Machine Learning Fault Detection for Piezoelectric Actuators in a Microassembly System

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Abstract: Piezoelectric actuators are essential for high-precision microassembly. However, monitoring their health state presents significant challenges due to their compact size and the inherent complexity of their modeling. This study presents a machine learning-based approach to predict failures in a micromanipulation system with four piezoelectric actuators. Log data was used to extract features, and autoencoders were trained on healthy-state data to detect deviations signaling faults. The method was validated using real-world training data and simulated failure scenarios, successfully distinguishing between healthy and faulty states. This approach offers a promising solution for monitoring the health of piezoelectric actuators in precision systems.

Keywords: Machine Learning, Data-driven, Piezoelectric actuators, Fault detection, Autoencoder, Microassembly.

1. INTRODUCTION

Piezoelectric actuators (PZA) have attracted considerable attention in fields such as robotics, optical engineering, and precision machining due to their compact size, high motion resolution, rapid response characteristics and high precision (Xu et al., 2022; Luo et al., 2020). These actuators function based on the inverse piezoelectric effect, producing small mechanical deformations in response to an applied voltage (Mohith et al., 2020). However, PZA are frequently exposed to repeated loading during operation, which can result in their failure and disrupt the functionality of the associated system. Consequently, degradation mechanisms and lifecycle performance have become critical areas of focus for researchers and engineers (He et al., 2005).

This study is conducted within the context of a French startup specializing in the design and production of high-throughput microassembly machines for large-scale microscopic production. These machines consist of multiple subsystems, including power supply, visualization, gripping, and positioning.

Our focus is specifically on the positioning subsystem, which incorporates a horizontal platform actuated by four stick-slip piezoelectric actuators (Pan et al., 2016). The actuators are configured in a master-slave arrangement, with two actuators operating in parallel to control the platform along a specific axis (X or Y) (Fig. 1).

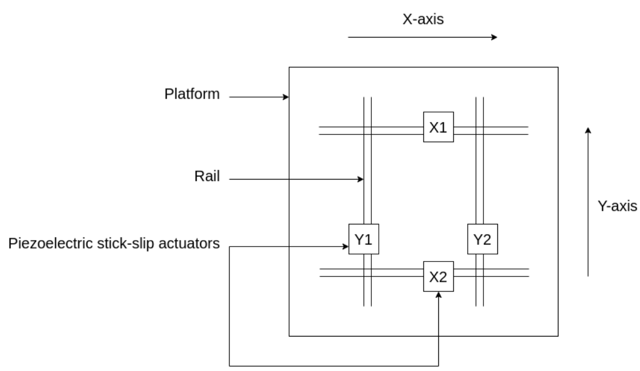


Fig. 1. Descriptive illustration of the studied subsystem

This subsystem has exhibited poorly understood and difficult-to-predict failures, resulting in production interruptions. Currently, a corrective maintenance strategy (Mosallam et al., 2016) is employed. This approach, triggered only upon unexpected failures, leads to extended production downtimes due to the complexity and time required for fault diagnosis, repair, and machine restart. Such a reactive strategy is inadequate to meet industrial production demands.

The absence of an analytical model provided by the manufacturer, coupled with the complexity of the system (stemming from interactions between subsystems and external factors), makes mathematical modeling particularly challenging. Consequently, a data-driven approach emerges as

a promising alternative in this context.
However, this approach faces significant challenges related to data collection. Previous studies have identified variables correlated with the remaining useful life of PZA, including control voltage, operating frequency, temperature, and humidity (Luo et al., 2020; Lipscomb et al., 2009; Nakamura et al., 2001). Nonetheless, the configuration, size, and operation of the actuators used in the system make it infeasible to integrate sensors for measuring these key operating variables.
This work introduces a novel data-driven approach to predict failures in piezoelectric actuators under limited data conditions. Machine log data is utilized to compensate for the lack of physical operating data. Additionally, we propose an approach to simulate actuator failures based on experts' knowledge. These simulated data will be used to evaluate the capability of the proposed solution to accurately detect both healthy and faulty states of the studied system.

