

Anomaly Detection for Electro-Hydrostatic Actuators using LSTM Autoencoder.

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Electro-Hydrostatic Actuators (EHAs) are widely used in aerospace and industrial systems, where timely detection of sensor anomalies is essential to ensure safe and reliable operation. However, the large volume and high sampling frequency of EHA sensor data pose challenges for accurate and efficient anomaly detection. Conventional statistical and classical machine-learning methods such as Z-score, Interquartile Range (IQR), Median Absolute Deviation (MAD), Isolation Forest, Gaussian Mixture, and k-means often fail to capture the temporal dependencies inherent in EHA signals, resulting in limited detection accuracy and elevated false-alarm rates. Furthermore, systematic evaluations of data-driven anomaly detection approaches for EHA systems remain scarce, particularly under varying operational conditions. This study presents an offline anomaly-detection framework for univariate EHA sensor signals, focusing on temperature and pressure data collected from a controlled test bench. The method employs a reconstruction-based Long Short-Term Memory (LSTM) autoencoder, calibrated and evaluated using validation-set reconstruction-error distributions. Performance is assessed across multiple fault-injection scenarios using accuracy, precision, recall, and F1-score, complemented by sensitivity analyses under varying operating conditions. The LSTM autoencoder achieved an average accuracy of 99.0%, precision up to 100%, recall between 90.2% and 99.6%, and F1-scores from 93.1% to 99.8%, demonstrating high detection sensitivity and a very low false-alarm rate across all evaluated sensors. These results highlight the feasibility of data-driven offline anomaly detection for EHAs. Future work will focus on adapting the developed framework for an online (real-time) environment, enabling the algorithm to detect anomalies while the system is operating. The goal is to achieve near-real-time performance with minimal latency and maintain high accuracy under varying operational conditions.

Keywords: Anomaly Detection, LSTM Autoencoder, Deep Learning, Reconstruction Error, Fault Detection

1. Introduction

Electro-Hydrostatic Actuators (EHAs) are increasingly deployed in aerospace and industrial systems due to high power density, compactness, and improved energy efficiency compared to conventional hydraulic actuation solutions Qiao et al. (2017). Because EHAs often operate in safety-

critical contexts, reliable monitoring is essential: sensor anomalies can corrupt state estimation, degrade performance, or mask developing faults. Modern EHA test benches and fielded systems are instrumented with multiple sensors at high sampling rates, producing large volumes of time-series measurements during operation Guo et al. (2022), which makes robust anomaly detection

both important and challenging. Classical statistical methods (e.g., Z-score, IQR, MAD) and traditional machine-learning approaches (e.g., clustering, mixture models, Isolation Forest) typically rely on stationarity or weak temporal assumptions and therefore struggle to represent the temporal dependencies and nonlinear dynamics characteristic of EHA signals Khan et al. (2025). Reconstruction-based deep learning, and in particular LSTM-based autoencoders, offers a practical alternative because LSTM architectures are designed to capture long-range temporal dependencies in sequential data Gers et al. (2000); Zhang et al. (2021b). However, systematic studies applying LSTM-based anomaly detection to EHA systems, especially under controlled operating conditions and reliability-oriented evaluation, remain limited. This paper addresses this gap by proposing an offline LSTM autoencoder framework for univariate EHA sensor signals, calibrated using validation reconstruction-error distributions and evaluated under fault-injection scenarios across operating conditions.

2. Related Work

Anomaly detection for sensor and actuator systems is widely studied for condition monitoring in safety-critical domains. Because labelled fault data are scarce in operational settings, most practical methods adopt unsupervised or semi-supervised formulations. Early approaches rely on statistical and shallow-learning techniques such as threshold monitoring, PCA variants, density estimation, and clustering Paffenroth et al. (2018). While efficient and interpretable, these techniques often assume stationarity or linear structure and can degrade under nonlinear and temporally correlated actuator telemetry.

Classical machine-learning extends this line via one-class learners and forecasting-based detection. One-Class SVM and Support Vector Data Description model nominal behaviour using a learned boundary Tax and Duin (2004), while autoregressive forecasting flags anomalies through large prediction residuals Günnemann et al. (2014). However, these methods typically struggle to scale to high-frequency time-series and

to represent long-horizon temporal dependencies.

