Air Leakage Detection for Pneumatic Drives using MEMS Microphones and Machine Learning

Christian Fuchs[1], Steffen Klein[1,a], Stefan Saller[2], Daniel Spies[2], Andreas Schütze[1], Tizian Schneider[1,b]

[1] *Saarland University, Lab for Measurement Technology, 66123 Saarbruecken, Mail: c.fuchs@lmt.uni-saarland.de*
[2] *Festo SE & Co. KG, 73734 Esslingen, Mail: stefan.saller@festo.com*
[a] *Current Adress: Hydac Electronic GmbH, Hauptstraße 27, 66128 Saarbruecken*
[b] *Current Adress: iMAR Navigation GmbH, Im Reihersbruch 3, 66386 St. Ingbert*

Abstract

Some defects in industrial machines and pipe systems can be detected by experts based on acoustic events. The previous success in speech recognition motivates the ongoing development of machine learning methods for industrial acoustic measurements. This contribution introduces a concept to detect air leakages at piston rod seals of pneumatic drives at a low cost and with small dimensions. It describes how these leakages can be detected with machine learning. For this approach, MEMS microphones are installed close to the seals, and their leakages are predicted by extracting interpretable features and using a supervised regression method. The use of MEMS microphones offers economic and integrative advantages. The first focus of this investigation lies on the interpretability of the results, which motivates the use of a supervised "Feature Extraction, Selection, and Regression" (FESR) approach. Extracting physically meaningful features followed by feature selection provides tools for interpretability. The second focus lies on the robustness of the method. Due to individual damages, quantitatively identical leakages may appear differently in the measurement data. This should enable broad applicability in the field.

I. Introduction

There are various options and use cases for leakage detection. Detecting pressure drops in (water) pipe systems [1,2], using gas sensors [3], simulating acoustic leakage detection [4], and performing acoustic detection with different sensor types [5-9]. Those sensor types are vibration sensors in [5], acoustic cameras in [6], acoustic emission sensors in [7,8], and a single microphone in [9]. This work aims to detect air leakages at piston rod seals of pneumatic drives at a low cost and with small dimensions. Therefore, a MEMS microphone is used.

Looking for ways to understand the results [10-12] motivates the use of supervised "Feature Extraction, Selection, and Regression" (FESR) [13,14]. Especially extracting physically meaningful features with a following supervised feature selection provides tools for interpretability [15]. Lastly, the robustness against individual drives is considered to return a more realistic statement about the applicability in the field.

II. Design of Experiment

A. Measurement Setup

Measurements were conducted on pneumatic drives whose piston rod seals were manually damaged. The goal was to detect the amount of air leakage in l/h using a MEMS microphone and a regression method stack.

Data with different amounts of leakages and applied pressures were collected to meet the statistical requirements and achieve robustness against physical influences. In addition, 13 individual drives of the type DSBC32 were used for the measurements.

On top of the cylinders, a MEMS microphone was installed on the side of the piston rod seal (compare Fig. 1). For every individual drive, the piston rod seal was manually damaged to various degrees, with some remaining undamaged. The resulting leakage was measured afterwards as the target value for a supervised regression.

Leakage only occurs as long as there is pressured air between the piston and the piston rod seal. As soon as the drive is moving, the sound of the leakage is masked. Even during operation, the drive would rest at the turning points for a short period. Therefore, the measurements were conducted with resting drives with retracted piston rods as depicted at the bottom of Figure 1.

B. Influencing Parameters

The strongest influence is considered to be the manual damaging of the 13 individual drives. Because of the limitations in experiment design, each seal of each drive is related to its leakage as the damaging of the seal remains the same throughout the experiments. So, more than 20 different pressure levels between 4 and 8 bar were applied for every drive. To explore the potential of these measurements, ambient noise has not been considered so far.

III. Method

A. Raw Data Analysis

The sound of leakages is comparable to "S"-like sounds in speech and singing and is known to occur around 7 kHz and higher (De-Essing, [16]). So, when the band from 7 kHz to 12 kHz is plotted for all measurements in the order of increasing leakage, a trend of increasing amplitude can be observed (compare Fig. 2).

