DOI 10.5162/SMSI2025/P28

Enhancing Predictive Maintenance with Temporal Convolutional Networks

Florian Rieger [1], *Raphael Schilling* [1], *Ferdinand Heinrich* [1], *Franz Wenninger* [1] *
[1] Fraunhofer Institute for Electronic Microsystems and Solid State Technologies
Hansastr. 27d, 80686 Munich
florian.rieger@emft.fraunhofer.de

Summary: Predictive maintenance is a crucial technique for reducing machine downtime. One challenge is the absence of labeled run-to-failure data. We propose a semi-supervised anomaly detection approach using Temporal Convolutional Networks, a regression model that has multivariate data as input and estimates vibration data. Our study reveals that our sensor signal estimation is quite accurate for normal data. The estimation error serves as a score that is useful for identifying anomalies.

Keywords: predictive maintenance, machine learning, vibrations, neural networks, temporal convolutional networks

Introduction

Predictive maintenance (PdM) is a crucial technique to reduce machine downtime and improve operational efficiency. Traditionally, PdM relies on labeled run-to-failure data to train machine learning models that can predict equipment failures. However, obtaining such data is often challenging and impractical in many industrial settings [1]. This paper addresses the challenge of detecting anomalies in machine behavior without labeled run-to-failure data by leveraging control loop data to predict system responses, particularly vibrations.

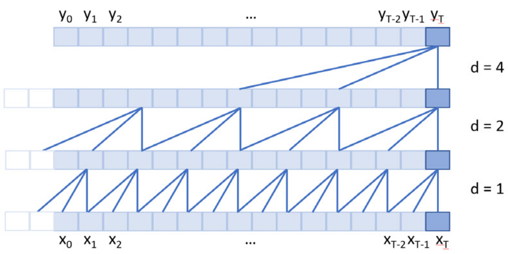

Fig. 1: Basic concept of a Temporal Convolutional Network. By using dilated causal convolutions, long-range dependencies (blue lines) can be captured without increasing the complexity of the model.

PdM finds applications across various industries, including oil, gas, and wind. The potential of PdM is significant, with studies estimating that a properly functioning PdM program can provide savings of 8% to 12% over preventive maintenance alone [2]. Depending on a facility's reliance on reactive maintenance and material condition, savings opportunities could exceed 30% to 40% [2].

This paper uses a Temporal Convolutional Network (TCN) approach as shown in Fig. 1 to perform anomaly detection on a die ejector machine. The die ejector is a critical component , where it is used to precisely place bare-dies onto substrates. The machine operates at high speed, which results in vibrations. Distinguishing normal from abnormal vibrations is a challenge. Using our adapted TCN-AD approach to predict the system's physical response to input signals, it is possible to detect anomalies in the die ejector's behavior, ensuring timely maintenance and reducing the risk of machine failure.

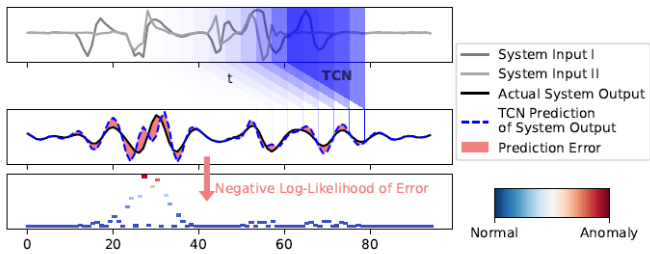

Fig. 2: Estimation error based anomaly detection using Temporal Convolutional Networks. Estimation errors lead to an increase in anomaly score.

Methodology

The methodology revolves around the development and evaluation of the Temporal Convolutional Network for Anomaly Detection (TCN-AD) approach, which was first used in [3]. What distinguishes our approach from that in [3] is that

*This research is funded by the Bavarian State Ministry of Economic Affairs, Regional Development and Energy under the identification number DIE0147.

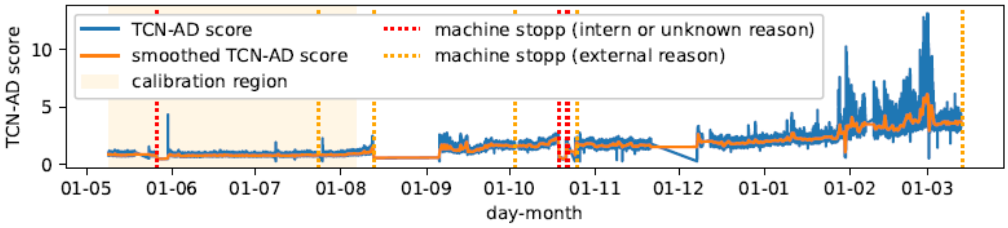

Fig. 3: TCN-AD anomaly score (blue) and smoothed score (orange) tracked over several month. Towards the end of the shown time period the machine condition gets worse, which already was indicated by our model.

there is no prediction of future time steps, but rather a regression of measured signals, in particular vibrations, based on a set of other signals, in our case control loop data. The primary goal is to detect anomalies in machine behavior by predicting the system's physical response to external impulses. In this way, the algorithm intrinsically models the physical system during normal operation. If the physical properties change over time, the regression error, which is the difference between the estimated and actual sensor signals, increases. Thus, this regression error makes a good indicator for anomalies (see Fig. 2).

The TCN model used in our approach consists of several key components, including dilated causal convolutions and residual connections. Dilated causal convolutions allow the model to capture long-range dependencies in the time series data without increasing the model complexity, while residual connections help in training deeper networks by allowing gradients to flow more easily through the network.

The model is trained using normal sequences of control loop data by minimizing the estimation error on these sequences. It is then validated with a separate set of normal sequences to ensure good generalization to unseen data. During anomaly detection, the trained TCN model estimates sensor signals for new input sequences, and sequences with high estimation errors are flagged as anomalies. What sets our approach apart from the state of the art is its ability to model the physical response of a system to input signals using control loop data, without relying on labeled run-to-failure data. This semi-supervised method is a robust and practical solution for predictive maintenance across various machines and systems without the need for extensive labeled datasets.

The approach is evaluated using a dataset that contains vibration data from a die ejector machine. The results demonstrate the effectiveness in detecting anomalies in machine behavior, highlighting its potential for improving predictive maintenance strategies and reducing machine downtime.

Results

The evaluation of the TCN-AD approach demonstrated its effectiveness in detecting anomalies in machine behavior using vibration data. The key findings from the evaluation are as follows:

The approach showed high accuracy in detecting anomalies in the vibration data of the die ejector machine. The estimation error, which is used as the anomaly score, effectively identified abnormal behavior in the machine's operations (Fig. 3). The model was found to be robust to noise in the sensor data. The use of dilated causal convolutions and residual connections in the architecture allowed the model to capture long-range dependencies and filter out noise, leading to more accurate anomaly detection. The model demonstrated good generalization to unseen data. During inference, the model successfully identified anomalies in new input sequences, indicating its ability to generalize well to new data.

The evaluation highlighted the advantages of using a semi-supervised learning method that uses normal operational data for anomaly detection, making it a practical solution for predictive maintenance. The findings from the evaluation in Fig. 3 suggest that the system changed significantly over time compared to the modeled one and thus the machine might have a damage.

Acknowledgements

We would like to thank our consortium partner *Mühlbauer* for giving us access to the data and providing us valuable feedback. In particular we would like to thank Patrick Grössing and Sebastian Heinrich.

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