Fault Detection and Accommodation of Time Series Pressure Measurements in Hypersonic Vehicles

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Agenda

Motivation

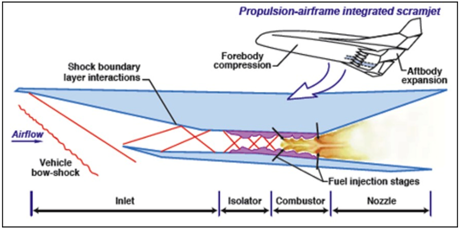

Figure: Hypersonic Engine. Source: NASA Langley Website (https://www.researchgate.net/figure/Scramjet-engine-Source-NASA-Langley-website_fig1_337655900).

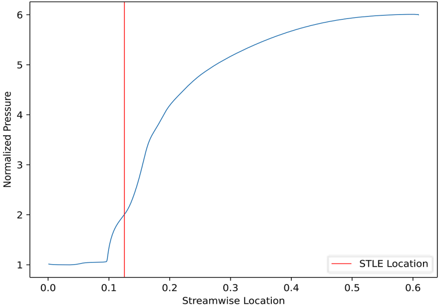

Figure: A computational fluid dynamics (CFD) pressure profile with indicated STLE location.

- Shocks increase pressure and temperature, which aids combustion.
- Tracking the shock train leading edge (STLE) is important for engine efficiency and stability, but it moves around the engine rapidly and unsteadily.
- The pressure profile provides insight into the location of the STLE.

Motivation

The Adaptive Pressure Profile (APP) + base method model has seen success in predicting the STLE location using pressure measurements. Thus, we need accurate pressure measurements to track the STLE position.

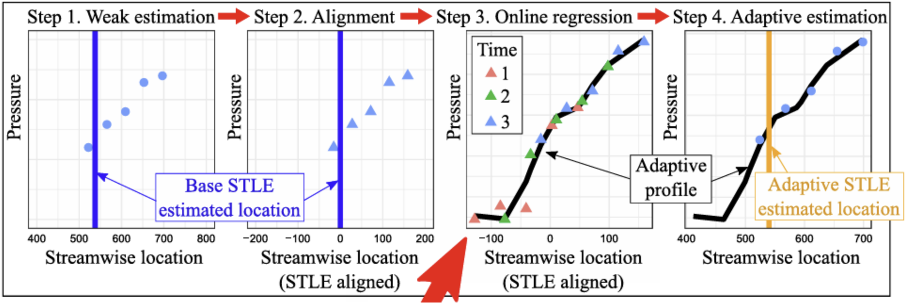

Figure: APP Method.

Hunt, G., and R. Hunt. "Locating the isolator shock-train leading edge with limited pressure information." *Journal of Propulsion and Power* 37, no. 6 (2021): 876-892.

Fault Modes

The hostile environment inside the engine causes failures in the pressure sensors, obscuring the STLE position.

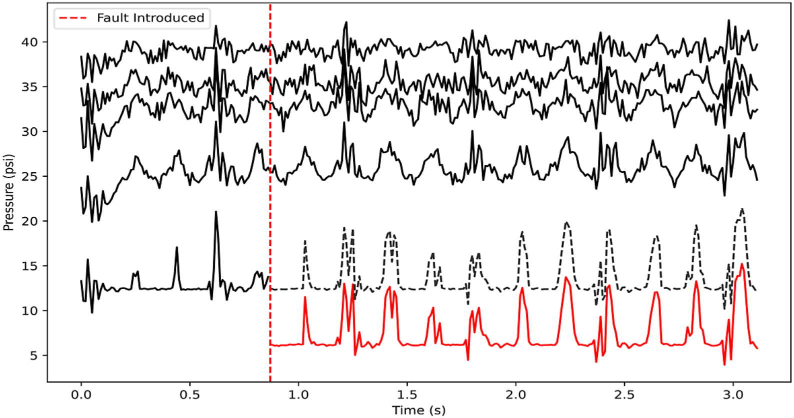

Figure: Bias fault applied to a Michigan run.

