Health Index estimation for SOFCs using Deep Neural Networks

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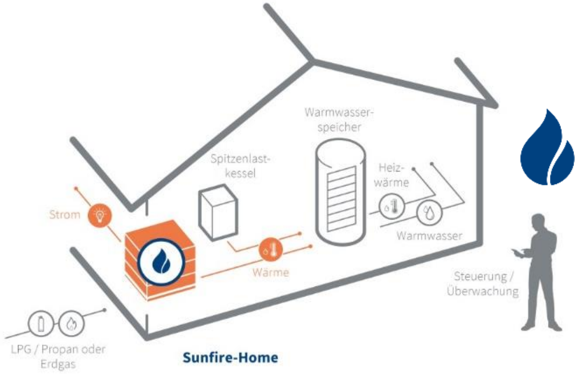
Deep Neural Networks for condition monitoring of SOFCs

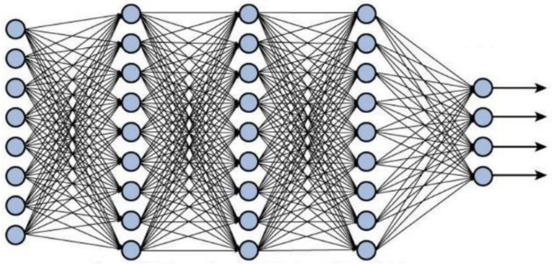
Unsupervised data-driven **Deep Learning** approach for condition monitoring of SOFCs (Health Index estimation)

Datasets collected from real installations of Sunfire Home750, a heat and power appliance based on SOFCs



sunfire®

Deep Neural Networks for
- Degradation monitoring / anomaly detection (Variational AutoEncoder)
- Time sequences modeling (LSTM recurrent networks)
- Domain adaptation of neural models (Adversarial training)



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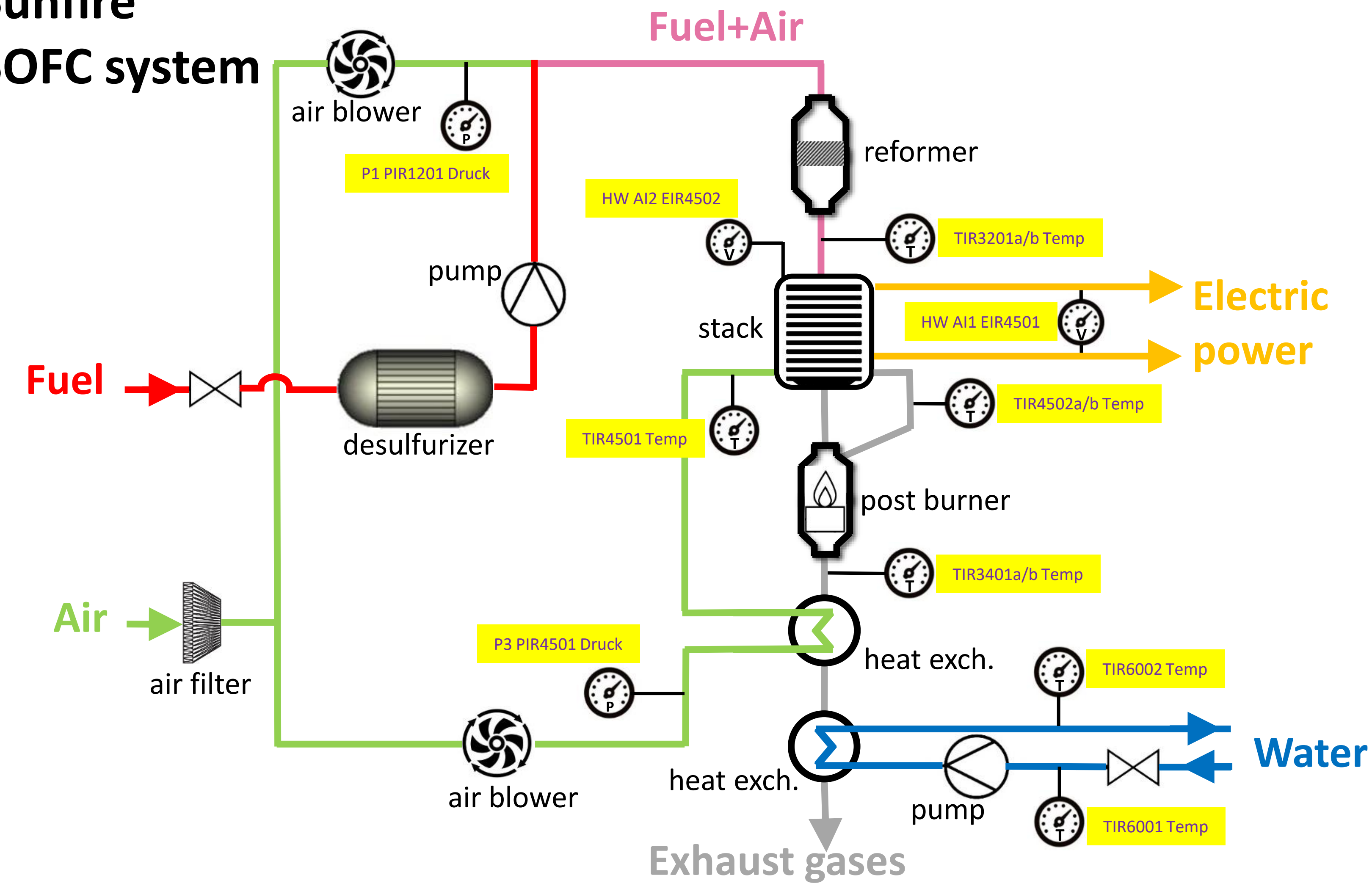
Input signals for the Deep Neural Networks

Sunfire SOFC system



signal	label
Inlet pressure CPOX	P1 PIR1201 Druck
Inlet cathode pressure	P3 PIR4501 Druck
Reformer output temperature	TIR 3201a/b Temp
Inlet cathode temperature	TIR 4501 Temp
Outlet cathode temperature	TIR 4502a/b Temp
Post-burner output temperature	TIR 3401a/b Temp
Inlet water temperature	TIR 6001 Temp
Outlet water temperature	TIR 6002 Temp
Output voltage	HW AI1 EIR4501
Open circuit voltage	HW AI2 EIR4502

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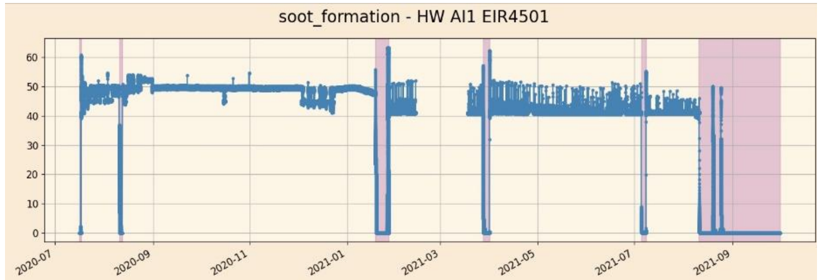
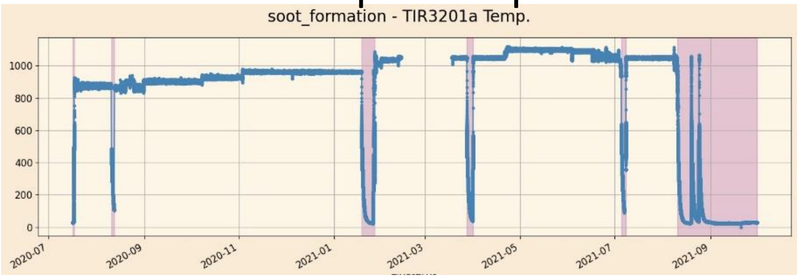
Sunfire Home750 datasets (same system, different installations)

