Enhancing Predictive Maintenance in Used Oil Re-Refining: a Hybrid Machine Learning Approach

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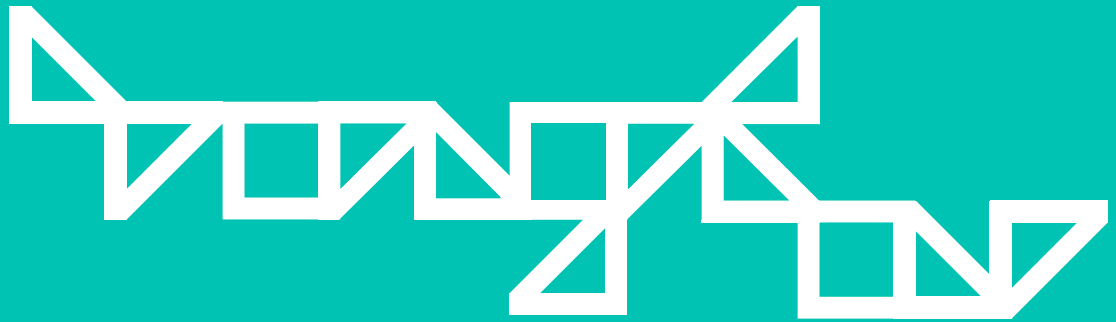

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July 6 - 9, 2025, Ghent, Belgium

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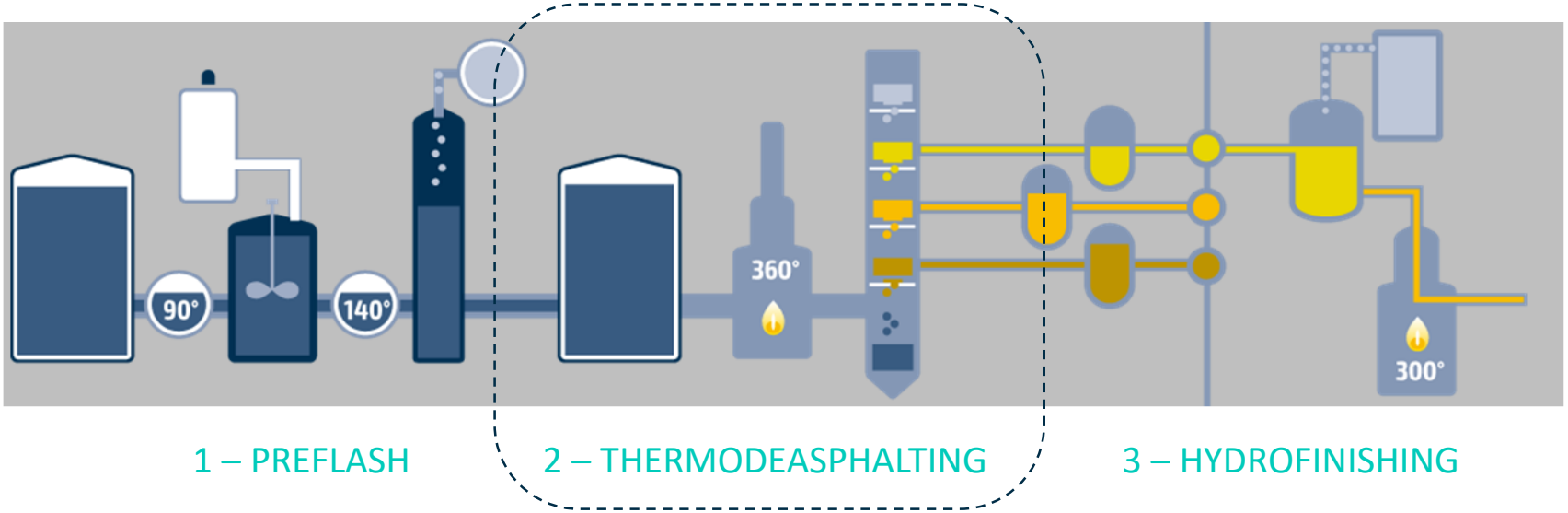
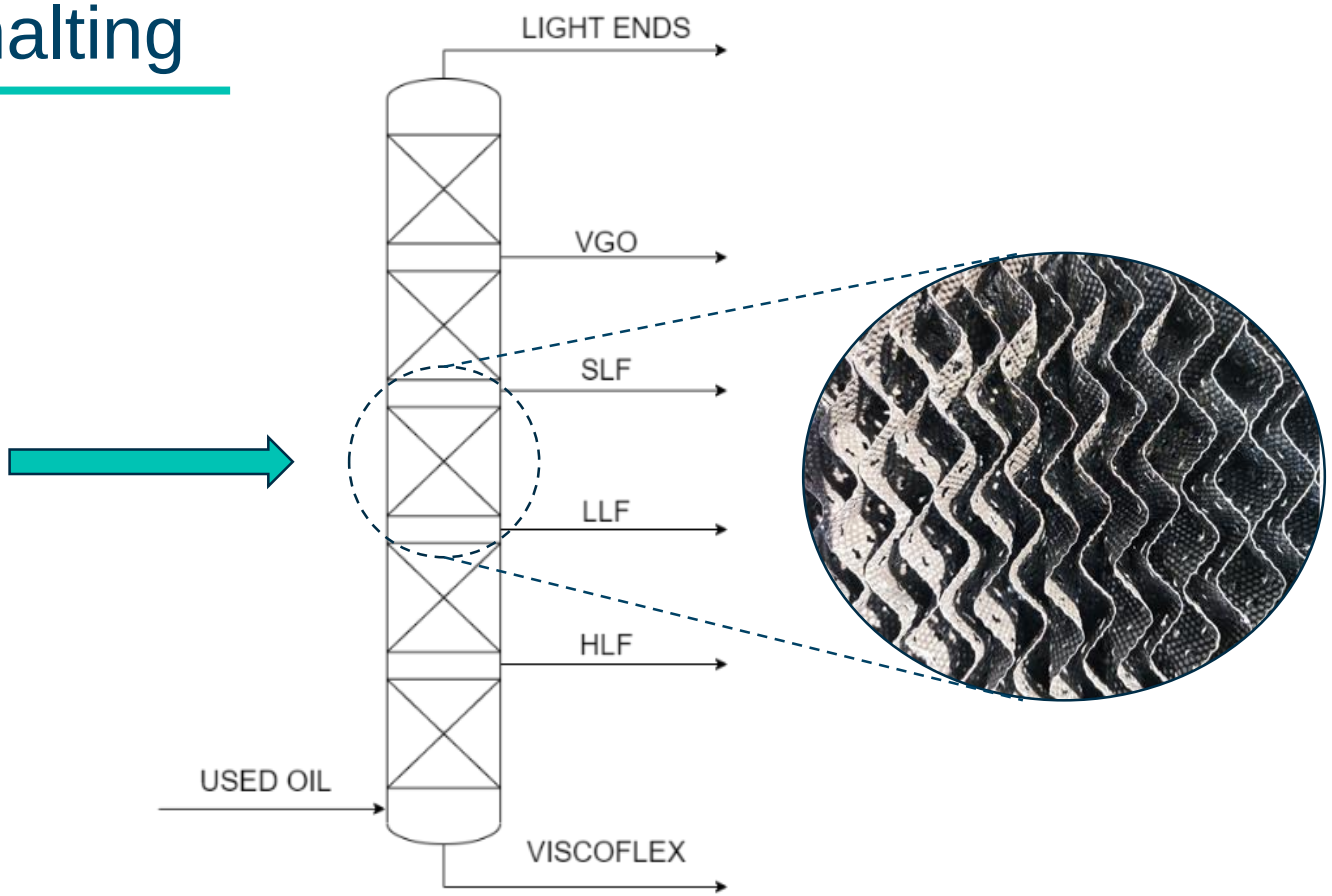
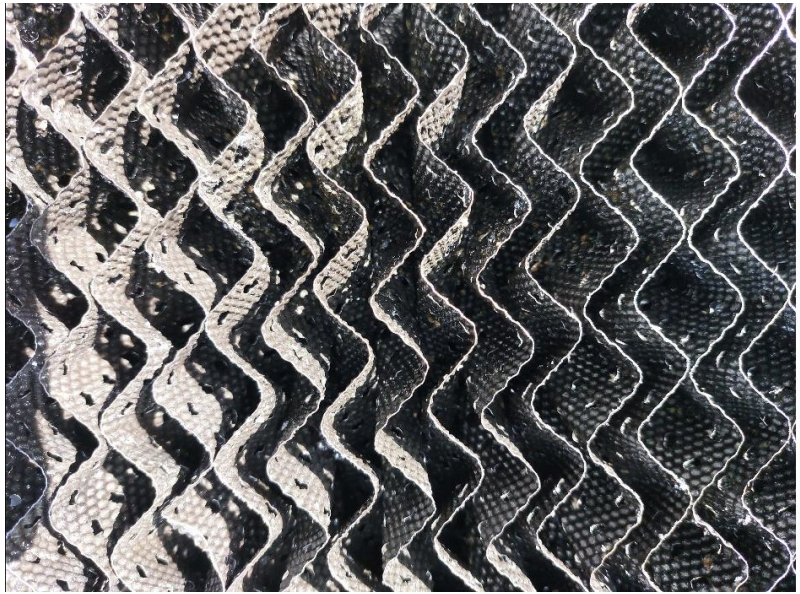