Fault Modes

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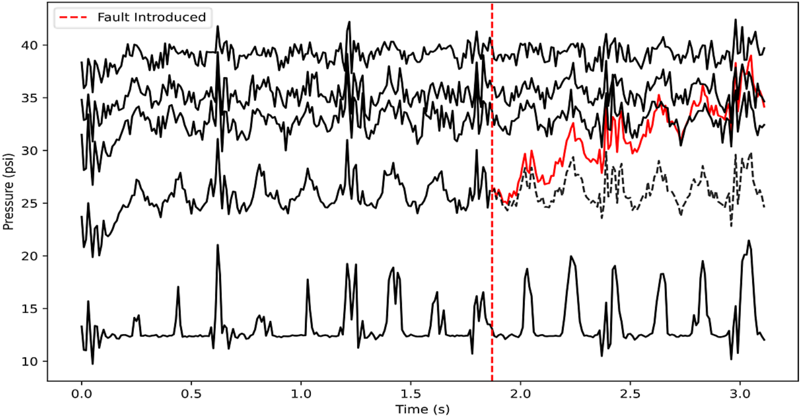

Figure: Drift fault applied to a Michigan run.

Fault Modes

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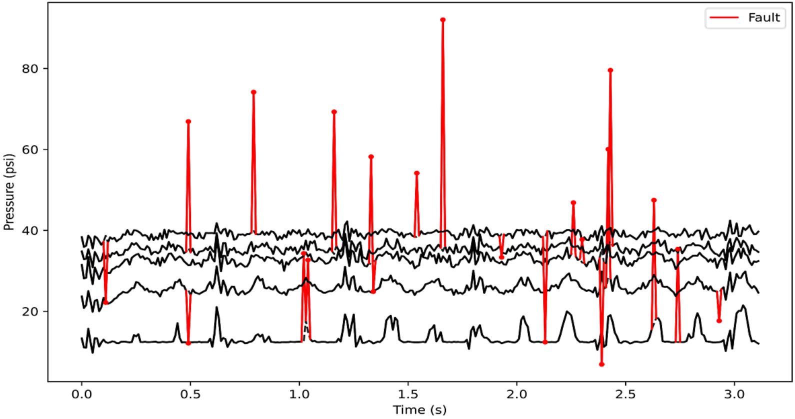

Figure: Intermittent faults applied to a Michigan run.

Fault Modes

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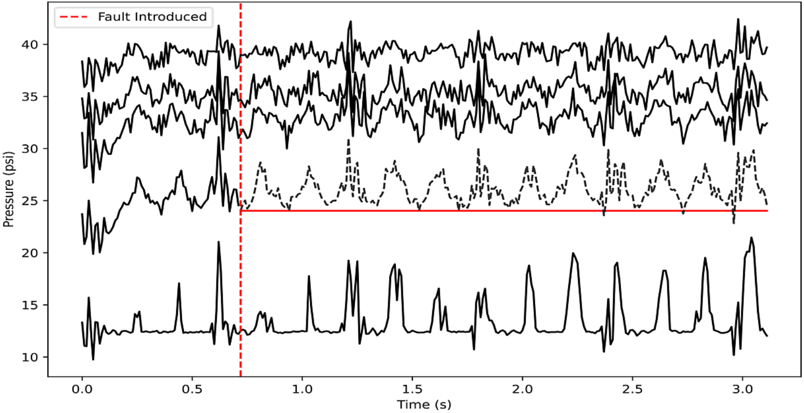


Figure: Constant fault applied to a Michigan run.

Models

Algorithmic model-based fault detection in pressure sensors

- Traditional anomaly detection algorithms: Isolation forests, One-class SVMs, Windowed z-score.
- Gaussian Process Regression spline fit to ground test data.
- Autoencoder neural networks with predictive models and fault detection strategies:
    - Model architectures: Simple Feedforward, CNN, LSTM with self-attention (SLAE).
    - Strategies: Threshold for L_2 reconstruction error from training, Probability distribution reconstruction.