2. RELATED WORKS

2.1 Piezoelectric actuators failures prediction

Predicting failures in piezoelectric actuators is crucial for ensuring their reliability and performance in various applications. Admittance measurements are generally used to estimate the degradation of piezoelectric bending actuators (Hemsel et al., 2016). However, this method necessitates interrupting the production process, resulting in higher operational costs. In the literature, only a limited number of studies have addressed the prediction of remaining useful life or failures in piezoelectric actuators. For instance, Bender (2023) proposed a model-based approach leveraging the Butterworth-Van Dyke model to predict actuator failure. However, this model is limited to assessing the health state of individual actuators and is not suited for complex systems involving multiple interconnected PZA. Additionally, the prediction of exact model parameters remains empirical, adding to the challenge of applying this approach effectively.
In order to overcome the challenges of model-based approaches, some works have provided data-driven solutions to predict PZA failures. For instance, Aimiyekagbon et al. (2024) developped a data-driven approach based on operations between physcial measures (voltage and current). Their approach is capable of detecting actuators failures under different operating conditions by supervising those computed features.
To the best of the author's knowledge, only Kimotho et al. (2017) investigated the use of Machine Learning (ML) techniques to predict PZA's remaining useful lifetime. They employed 23 physical features derived from vibration and current measurements as inputs to three models: Extreme Learning Machine, Random Forest, and Support Vector Machine.
However, the proposed approaches rely on the use of physical parameters. In this work, we introduce a fault prediction method that operates in the absence of these variables.

2.2 Machine Learning anomaly detection

Anomaly detection refers to the process of detecting data instances that are different from the majority of data (Pang et al., 2021). According to Nassif et al. (2021), two primary algorithms are commonly employed for anomaly detection: Support Vector Machines (SVM), specifically the One-Class SVM (OCSVM), and Neural Networks, particularly Autoencoder (AE) models.
One-Class Support Vector Machines (OCSVMs) are a specialized form of SVMs tailored for outlier and anomaly detection tasks. They function by constructing a decision boundary that encapsulates the majority of data points in the feature space, thereby maximizing the margin between normal instances and potential anomalies (Alam et al., 2020). Unlike conventional SVMs, OCSVMs are trained exclusively on data from a single class and do not rely on labeled examples from multiple classes. However, the scalability of OCSVMs is limited when handling very large datasets, posing challenges for their application in big data scenarios. In addition, they tend to exhibit a high false positive rate, which undermines the reliability of their results (Nassif et al., 2021).
On the other hand, Autoencoder Neural Networks (AE) are an effective technique for identifying anomalies using data. This method makes use of autoencoders' capacity to learn condensed representations of normal data, which enables them to reconstruct normal samples with minimal error but gives a high error when reconstructing anomalous samples (Li et al., 2023). Reconstruction error can thus be used as an indicator to distinguish between healthy and faulty data. While Autoencoders can be sensitive to the choice of architecture and hyperparameters, potentially resulting in inconsistent performance (Holly et al., 2022), they remain effective and robust tools for anomaly detection.

3. METHODOLOGY

As presented in section 1, the problem consists in predicting piezoelectric actuators' failure using log data from the microassembly machine. For this purpose, a workflow model is presented in Fig. 2. In this workflow, two use cases are distinguished, (i) the training of the prediction model (with black arrows in Fig. 2) and, (ii) the testing of the trained model (with red arrows in Fig. 2).

Log data from the microassembly machine is collected to train the prediction model. Relevant features are engineered, and the dataset, initially containing only healthy actuator data, is expanded with simulated fault scenarios based on expert input. The data is divided into training, testing, and fault sets, then preprocessed for AI model training. Autoencoders trained on healthy data distinguish normal from abnormal behavior. Model performance is evaluated using evaluation metrics, and the final model predicts actuator states using preprocessed test and fault data.

