Real-Time Outlier Detection with Dynamic Process Limits

Process Control 2023

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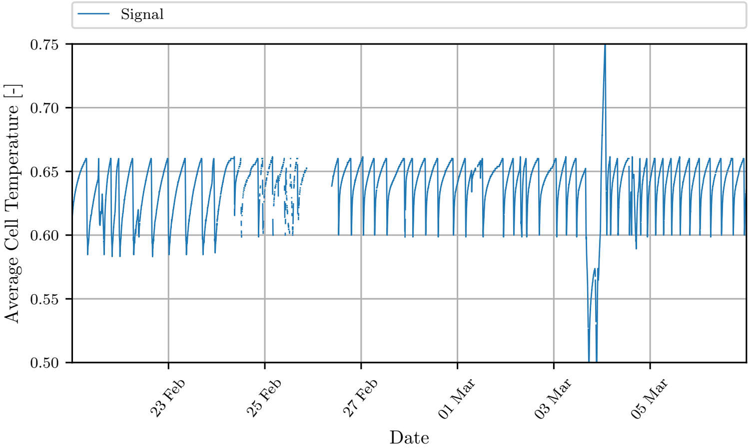
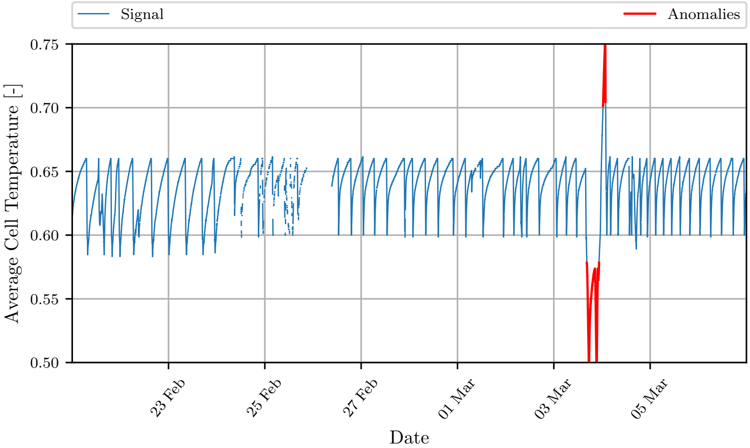
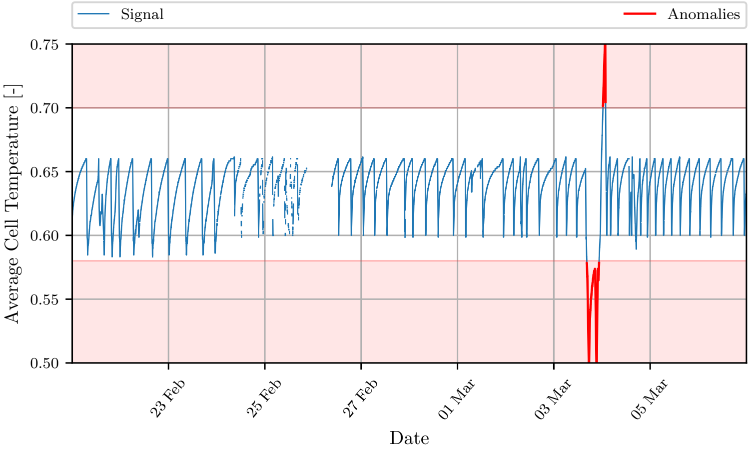
Real World Data



