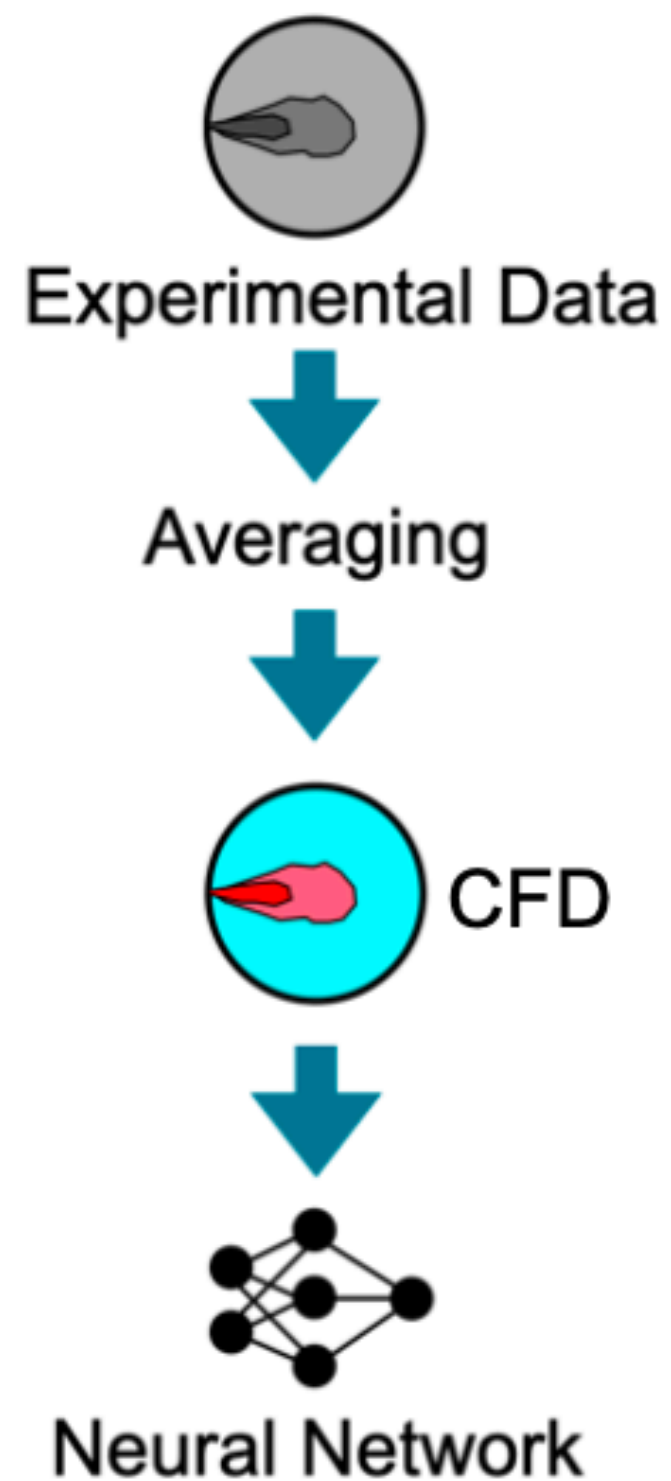
Complete study available in:

Richards, Bryn, and Nwabueze Emekwuru. *Prediction of spray and vapour tip penetration of diesel, biodiesel and synthetic fuels using artificial neural networks with confidence intervals*. SAE Technical Paper 2023-01-0315.