3.1 Microassembly machine Log data

The study relies on machine log data instead of sensor-based physical variables to analyze the operation of a microassembly machine. Log data, which record system

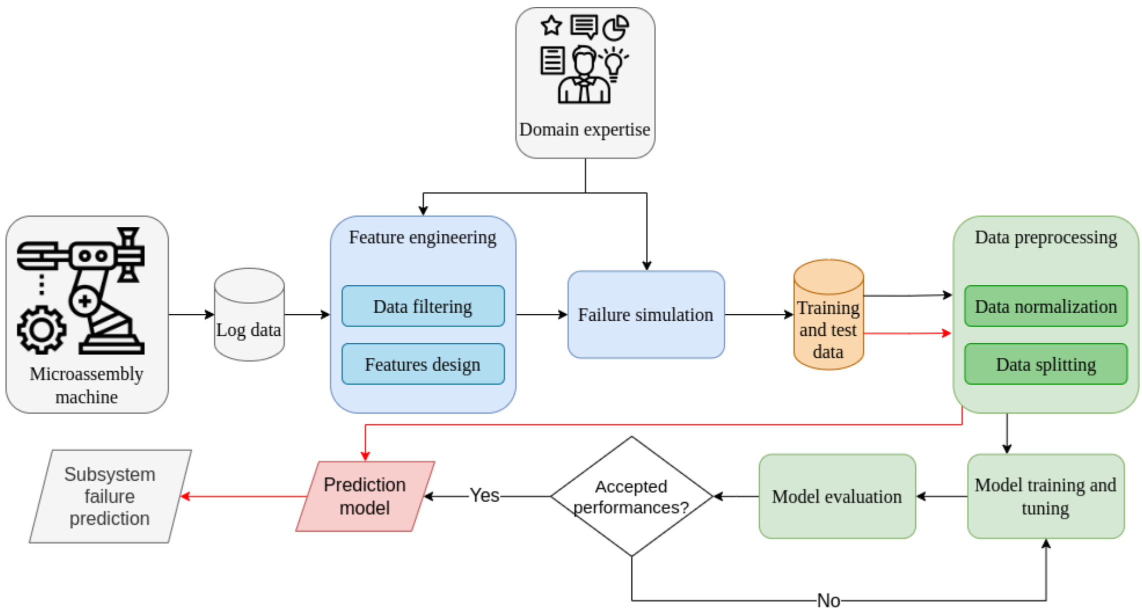


Fig. 2. Proposed methodology for data-driven piezoelectric actuators fault detection

states and activities chronologically, were collected over a 6-hour period, resulting in 421,389 measurements recorded every 51 ms. Each record includes the timestamp and both target and actual positions of two actuators (master and slave) along the X and Y axes. Throughout the paper, we denote $X_{t,n}(t)$ and $X_{r,n}(t)$ as, respectively, the target and actual positions of actuator n at timestamp t along the X-axis, and $Y_{t,n}(t)$ and $Y_{r,n}(t)$ as, respectively, the target and actual positions of actuator n at timestamp t along the Y-axis, with $n \in \{1, 2\}$. Notably, when n=1, the actuator corresponds to the master, and when n=2, it corresponds to the slave.