Models

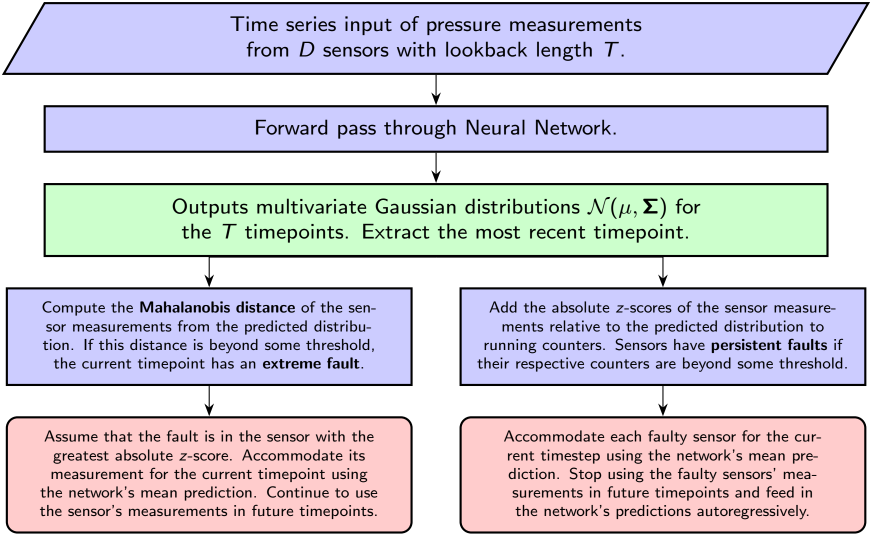
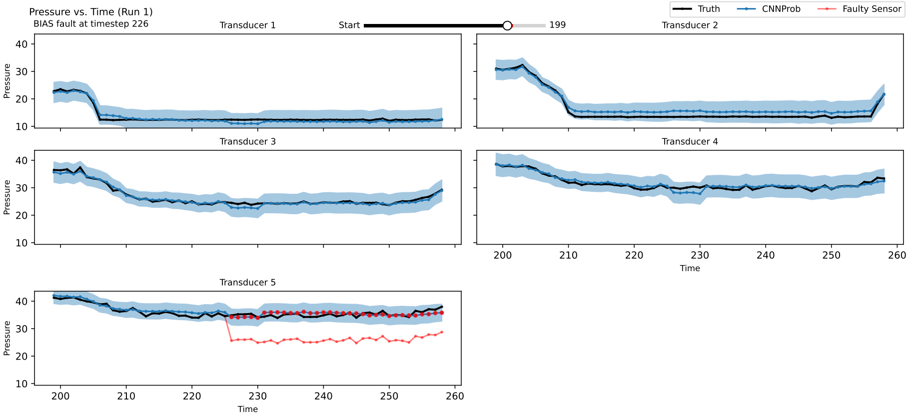


Figure: Probabilistic detection strategy.

Detecting and Accommodating Faults

The probabilistic CNN autoencoder detects most significant faults.



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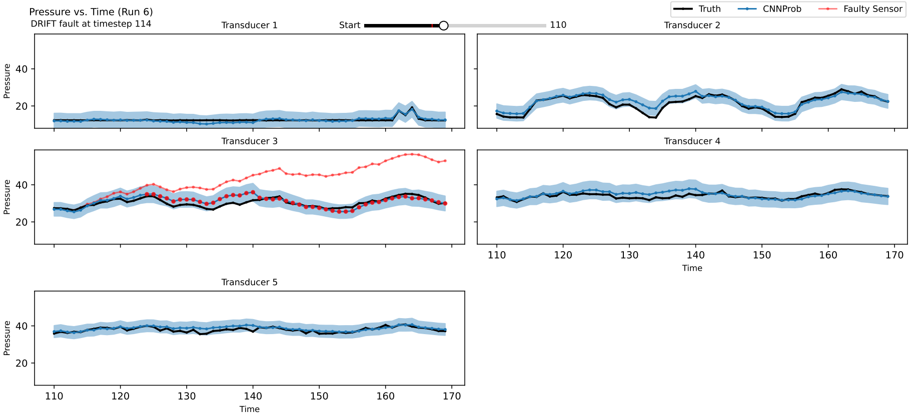

Figure: Drift fault in a Michigan run.

Detecting and Accommodating Faults

The probabilistic SLAE autoencoder often has even better performance and can effectively detect upstream faults and multiple faults.