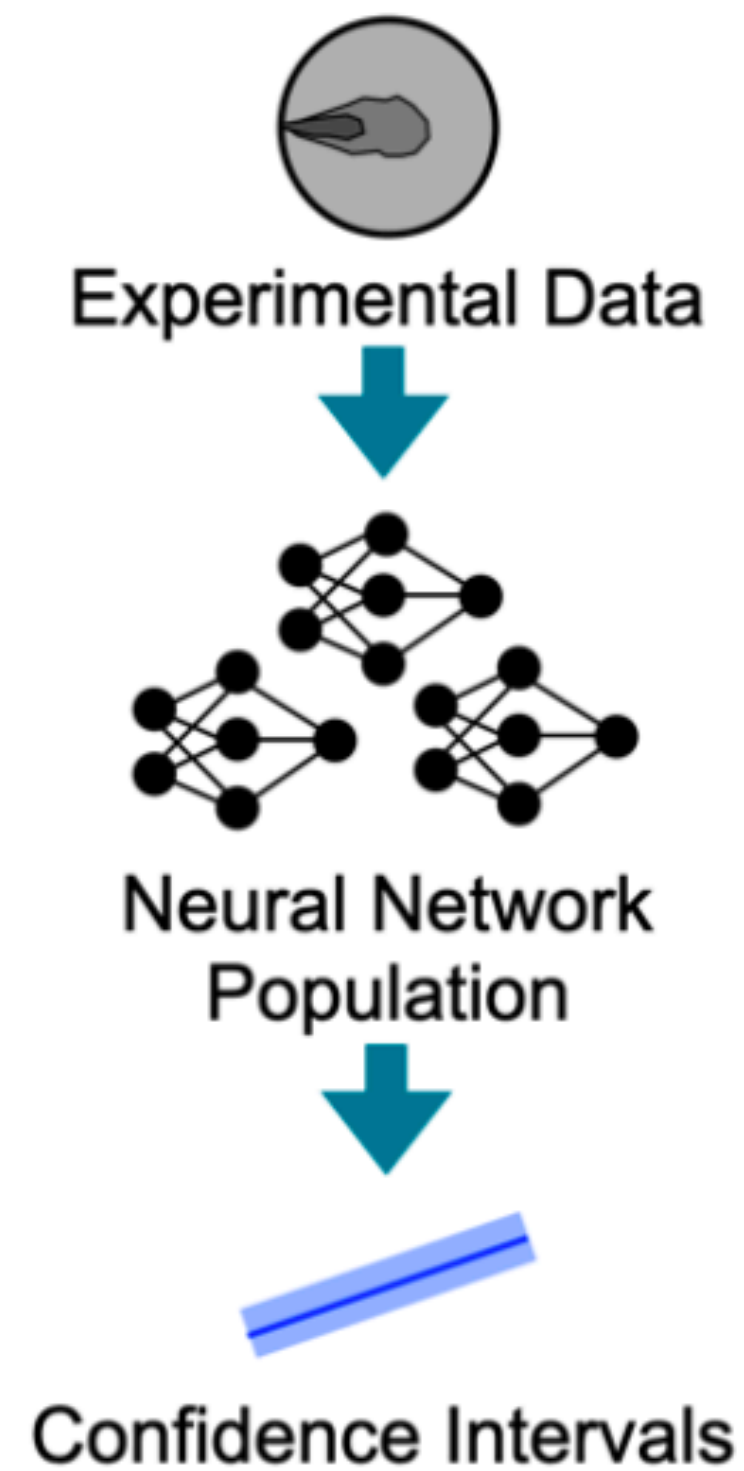


Introduction

CFD Data Augmentation



Neural Network Confidence Intervals



Problem: There isn't enough experimental data to train a neural network.

- ❖ If we use our limited data to train a suitably complex network, we over-fit the data.
- ❖ Networks that we can train robustly are too simple to fit the data.
- ❖ We must 'rob' our limited data for testing and validation.

Can we reach useful conclusions from machine learning without huge data sets or CFD?

We break the over-simple / over-fit dilemma by coping with uncertainty and confidence intervals.

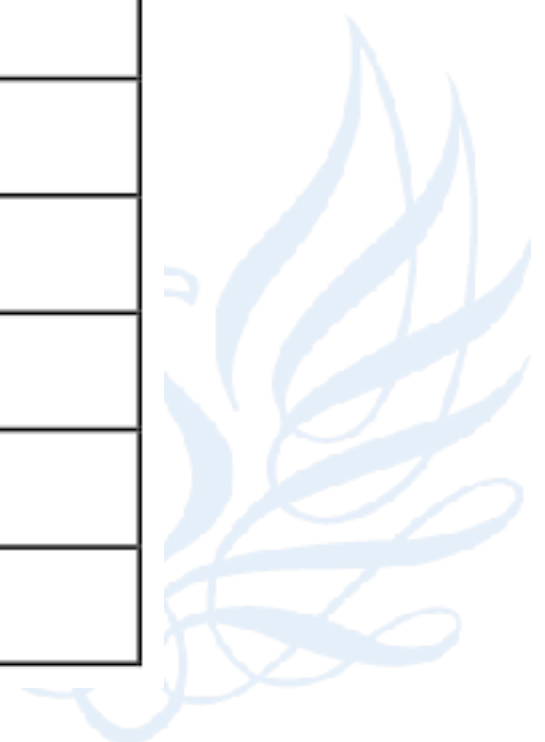


Experimental Setup

- ❖ Spray penetration data of Liu et al. [Liu, Yu, Junjian Tian, Zhihui Song, Fengyu Li, Wenliang Zhou, and Qizhao Lin. “Spray Characteristics of Diesel, Biodiesel, Polyoxymethylene Dimethyl Ethers Blends and Prediction of Spray Tip Penetration Using Artificial Neural Network.” Physics of Fluids 34, no. 1 (2022): 015117]
- ❖ Constant volume combustion chamber, quartz windows, back-lit, 20k frames per second camera
- ❖ 4x injection pressures, 4x fuel blends, spray penetration measured every 0.05 ms
- ❖ Each injection condition was repeated five times, average and standard deviation were reported
- ❖ This study uses average and standard deviation to reproduce 5x repeat samples per measurement