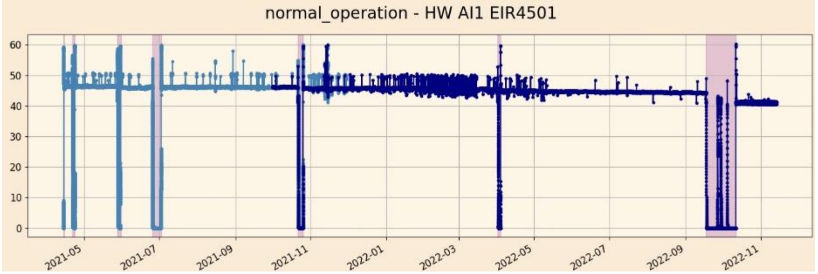
output voltage | reformer output temperature

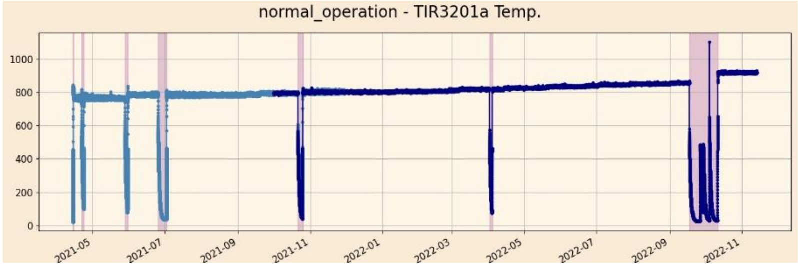
Soot formation
LPG



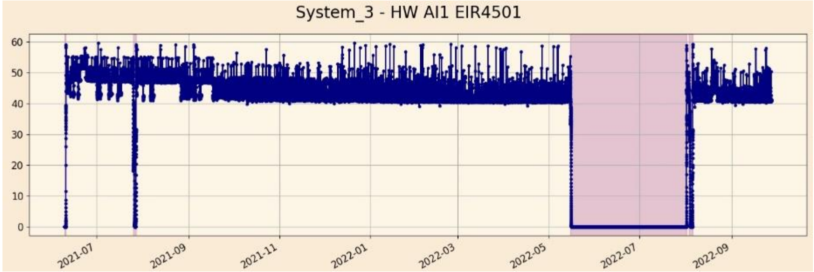


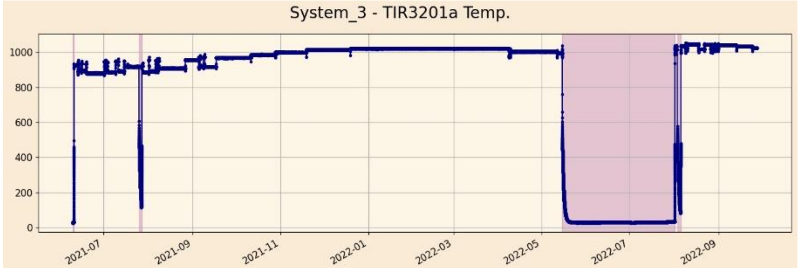
Normal operation
NG



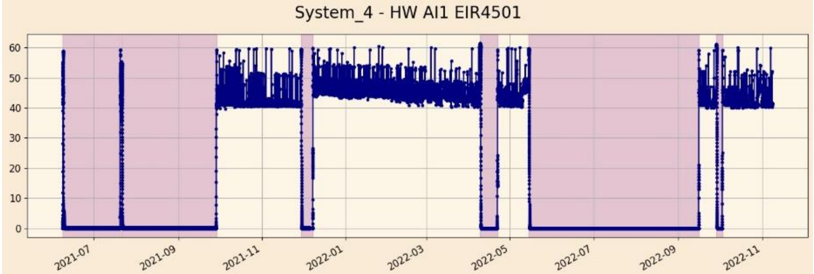


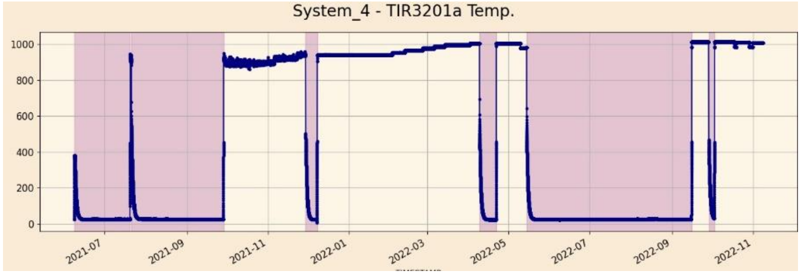
System 3
NG





System4
NG





sampling period:
17 s
7 m

shutdown intervals

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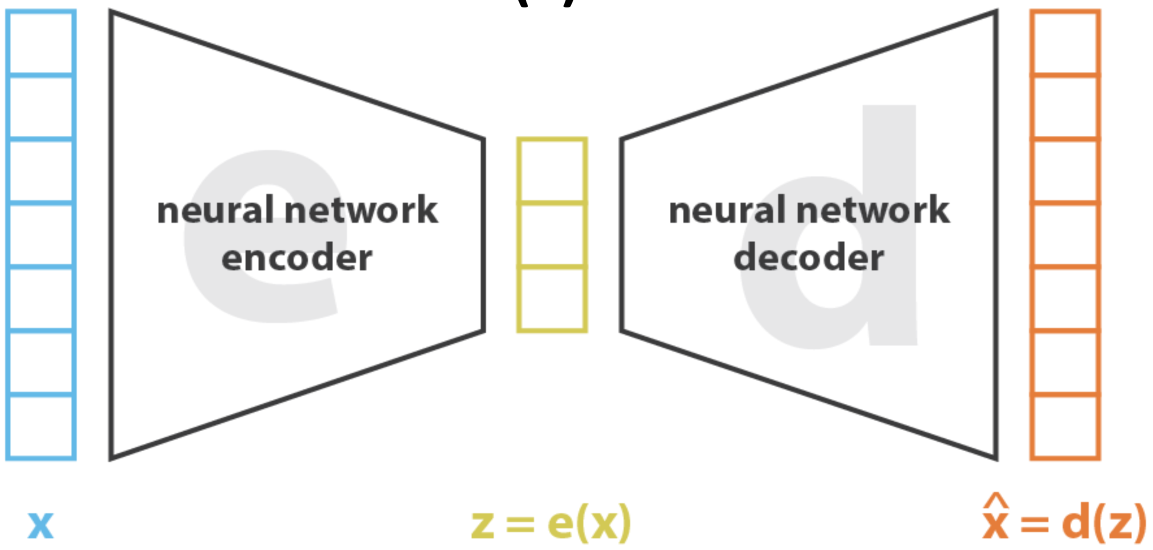
Implicit data modeling: the Autoencoder

input x | encoding → | latent representation z=e(x) | decoding → | input reconstruction d(z)



$$\text{loss} = \|x - \hat{x}\|^2 = \|x - d(z)\|^2 = \|x - d(e(x))\|^2$$

Image from https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

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A more regularized model: the Variational Autoencoder

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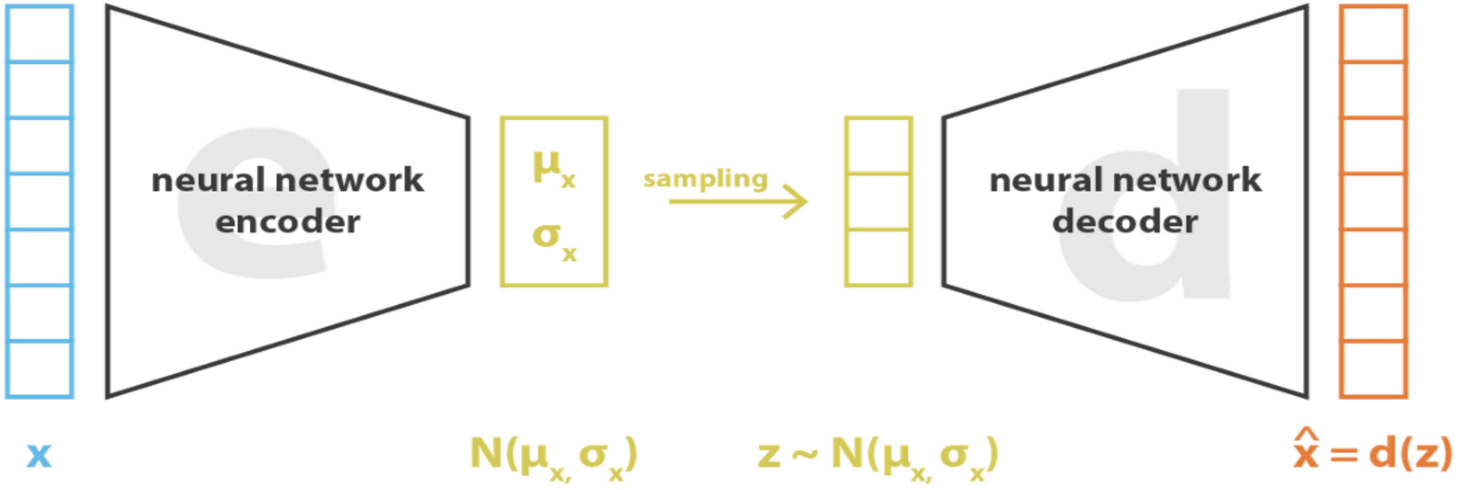
input x → encoding → latent distribution p(z|x) → sampling → sampled latent representation z~p(z|x) → decoding → input reconstruction d(z)