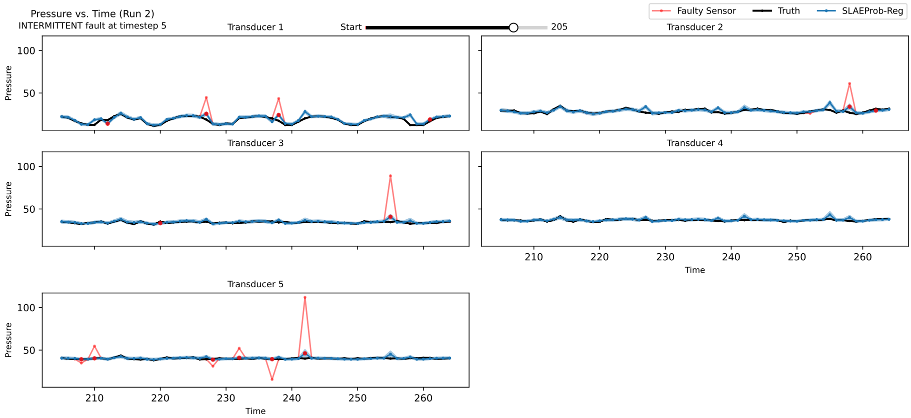

Figure: Intermittent faults in a Michigan run.

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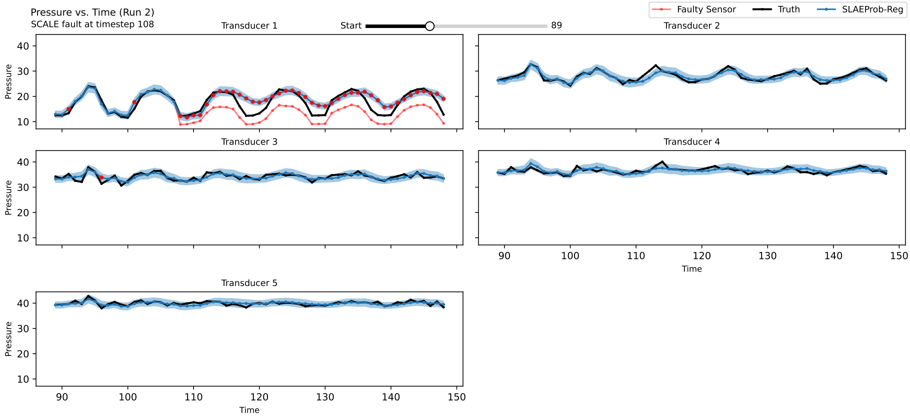

Figure: Upstream scale fault in a Michigan run.

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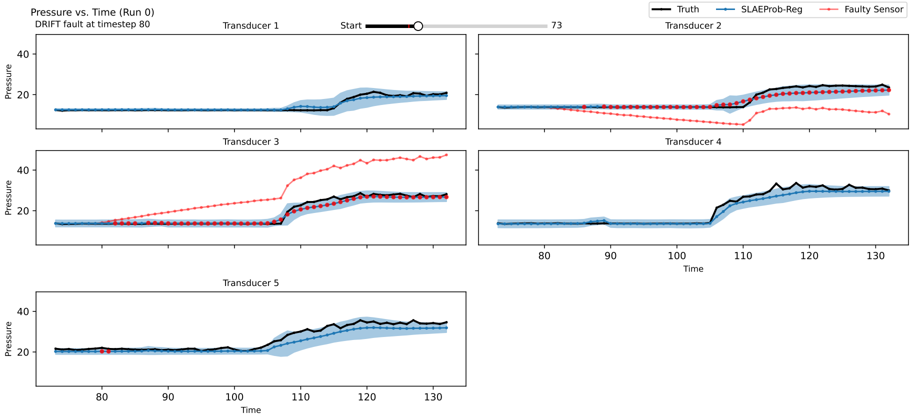

Figure: Multiple drift faults in a Michigan run.

Detecting and Accommodating Faults

The models see success in simulations with challenging conditions.