Data with Outliers



Static Threshold Limits



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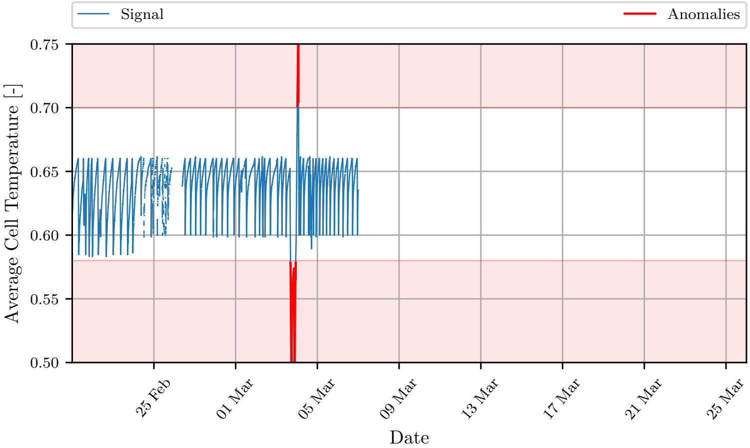
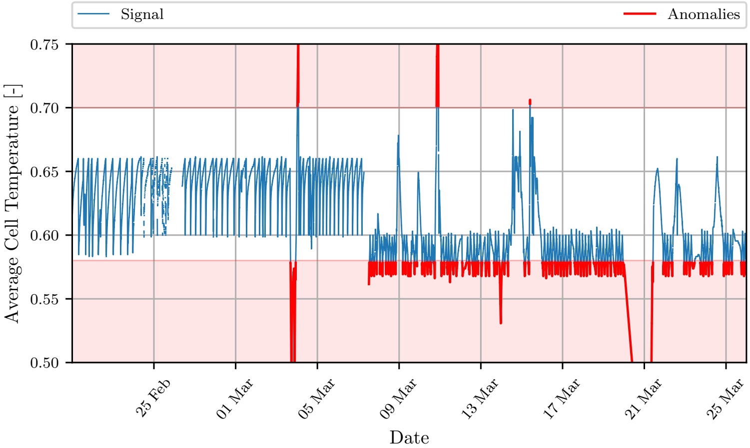
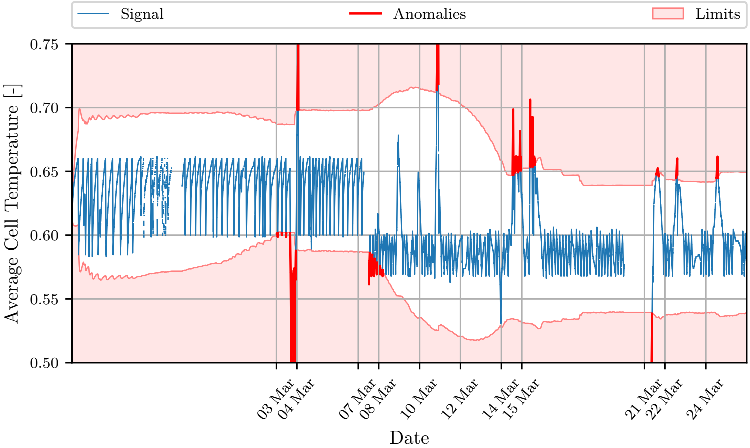


Comming Problem



Control Engineering Meets Artificial Intelligence



Goals

We need to design a detector that:

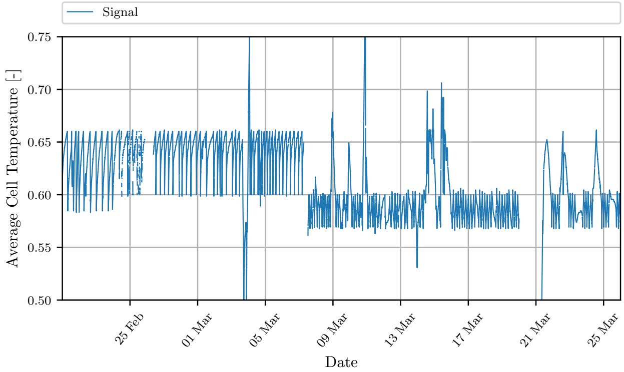
- does not require huge amount of data
- adapts to unseen operation
- provides conservative process limits
- operates with existing infrastructure