$$\text{loss} = \| x - \hat{x} \|^2 + \mathrm{KL}[\, N(\mu_x, \sigma_x), N(0, I) \,] = \| x - d(z) \|^2 + \mathrm{KL}[\, N(\mu_x, \sigma_x), N(0, I) \,]$$

Image from https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

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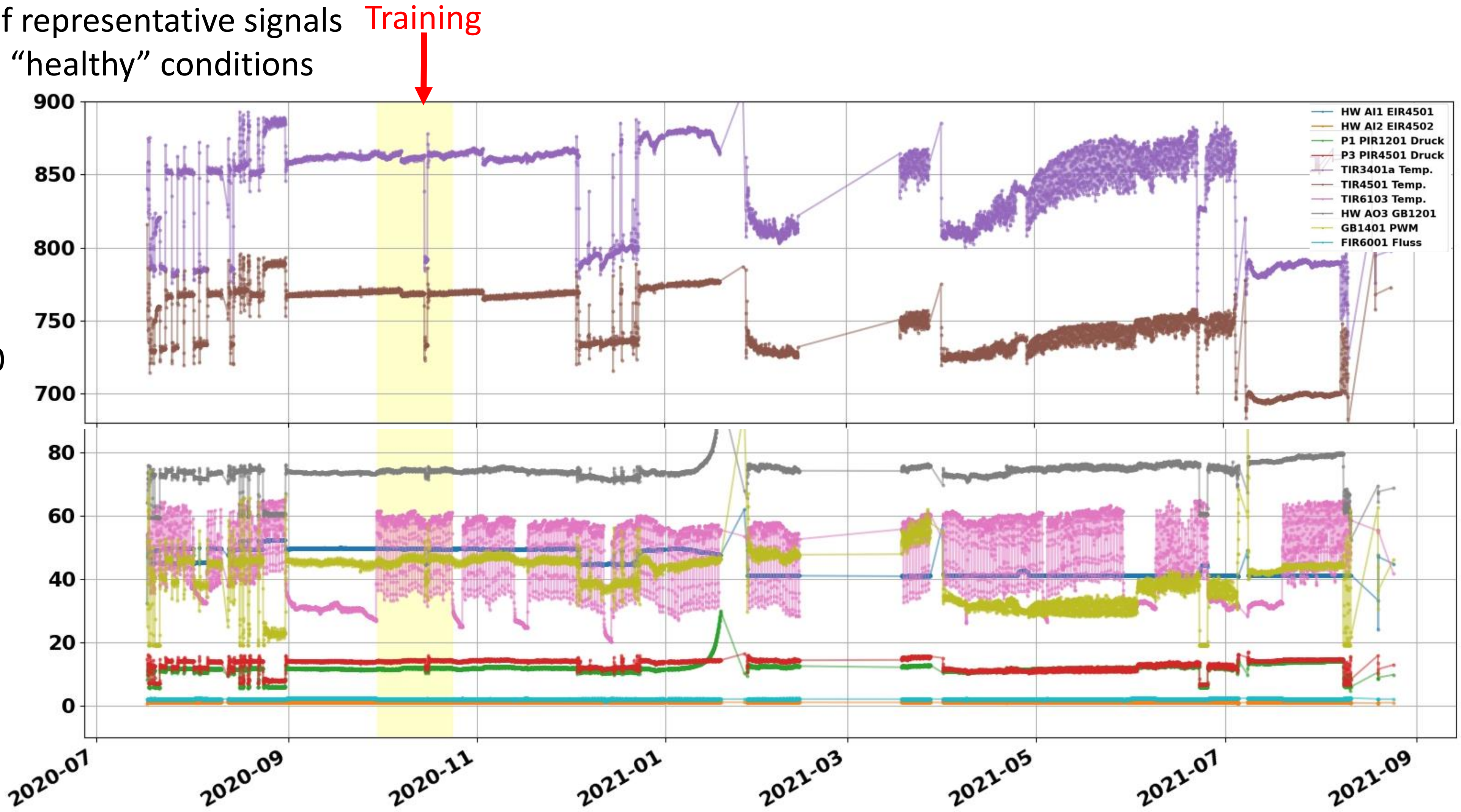
Condition monitoring by means of a variational autoencoder (VAE)

- Selection of representative signals
- Training on “healthy” conditions

Sunfire Home750 “soot formation” case



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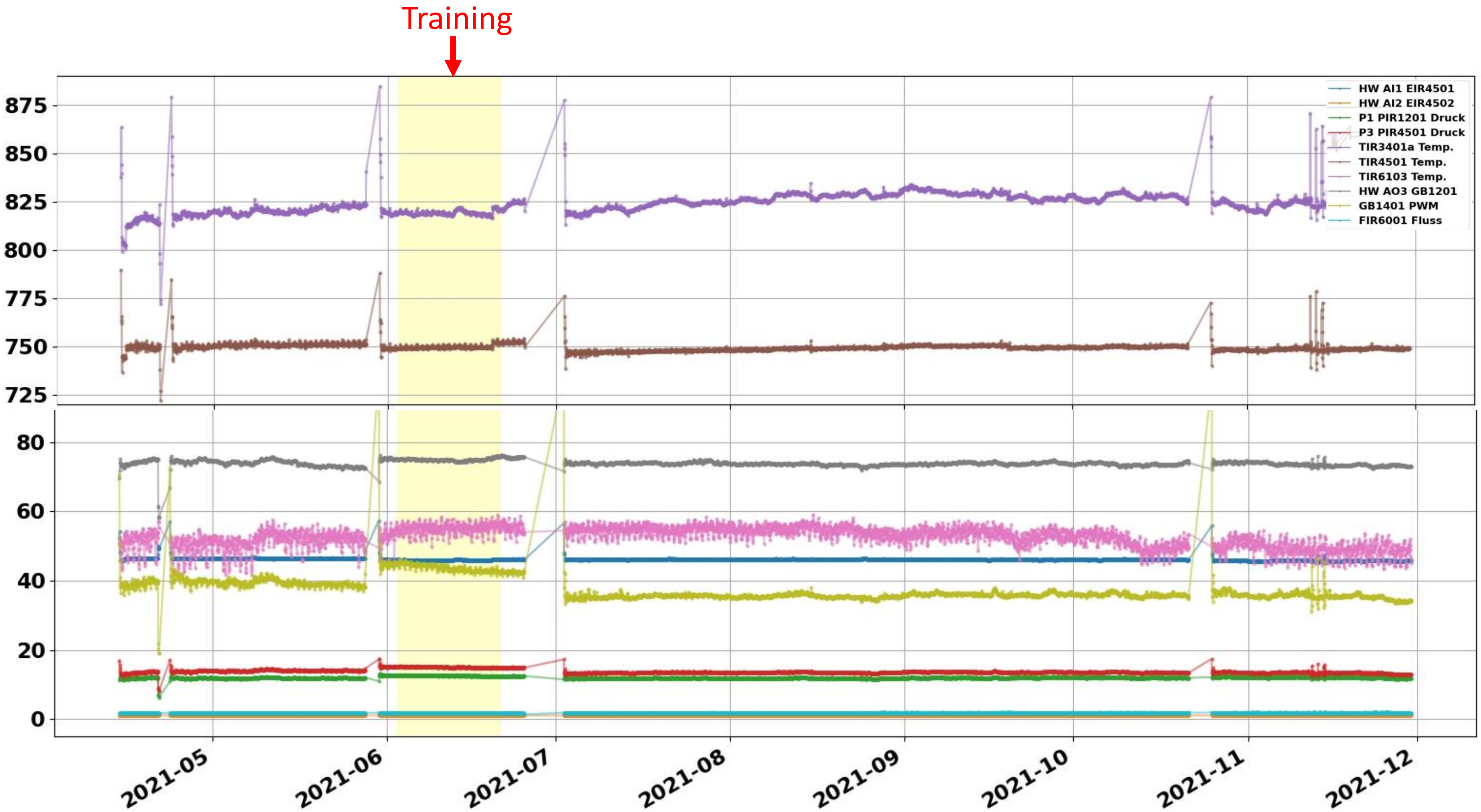
Condition monitoring by means of VAE