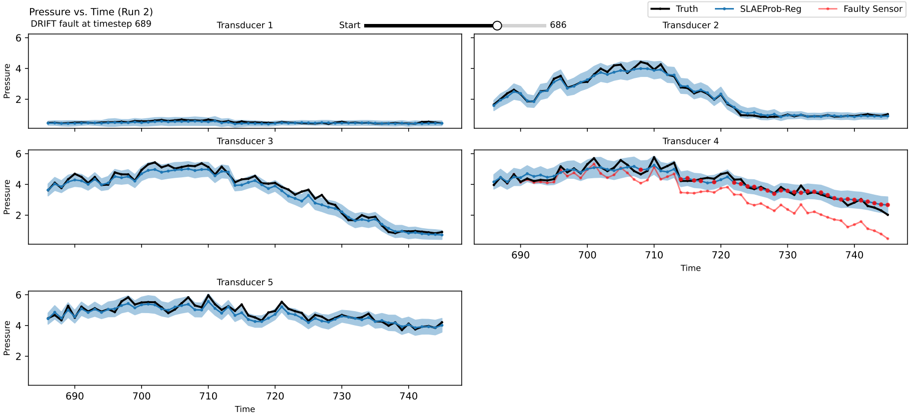

Figure: Drift fault in simulated data.

Some models can also generalize reasonably well from training purely on simulated data to detecting faults in Michigan data.

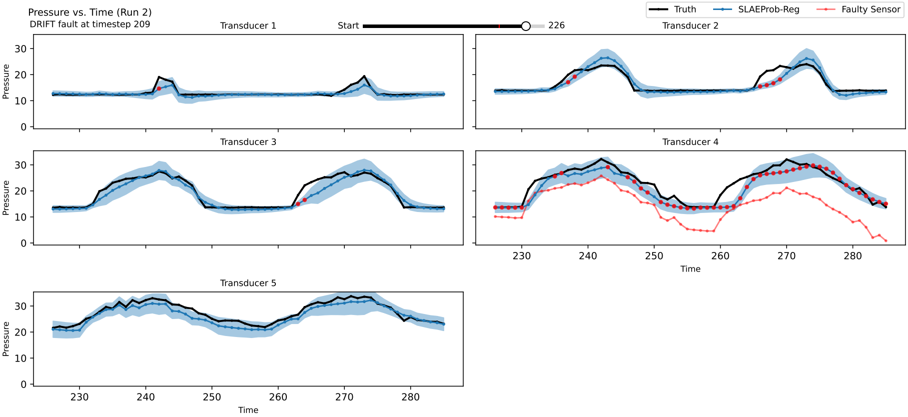

Figure: Drift fault in Michigan data.

STLE Tracking

Accommodation significantly improves STLE prediction and uncertainty.

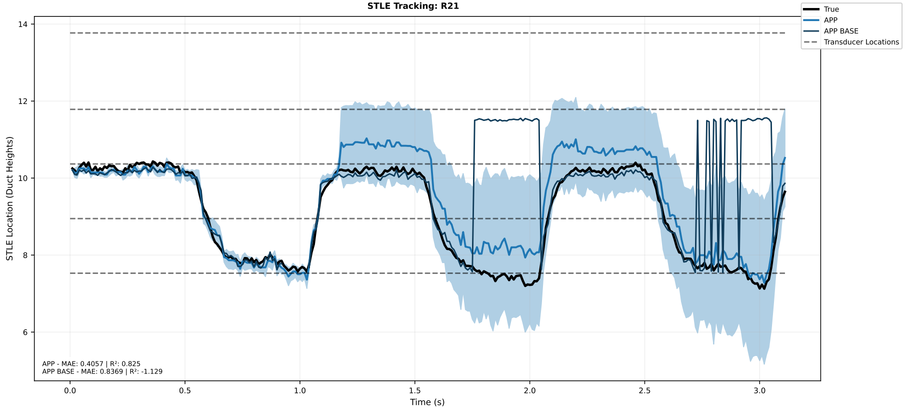

Figure: Predictions under a scale fault before accommodation in a Michigan run.

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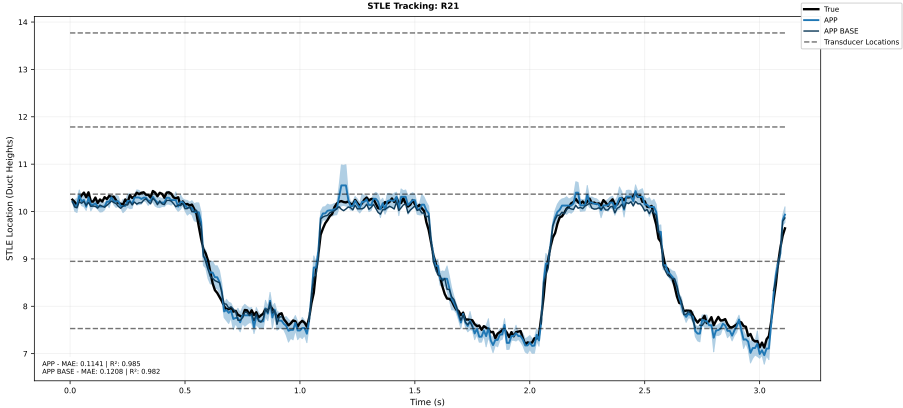