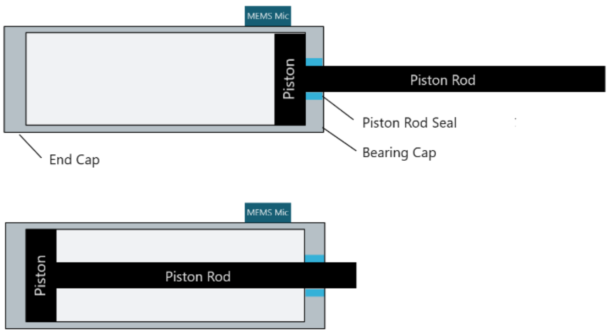

Figure 1: Measurement Setup Schematic [17].

This behavior is a good basis for further analysis. It is to be noted that leakages could also show characteristic behavior in other frequency bands. Faults in the labeling process can mess with that behavior quickly, as previous investigations indicate [17].

B. Feature Extraction, Selection, and Regression (FESR)

To be able to interpret the physical meaning behind the machine learning models, the FESR method is used. It means, that physically meaningful features are extracted and selected from the raw data. Finally, a regression method is applied to return the resulting model and its prediction (compare Fig. 3).

Following the suggested open-source toolbox in [13,14], different methods are used and benchmarked to find the most suitable combination of methods for this application.

1) Feature Extraction:

For the feature extraction, five methods were used and compared:

- Adaptive Linear Approximation (ALA) [13,14]
- Best Daubechies Wavelet Coefficients (BDW) [13,14]
- Best Frequency Coefficients (BFC) [13,14]
- Statistical Moments (Moments) [18]
- Time Frequency Extractor (TFEx) [15, 19]

The TFEx is explained here, as it will later be a core component for the interpretability of the results (Fig. 4). The TFEx extracts statistical features from linearly divided time segments and frequency bands. The interpretability of the results is physically discussed by visualizing the best extracted feature (Ch. IV.B, Fig. 5).

With this approach, backtracking of resulting features to their originating time and frequency segments as well as their physical interpretation is possible (compare [15] for a more detailed description of the TFEx).

2) Feature Selection:

For the feature selection, two methods were used and compared:

- Pearson Correlation [20]
- Recursive Feature Elimination Support Vector Regression (RFESVR) [21]

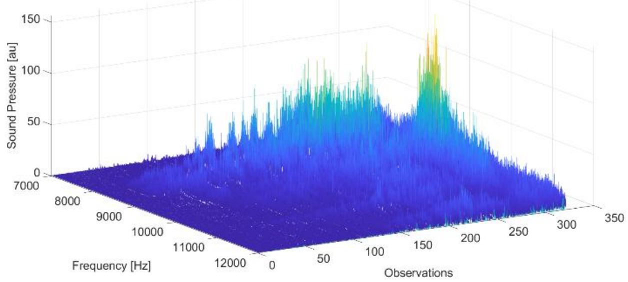

Figure 2: Waterfall Plot of amplitude spectra of all recorded data with observations ordered by ascending leakage.

Figure 3: FESR schematic.

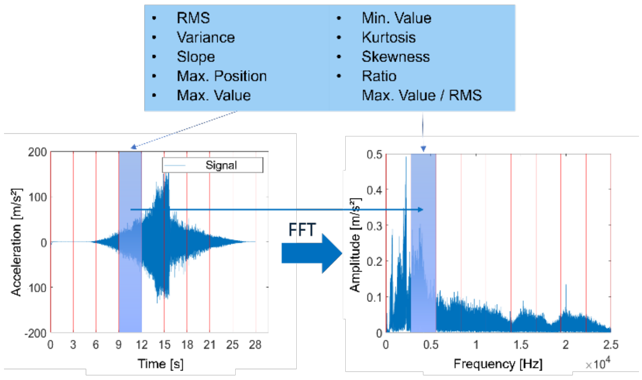

Figure 4: TFEx functionality [15].

One of the RFESVR's tasks here is reducing redundancies that can occur with the high amount of features generated by the TFEx.

3) Regression:

For the regression, three methods were used and compared:

- Partial Least Squares Regression (PLSR) [22]
- Artificial Neural Network (ANN) Regression [23]
- Support Vector Regression (SVR) [24]

Here, the PLSR is highlighted, as its strength is a low risk of chance correlation which is beneficial for data knowingly showing a correlation to the target. That helps the goal of making the prediction rely on that correlation instead of any unknown phenomena.