3.2 Feature engineering

After collecting the microassembly machine log data, a feature engineering phase is conducted. Since the log data encompasses the entire machine, the first step is filtering to retain only data relevant to the positioning subsystem. Subsequently, the dataset is enriched with new variables. This process involved brainstorming sessions with the company's engineers and operators, resulting in a list of additional variables that were selected and computed:

- Velocity : This variable represents the instantaneous velocity of each actuator, a critical parameter since a decrease in speed may indicate actuator degradation. The velocity of every actuator is calculated as the change in position between two successive timestamps. For example, Eq. 1 details the formula to determine the instantaneous velocity of X_1.
$$V_{X1}(t) = \frac{X_{r,1}(t) - X_{r,1}(t-1)}{t-(t-1)} \qquad (1)$$
- T-A error : This variable represents the difference between the target position and the actual position of the actuator. A high error may indicate that the actuator is struggling to follow commands, potentially signaling a degradation phase. the T-A error of actuator X_1, for example, is calculated using Eq. 2
$$TAE_{X1}(t) = X_{t,1}(t) - X_{r,1}(t) \qquad (2)$$
- S-M error : This variable represents the position difference between the master and slave actuators. Two variables were created: one for the X-axis and another for the Y-axis. For illustration, the X-axis S-M error is defined by the formula in Eq. 3.
$$SME_{X1}(t) = X_{r,1}(t) - X_{r,2}(t) \qquad (3)$$

3.3 Failure simulation

The collected data covers 6 hours of normal operation without anomalies. Therefore, a failure simulation step is essential to enrich the dataset with fault cases. These cases are crucial for testing the model, as the training process will be conducted solely on healthy data.
Discussions with production and maintenance experts revealed that piezoelectric actuator degradation is reflected in a decline in instantaneous velocity. Specifically, as the actuator enters a faulty state, the maximum achievable velocity gradually decreases. To simulate failures, we propose gradually reducing the maximum achievable instantaneous velocity until a complete stop. Two different degradation models were applied: (i) linear (Eq. 4) and (ii) exponential (Eq. 5). For every model, different numerical parameters were tested in order to test the machine learning model ability to detect different failures modes.

$$|V_{max}(t)| = -a.t + b \qquad (4)$$
$$|V_{max}(t)| = \beta.e^{-\alpha.t} \qquad (5)$$

with :

- t : time variable
- $V_{max}(t)$: maximum achievable instantaneous velocity in the failed operating mode
- a, b, α, β : constants

The simulation procedure is as follows:

(1) Select the last 30% of the dataset instances.

(2) Apply a linear or exponential degradation model for the maximum achievable instantaneous velocity.
(3) Limit the instantaneous velocity to the minimum of the actual velocity and the selected degradation model.
(4) Adjust the timestamps to align with the modified velocity.

3.4 Data preprocessing

Data preprocessing refers to the process of transforming raw data into a suitable format to be fed to the machine learning algorithms. To achieve this, two preprocessing techniques were applied.

First, data splitting was performed to create training, testing, and failure assessment datasets. Since the last 30% of the data instances contain altered data with failure simulations, the remaining 70% were divided into 50% for training the model and 20% for testing the model's performance on healthy data and its ability to recognize healthy patterns. However, this 20% test set will be further divided into two separate parts, with details to be illustrated in the results section.

Second, the data was normalized using the min-max normalization technique (Patro, 2015). In fact, normalization is an important technique when using neural networks. This method transforms the data linearly to a range between 0 and 1, preserving the original distribution while ensuring all features contribute equally to the model.

3.5 Model training and evaluation

In this study, two autoencoder models, the Long Short-Term Memory Autoencoder (LSTMAE) and the One-Dimensional Convolutional Autoencoder (1-DCAE), were employed for fault detection in piezoelectric actuators. Autoencoders are neural networks designed to learn and reconstruct a compressed representation of input data through an encoder-decoder architecture. The reconstruction error, measured using the Mean Absolute Error (MAE) (Hodson, 2022), quantifies the difference between the original and reconstructed data.

Autoencoders, typically used for dimensionality reduction and feature extraction, were leveraged here for anomaly detection. The models were trained exclusively on healthy data to learn the normal actuator behavior with a low reconstruction error. New, unseen data was then evaluated, where a low reconstruction error indicated healthy operation, while a high error signaled a fault.