Figure: Predictions under a scale fault after accommodation with the probabilistic SLAE model in a Michigan run.

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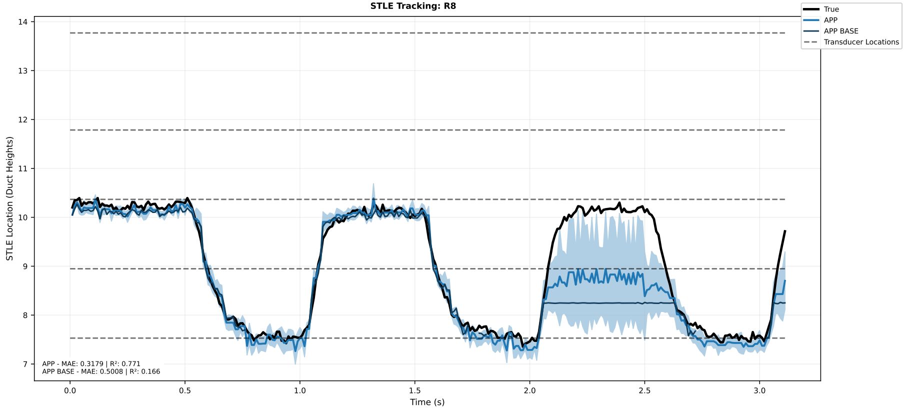

Figure: Predictions under a constant fault before accommodation in a Michigan run.

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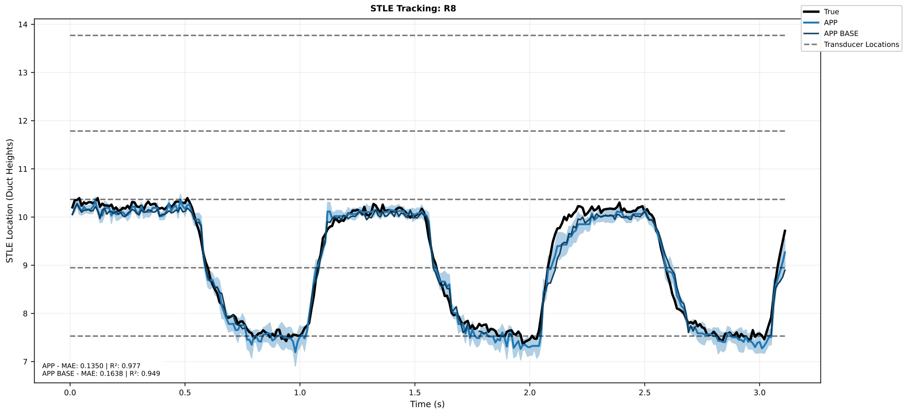

Figure: Predictions under a constant fault after accommodation with the probabilistic SLAE model in a Michigan run.

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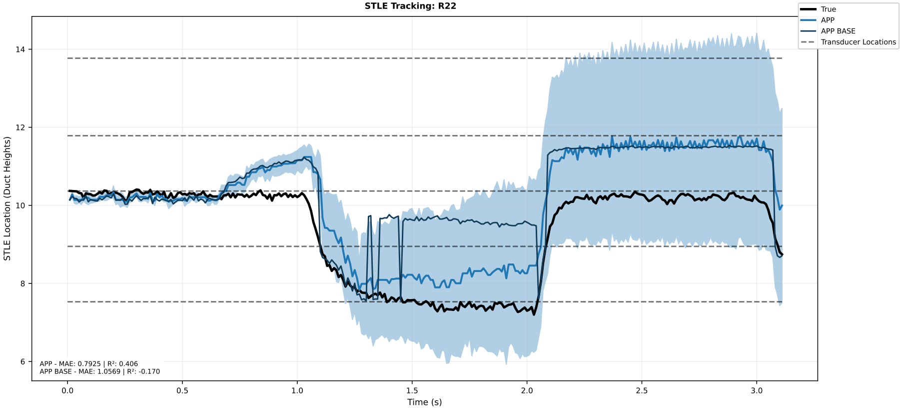

Figure: Predictions under a drift fault before accommodation in a Michigan run.