Thermodeasphalting



Fouling



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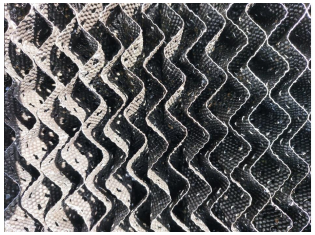
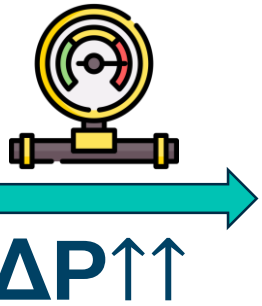
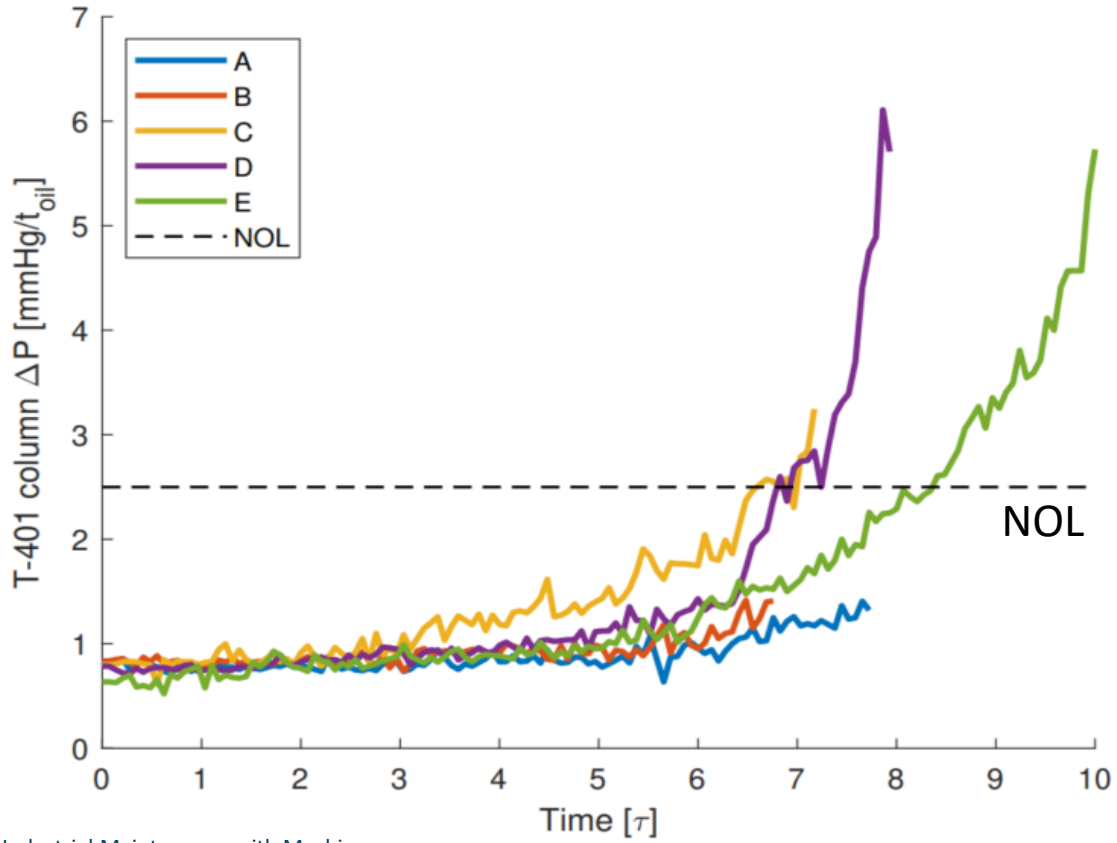