Proposed Solution

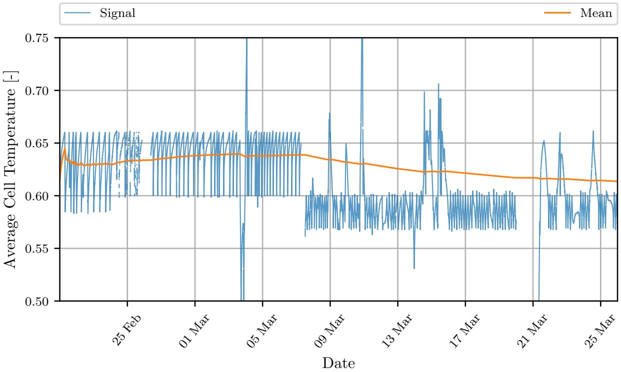
Real-Time Outlier Detection with Dynamic Process Limits combining:

- online learning
- invertible probabilistic model
- outlier detection
- self-supervised learning

Real Opeartion Data

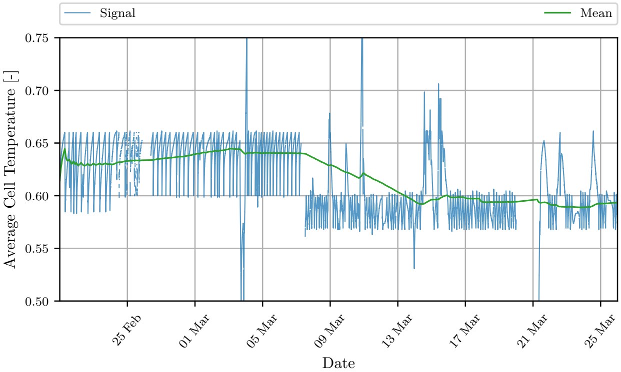


Online Learning via Welford Algorithm



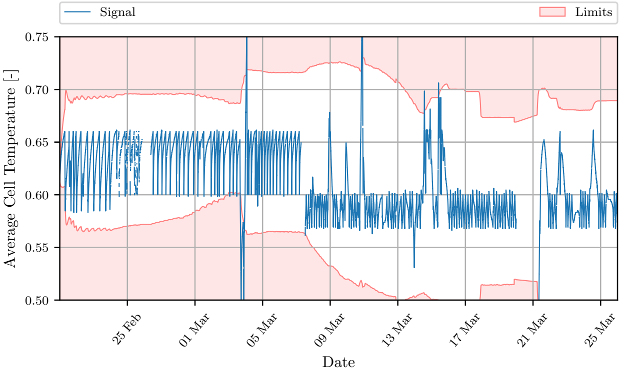
+ One-Pass Algorithm | − Adaptation Slows Down

Online Learning via Invertible Welford Algorithm



\+ Constant Adaptation | − Memorizes Data Window

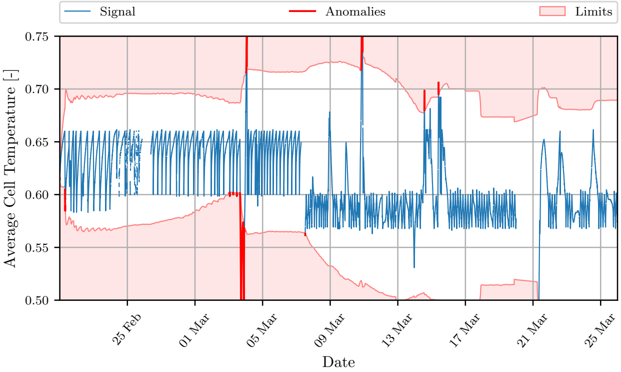
Dynamic Threshold Limits via Inversion



$$x_{\mathrm{l}} = F_X(1 - q; \bar{x}_n, s_n)^{-1}$$

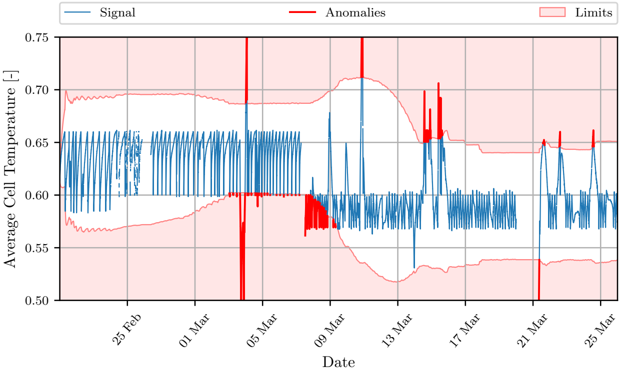
$$x_{\mathrm{u}} = F_X(q; \bar{x}_n, s_n)^{-1}$$

