Live Steam Prediction: Process, methods, data and Issues

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Motivation

Predictive maintenance might eliminate breakdowns by 70-75%, reduce breakdown time by 35-45%, and increase production by 20-25%

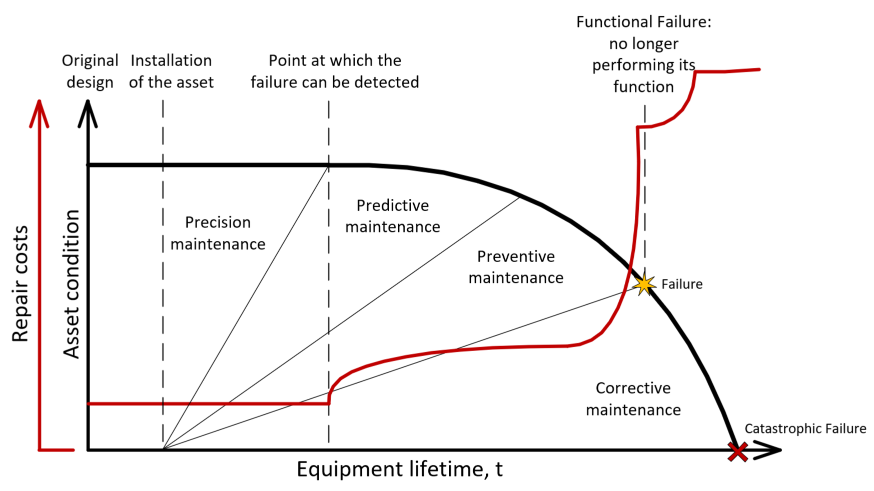


Fig. 1.Condition vs equipment lifetime.

State of the Art

Based on Supervised Learning algorithms identification of KPIs such as live steam flow, power output, COP etc.

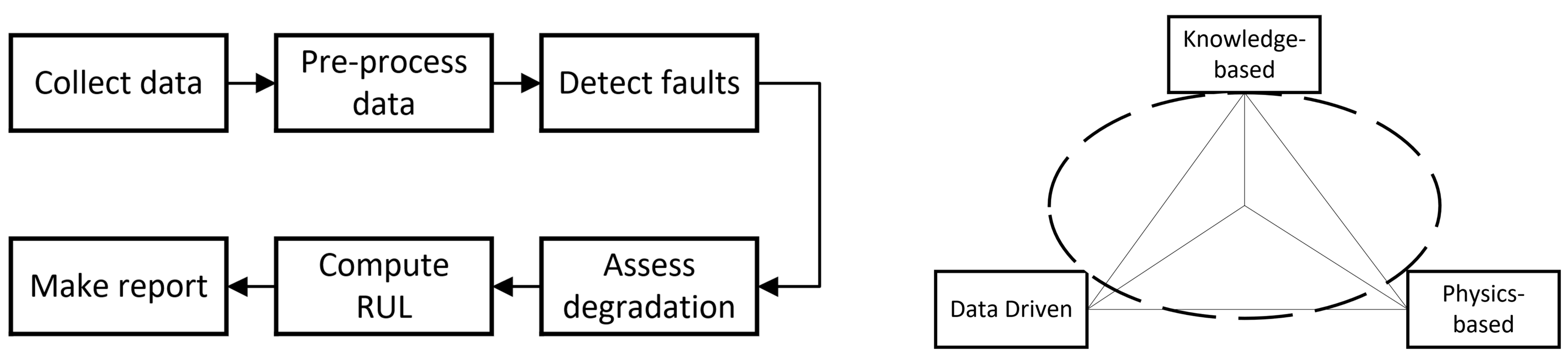


Fig. 2. Prediction maintenance schemes

The main challenges of applying prediction techniques on power plants:

- Lack/Excess of the data
- Difficult dependencies among indicators
- Big number of different prediction techniques with different internal parameters
- Selection of an appropriate training dataset