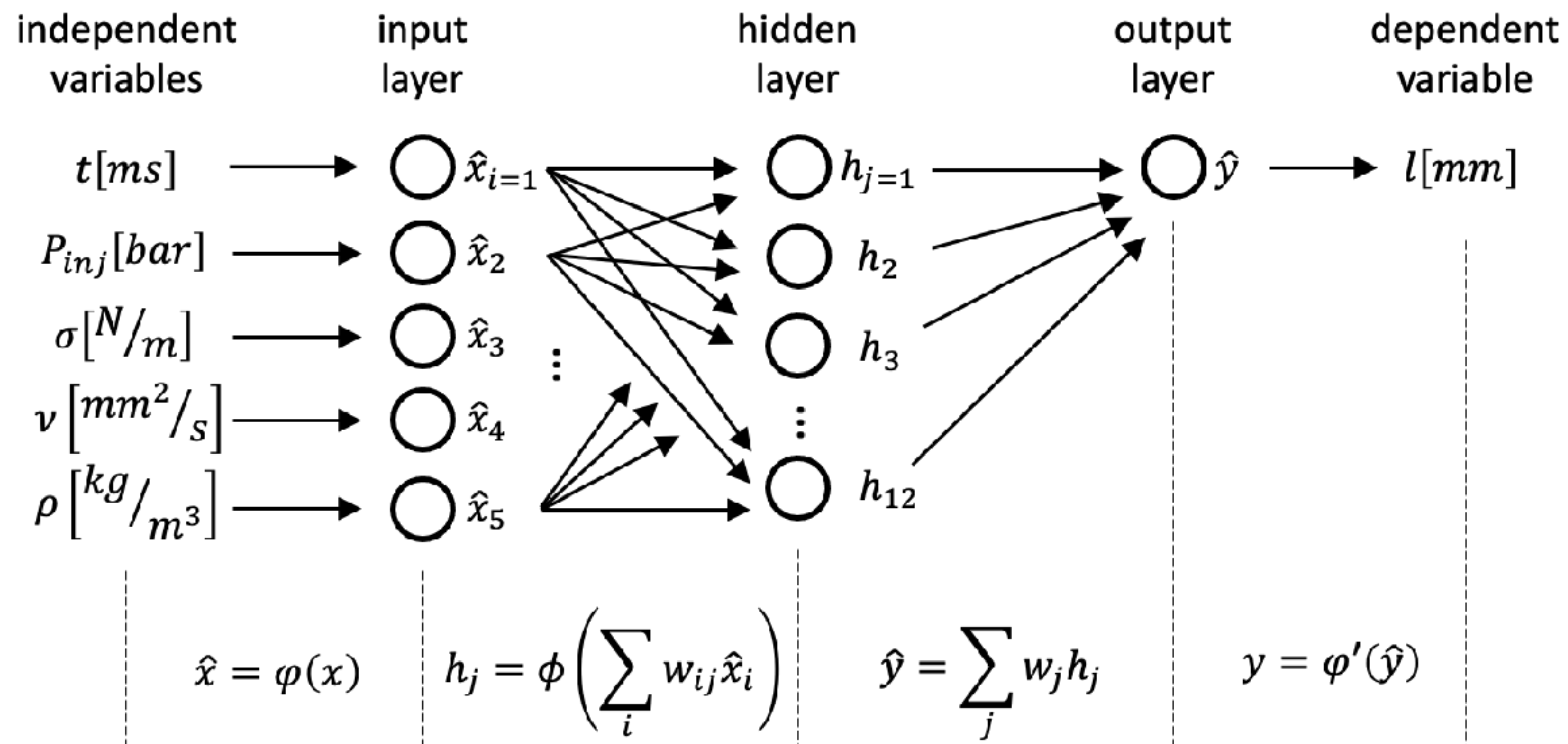
Fuel name	Density, ρ	Kinematic Viscosity, ν	Surface Tension, σ
–	$\left[\frac{kg}{m^3}\right]$	$\left[\frac{mm^2}{s}\right]$	$\left[\frac{N}{m}\right]$
D100 (Diesel 100%)	821	4.28	27.32
DP20 (Diesel 80%, OME 20%)	857	3.40	27.71
B100 (Biodiesel 100%)	865	6.88	29.43
BP20 (Biodiesel 80%, OME 20%)	894	4.67	28.89

Fuels	D100, DP20, B100, BP20
Injection pressure, P_{inj}	60, 90, 120, 150 MPa
Fuel temperature	300 K
Ambient pressure (chamber)	2 MPa
Ambient temperature (chamber)	300 K
Ambient gas (chamber)	Nitrogen
Injection duration, t	1.5 ms
Nozzle hole diameter	0.3 mm
Number of injector holes	1
Injector manufacturer	Bosch (0445120224)