Distance-based Outlier Detection



$$y_i = \begin{cases} 0 & \text{if } q \leq F_X(x_i; \bar{x}_n, s_n) \\ 1 & \text{if } q > F_X(x_i; \bar{x}_n, s_n) \end{cases}$$

Self-Supervised Learning



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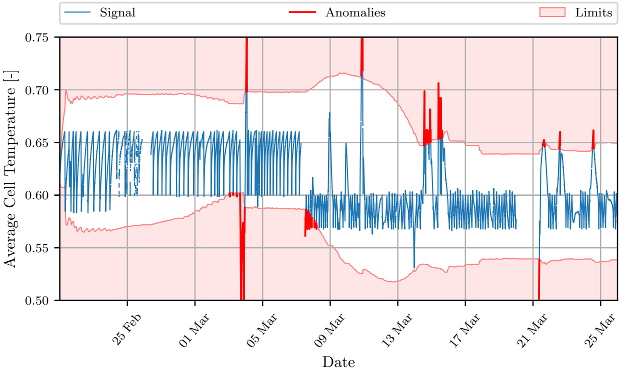
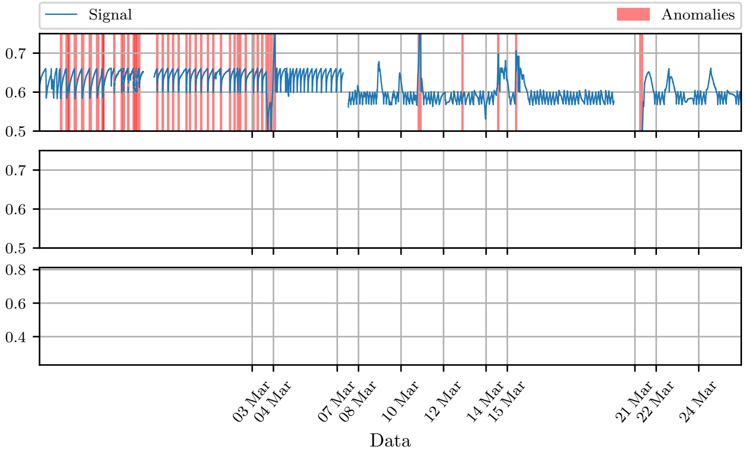
Self-Supervised Learning