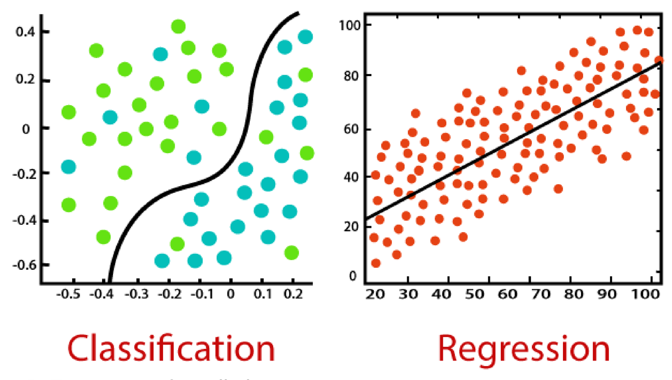


Fig. 3. Two types of prediction.

Methodology

Methodology contains

- The introduction of conducted algorithms
  - K-Nearest Neighbor (KNN)
  - Random Forest Regressor (RFR)
  - Multi-Layer Perceptron (MLP)
  - Least Absolute Shrinkage and Selection Operator (Lasso)
- Training data optimization
- Comparison of the prediction quality based on input fuel flow and more complex analysis which includes more sensors
- Investigation of the procedure of identification of anomalies