Deep-learning-based approaches address these limitations by learning temporal representations directly from data. Reconstruction-based autoencoders detect anomalies using elevated reconstruction error Chen et al. (2018), and recurrent encoder-decoder architectures (notably LSTM-based) further improve performance by explicitly modelling sequence dynamics Zhang et al. (2021a); Filonov et al. (2017). Variants using convolutional components, variational objectives, or adversarial training have shown strong results across multiple domains Memarzadeh et al. (2020); Siegel (2020), while hybrid frameworks combine reconstruction, forecasting, and density estimation to improve robustness Zong et al. (2018). A representative LSTM-autoencoder thresholding pipeline demonstrated strong accuracy and robustness on real-world environmental sensor data Wei et al. (2023a), motivating similar temporal architectures for actuator monitoring.

Across domains, unsupervised detectors commonly assume abnormal behaviour is statistically distinct from nominal behaviour Lee et al. (2001). This motivates clustering-based anomaly identification Rajasegarar et al. (2006) and probabilistic approaches based on low likelihood under Bayesian models Wang et al. (2008), although distributional drift remains a persistent limitation. To mitigate drift and deployment constraints, hybrid frameworks fuse statistical residual analysis with deep forecasting or reconstruction signals Munir et al. (2019). Survey studies summarize trade-offs among accuracy, computational complexity, and deployability Erhan et al. (2021), and recent work emphasizes scalable and efficient pipelines for resource-constrained and industrial IoT settings Jain et al. (2022); Nizam et al. (2022). Despite these advances, evaluations on actuator-specific telemetry under controlled fault-injection conditions remain limited, particularly for electro-hydrostatic actuators where prior work is often model-based or supervised.

Motivated by these gaps, this work investigates a reconstruction-based LSTM autoencoder for offline univariate anomaly detection in EHA sensor data for actuator health monitoring.

3. Problem Formulation

The anomaly detection literature offers mature families of methods for time-series monitoring, including statistical detectors, one-class learning, and deep temporal models. Nevertheless, evidence is still fragmented with respect to actuator health monitoring: many studies emphasize generic time-series settings, while comparatively fewer works report rigorous evaluations on actuator sensor streams acquired under controlled fault conditions and across changing operating regimes. In parallel, labelled fault data remain limited in practice, which constrains purely supervised formulations and motivates approaches that learn nominal behaviour and detect deviations with minimal annotation.

4. Contribution.

To address this gap, the present work investigates an offline, data-driven anomaly detection framework for *univariate* EHA sensor channels, focusing on capturing the temporal characteristics of nominal operation and identifying anomalous deviations in unseen recordings. The study is supported by a reliability-oriented experimental evaluation on high-resolution test-bench measurements spanning fault-injection scenarios and operating conditions, and includes benchmarking against representative baseline detectors to clarify the practical benefits and limitations of the proposed approach.

5. Methodology

We employ an offline, reconstruction-based anomaly detection approach for univariate sensor channels. The underlying assumption is that a model trained on nominal operation reconstructs normal temporal patterns accurately, whereas anomalous deviations lead to increased reconstruction discrepancy. To capture temporal dependencies in the signal, we use an LSTM encoder-decoder (autoencoder) architecture; the model structure is illustrated in Fig. 1. Anomalies are detected by scoring each window using reconstruction error and applying a threshold calibrated from nominal data.

Temporal Data Preprocessing. Let $x_{1:T} = \{x_1, \dots, x_T\}$ with $x_t \in \mathbb{R}$ denote a univariate sensor signal. The signal is normalized using statistics computed from nominal training data. It is then segmented into overlapping windows of fixed length L with stride r . Each window is denoted by

$$\begin{aligned} \mathbf{x}_i &= [x_i, \dots, x_{i+L-1}]^\top \in \mathbb{R}^L, \\ i &= 1, 1+r, 1+2r, \dots \end{aligned} \quad (1)$$

LSTM Autoencoder and Reconstruction Error.