C. Validation

Finally, a very important part of the analysis is the type of validation that is used for the models. As discussed in II. B., the main influencing parameters that require robustness are pressure and individual drives. For those, a group-based "Leave One Group Out" (LOGO) [25] Cross Validation (CV) [26] will be used. So, there will be three different types of validations for this application:

1) 13-Fold Random Cross-Validation
2) LOGO Cross-Validation for Pressure
3) LOGO Cross-Validation for Individual Drives

The random cross-validation gives a general idea about the statistical robustness of the model, while the LOGO cross-validations give an idea of how robust the model is against changes in the applied pressure or measuring a different device of the same type. For the pressure validation, four groups are chosen from 4 to 8 bar with a range of 1 bar for each group. For the drive validation, all 13 drives are considered as a single group, so that always a complete device is excluded from training and used for validation. Additionally, a test dataset is used by a random holdout of 10% of the data.

IV. Results

A. Benchmarking: Best Model

The methods described in Chapter III were combined to FESR stacks and compared using the best normalized root mean square error (NRMSE) for each validation type. The normalization factor is max-min of the target (leakage in l/h). The best results for each validation type are shown in Table 1. For comparability reasons, R^2 is also given here.

The results have a lot in common. The train and the test errors are the same for all three results, which makes sense as the data and the methods (feature extraction, selection, and regression) are identical. For the validation of individual drives, the error (9.59 %) is higher than the other two (7 - 8 %), suggesting that handling new individual drives is harder than handling pressure changes and being robust against random variations (random cross-validation).

B. Model Interpretation: Best Features

As the feature extraction and selection of the best model are the same for all validation types, interpreting the ranked features applies to all of them. The best feature was identified as the RMS value of the amplitude spectrum between 15 kHz and 20 kHz of the period of 0.5 sec to 1 sec. This feature is shown in Figure 5 and was scaled to the target (leakage in l/h). The resulting feature has a similar trend as the target which is comparable to the observations made in Fig. 2. Still, there are three noticeable deviations.

First of all, the feature has a lower slope and an offset in the range of low leakages than the target. Especially low leakages seem to not differ much in emitted sound pressure levels making them hard to distinguish from one another. Between observations 200 and 270, the feature is volatile, and in the area of observation 280 to 300, a peak occurs. This indicates that the corresponding leakages are not well represented in this feature. Therefore, the addition of further features (from different frequency bands) shall be beneficial.

Table 1: Best Results for the Three Validation Types

Extractor	Selector	Regressor	Training *NRMSE [%]*	Test Method	Test *NRMSE [%]*	Validation Method	Validation *NRMSE [%]*	Validation *R^2*
TFEx	RFESVR	PLSR	2.63	Random Holdout 10%	5.49	13-fold (Random cross-validation)	7.25	0.9
TFEx	RFESVR	PLSR	2.63	Random Holdout 10%	5.49	4 Pressure Groups (LOGO cross-validation)	7.96	0.88
TFEx	RFESVR	PLSR	2.63	Random Holdout 10%	5.49	**13 Drives Groups (LOGO cross-validation)**	**9.59**	0.83

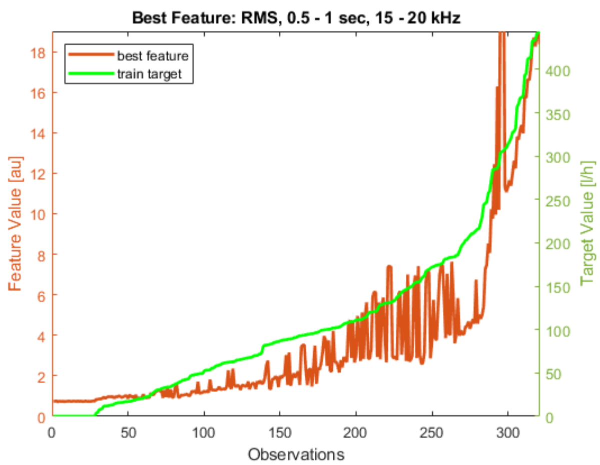

Figure 5: Best feature and target over observations sorted by leakage increasingly; RMS in spectrum 15 kHz to 20 kHz (of period 0.5 sec to 1 sec).

The second-best feature originates from the band 10 kHz to 15 kHz and the eighth and ninth-best feature from the band 20 kHz to 25 kHz. Those are both in the expected frequency range for "s" and "sch" sounds. The best and second-best features are in the audible range of most humans.