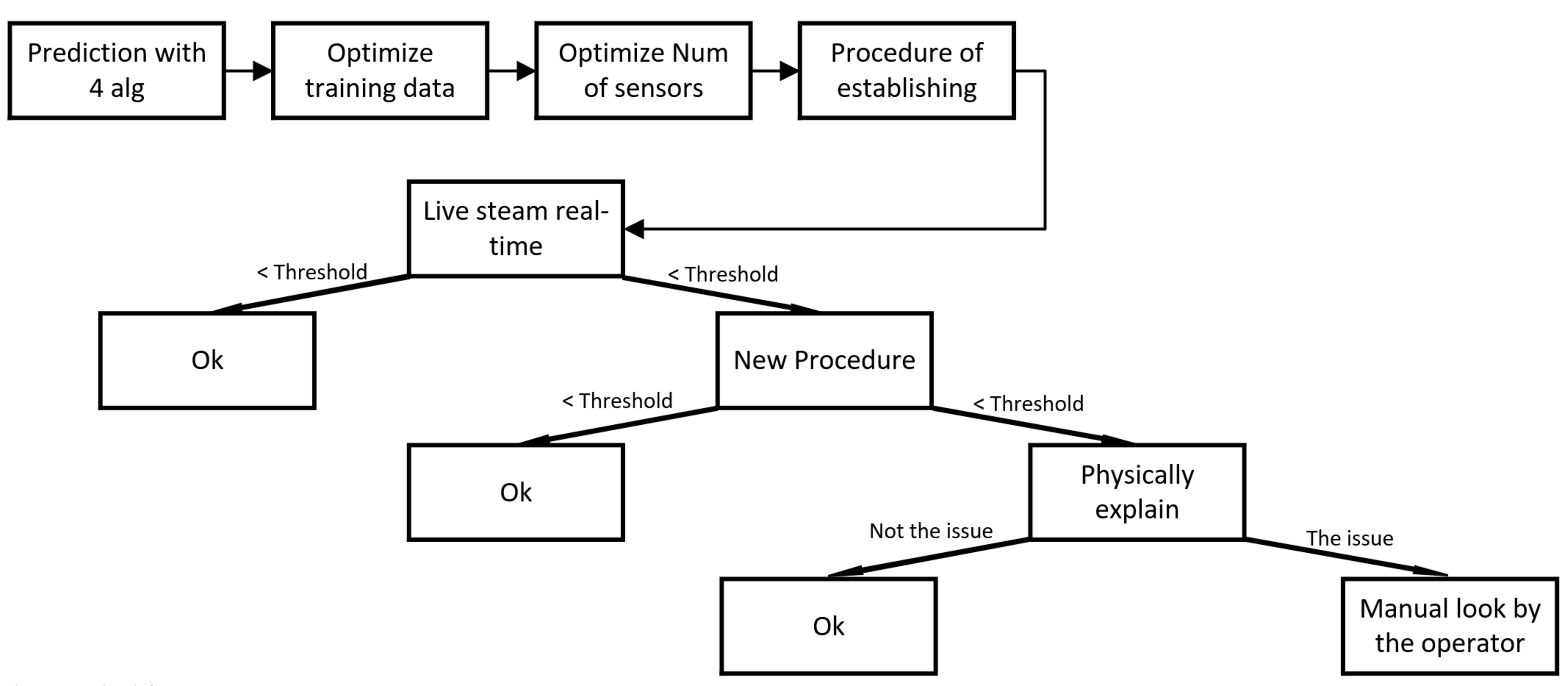


Fig. 4. Methodology.

Brief Results of prediction

Algorithm	Calculation time(sec)	The best result training / overall times (sec)	Coefficient of performance R^2	Mean Absolute Error (t/h)
KNN	10	0.001 / 0.118	0.315	6.84
RFR	11	0.02 / 0.13	0.302	6.85
MLP	36	8 / 27	0.841	3.18
Lasso	12	0.001 / 0.095	0.865	2.99