Sunfire Home750 “normal operation” case



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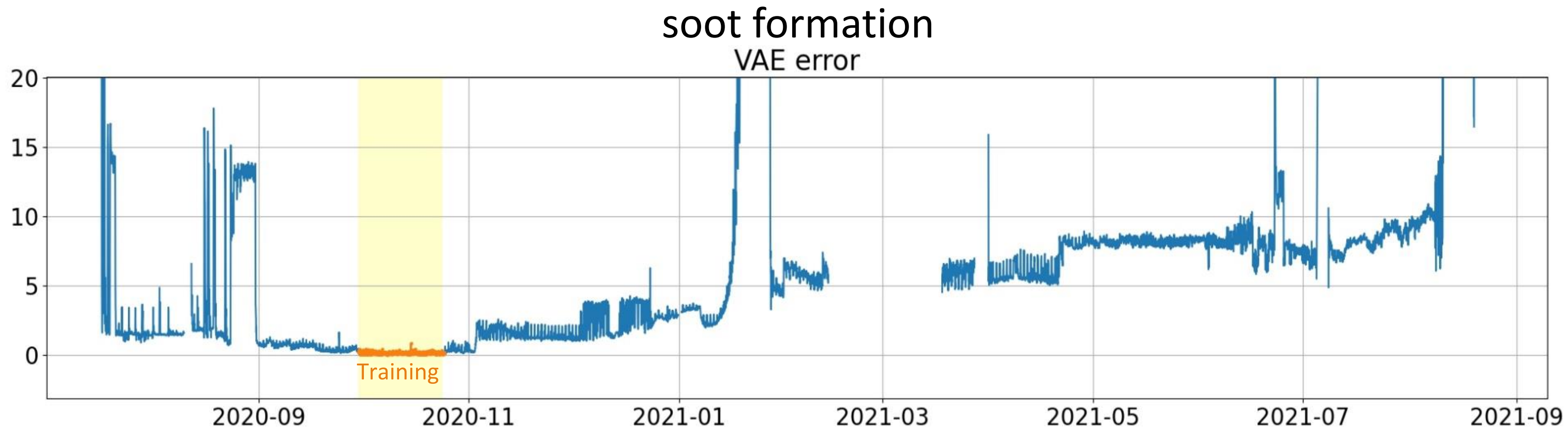
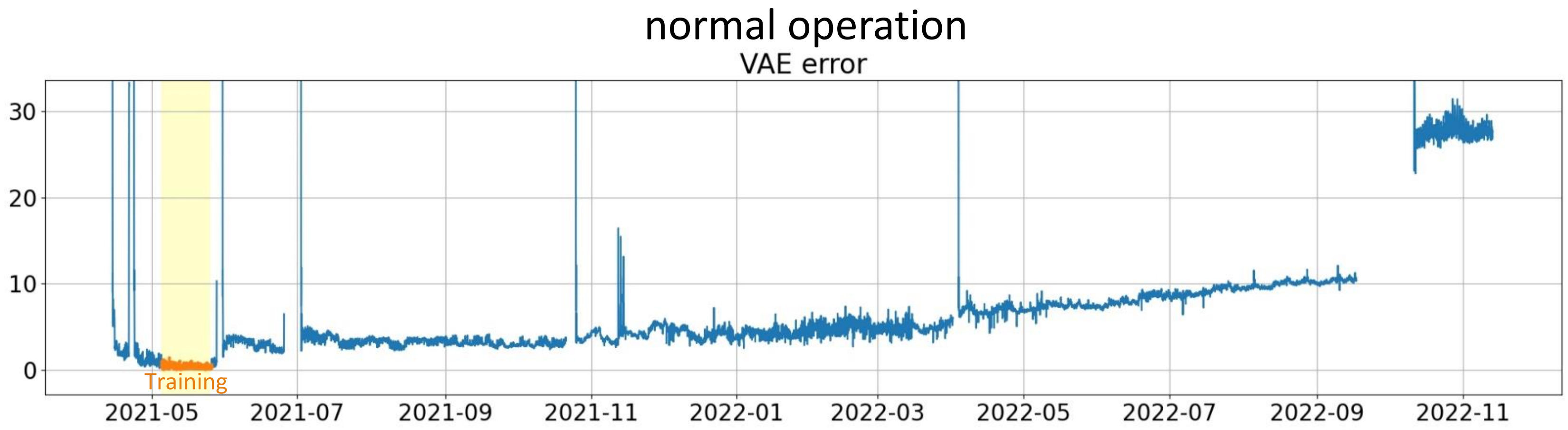
VAE reconstruction error as degradation index

- Degradation index estimated as reconstruction error of a Variational AutoEncoder

- Assumption: Stationary healthy conditions during training interval

- Limitation: Information learned with one system cannot be transferred to a new system (relative vs absolute index)





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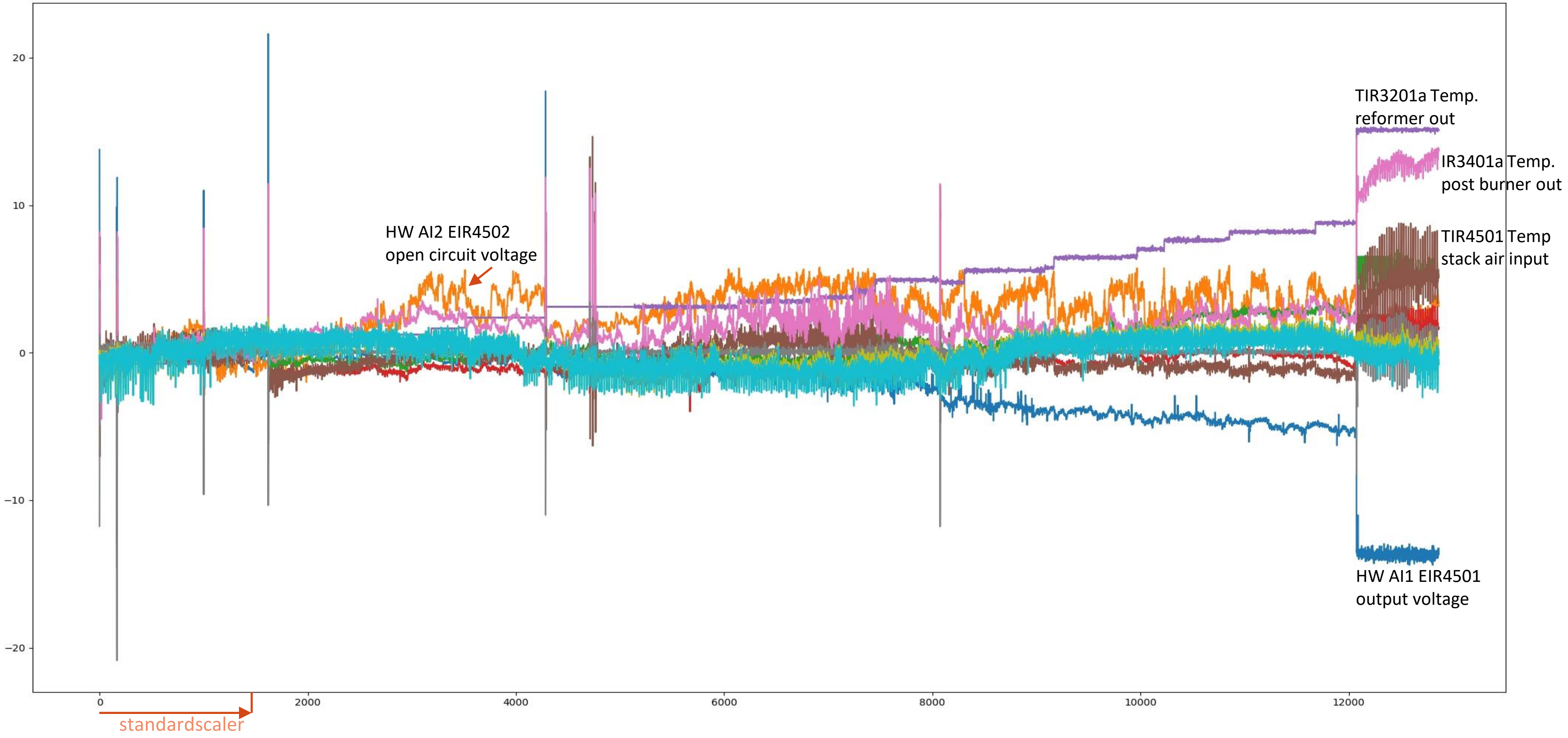
Sensor data as seen by the neural networks