Fouling

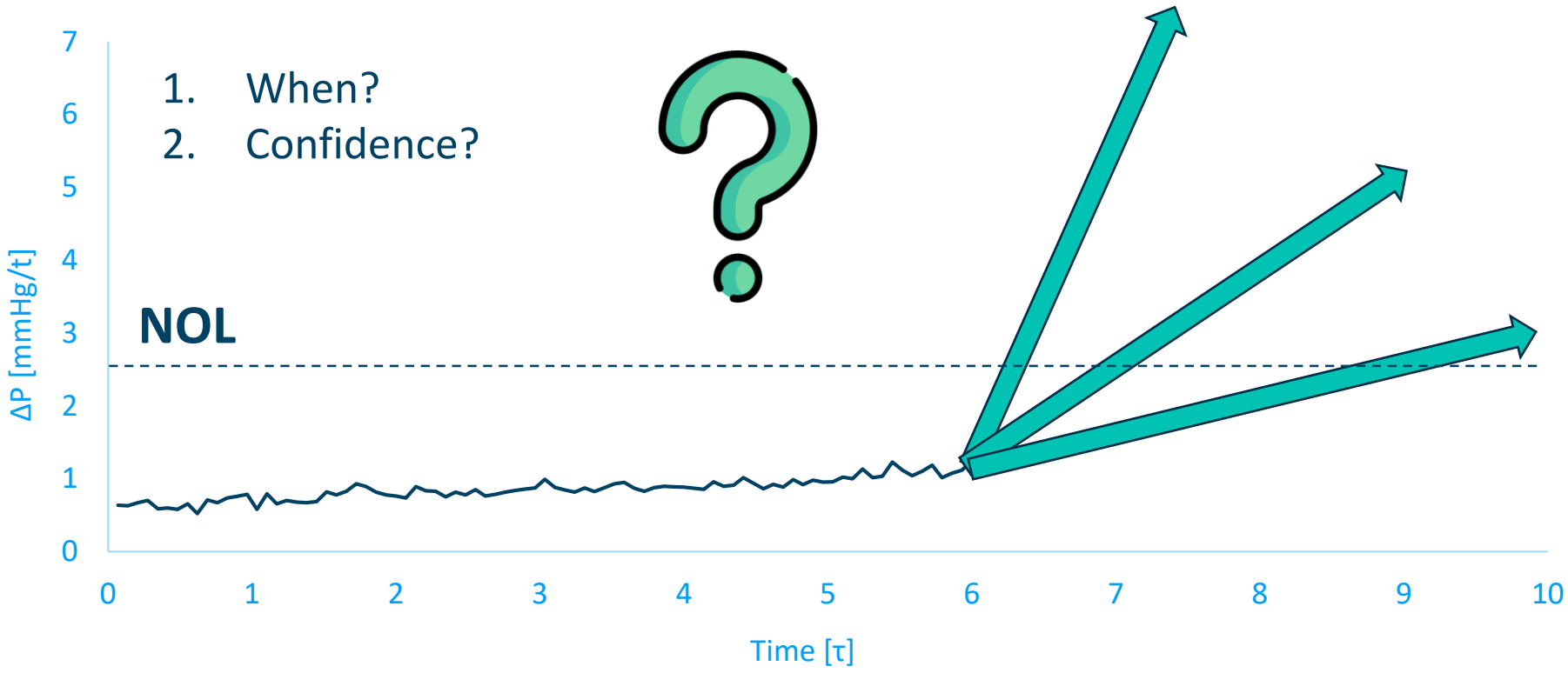
NOL: Normal Operations Limit

Operations become economically disadvantageous above the NOL



Negri, F., Galeazzi, A., Gallo, F., Manenti, F., 2025. Reshaping Industrial Maintenance with Machine Learning: Fouling Control Using Optimized Gaussian Process Regression. Ind. Eng. Chem. Res.

Predictive Maintenance



Gaussian Process Regression

$$f(\mathbf{t}) \sim \mathcal{GP}(m(\mathbf{t}), k(\mathbf{t}, \mathbf{t}'))$$

COVARIANCE KERNEL

$$k_{LIN}(t, t') = \sigma^2 + t \cdot t'$$

$$k_{RBF}(t, t') = \sigma^2 \exp\left(-\frac{(t - t')^2}{2\lambda^2}\right)$$

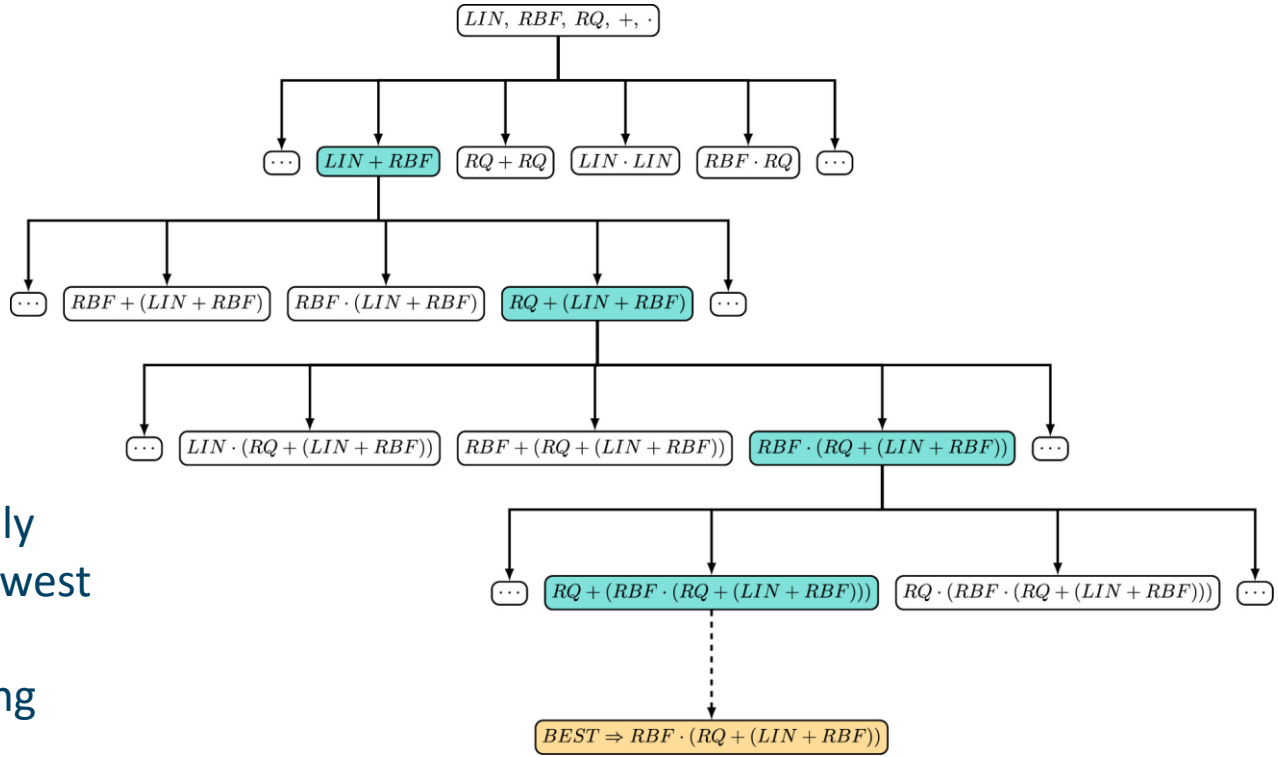
$$k_{RQ}(t, t') = \sigma^2 \left(1 + \frac{(t - t')^2}{2\alpha\lambda^2}\right)^{-\alpha}$$

Gaussian Process:

- Starts from N data points as input space
- Returns a Gaussian probability distribution as forecast, with intrinsic mean and variance
- Returns «natural» confidence intervals

Kernel Selection

Kernel selection and combination is crucial



Kernel selection algorithm:

- Kernels combined iteratively
- Select combination with lowest MAE on validation set
- Combination tree built using greedy search approach