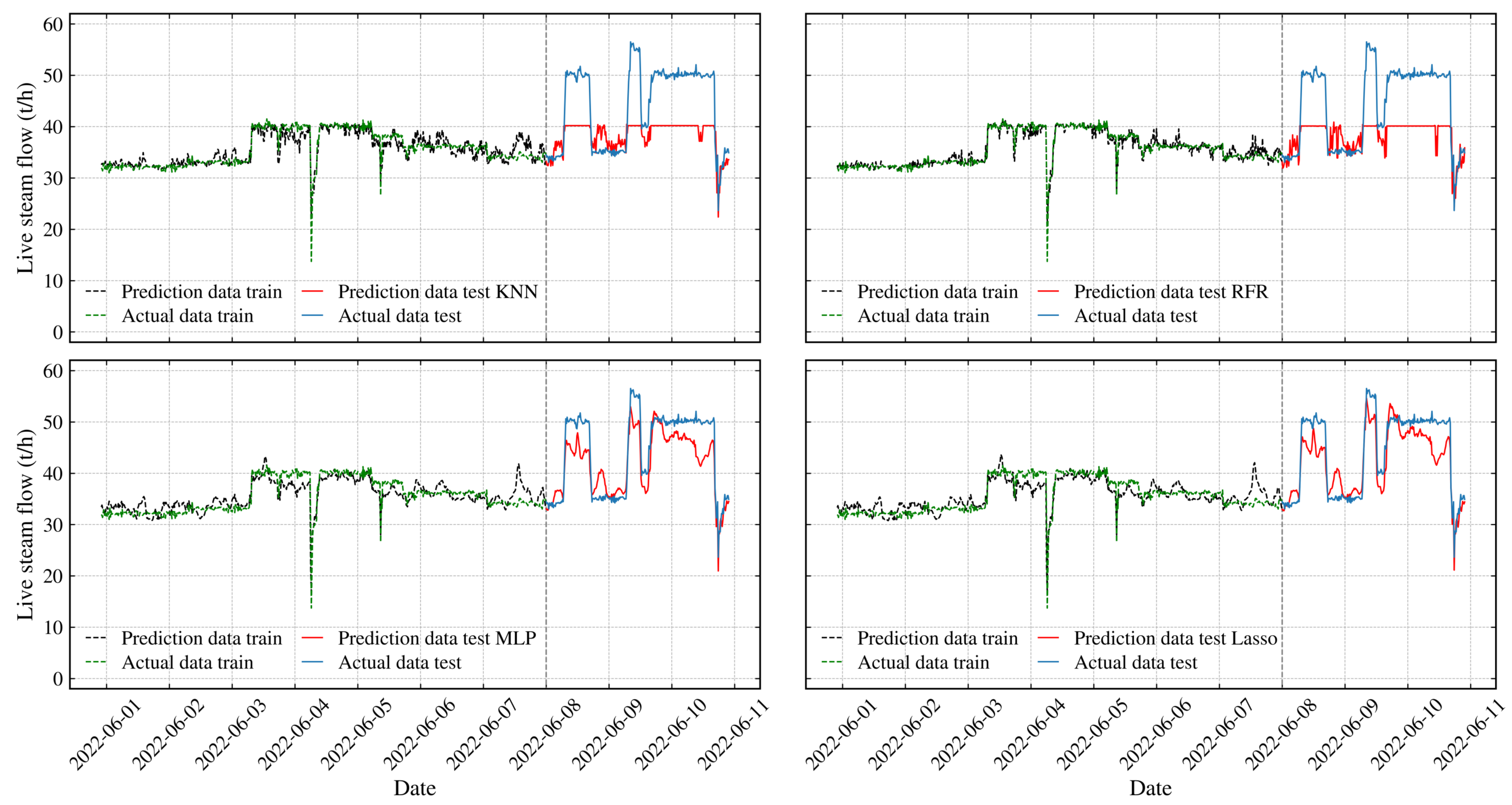
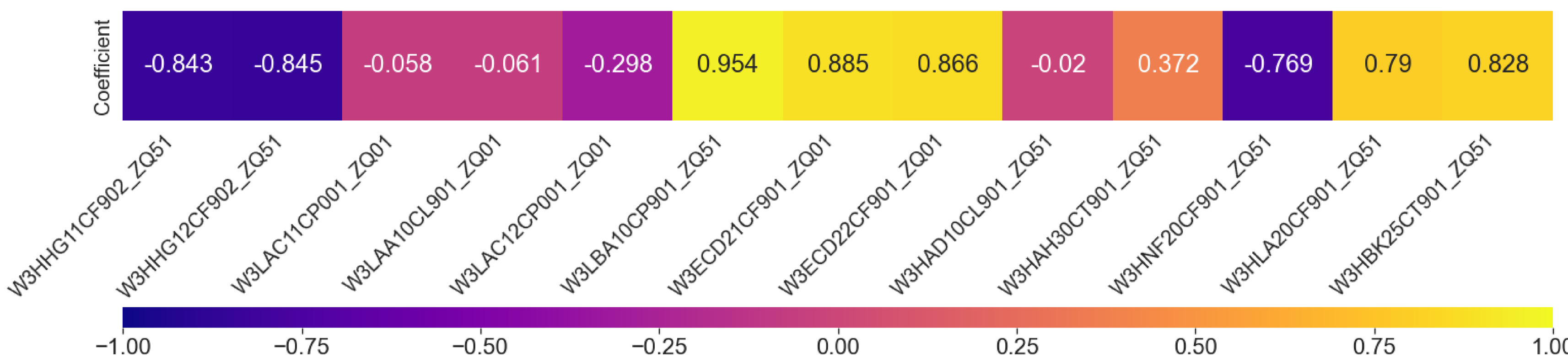


Fig. 5. Live steam prediction with 4 sensors

KNN and RFR suffer because they are not able to extrapolate, while MLP and Lasso work fine with sufficient quality

Correlation of sensors



Algorithm	Calculation time(sec)	The best result training / overall times (sec)	Coefficient of performance R^2	Mean Absolute Error (t/h)	Improvement
KNN	8	0.002 / 0.114	0.269	6.91	-1 %
RFR	11	0.03 / 0.125	0.419	5.96	13 %
MLP	30	8 / 23	0.878	2.86	10 %
Lasso	9	0.003 / 0.095	0.980	1.08	63 %