(1) **Long Short-Term Memory Autoencoder:** LSTMAEs combine the strengths of LSTM networks, which excel at capturing long-term dependencies, with the autoencoder's ability to learn compact representations. The LSTM units within the network use input, forget, and output gates to control information flow, allowing the model to selectively remember or forget information over long sequences. This structure enables LSTMAEs to effectively learn and preserve temporal patterns in data, making them particularly useful for tasks such as anomaly detection in time series data
(2) **One-dimensional convolutional autoencoder:** A 1-DCAE is a kind of neural network which applies one dimensional convolutional operation to the input data then compress it and then reconstruct it. This kind of autoencoder, the encoder has convolutional layers while the decoder has the deconvolutional layers or the transposed convolution. The convolution layer applies filters which view the input through the behavior of "convolution", and the filter size is usually defined by the parameters (Lee et al., 2023).

4. RESULTS AND DISCUSSIONS

Python and libraries like Pandas, Numpy, and Sklearn were used for data processing and ML analysis. The training was performed on an Intel i5-8350U CPU (1.70GHz, 16GB RAM). Hyperparameters were fine-tuned using grid search algorithm (Lerman, 1980) with the MSE metric and early stopping criterion. Table 1 details the obtained hyperparameters for each ML model.

Table 1. Machine Learning models hyperparameters

LSTMAE model	**1-DCAE model**
#L : 4	#L : 6
#N per Enc layer : [512, 256]	#N per Enc layer : [128, 64, 32]
#N per Dec layer : [256, 512]	#N per Dec layer : [32, 64, 128]
Batch size : 512	Batch size : 256
Number of epochs : 50	Number of epochs : 30
Learning rate : 0,001	Learning rate : 0,005

L : Number of layers, N : Number of neurons,
Enc : encoding, Dec : decoding

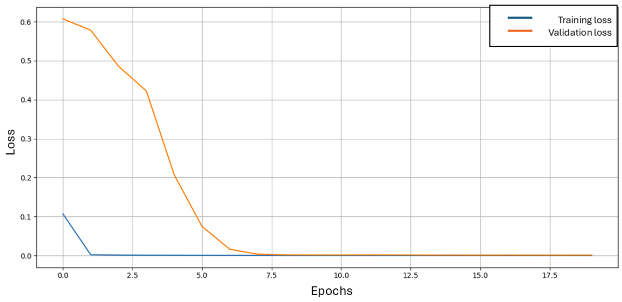
Fig. 3 displays the training and validation loss curves for the two trained models across training epochs. Fig. 3a demonstrates that, for the One-Dimensional Convolutional Autoencoder, training and validation errors converge to approximately zero. These results indicate that after 8 training epochs, the 1-DCAE model can effectively recognize healthy actuator operation without overfitting.

For the Long Short-Term Memory Autoencoder model, Figure 3b shows that the training and validation loss converge more slowly, only after 10 epochs. Moreover, the validation loss does not reach zero even after 49 training epochs. These results indicate that the 1-DCAE model outperforms the LSTMAE model on the training set.

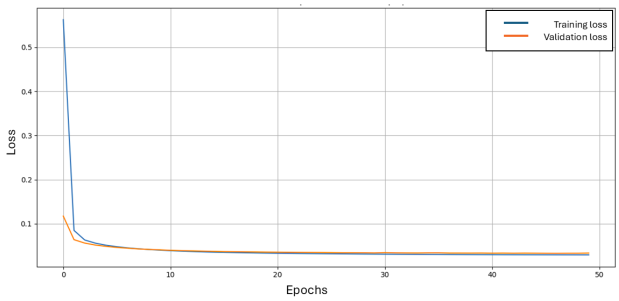
To evaluate the performance of the trained models, they were tested on a separate test set subjected to various failure modes. Examples of linear and exponential limitations on the maximum achievable instantaneous velocity are presented in Figures 4 and 5, respectively.

