Anomaly and Change Point Detection in Energy Valve Flow and Temperature Data

Contribution Toward Extended Recalibration Intervals to Enhance Longevity, and Reduce Waste and Costs

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Introduction: To reduce waste and operational costs, there is a need to extend recalibration periods for Heating, Ventilation and Air Conditioning (HVAC) devices, as current regulations often lead to premature replacement. This thesis presents a data-driven approach to detect irregularities and changes in device behaviour - an essential step toward verifying correct functioning based on device-generated data. It explores unsupervised anomaly detection and change point detection methods applied on time series data from Belimo's energy valves.

For anomaly detection, K-Means, Isolation Forest (I-Forest) and Local Outlier Factor (LOF) were selected, representing diverse algorithmic families. For change point detection, the Pruned Exact Linear Time (PELT) algorithm was used with the intention to combine it with engineered features to support interpretability. Evaluation relied on the Excess-Mass (EM) curve for anomaly detection and visual assessment for change points.

Result: LOF consistently outperformed the K-Means baseline, with the correlation-based feature notably improving performance at the originally selected window size. Two LOF variants showed complementary strengths: the 12-hour window variant (without correlation) was more robust and generalizable across unseen and long time series (see Figure 2), while the 3-hour variant (with correlation) better captured fine-grained anomalies in less cyclical data (see example shown in Figure 1). No single LOF configuration proved universally optimal, emphasizing the importance of aligning window size and features with specific data characteristics.

For change point detection, two systems were developed using PELT with tuned penalty parameters: one targeting major changes (e.g., frequency and outlier density), and an extended system also detecting minor shifts via rolling mean (see example in Figure 3). The Major System achieved 83% correct detections on unseen data with few false positives, while the Comprehensive System captured finer shifts but introduced more false positives. On long time series, results were mixed: major changes were plausibly detected in half the cases, while others showed extended false detections. These findings highlight the need for feature-specific penalty tuning and more robust evaluation methods to ensure reliability at scale.

Conclusion: This work lays foundational groundwork for developing a robust system adaptable to the diverse characteristics of energy valve data. The findings support existing research, emphasizing the effectiveness of distance-based methods and EM curves for unsupervised time series anomaly detection.

Future work could involve collecting expert-labelled ground truth to strengthen evaluation validity, exploring adaptive or ensemble models to handle varying data characteristics, and applying explainable AI to enhance interpretability. Testing on larger, longer time series is also recommended to assess scalability, potentially using sliding-window approaches to boost robustness and enable real-time detection.

Figure 1: Comparison of Anomaly Scores from Tuned Detection Models on Example Time Series
Own presentment

Figure 2: EM Curves on Long Time Series with Scalability Assessed Against Each Model's Tuning-Set Median EM
Own presentment

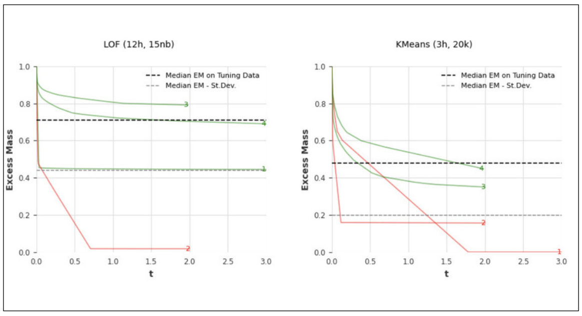

Figure 3: Example Time Series Showing Change Point Detection Results
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