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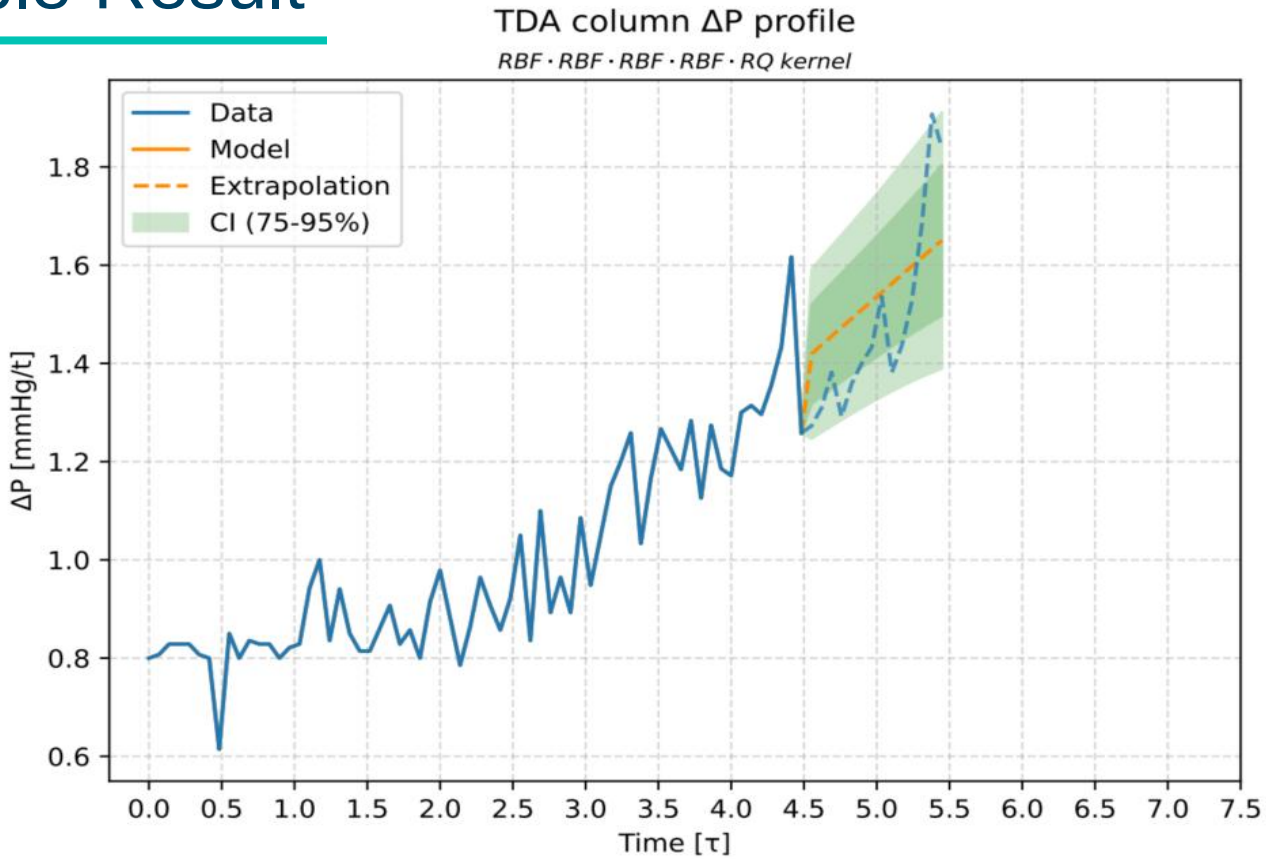
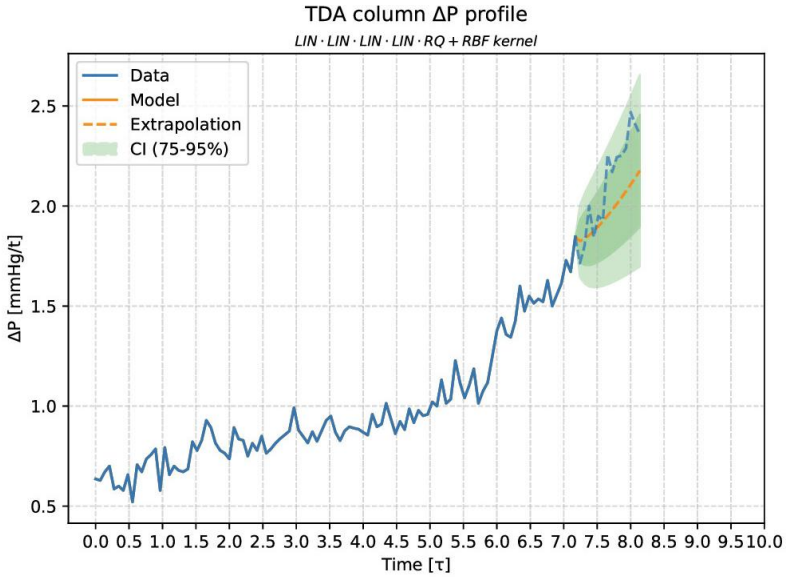
Example Result

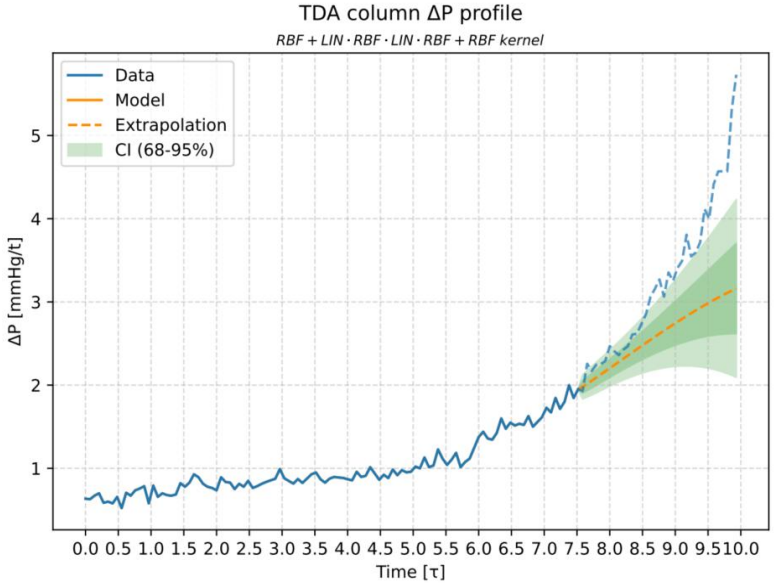


Standard Approach

Standard approach: assume that the variable of interest (ΔP) follows a normal distribution



Works well for short-term
(suitable for predictive maintenance)

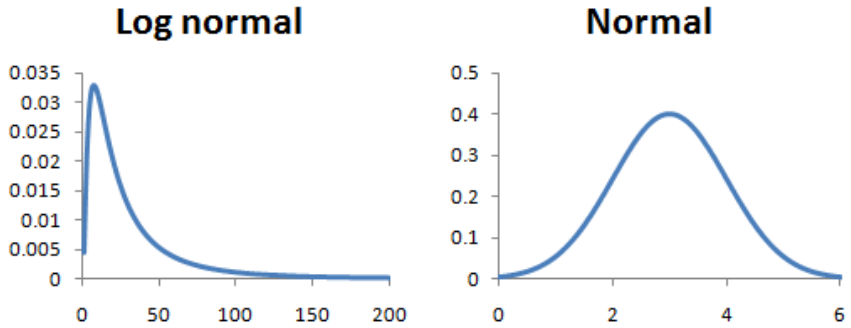


Less precise for long-term

Standard Approach

Long-term precision loss may be caused by several factors:

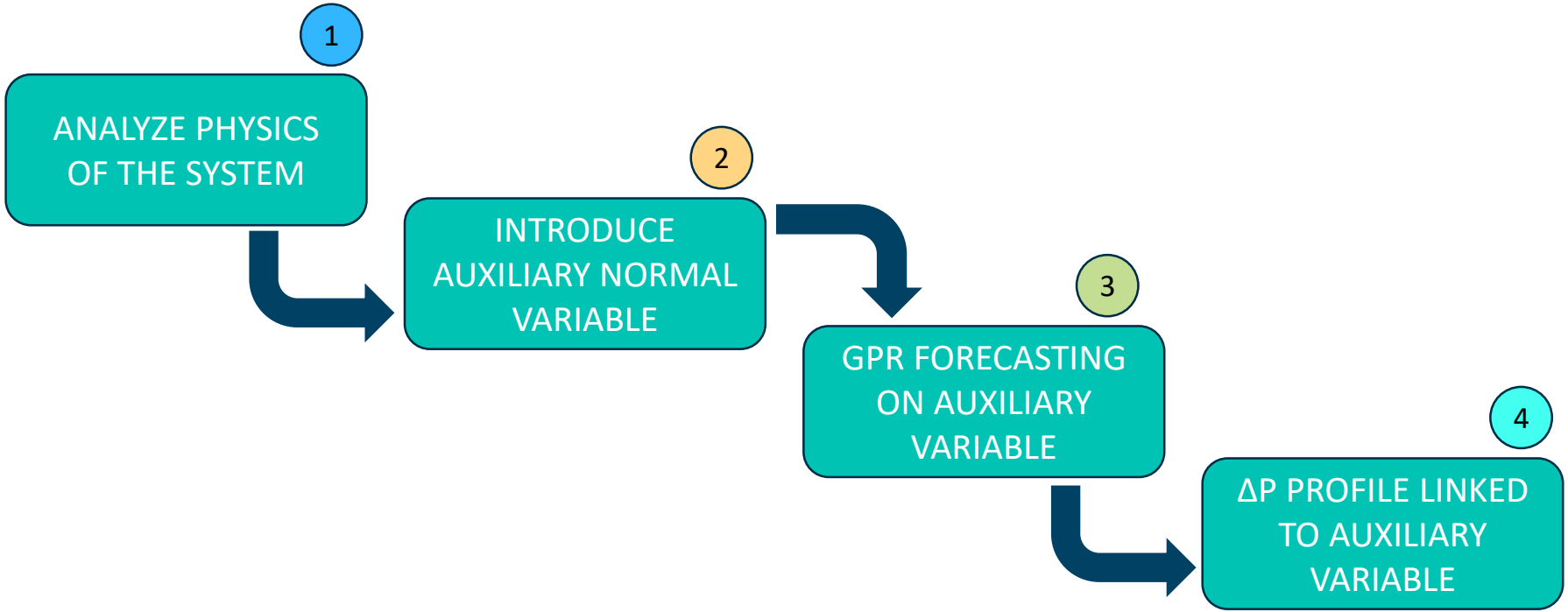
ΔP may not follow a Normal distribution



Long-term effects may be difficult to capture with a data-driven approach

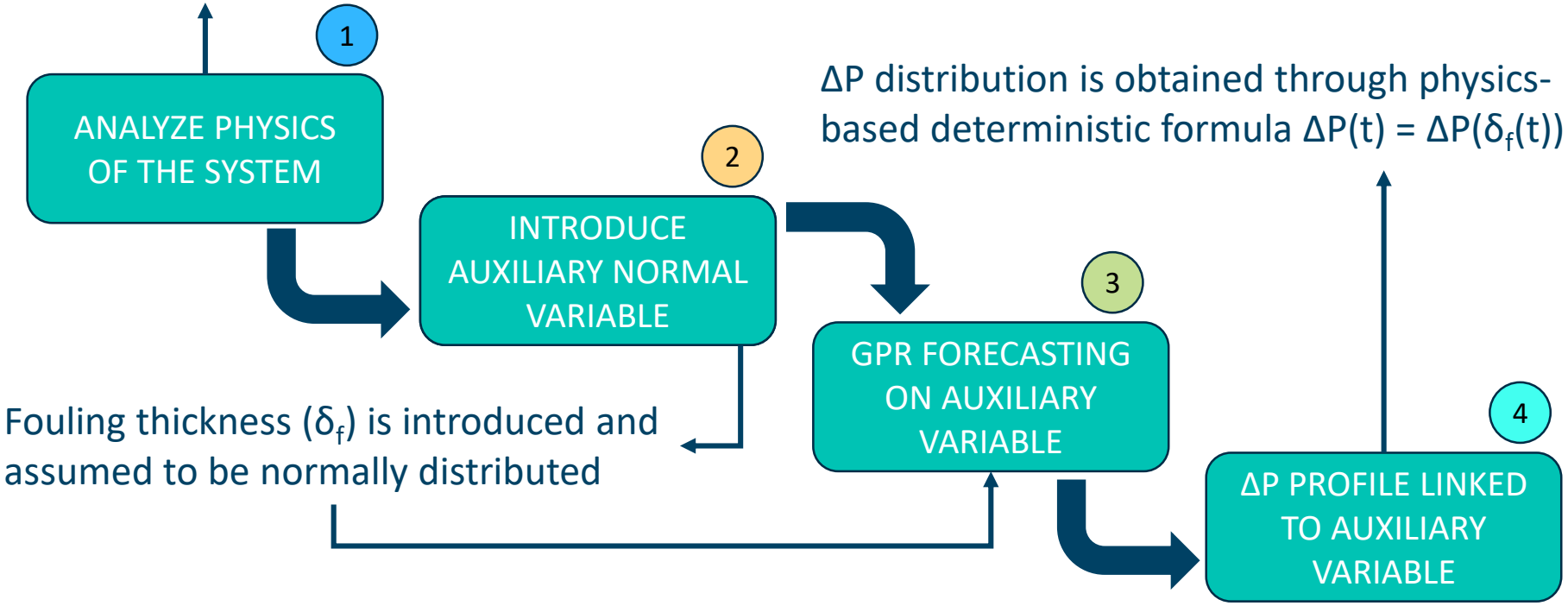
Hybrid Approach

Long-term precision may be increased with a Hybrid Machine Learning (HML) approach:



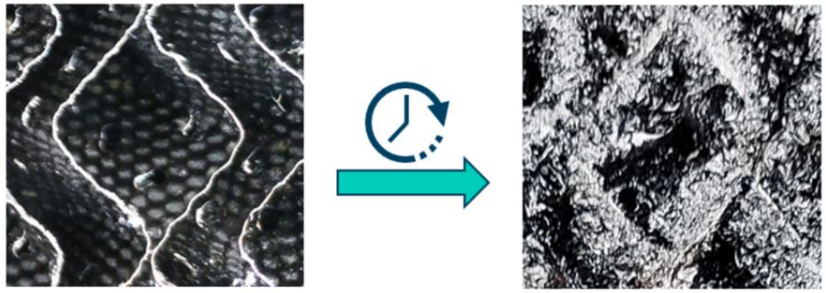
Hybrid Approach

Fouling reduces cross-sectional area, leading to pressure drop (ΔP)



Hybrid Approach

1



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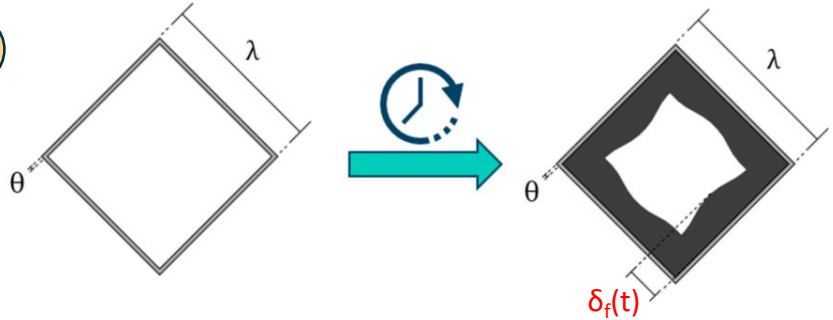