C. Validated Prediction: LOGO CV Individual Drives

The most interesting result is the cross-validated prediction for the 13 individual drives, as they achieved an NRMSE of 9.59 %, which means that a leakage at the piston rod seal of a drive that is unknown to the model can be detected with that error. As that is a cross-validated value, the possibility of a single drive being unpredictable remains. However, Fig. 6 shows that the general trend of the prediction matches the target line. The two differences that were present in the best feature (comp. Fig. 5) can be observed in the prediction. There is a low slope in lower leakage ranges, a volatile area between observations 200 and 270, and a peak in the area of observations 280 to 300. However, the general trend, even in the LOGO drive validated prediction, matches the target even better than the best feature, which indicates that the use of multiple features is helpful.

V. Discussion

In laboratory conditions, air leakages at piston rod seals of pneumatic drives can be detected at close distances (a few centimeters) using MEMS microphones and machine learning. However, two main challenges remain.

The first challenge lies in detecting low leakages (< 50 l/h) because of their low signal amplitude. The second challenge is the presence of various noise influences in the field, which will be a very impactful factor for the realization of measurement systems and respective analysis methods.

Additionally, the robustness of models to different types of drives is to be determined. All the measurements were conducted with the type DSBC32. An NRMSE of 9.59 % for the LOGO drive validated prediction is a very satisfying result.

Acknowledgment

This publication originates from the research project KI-MUSIK4.0 [27] funded by the German Federal Ministry of Education and Research (funding label 16ME0070).

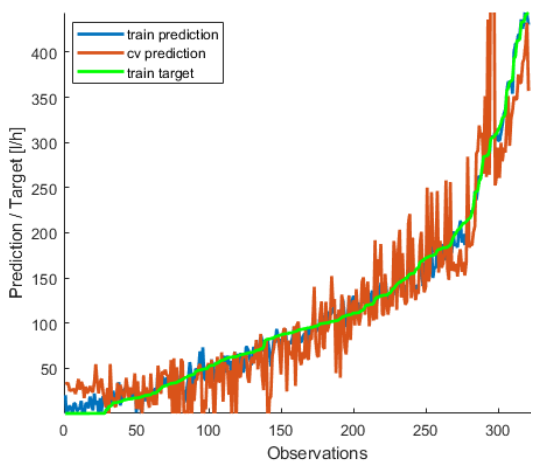

Figure 6: LOGO Individual Drives Cross-Validated Prediction over observations sorted by leakage increasingly.

References

[1] F. Mustapha, A. Abdulshaheed, A. Ghavamian, “A pressure-based method for monitoring leaks in a pipe distribution system: A Review,” Renewable and Sustainable Energy Reviews, 2017, https://doi.org/10.1016/j.rser.2016.08.024.

[2] L. Romero-Ben, D. Alves, J. Blesa, G. Cembrano, V. Puig, E. Duviella, “Leak detection and localization in water distribution networks: Review and perspective,” Annual Reviews in Control, 2023, https://doi.org/10.1016/j.arcontrol.2023.03.012.

[3] A. Shrivastava, R. Prabhaker, R. Kumar, R. Verma, „GSM Based Gas Leakage Detection System,“ International Journal of Technical Research and Applications, 2013 (Volume 1, Issue 2).

[4] K. Pugalenthi, H. Mishra, A. Ukil, J. Dauwels, “Leak detection in gas distribution pipelines using acoustic impact monitoring,” IECON, 2016, https://doi.org/10.1109/IECON.2016.7793352.

[5] S. Lee, B. Kim, “Machine Learning Model for Leak Detection Using Water Pipeline Vibration Sensor,” Sensors, Basel, 2023, https://doi.org/10.3390/s23218935.

[6] S. Ahmad, Z. Ahmad, C.-H. Kim, J.-M. Kim, “A Method for Pipeline Leak Detection Based on Acoustic Imaging and Deep Learning,” Sensors, Basel, 2022, https://doi.org/10.3390/s22041562.

[7] N. Ullah, Z. Ahmed, J.-M. Kim, “Pipeline Leakage Detection Using Acoustic Emission and Machine Learning Algo-rithms,” Sensors, 2023, https://doi.org/10.3390/s23063226.

[8] V.V. Shanbhag, T.J.J. Meyer, L.W. Caspers, R. Schlanbusch, “Condition monitoring of hydraulic cylinder seals using acoustic emissions,” Int J Adv Manuf Technol 109, 2020, https://doi.org/10.1007/s00170-020-05738-4.

[9] D. Diaz Ocampo, M. Heizmann, M. Lyashenko, S. von Dosky, „Merkmalsbasierte luftakustische Diagnose von Druckluftleckage mithilfe maschineller Lernverfahren“, 22. GMA/ITG-Fachtagung Sensoren und Messsysteme, 2024, https://doi.org/10.5162/sensoren2024/A1.1.