In these figures, the colors blue, green, and red correspond, respectively, to the error associated with healthy data used for training, healthy data used for testing (unseen during the algorithm's training), and faulty data employed to evaluate the algorithm's capability in detecting actuator faults. The results demonstrate that both algorithms effectively detect actuator failure modes. Specifically, the relatively low error on test data (green color) indicates that the models successfully classified these data as representing healthy operation, despite not having encountered them during training. However, for failure data, the reconstruction error increases sharply, signaling anomalous actuator behavior.

For the 1-DCAE model (Figures 4c and 5c), the reconstruction error is nearly zero on the training and test



(a) Training and test loss for the 1-DCAE model



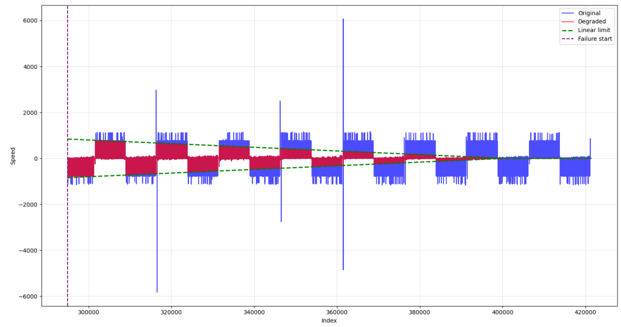
(b) Training and test loss for the LSTMAE model

Fig. 3. Training and test loss for the trained ML models

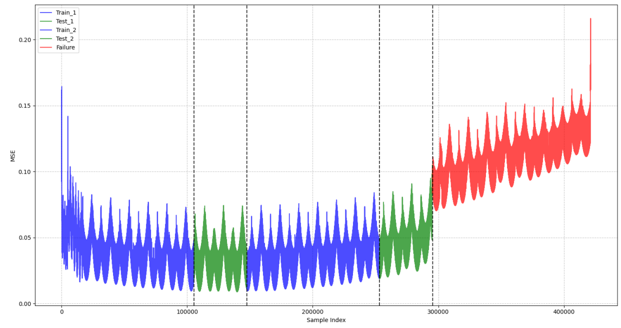
sets. In contrast, a sharp increase of approximately 400% is observed as soon as the actuators enter the failure mode. Subsequently, the error continues to rise, reaching values between 0,05 and 0,175 for the exponential failure simulation and between 0,04 and 0,150 for the linear failure simulation.
However, for the LSTMAE model, the distinction between normal and faulty actuator behavior is less pronounced. The model's loss fluctuates between values of 0,02 and 0,07, which is higher than the loss of the 1-DCAE model. Furthermore, the increase in error at the onset of the failure regime is approximately 50%, with values continuing to rise until reaching a maximum of 0,2 when the actuators stop operating, for both simulated failure modes. These results support the use of the one-dimensional convolutional autoencoder for failure detection of piezoelectric actuators. Furthermore, we recommend using a loss threshold of 0.05 for failure detection. Indeed, the reconstruction error on healthy data remains well below this value. In contrast, the error quickly reaches 0.05 at the onset of the failure mode, allowing for failure detection within 1 hour and 45 minutes for both studied cases.

5. CONCLUSIONS

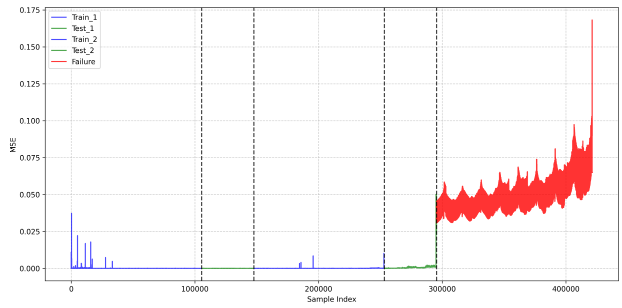
In this study, we proposed an approach for failure detection of piezoelectric actuators in micro-assembly machines. Given the complexity of the system, a data-driven approach was employed. To achieve this, we collected the machine log data, which was then filtered and enriched with additional variables. We subsequently simulated failures at the end of the operating sequences based on linear and exponential degradation modes, leveraging human expertise. Two autoencoder algorithms were trained exclusively on healthy operation data: the LSTM autoencoder and the one-dimensional convolutional autoencoder (1-DCAE). Both models proved effective in distinguishing between healthy and faulty data through variations