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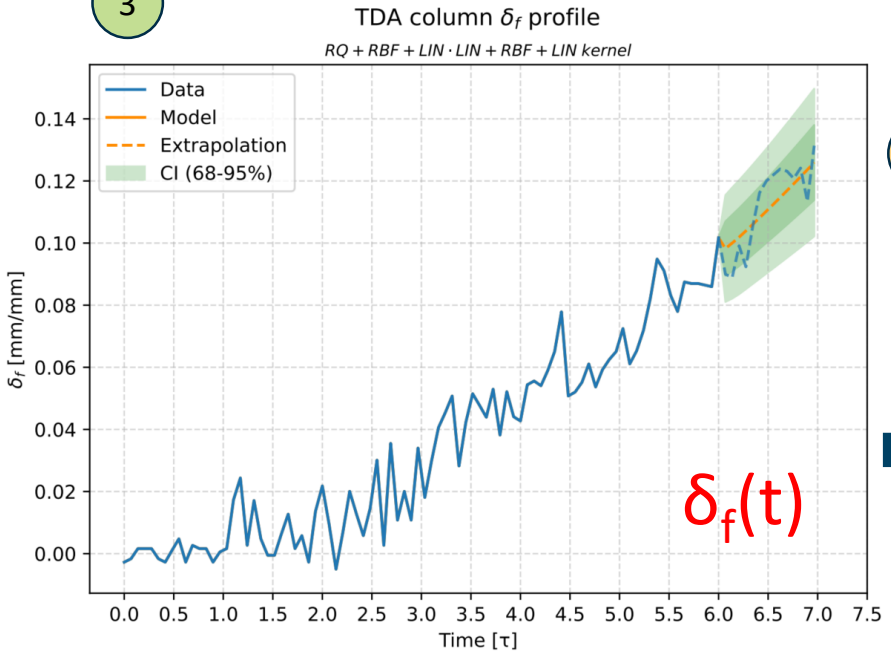
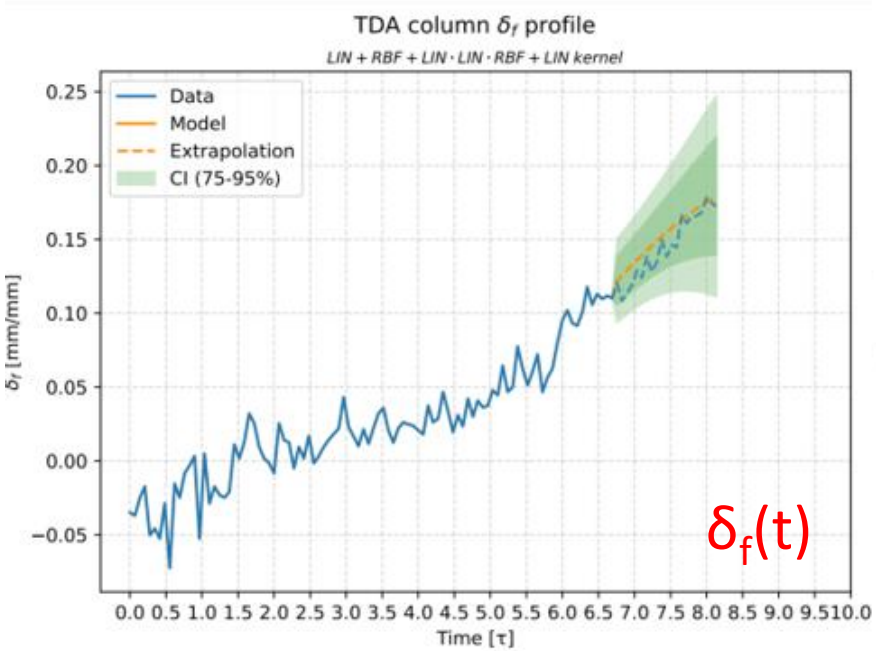
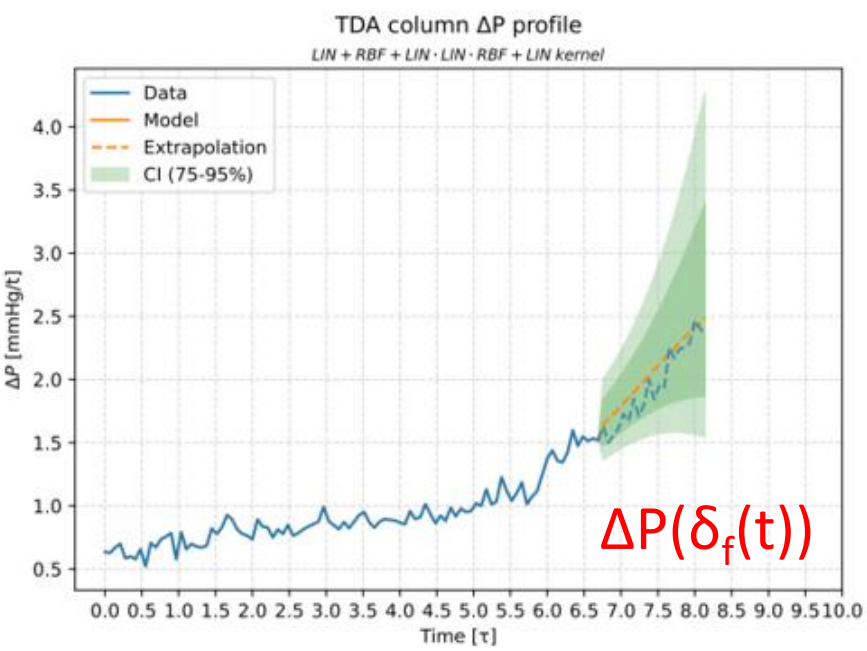


4

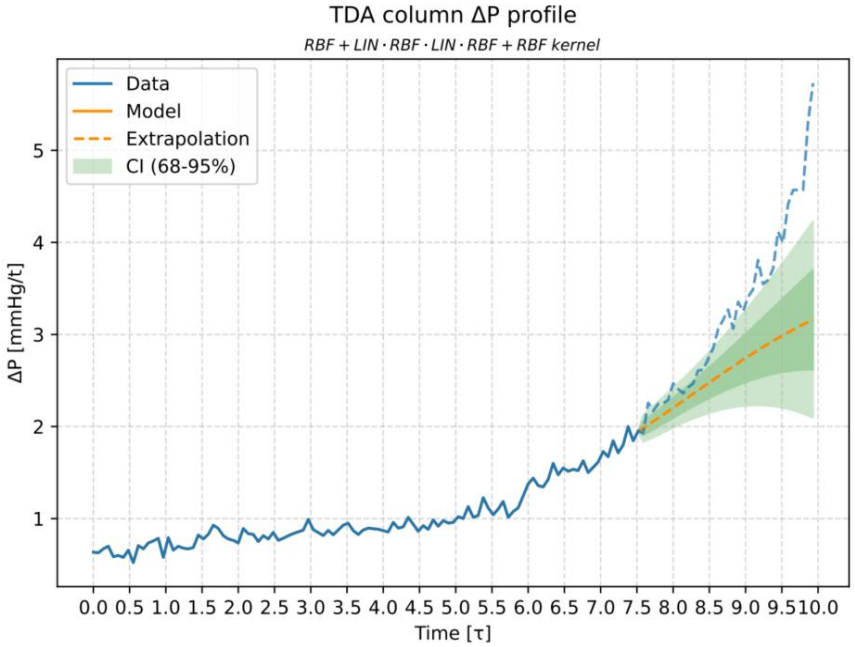
$$\Delta P = \frac{\alpha}{\lambda} \cdot \left[1 - \frac{2}{\lambda}\left(\theta + \delta_f(t)\right)\right]^{-4}$$