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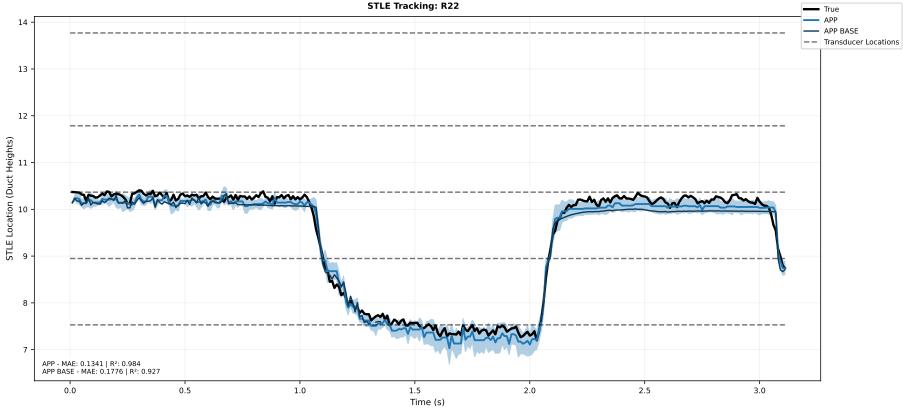

Figure: Predictions under a drift fault after accommodation with the probabilistic SLAE model in a Michigan run.

Results

Table: Fault detection metrics with 95% confidence intervals on Michigan test runs.

Model	Experiment	Recall	F1 Score	Reconstruction MAE	STLE MAE
One-class SVM	Test runs	0.41 ± 0.05	0.14 ± 0.03	—	0.23 ± 0.03
	Many faults	0.30 ± 0.04	0.12 ± 0.02	—	0.33 ± 0.05
	Upstream faults	0.31 ± 0.04	0.06 ± 0.01	—	0.27 ± 0.03
CNN–Prob	Test runs	0.49 ± 0.05	0.33 ± 0.04	0.091 ± 0.004	0.18 ± 0.01
	Many faults	0.37 ± 0.04	0.29 ± 0.04	0.135 ± 0.021	0.25 ± 0.04
	Upstream faults	0.37 ± 0.04	0.20 ± 0.02	0.090 ± 0.005	0.20 ± 0.01
SLAE–Prob	Test runs	0.79 ± 0.02	0.26 ± 0.03	0.070 ± 0.005	0.17 ± 0.01
	Many faults	0.68 ± 0.04	0.29 ± 0.04	0.092 ± 0.011	0.21 ± 0.03
	Upstream faults	0.72 ± 0.05	0.15 ± 0.01	0.067 ± 0.004	0.16 ± 0.01
SLAE–Thresh	Test runs	0.70 ± 0.04	0.32 ± 0.04	0.074 ± 0.004	0.18 ± 0.01
	Many faults	0.55 ± 0.05	0.30 ± 0.03	0.110 ± 0.016	0.26 ± 0.04
	Upstream faults	0.64 ± 0.05	0.22 ± 0.02	0.096 ± 0.004	0.19 ± 0.01

Reconstruction and STLE errors are normalized by tare pressure and duct height, respectively.
The STLE MAE without faults is 0.13, and that with faults but no accommodation is slightly worse than when using the SVM model.

Conclusions and Future Work

- Realistic faults can cause significant problems for STLE prediction.
- Faults tend to be harder to detect in upstream transducers and when multiple faults are present.
- The autoencoder neural network systems can detect many problematic faults, and false positives are often fine because the mean predictions are close to the real pressures.
- Probabilistic methods show promise in being more effective for fault detection in time series analysis than traditional methods.
- Fault detection and accommodation drastically improves STLE prediction in the presence of most faults across datasets.

- Ensemble methods may increase efficacy at the cost of efficiency.
- Using new time series neural networks might improve performance.