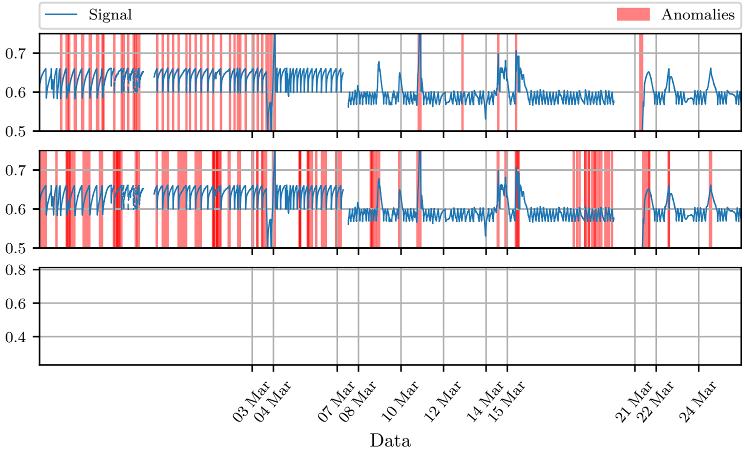
$$\frac{\sum_{y \in Y} y}{|Y|} > q$$

Battery Energy Storage System - BESS

Case Study - BESS



Case Study - BESS



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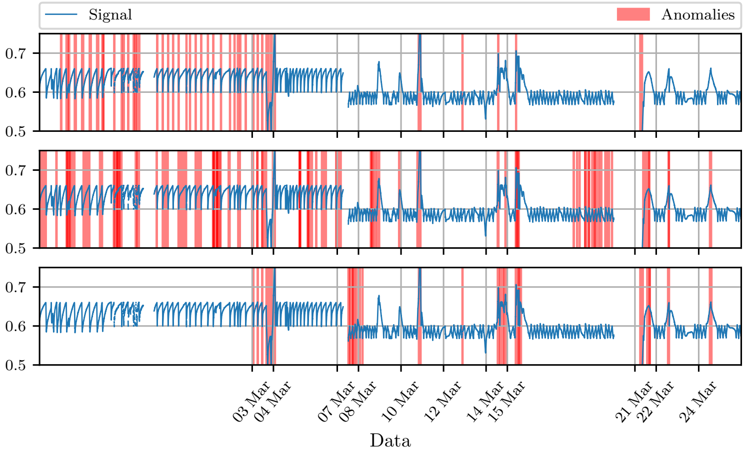
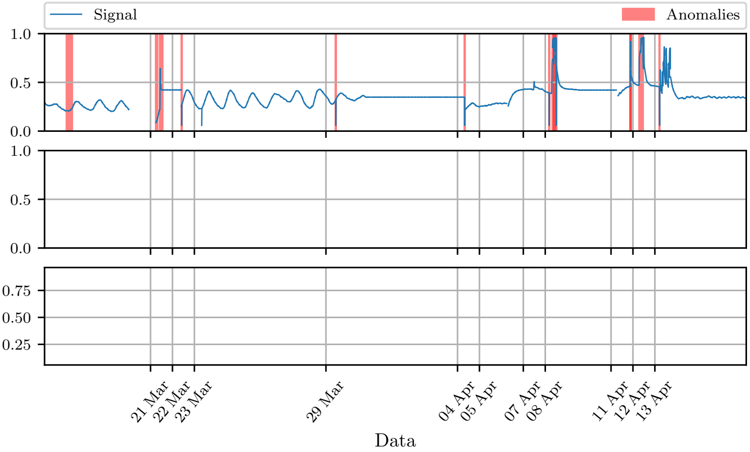


Case Study - Inverter



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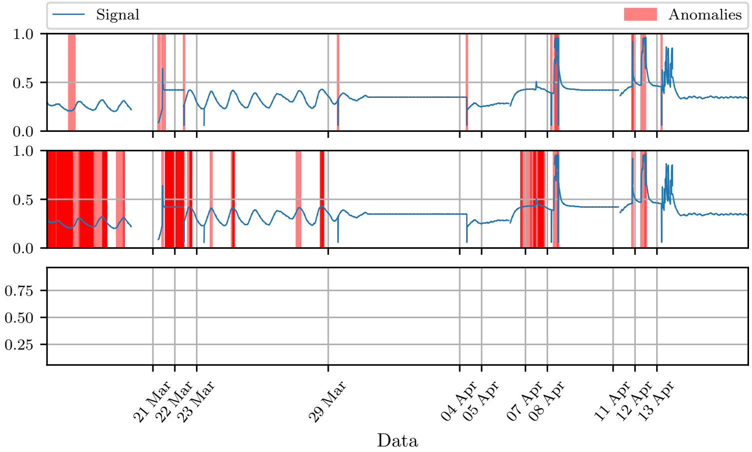