Given a window $\mathbf{x}_i$, the encoder maps the sequence to a latent representation and the decoder produces a reconstruction $\hat{\mathbf{x}}_i$. The model is trained on nominal windows only by minimizing the average reconstruction loss

$$\begin{aligned} (\theta^*, \phi^*) &= \arg \min_{\theta, \phi} \frac{1}{N} \sum_{i=1}^N \ell(\mathbf{x}_i, \hat{\mathbf{x}}_i), \\ \hat{\mathbf{x}}_i &= g_\phi(f_\theta(\mathbf{x}_i)). \end{aligned} \quad (2)$$

In this work, $\ell(\cdot, \cdot)$ is defined as the mean absolute error (MAE),

$$\ell(\mathbf{x}_i, \hat{\mathbf{x}}_i) = \frac{1}{L} \sum_{j=1}^L |x_{i+j-1} - \hat{x}_{i+j-1}|, \quad (3)$$

We adopt MAE because it preserves the physical units of the sensor signal and is less sensitive to occasional large spikes compared to squared-error losses, which improved empirical stability in our experiments. Training uses gradient-based optimization with early stopping based on nominal validation loss.

Anomaly Score and Thresholding. For each window, we define an anomaly score as its reconstruction error:

$$E_i = \ell(\mathbf{x}_i, \hat{\mathbf{x}}_i), \hat{y}_i = \mathbb{I}[E_i > \tau]. \quad (4)$$

A decision threshold τ is calibrated from nominal reconstruction errors (e.g., using an upper-tail cutoff such as a high quantile or a conservative maximum-error rule). Due to window overlap, sustained deviations typically yield consecutive anomalous windows, facilitating event-level localization in offline analysis.

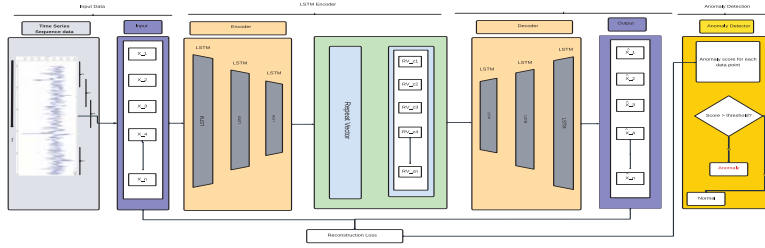


Fig. 1.: LSTM autoencoder architecture with reconstruction for nominal temporal behaviour.

Algorithm 1 Offline reconstruction anomaly detection using an LSTM AE

Require: Nominal signal $x_{1:T}$, test signal $x'_{1:U}$, window length L , stride r

Ensure: Test-window scores $\{E'_i\}$ and labels $\{\hat{y}_i\}$

- 1: Normalize using nominal training statistics; extract windows $\{\mathbf{x}_i\}$, $\{\mathbf{x}'_i\}$ via (1).
- 2: Train LSTM-AE on $\{\mathbf{x}_i\}$ by minimizing MAE loss (2)–(3).
- 3: Compute nominal errors $E_i = \ell(\mathbf{x}_i, \hat{\mathbf{x}}_i)$ and set threshold τ from their upper tail.
- 4: **for all** test windows $\mathbf{x}'_i$ **do**
- 5: Reconstruct $\hat{\mathbf{x}}'_i$; compute $E'_i = \ell(\mathbf{x}'_i, \hat{\mathbf{x}}'_i)$.
- 6: Predict $\hat{y}_i \leftarrow \mathbb{I}[E'_i > \tau]$ using (4).
- 7: **end for**

6. Experimental Setup

All measurements used in this study were acquired on a controlled EHA test bench and measurement infrastructure described in Leitenberger and Matthiesen (2021); Dörr et al. (2022). The experimental platform provides repeatable operation under well defined regimes and synchronized high frequency sensing, supporting a reliability oriented evaluation.

6.1. EHA Test Bench

The employed actuator design is shown in Fig. 2. The bench is operated using an ADwin Pro2 measurement and control system interfaced via EtherCAT to an external inverter. The outer position control loop runs at 2 kHz using a magnetostrictive position senso, while the internal speed and current loops are implemented on the inverter at 4

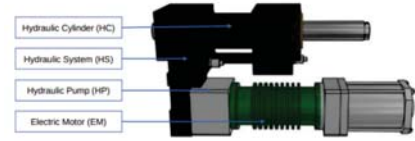


Fig. 2.: Design of the EHA used in the experimental setup Leitenberger and Matthiesen (2021).

kHz and 16 kHz, respectively.

Experiments were conducted under two representative load conditions. The first is an inertial load realized by an attached mass of 11.83 kg. The second is a spring load with stiffness 241.381 N/mm. The bench is instrumented with multiple sensors; this study reports results on univariate temperature and pressure channels recorded as continuous time series at high sampling rate, capturing transient dynamics and regime dependent behaviour.