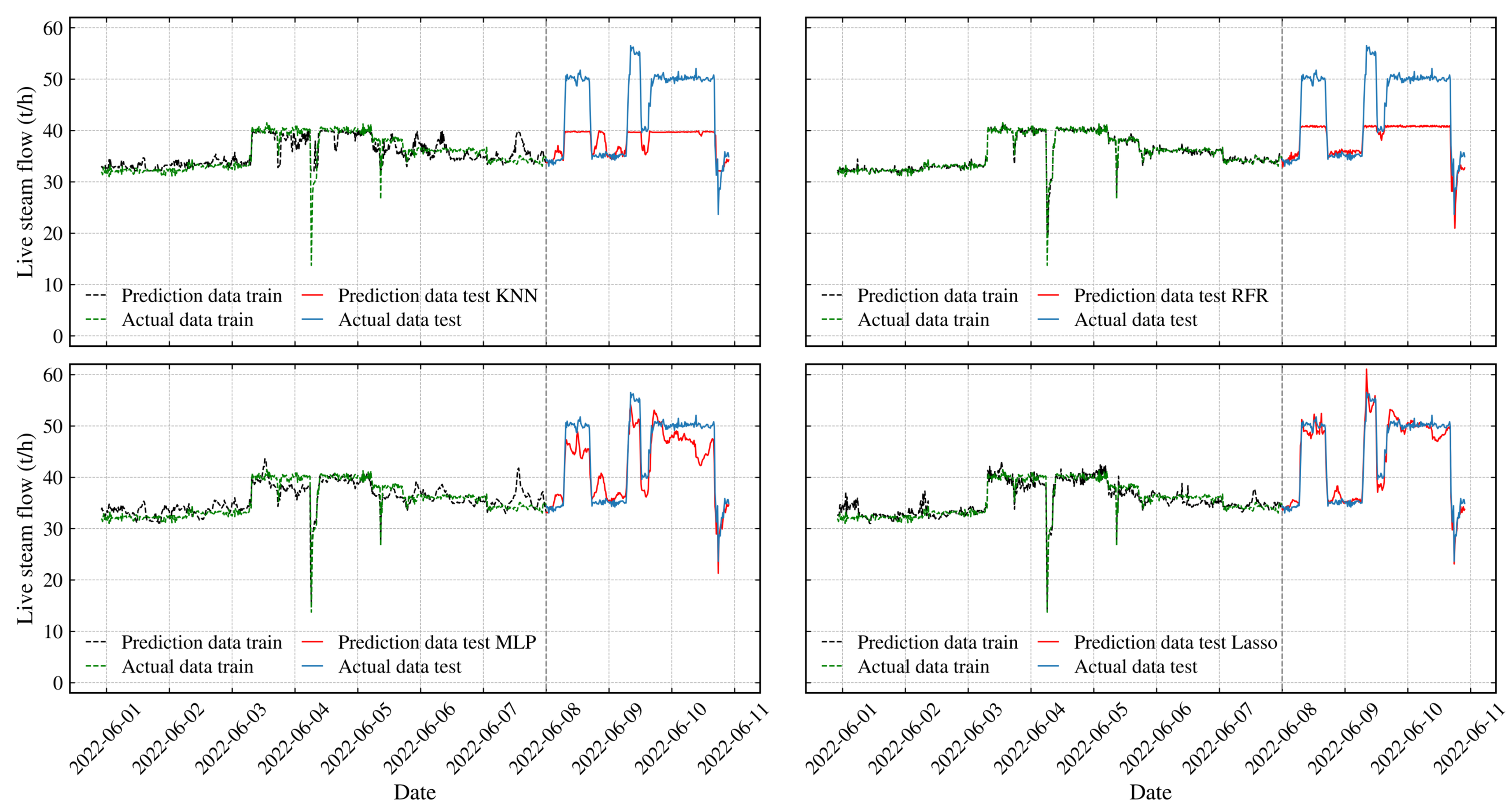


Fig. 6. Live steam prediction with 13 sensors

There is almost no prediction quality improvements in KNN and RFR, while Lasso gets a massive performance uplift after addition more of necessary sensors

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