Normalized signals from the “normal operation” dataset



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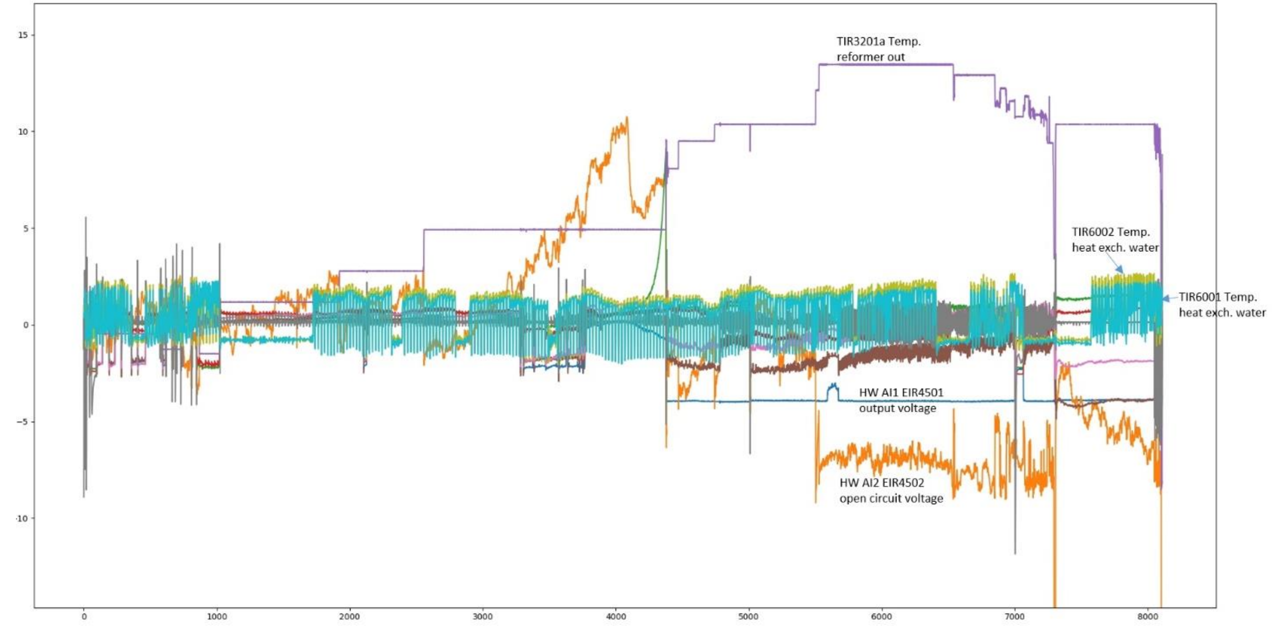
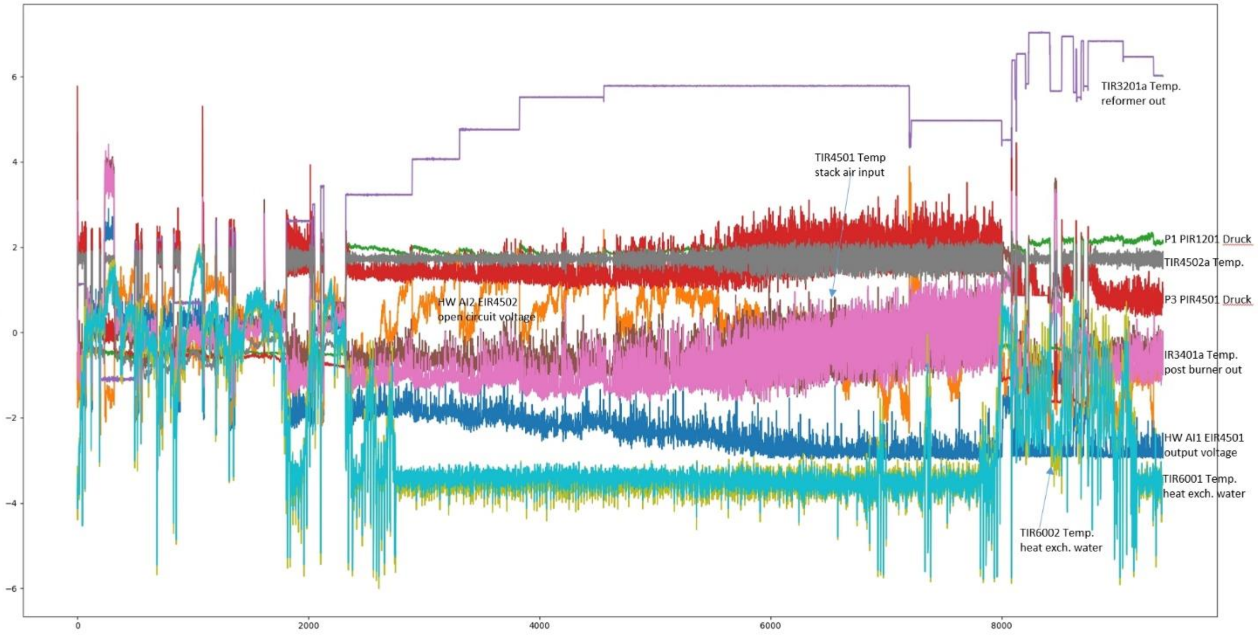
Sensor data as seen by the neural networks

soot formation (scaled)



system 3 (scaled)



The 4 *Sunfire Home750* datasets are collected from systems operating under different and uncontrolled conditions.

A model trained on the dataset acquired from one system cannot be used directly to perform condition monitoring of a different system.

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Domain adaptation to address different system installations

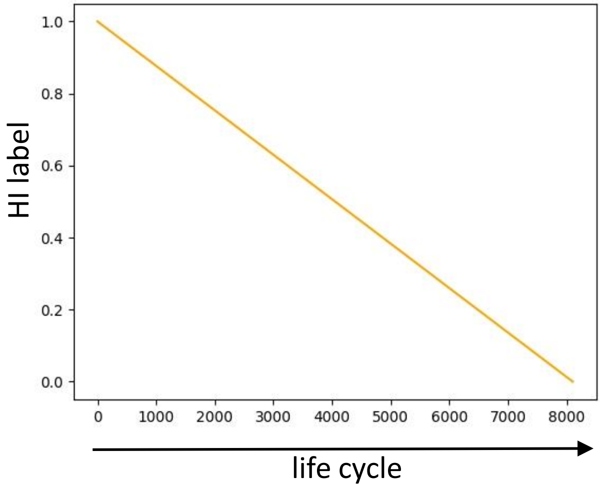
Learning a data-driven model in the presence of a shift between training and test data distributions is known as **domain adaptation** from a Source system (training time) to a Target system (test time).