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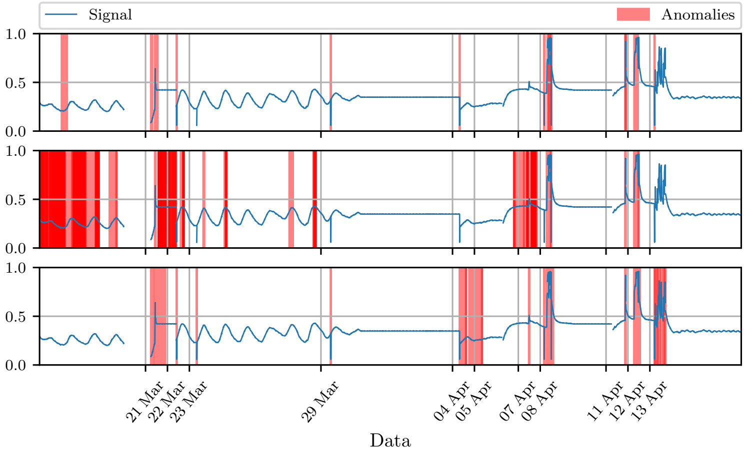
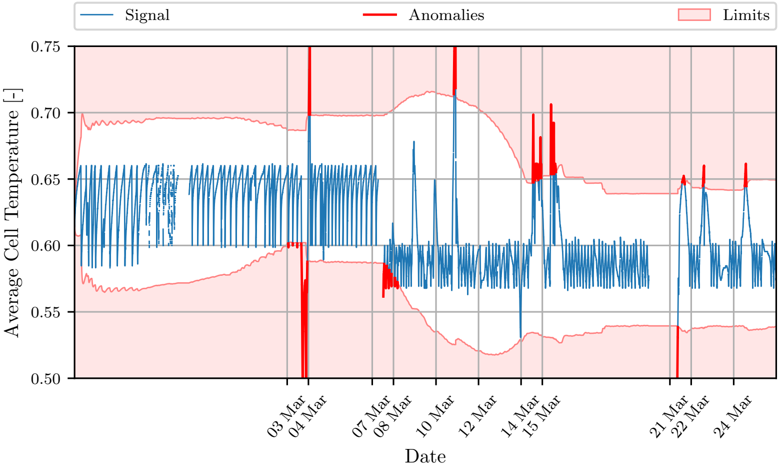
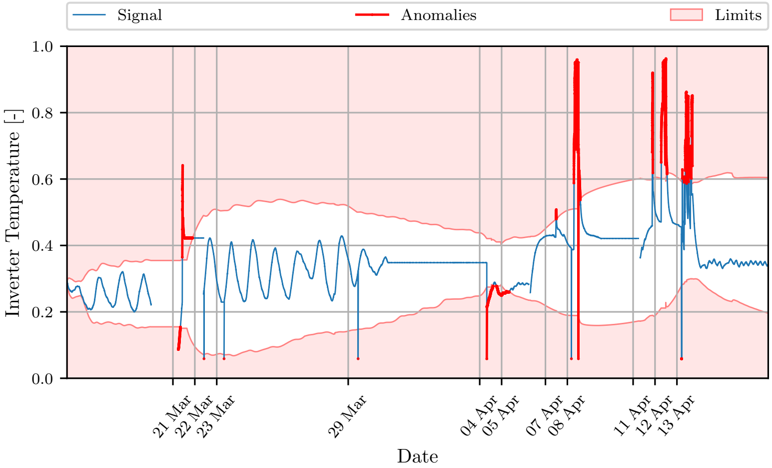