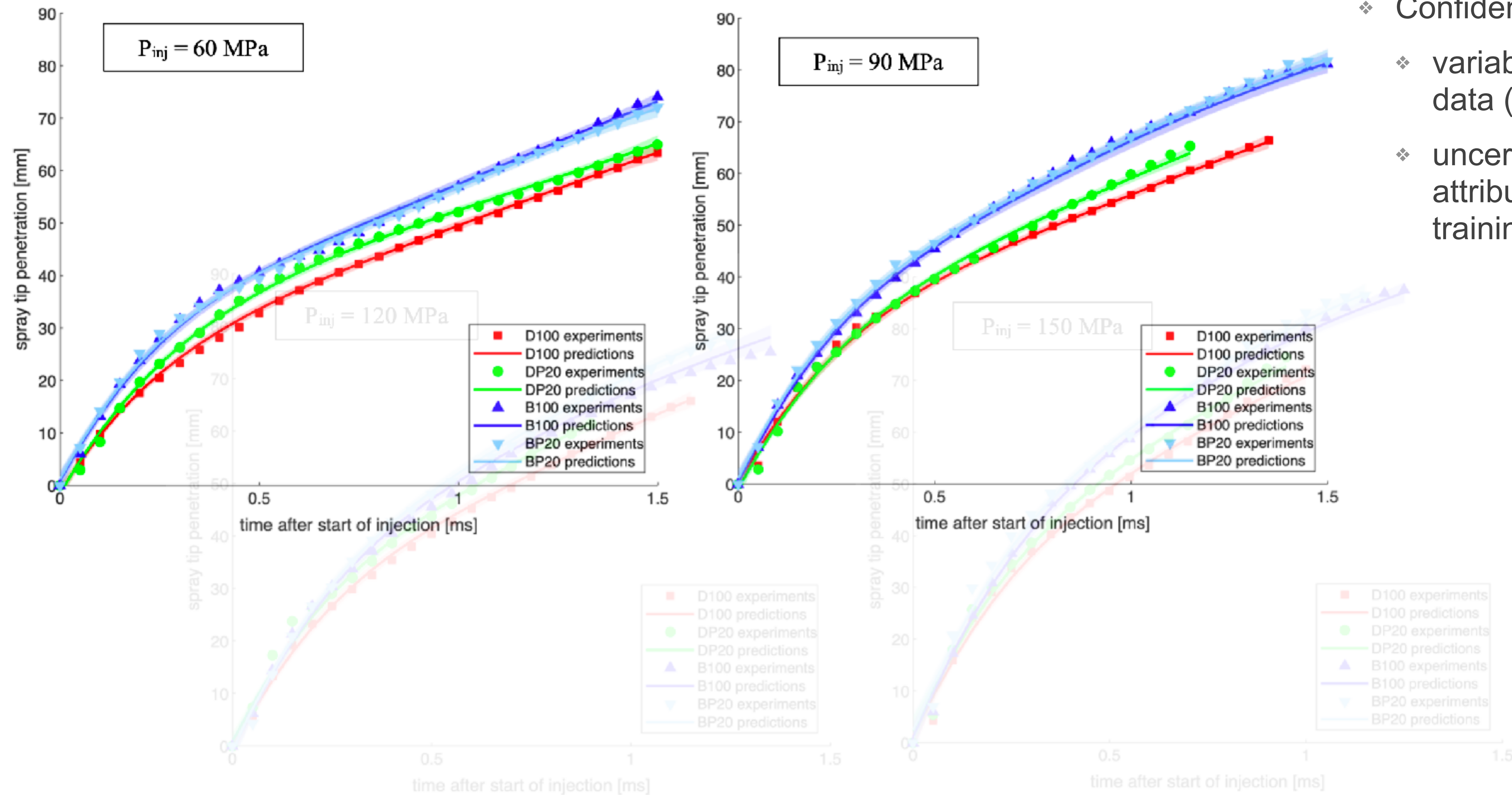


Neural Network Setup

- ❖ Fixed learning rate (0.001) with Levenberg-Marquardt training algorithm [Zhang (2019) Carbon 148:115-123]
- ❖ Hyperbolic tangent activation function [Ansari (2018) Int. Comm. Heat and Mass Transfer 91:158-164]
- ❖ used MatLab's NN Toolbox, MathWorks' cloud server
- ❖ suppressed default convergence criteria / trained to a fixed epoch number