Source system:
- Full life-cycle dataset
- Labeled data: health index
- Model training using full life

Target system:
- Unknown degradation during dataset time span
- **No labeled data**
- Healthy condition assumed during initial phase
- Health index estimation on full dataset

- In our case the domain difference consists of environment and usage characteristics in the SOFC installation
- No health-index labels available for the Home750 datasets
- We chose “Soot formation” dataset as Source domain
- We hypothesized linear degradation of the Health Index

Health Index “Source”



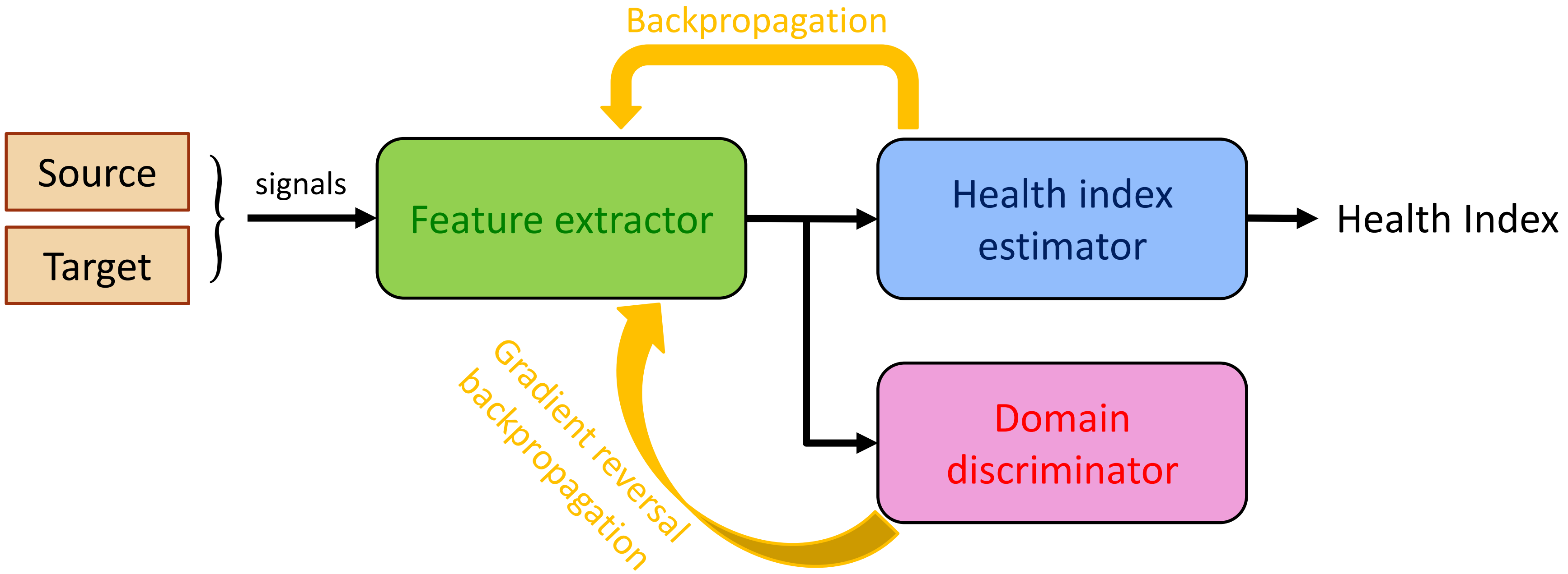
Domain adaptation by means of adversarial networks

With a *domain-adversarial neural network* (DANN) approach

- NNs are trained on labeled data from the source domain and some unlabeled data from the target domain
- the additional loss in domain discrimination is adversarially exploited by the feature extractor in order to deceive the discriminator

As the training progresses, this approach promotes the emergence of features that

- can achieve the main learning task on the source domain (HI estimation)
- are invariant with respect to the shift between the domains



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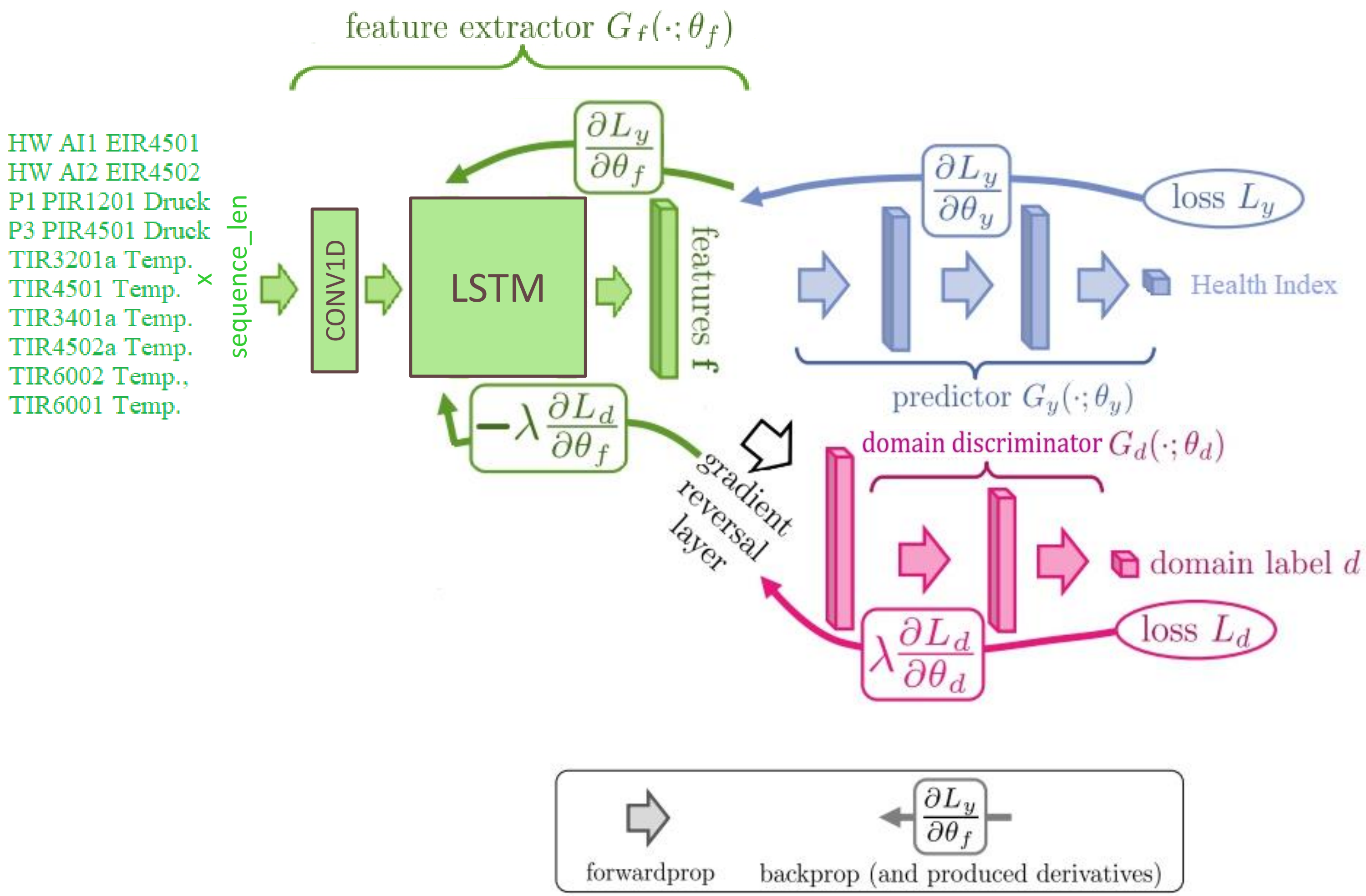
Scheme of the proposed system



Schema modified from: Y. Ganin, E. Ustinova et al. *Domain-Adversarial Training of Neural Networks,* Journal of Machine Learning Research 17 (2016)

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Time series modeling with Long Short Term Memory networks