Hybrid Approach

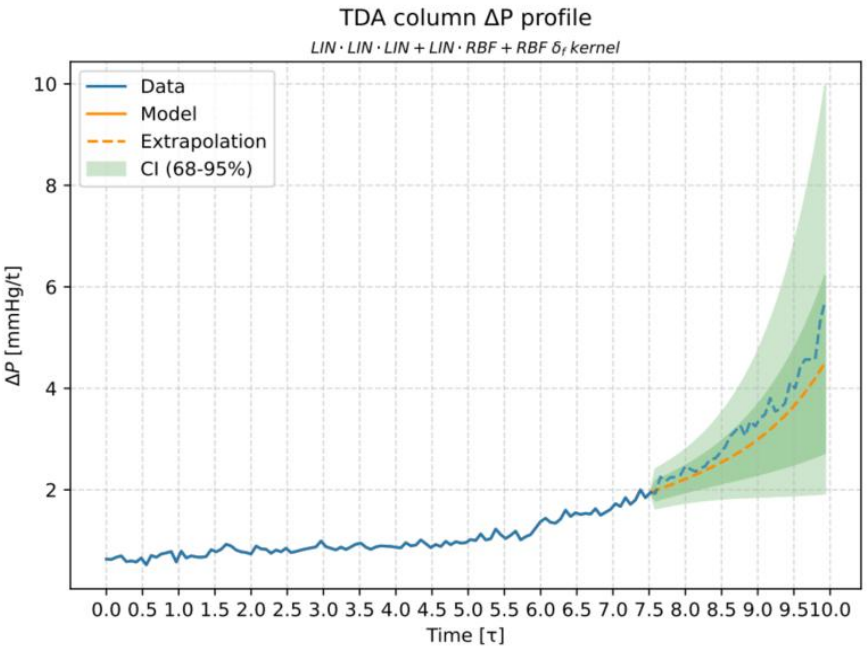




Long-term Forecasting



STANDARD APPROACH

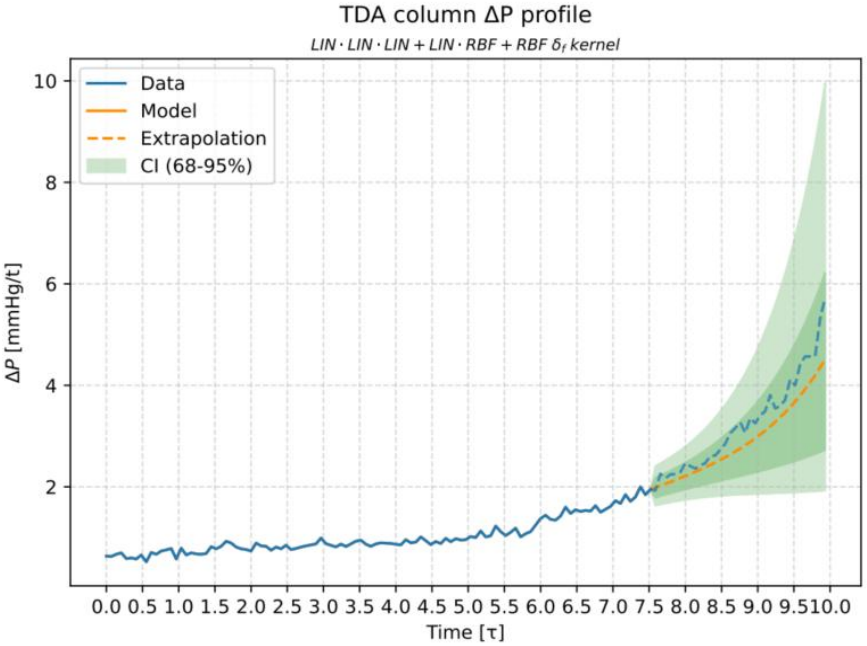


HYBRID APPROACH

Long-term Forecasting

Hybrid approach leads to:

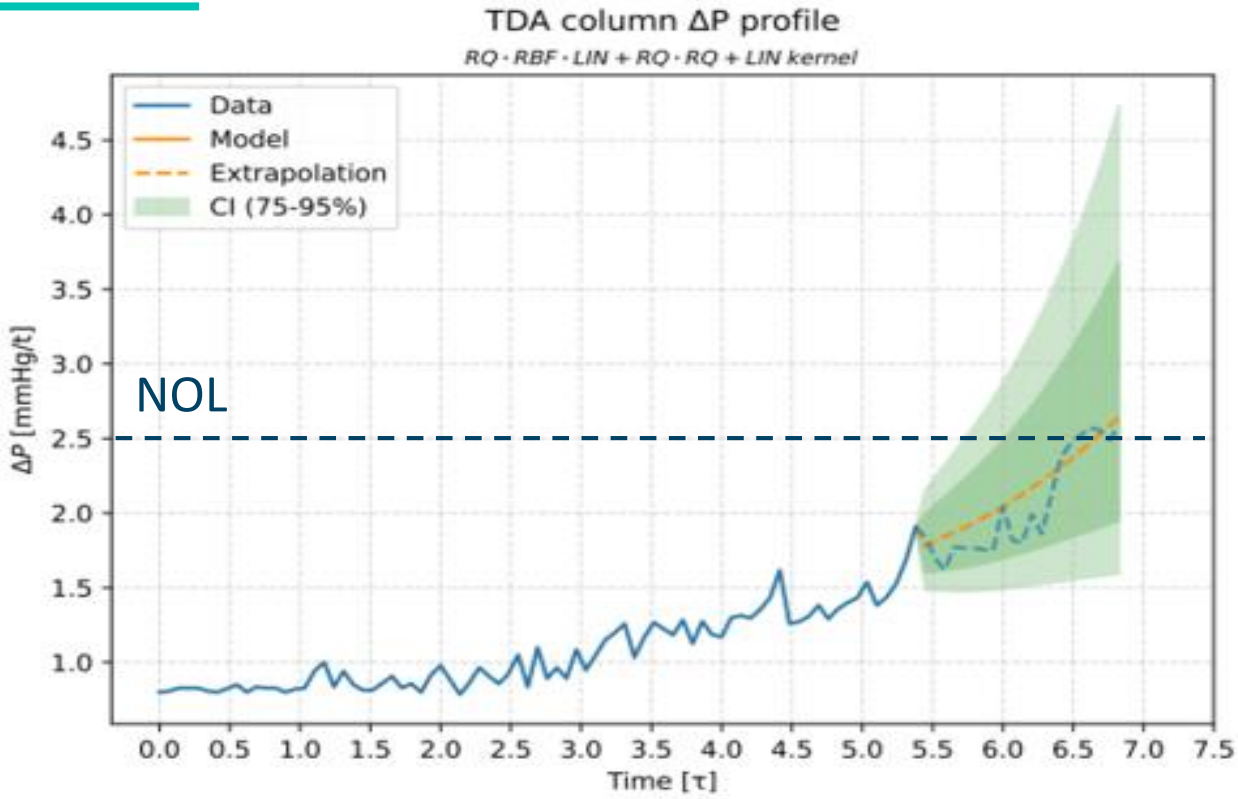
- Probability distributions for ΔP show positive skewness (high ΔP values are more probable than low ones)
- Larger confidence interval (uncertainty is magnified when transforming δ_f to ΔP)
- Physical model shows asymptote, coherently with the physical system (gradual blockage of packing)