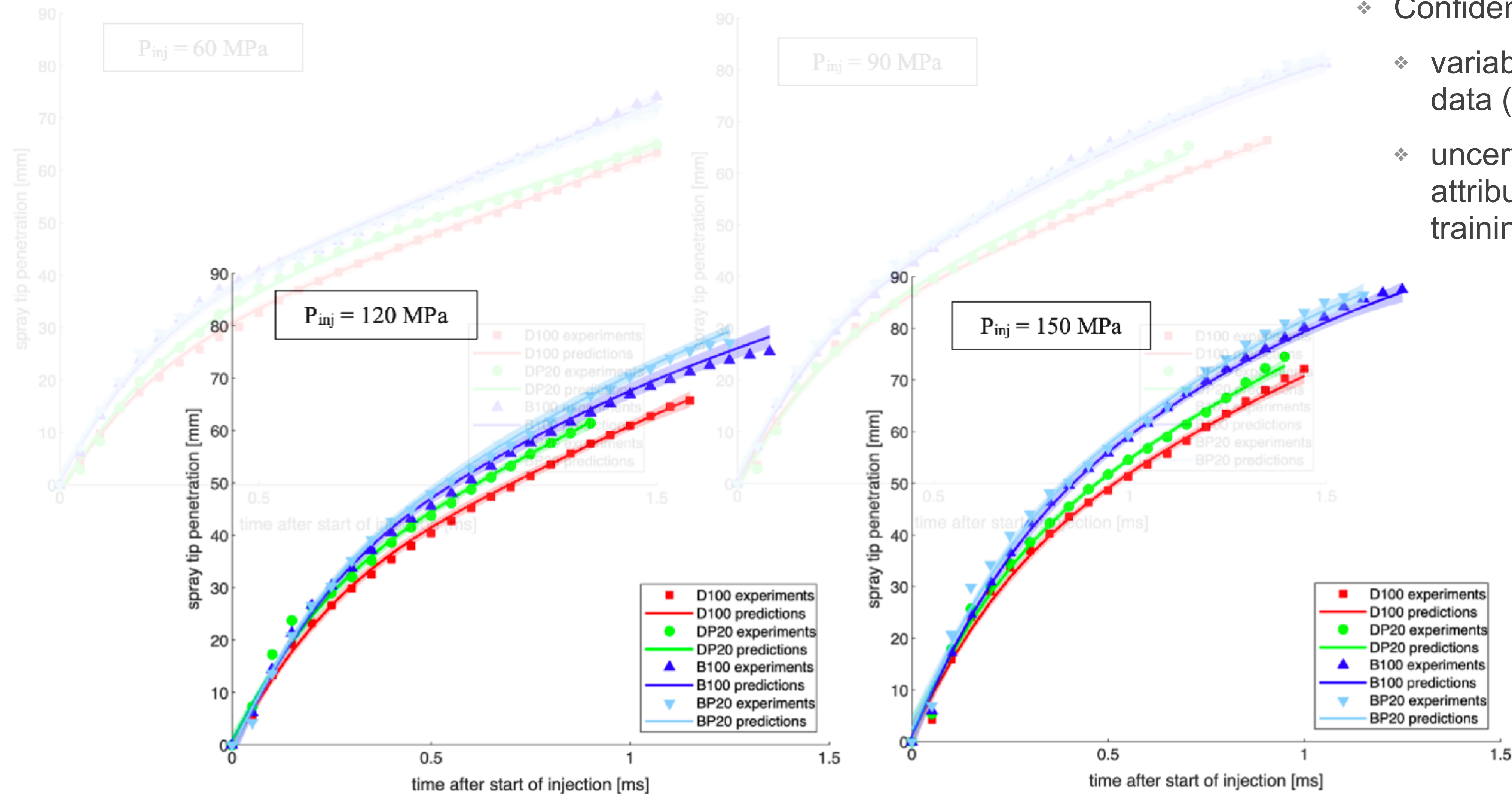
Results



- ❖ Confidence intervals reflect:
 - ❖ variability in experimental data (repeat sampling) and
 - ❖ uncertainty in the model attributed to of under-training