6.2. Data Acquisition

Recordings were checked for invalid or missing samples. Temperature and pressure signals were acquired as continuous time series and prepared consistently with the preprocessing described in the Methodology section. The dataset was split into training and test subsets using a 70/30 ratio. The anomaly detection model was trained exclusively on nominal data.

6.3. Dataset Construction and Labelling

To obtain a clean nominal training set, a channel wise sigma filtering rule was applied on fault free recordings. For each sensor channel, the mean μ and standard deviation σ were computed from

Table 1.: LSTM-AE training parameters.

Hyperparameter	Value
Learning rate	0.0001
Dropout	0.20
Batch size	64
Epochs (max)	30
Loss function	MAE
Validation split	Last 10%

nominal samples, and observations exceeding

$$x(t) > \mu + k\sigma, \quad k \in \{3, 4\} \quad (5)$$

were removed, where k was selected according to channel variability. The test set preserves the full sensor range and contains nominal and anomalous segments. For quantitative reporting, binary evaluation labels follow the same operational definition, with $x(t) \leq \mu + k\sigma$ treated as nominal and $x(t) > \mu + k\sigma$ treated as anomalous. These labels are used only for evaluation and do not enter training. Figure 3 summarizes the nominal distribution used to select σ bounds, the nominal filtering procedure used for training set construction, and the test set labeling workflow.

7. Results

The proposed LSTM-AE is evaluated using offline EHA datasets under nominal and fault-injection conditions. The model is trained exclusively on nominal data, with a chronological validation split used for early stopping and threshold calibration. The final training configuration and hyperparameters are summarized in Table 1. Model convergence is illustrated in Fig. 4, which shows smooth and stable training and validation loss curves over the training epochs, indicating effective optimisation and good generalisation without overfitting. Detection performance is assessed using classification metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. To provide a system-level evaluation, results are reported as averages across representative pressure and temperature sensor channels. Table 2 compares the proposed LSTM-AE with statistical, classical machine-learning, and deep autoencoder baselines. Statistical methods and classical models achieve high nominal accuracy but exhibit near-

zero precision and F1-scores due to class imbalance and the absence of temporal modelling. Deep autoencoder baselines improve reconstruction fidelity but remain limited in recall and robustness. In contrast, the LSTM-AE consistently achieves high precision, recall exceeding 90%, and ROC-AUC values close to unity across sensors, demonstrating a substantially improved balance between sensitivity and false-alarm suppression. Qualitative inspection supports the quantitative findings. Fig. 5 and Fig. 6 show representative spike events, where abrupt transients in the raw sensor signal are correctly identified as anomalies. Detected anomalies form coherent segments rather than isolated points, while normal fluctuations before and after the event are not falsely flagged. This highlights the benefit of temporal context in suppressing spurious alarms.

8. Discussion

The results indicate that modeling temporal dependencies with an LSTM AE yields more reliable anomaly detection on EHA sensor streams than non temporal baselines. The main contribution is a practical detection pipeline that achieves a favorable precision recall trade off across both pressure and temperature signals, and qualitatively produces contiguous anomalous segments rather than isolated outliers, which is more suitable for condition monitoring. The baseline comparison also highlights that high accuracy is not informative under class imbalance, as several detectors appear accurate while exhibiting near zero precision and F1 score. In contrast, the LSTM AE improves precision, recall, and ROC AUC, consistent with improved separability when temporal structure is represented. Three key limitations were noted, labels are derived from a transparent σ -rule, yet may not reflect fault criticality or slow degradation that remains within nominal bounds; the analysis is univariate and therefore does not exploit cross-channel dependencies; and performance depends on threshold calibration, which may require retuning under regime shifts or sensor drift. Addressing these in future work would strengthen the link between anomaly detection outputs and maintenance decision-making.

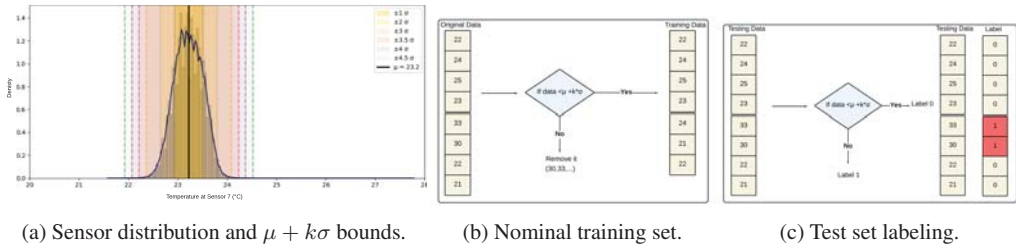


Fig. 3.: Dataset preparation and evaluation protocol.