[10] A. Adadi, M. Berrada, “Peeking Inside the Black Box: A Survey on Explainable Artificial Intelligence (XAI),” IEEE Access, 2018 (Volume 6).

[11] D, Rudresh, D. Devam, N. Het, S. Smiti, O. Rana, P. Pankesh, Q. Bin, W. Zhenyu, S. Tejal, M. Graham, R. Rajiv, “Explainable AI (XAI): Core Ideas, Techniques, and Solutions,” ACM Comput. Surv. 55, 9, Article 194, 2023, https://doi.org/10.1145/3561048.

[12] P. Hammersborg, I. Strümke, “Concept backpropagation: An Explainable AI approach for visualising learned concepts in neural network models,” arXiv preprint arXiv:2307.12601, 2023.

[13] T. Schneider, N. Helwig, A. Schütze, “Industrial condition monitoring with smart sensors using automated feature extraction and selection,“ IOP IOP Publishing Ltd, Meas. Sci. Technol. 29 094002, 2018, https://doi.org/10.1088/1361-6501/aad1d4.

[14] T. Dorst, Y. Robin, T. Schneider, A. Schütze, “Automated ML Toolbox for Cyclic Sensor Data,“ Joint Virtual Workshop of ENBIS and MATHMET Mathematical and Statistical Methods for Metrology MSMM, 2021.

[15] C. Fuchs, S. Klein, J. Schauer, A. Schütze, T. Schneider, „Eine Methode zur erklärbaren Merkmalsextraktion aus dem Zeit- und Frequenzbereich für Condition Monitoring,“ 22. GMA/ITG-Fachtagung Sensoren und Messsysteme, 2024, https://doi.org/10.5162/sensoren2024/P36.

[16] K. Linhard, P. Bulling, A. Wolf, „Frequency Domain De-Essing for Hands-free Applications,” DAGA proceedings, 2017, pp. 315 – 318.

[17] C. Fuchs et. al., „Analyse zum Einfluss von Labeling-Fehlern im Kontext von Luftschall- und Vibrationsdatensätzen für maschinelles Lernen,“ DAGA proceedings, 2023, pp. 80–83.

[18] S. Lomba, J., F. Alves, M.I., “Moments,” In: B. Daya Sagar, Q. Cheng, J. McKinley, F. Agterberg, (eds) “Encyclopedia of Mathematical Geosciences,” “Encyclopedia of Earth Sciences Series,” Springer, 2021, Cham, https://doi.org/10.1007/978-3-030-26050-7_454-1.

[19] P. Goodarzi, S. Klein, A. Schütze, T. Schneider; "Comparing Different Feature Extraction Methods in Condition Monitoring Applications," IEEE I2MTC, 2023.

[20] A. Razak M. S. et. al., “Online feature Selection using Pearson Correlation Technique," 2022 IEEE 7th International Conference on Recent Advances and Innovations in Engineering (ICRAIE), MANGALORE, India, 2022, pp. 172-177.

[21] X. -w. Chen, J. C. Jeong, "Enhanced recursive feature elimination," Sixth International Conference on Machine Learning and Applications (ICMLA 2007), Cincinnati, 2007, pp. 429-435.

[22] R. D. Cramer, “Partial Least Squares (PLS): Its strengths and limitations,” Perspectives in Drug Discovery and Design 1, 1993, pp. 269–278.

[23] M. Rahman and M. Asadujjaman, "Implementation of Artificial Neural Network on Regression Analysis," 2021 5th Annual Systems Modelling Conference (SMC), Canberra, Australia, 2021, pp. 1-7.

[24] M. Awad, R. Khanna, “Support Vector Regression. In: Efficient Learning Machines,” Apress, Berkeley, CA, 2015, https://doi.org/10.1007/978-1-4302-5990-9_4.

[25] P. Goodarzi, A. Schütze, T. Schneider, "Comparing AutoML and Deep Learning Methods for Condition Monitoring using Realistic Validation Scenarios," arXiv preprint arXiv:2308.14632, 2023.

[26] P. Refaeilzadeh, L. Tang, H. Liu, “Cross-Validation,” In: L. Liu, M.T. Özsu, (eds) “Encyclopedia of Database Systems,” Springer, 2009, Boston. https://doi.org/10.1007/978-0-387-39940-9_565.

[27] KI-MUSIK4.0 Homepage, available online: https://www.elektronikforschung.de/projekte/ki-musik4.0, last checked: 05/27/2024.