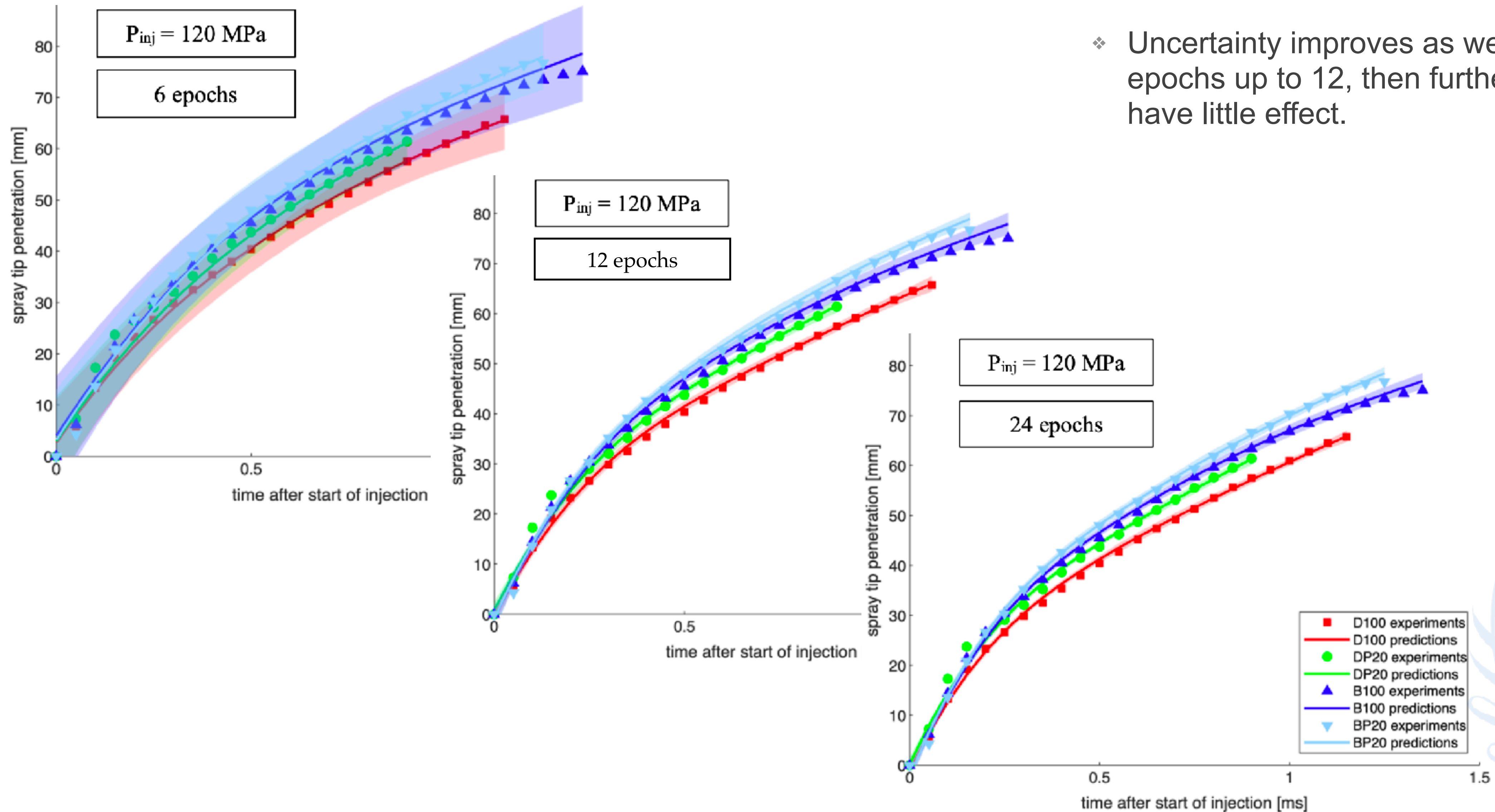
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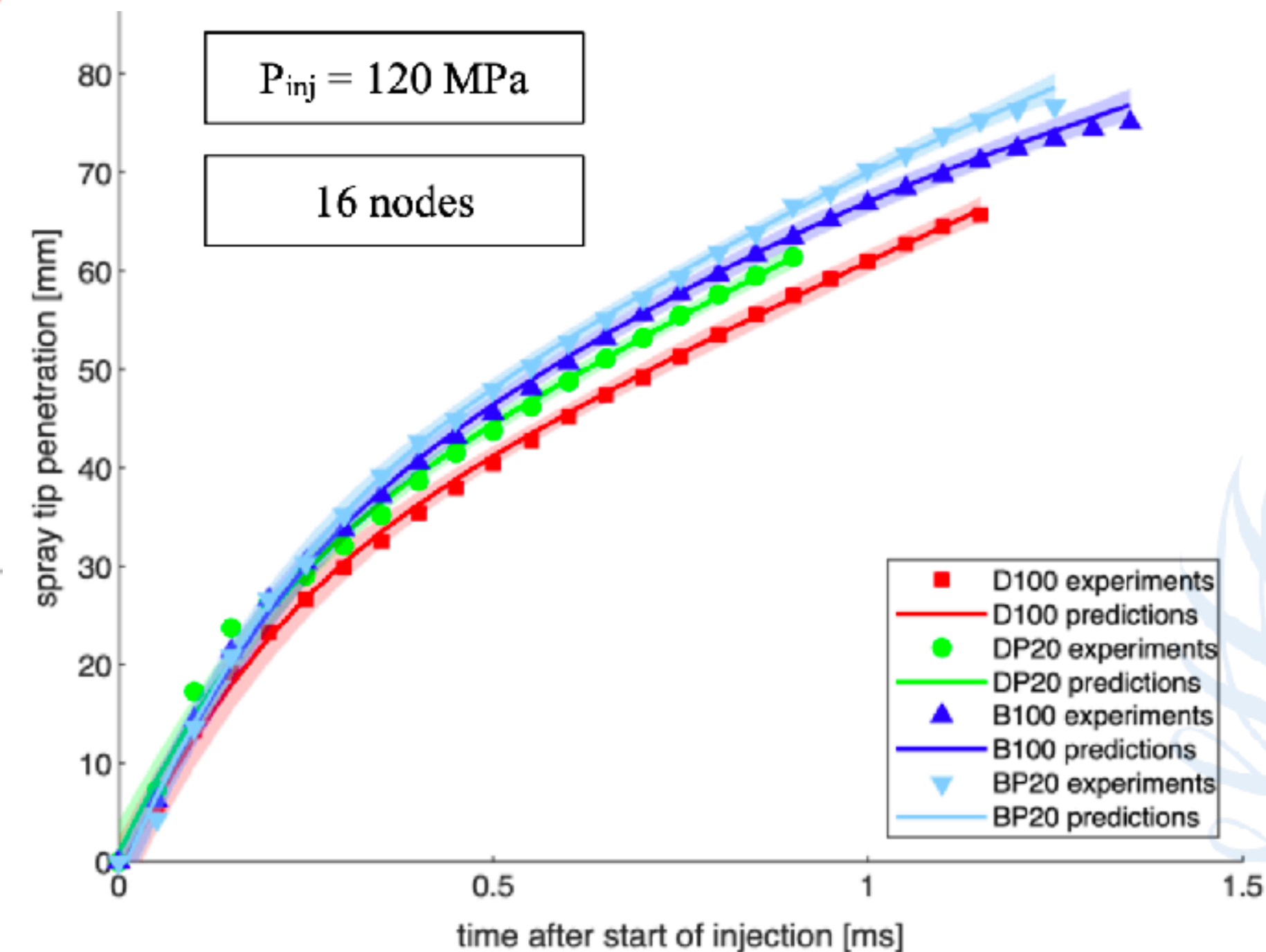
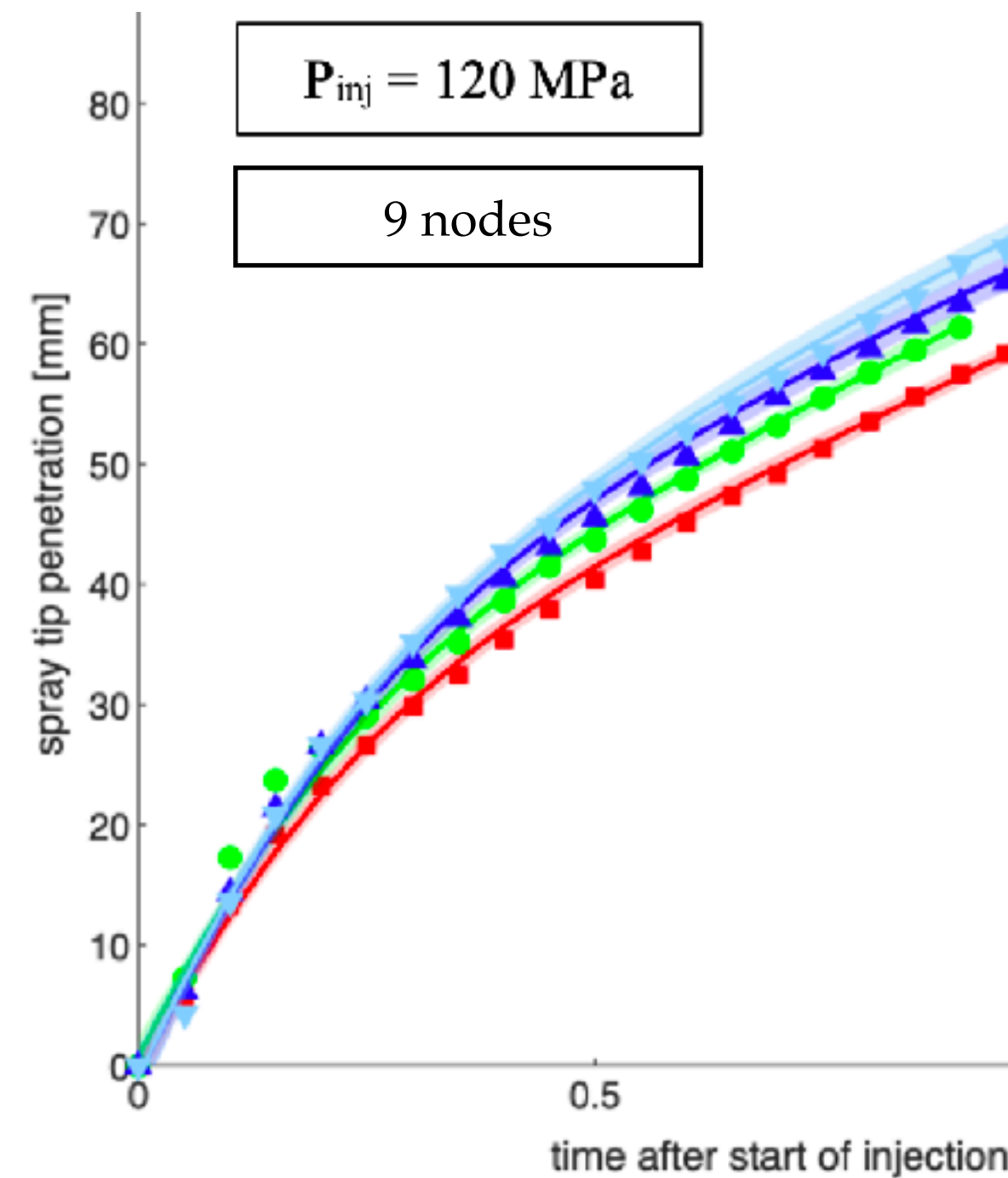
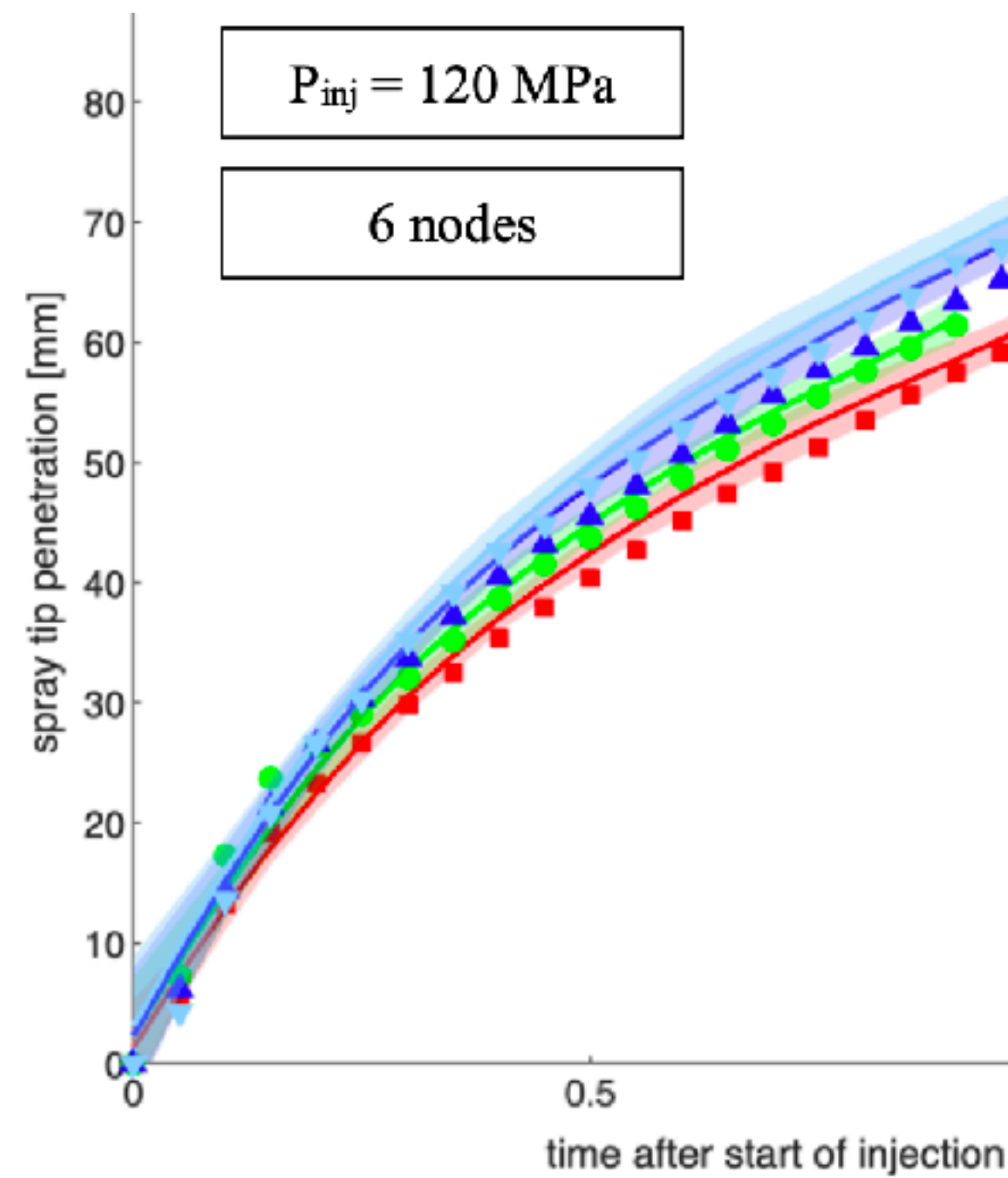


Results — Sensitivity Studies



- ❖ Uncertainty improves as we add training epochs up to 12, then further training epochs have little effect.

Results — Sensitivity Studies



- ❖ Mean predictions move closer to experimental values when more nodes are used (with diminishing returns)
- ❖ Computation time increases markedly with increasing node number
- ❖ Confidence intervals also become tighter (marginally)

Next Steps

A **weakness** of the present work is its ability to extrapolate from results beyond the experimental input data

Next we aim to improve the predictive power of our method by introducing **physics-informed** constraints to the models.

We would like to **partner** with labs in the **ECN**

- ❖ Making use of **raw data** with repeat sampling (not resampled averaged data)
- ❖ Especially working across a range of fuel blends



Conclusions

Confidence intervals improve the usefulness of neural networks for engineering applications

- ❖ **Confidence intervals** make neural networks feasible in situations with limited training data

We aim to improve the **predictive power** of neural networks using **physics-informed** model constraints

We welcome **partnership** with labs in the **ECN**.

Please see the **complete study** available in:

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