Table 2.: Comparative performance of baseline models and the proposed LSTM-AE, averaged across key EHA sensor signals.

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Z-score	0.918	0.001	0.316	0.003	0.617
IQR	0.873	0.001	0.376	0.002	0.625
MAD	0.979	0.003	0.175	0.006	0.577
Isolation Forest	0.360	0.000	0.697	0.001	0.528
Gaussian Mixture	0.905	0.001	0.341	0.003	0.623
k -means	0.905	0.001	0.343	0.003	0.624
Local Outlier Factor	0.999	0.016	0.008	0.010	0.504
AE	0.9997	1.000	0.249	0.398	0.624
CNN-AE	0.995	0.030	0.115	0.048	0.556
LSTM-AE	0.995–0.999	0.96–1.00	0.90–0.99	0.93–0.99	0.95–0.99

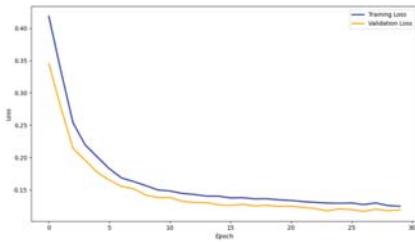


Fig. 4.: Training and validation loss of LSTM-AE.

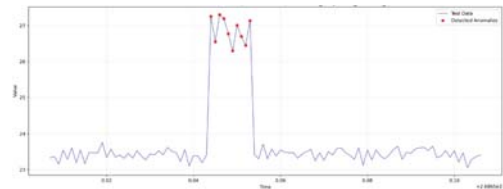


Fig. 6.: Sustained spike event: raw sensor signal (blue) and detected anomalies (red).

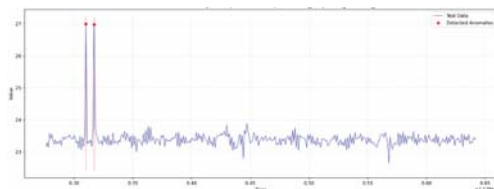


Fig. 5.: Spike event example: raw sensor signal (blue) and detected anomalies (red).

9. Conclusion

This work developed an offline anomaly detection pipeline for unlabeled EHA sensor time-

series using a univariate LSTM autoencoder. The model learns nominal temporal dynamics from data and flags deviations through reconstruction error, avoiding the need for fault labels during training. The workflow includes sigma-based cleaning, z-score normalization, sliding-window segmentation, and validation-based threshold selection to support reproducible evaluation. Test-bench experiments with expert-defined fault injections showed high detection performance across operating conditions, with accuracy above 99% and low false-alarm rates relative to statistical and conventional machine-learning baselines, indicating that reconstruction-based sequence models are

Table 3.: Comparison with representative anomaly detection approaches reported in the literature.

Reference	Technique	Dataset	Acc.	Prec.	Rec.	F1
Yin et al. (2022)	LSTM-AE	Yahoo Webscope S5	99.25	97.84	94.16	95.97
Nguyen et al. (2021)	LSTM-AE	+ Generated dataset	98.36	98.45	95.99	96.98
	OCSVM					
Li and He (2019)	Adversarial LSTM-AE	CCV (video)	83.03	75.08	73.26	74.16
Sharma et al. (2020)	LSTM-AE	CERT insider threat	90.17	–	91.03	–
Wei et al. (2023b)	LSTM-AE	CO ₂ dataset	99.50	100	89.90	94.68
Tran et al. (2020)	LSTM-AE + iForest	Fashion data	95.00	100	94.00	87.00
This work	LSTM-AE	EHA sensor data	99.0–99.8	99–100	93–98	93–98

suitable for offline EHA condition monitoring. Key limitations are that evaluation labels follow an operational σ -rule that may not reflect fault criticality or slow within-bounds degradation, the univariate setup does not capture cross-channel dependencies, and thresholds may require retuning under regime shifts or sensor drift. Future work will address these points by extending the method to real-time deployment (e.g., compression and low-latency inference), integrating multivariate sensor fusion, broadening fault coverage for validation, and assessing robustness under long-term operational conditions.

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