(a) Failure simulation results for the instantaneous velocity of X1



(b) Train, test and failure loss for the LSTMAE model

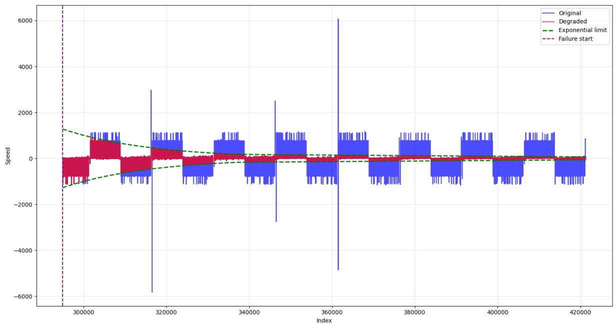


(c) Train, test and failure loss for the 1-DCAE model

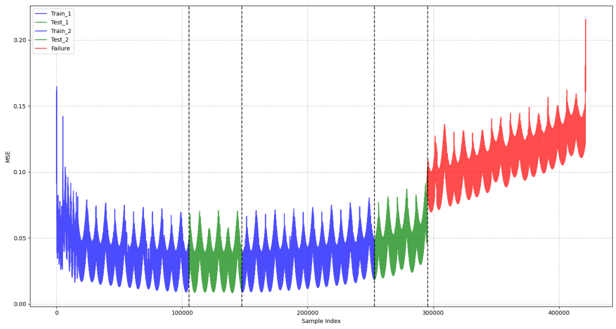
Fig. 4. Failure detection results with linear degradation (a=0,156 and b=3192)

in reconstruction error. However, the 1-DCAE algorithm delivered superior results, producing a very low error for healthy data and a relatively high error for failure data, enabling failure detection over an hour before actuator shutdown.
However, this work has certain limitations. First, the methodology assumes that the algorithm is exposed to all possible normal operating modes during the training phase. In other words, an increase in reconstruction error could correspond either to a failure or to a new normal operating mode that was not included in the training data. Second, the method is sensitive to the empirically defined detection threshold, which can significantly impact the prediction horizon.
In conclusion, this work represents a first step toward failure detection of piezoelectric actuators without relying on physical operating variables. Future research directions include testing these approaches with larger datasets that encompass sufficient operating modes and real-world failures to better evaluate algorithm performance. Additionally, a post-predictive solution could be developed

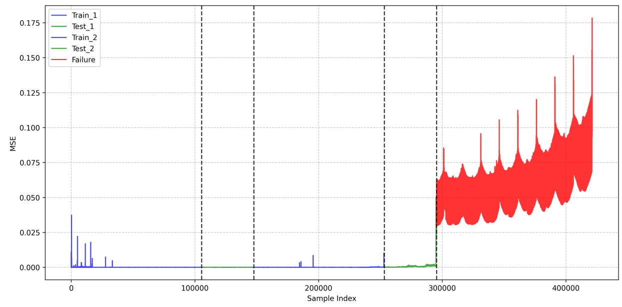
to leverage predictions for decision support in predictive maintenance, machine allocation, and scheduling.



(a) Failure simulation results for the instantaneous velocity of X1



(b) Train, test and failure loss for the LSTMAE model



(c) Train, test and failure loss for the 1-DCAE model

Fig. 5. Failure detection results with exponential degradation ($\alpha = 9,3 \times 10^{-5}$ and β=1500)

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