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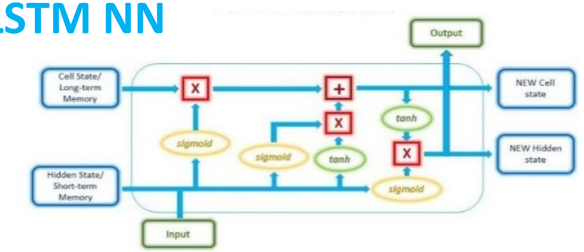
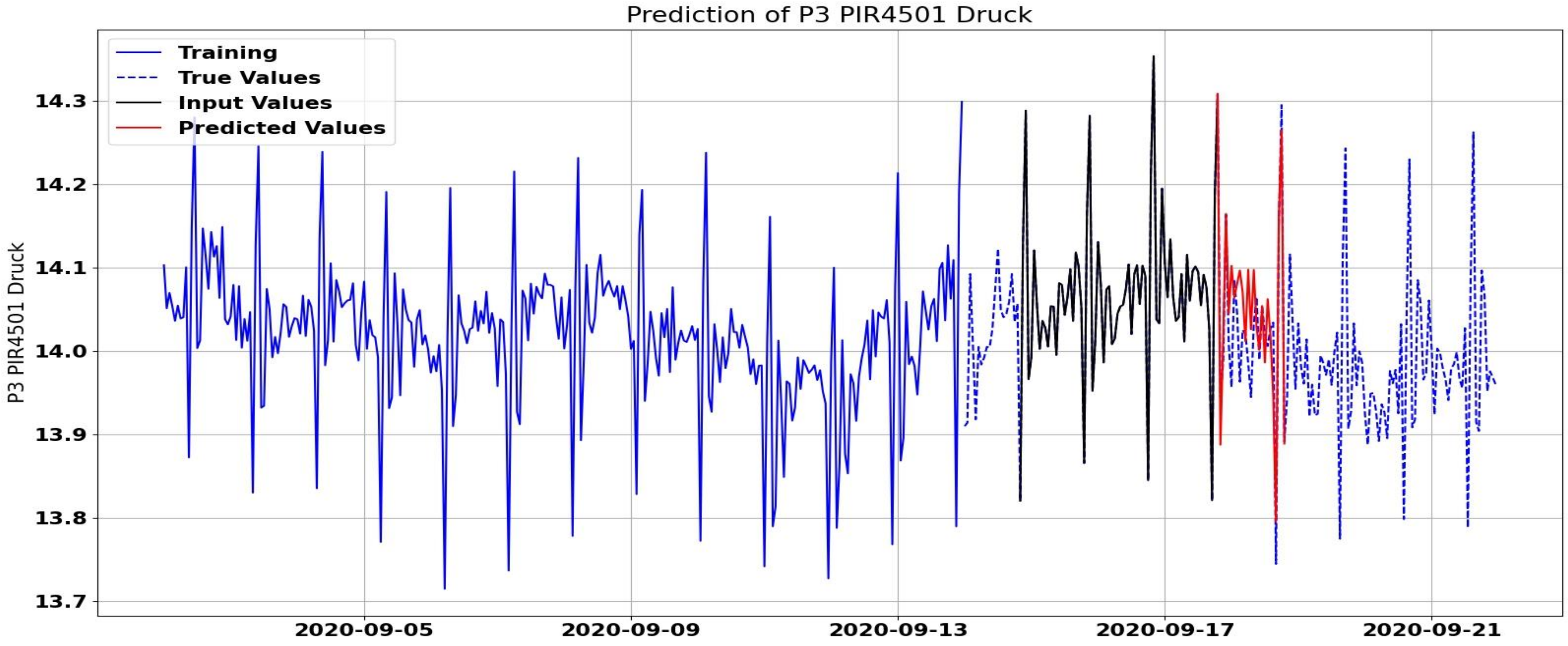
Modeling of periodicities and trends

past 72 h

LSTM NN



next 24 h



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Application of domain adaptation to the Sunfire dataset

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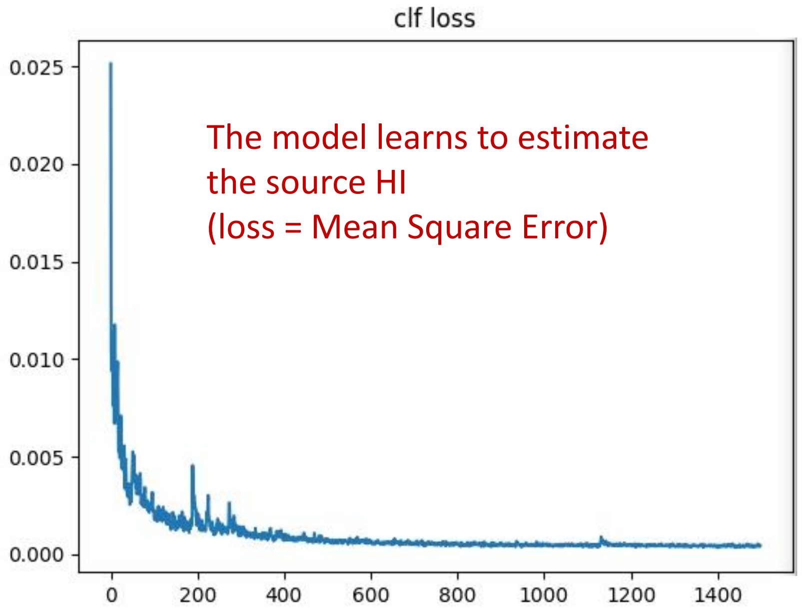
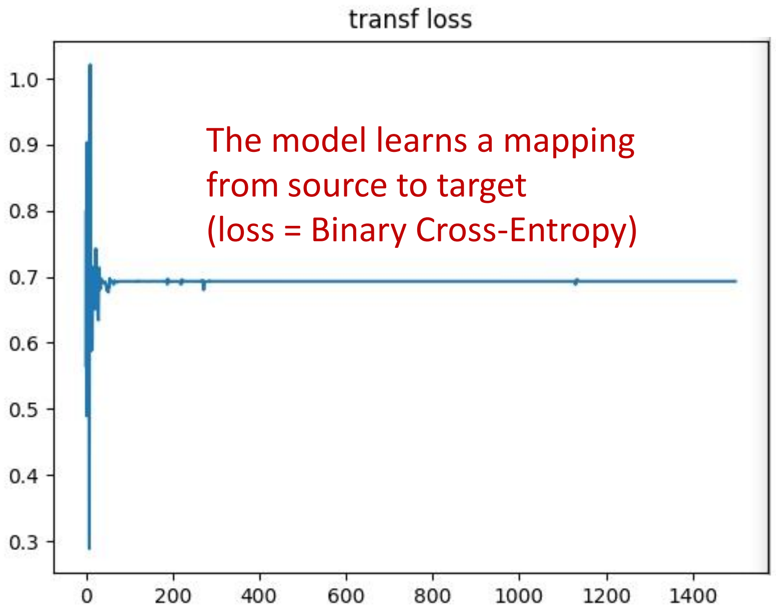
Example:
source = "soot formation", target = "normal operation"

- The full life-cycle of the source is used to train the HI estimator
- Only the initial portion of the target dataset (unlabeled) is used to perform domain adaptation during the training
- Two different **losses** are exploited during the training: **MSE** for the HI classifier and **BCE** for the domain discriminator.