HYBRID APPROACH

Predictive Maintenance

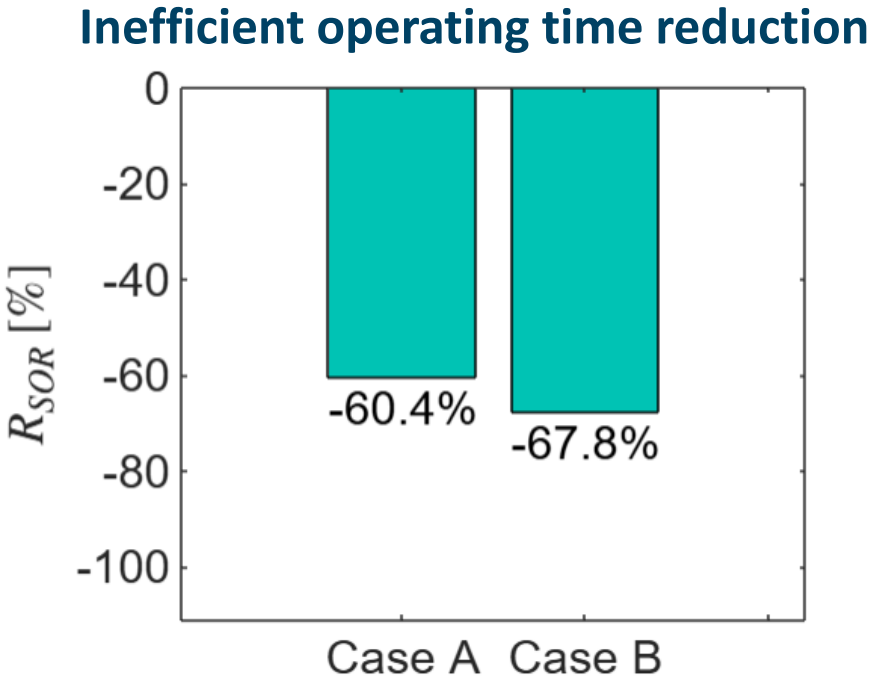
- Rolling window forecasting
- HML approach
- Schedule maintenance when NOL overcoming is forecasted
- 2 different TDA runs analyzed



Predictive Maintenance

Predictive maintenance based on HML approach:

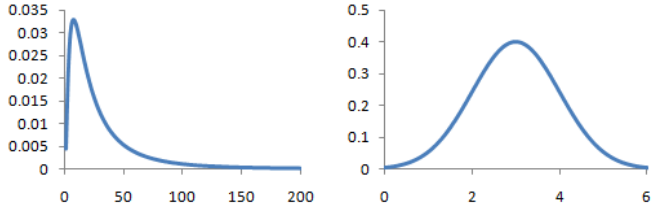
- Predictive maintenance aims at reducing inefficient operating time with the system running above NOL
- Runtime within inefficient operating region is reduced more than 60% for both case studies

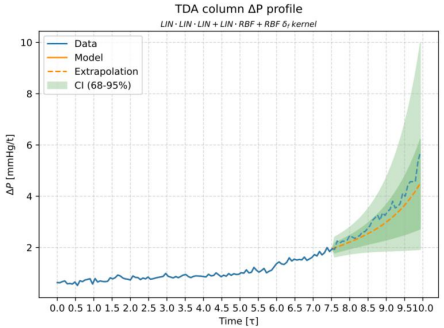


Hybrid-based Predictive Maintenance

Main goals achieved with this work:

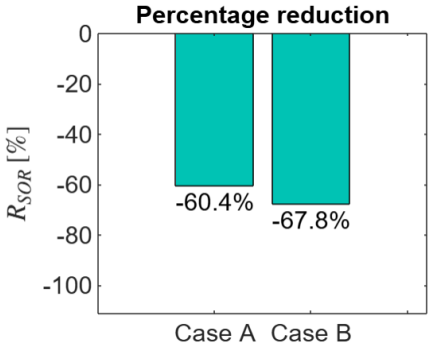
- GPR forecasting has been generalized to random variables which are not normally distributed thanks to a hybrid approach





- Hybrid forecasting models have shown long-term accuracy thanks to underlying physics

- Suboptimal operating time has been reduced by more than 60% for both analyzed runs

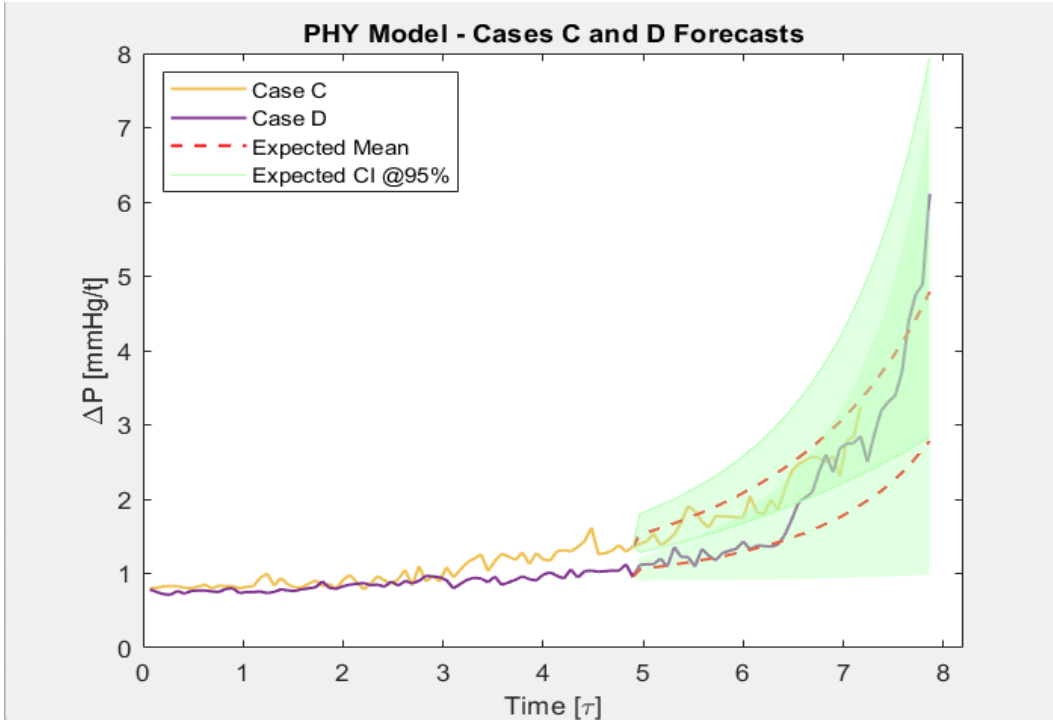


Future Developments

Hybrid approach introduces statistical forecasting which retain physics of the system

Real-time forecasting and operations monitoring can be integrated with runtime optimization

Lenght of run will not be decided anymore based on a fixed technical threshold, but on economic optimization



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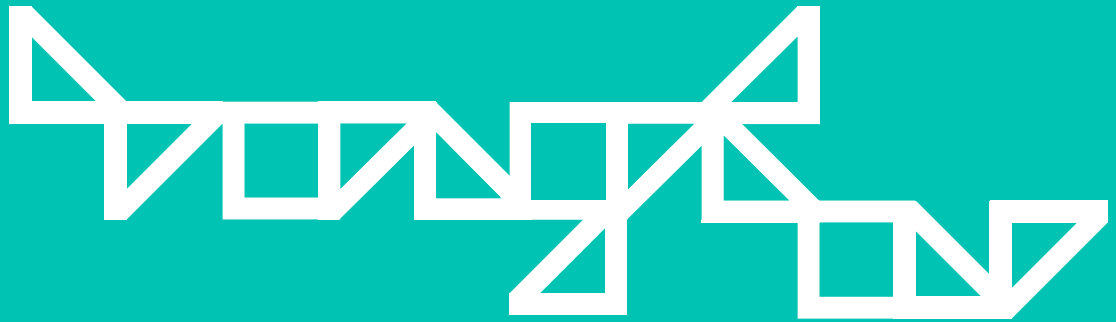

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