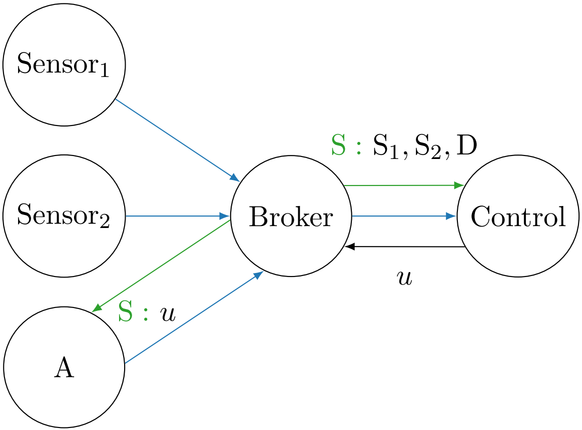
Dynamic Process Limits - BESS



Dynamic Process Limits - Inverter



Utilize Existing Infrastructure



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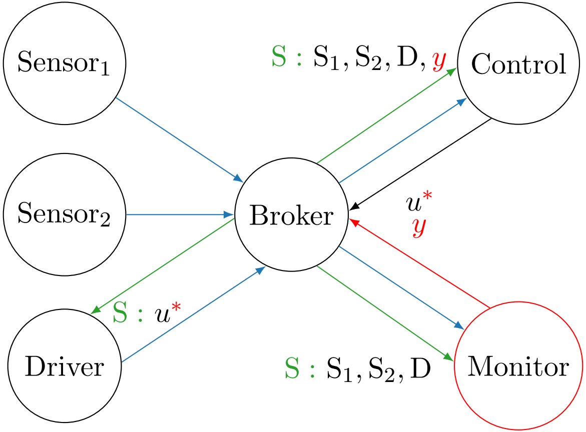
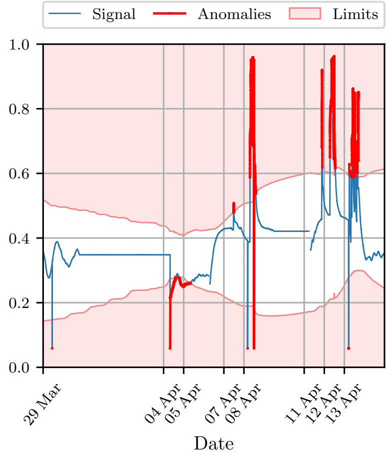


Summary

- outlier detection on streamed data
- adaptation to external conditions
- online self-learning approach
- dynamic process limits for individual signals
- integration with existing IT infrastructure



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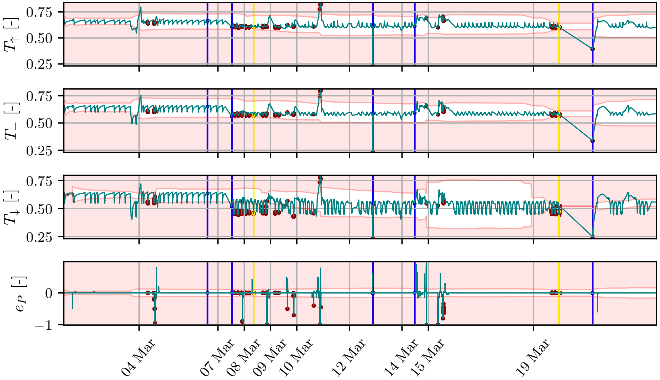
Follow-up research



[1]

[1] M. Wadinger and M. Kvasnica. Adaptable and interpretable framework for novelty detection in real-time iot systems. In Proceedings of the 62nd IEEE CDC, Singapore, 2023. under review.

Process Time Evaluation

Evaluation Time [μs]	BESS		Inverter	
	average	max	average	max
Half-Space Trees	218 ± 198	10129	216 ± 196	11281
One-Class SVM	8 ± 7	1233	9 ± 9	1711
Proposed	57 ± 55	9431	60 ± 75	12330

Online Anomaly Detection Workflow

Input: expiration period t_e, time constant t_c
Output: score y_i, threshold $x_{\mathrm{q},i}$

Initialisation :
$i \leftarrow 1;\ n \leftarrow 1;\ q \leftarrow 0.9973;\ \bar{x} \leftarrow x_0;\ s^2 \leftarrow 1;$
compute $F_X(x_0)$;
LOOP Process
loop
  $x_i \leftarrow$ RECEIVE();
  $y_i \leftarrow$ PREDICT(x_i) ;
  $x_{\mathrm{q},i} \leftarrow$ GET$(q, \bar{x}, s^2)$;
  if (1a) **or** (3) **then**
    $\bar{x},\ s^2 \leftarrow$ UPDATE$(x_i, \bar{x}, s^2, n)$;
    $n \leftarrow n + 1$;
    for x_{i-t_e} **do**
      $\bar{x},\ s^2 \leftarrow$ REVERT$(x_{i-t_\mathrm{e}}, \bar{x}, s^2, n)$;
      $n \leftarrow n - 1$;
    end for
  end if
  $i \leftarrow i + 1$;
end loop