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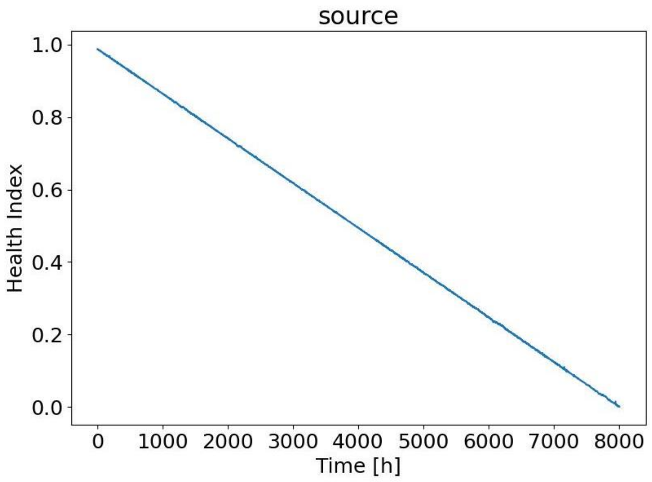
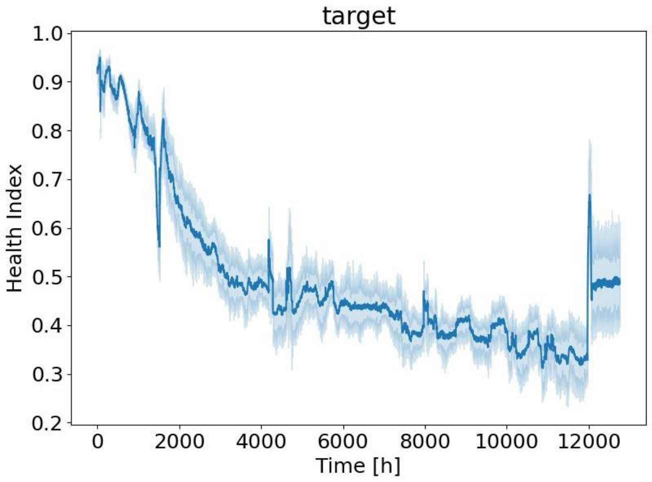
Effect of domain adaptation on Health Index estimation (1)

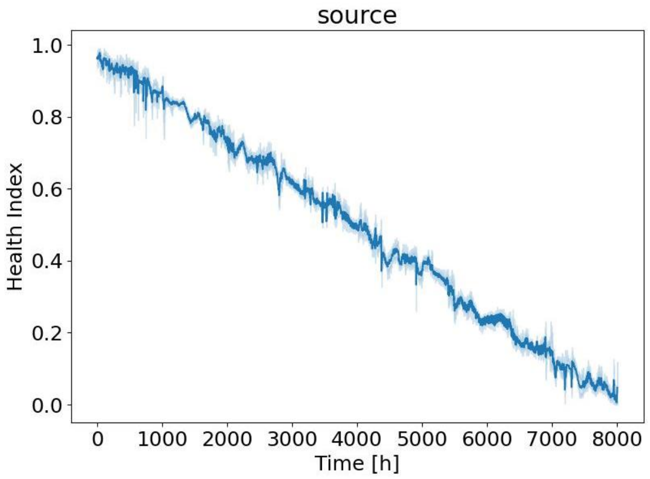
soot formation | normal operation

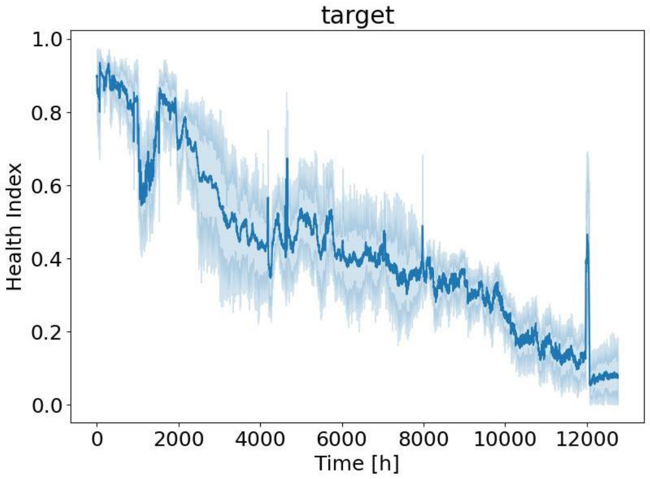
No domain adaptation
(only training on source)





With domain adaptation
(adversarial NNs)





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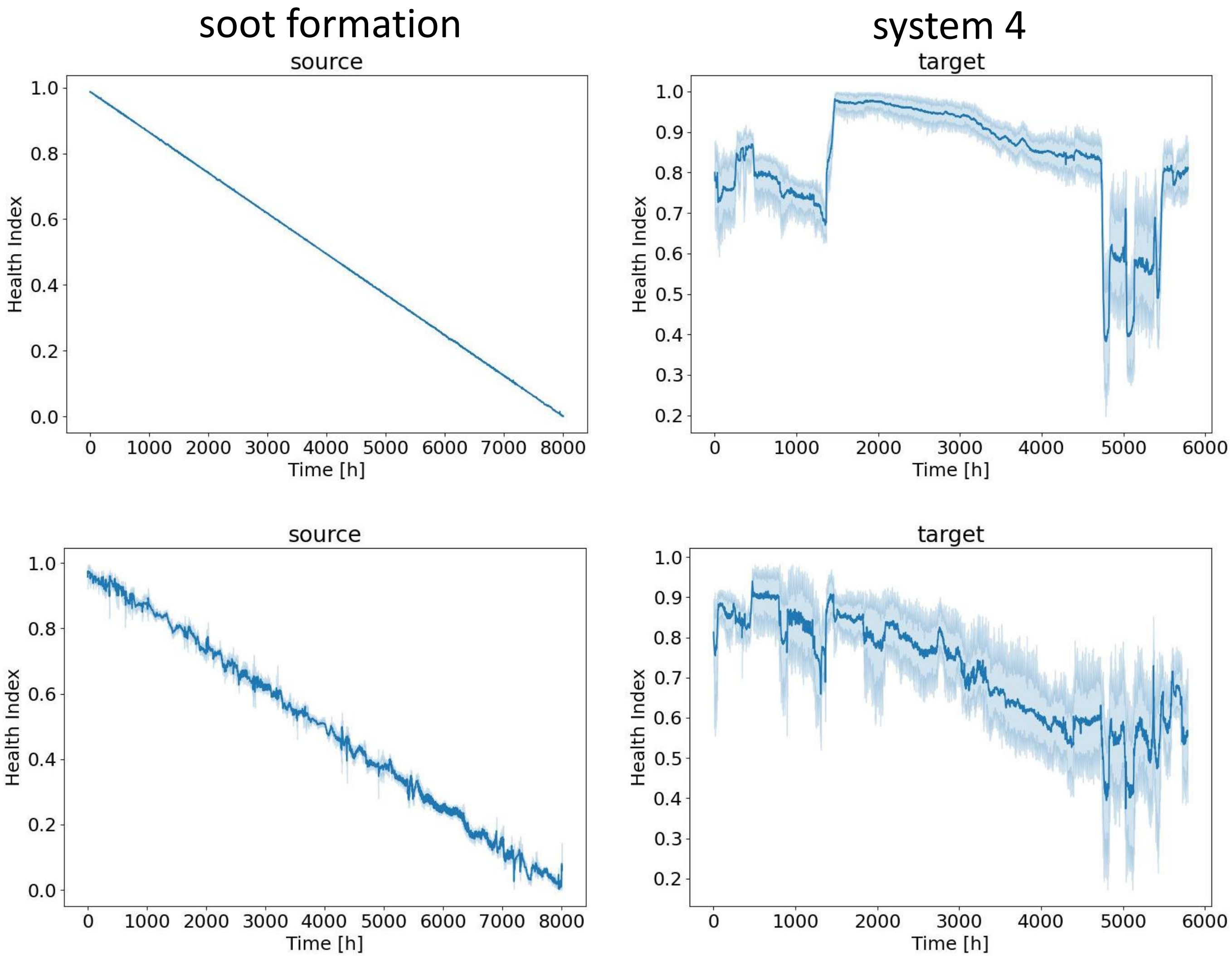
Effect of domain adaptation on Health Index estimation (2)

No domain adaptation
(only training on source)

With domain adaptation
(adversarial NNs)



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Conclusions

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Domain adaptation enables the transfer of a model trained on a reference case (source) to the monitoring of a new SOFC installation (target).
Only an initial small calibration dataset is required from the target system in its initial healthy condition.

With the available datasets several assumptions were required:

- Signals of the datasets do contain sufficient info for reliable HI estimation
- A representative device deterioration life-cycle is provided by the "soot formation" dataset
- The HI of "soot formation" is decreasing linearly from 1 to 0

The approach deserves further validation, possibly with:

- Labeled data (ground-truth HI reference)
- Datasets acquired under controlled device operation (for supervised training and for accuracy evaluation)

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Thank you
for your attention

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