Acta Polytechnica CTU Proceedings **52**:63–68, 2025
https://doi.org/10.14311/APP.2025.52.0063

ABRUPT CHANGE DETECTION IN RAILWAY NOISE DATA

Jan Kruntorád[a,*], Tetiana Reznychenko[b], Petr Červenka[a]

[a] *Czech Technical University in Prague, Faculty of Transportation Sciences, Department of Transport Engineering, Konviktská 20, 110 00 Prague, Czech Republic*

[b] *Czech Technical University in Prague, Faculty of Transportation Sciences, Department of Applied Mathematics, Konviktská 20, 110 00 Prague, Czech Republic*

[*] corresponding author: kruntjan@fd.cvut.cz

Abstract. Current methods for diagnosing the quality of the railway superstructure are mainly based on optical sensors, which are relatively expensive compared to acoustic sensors. As part of the HLUKOS research project, a pair of microphones is installed near the wheel-rail contact point on a diagnostic vehicle of the Railway Administration (Czech railway infrastructure manager). The research task is to detect when the sound level changes significantly. A likelihood ratio method has been used in this paper to detect abrupt changes, which is a current scientific topic. Experiments with different input thresholds are performed on a sample of 250 m of track data. Initial experimental results show that this method is meaningfully able to detect locations of abrupt changes with input threshold values $h = 4.58$ and number of steps from $N = 5$ to $N = 40$.

Keywords: Abrupt change, change detection, likelihood ratio, railway diagnostics, railway noise, wheel-rail contact.

1. Introduction

The last decades have been marked by the development of technological processes and sophisticated sensors, followed by the need for sophisticated information processing systems. Addressing these issues is important for a number of reasons, particularly safety, environmental and economic. The large amount of data from a wide range of sensors means that algorithms must be found or developed to analyse the information. The core of the interest is the detection of one or more abrupt changes in some characteristic of the system under consideration.

An abrupt change is considered to be any change in system parameters that occurs either immediately or at least very quickly relative to the measurement sampling period used. Abrupt changes certainly do not refer to changes of large magnitude; on the contrary, in most applications the main problem is the detection of small changes. Moreover, in some specific cases, early warning of small (and not necessarily fast) changes is essential to avoid economic or even fatal consequences, such as small malfunctions in the sensors of aircraft navigation systems or small variations in the geometric position of the track [1].

The quality of track geometry, respect of clearance profile and other parameters necessary for safe railway operation are continuously monitored and evaluated by infrastructure managers. One of the objectives of the HLUKOS research project is to determine whether abrupt changes in rolling noise recordings at the wheel-rail contact point can be detected, and to use these changes to warn of possible local degradation (defects) of the railway superstructure.

2. Theoretical background

Abrupt change detection in noisy signals is a critical area of research that spans various fields, including signal processing, climate science, and power systems. The methods employed for detecting these changes can be broadly categorized into wavelet-based techniques, statistical approaches, and machine learning methods. Each of these methodologies offers unique advantages and is suitable for different types of signals and noise characteristics.

2.1. Current methods used

Wavelet transforms have emerged as a powerful tool for detecting abrupt changes in signals, particularly in the presence of noise. The wavelet transform allows for the decomposition of a signal into its constituent components at various scales, making it easier to identify discontinuities or abrupt changes. For instance, Ukil and Živanović [2] demonstrated the effectiveness of using an adjusted Haar wavelet for segmenting power system disturbance signals into event-specific sections, highlighting the method's robustness in noisy environments.

In addition to wavelet methods, statistical techniques such as the Kolmogorov-Smirnov statistic have been utilized for abrupt change detection. Qi et al. [3] proposed a fast framework based on binary search trees and the Kolmogorov statistic to identify changes in the statistical properties of signal series, which are indicative of qualitative transitions in the underlying data generation mechanism. This approach is more efficient due to the shortest computation time, the highest hit rate and accuracy than compared conventional methods Kolmogorov-Smirnov statistic, t-statistic and singular-spectrum analyses which was tested on real EEG recordings.

Another significant method for detecting abrupt changes is the use of Bayesian approaches, particularly in online applications such as automatic speech recognition (ASR). Chowdhury et al. [4] emphasized the importance of developing noise estimation algorithms that continuously track and estimate noise levels, enabling the detection of abrupt changes in the noise spectrum. This adaptability is crucial in real-time systems where the acoustic environment can vary significantly.

In the realm of climate science, various detection methods have been developed to identify regime shifts, which can be classified into categories based on the type of change – mean value, variance, frequency, probability density changes, and multivariable analysis [5]. These methods provide a comprehensive framework for analyzing abrupt changes in climate data, emphasizing the need for tailored approaches depending on the nature of the data.

The integration of machine learning techniques into abrupt change detection has also shown promise. For instance, sparse identification of nonlinear dynamics has been utilized for rapid model recovery in chaotic systems, allowing for efficient detection of abrupt changes with reduced data requirements [6]. This approach exemplifies the trend towards leveraging advanced computational techniques to enhance detection capabilities in complex systems.

In summary, the methods for detecting abrupt changes in noisy signals are diverse and multifaceted, encompassing wavelet transforms, statistical techniques, Bayesian approaches, and machine learning. Each method has its strengths and is suited to particular types of signals and noise characteristics. In this paper we focus on another technique for detecting abrupt changes, namely the use of likelihood ratio. It is based on the principle of change detection on difference synthetic aperture radar images [7] or pipeline damage detection using torsional guided wave mode [8].

2.2. Problem formulation

Lets have a dataset which a sequence of signal level observations $X = [x_1, x_2, \dots, x_n]$, where n is a number of observations.

The task is to find a sufficient change in the signal level. This is achieved by identifying the intervals at which significant changes in signal strength occur. This allows for the identification of potential issues and an improvement in the accuracy of data analysis.

2.3. Likelihood-ratio change detection

Likelihood-ratio change detection is a statistical method that is used to detect a point in time when the distribution of signal y_t changes [9, 10]. The goal of the detection algorithm is to determine $S(y_t)$ when the distribution shifts from $f(y_t, \theta_0)$ to $f(y_t, \theta_1)$ where it is assumed that θ_0 and θ_1 are known.

At each time step t, the log-likelihood-ratio is computed as:

$$S(y_t) = \log \frac{f(y_t, \theta_1)}{f(y_t, \theta_0)} \tag{1}$$

This ratio in Eq. (1) compares the probability of observing the current value of the signal y_t under the assumption that a change has already taken place (with parameter θ_1) to the probability of observing the same value under the assumption that no change has yet occurred with θ_0.

The following algorithm solves the detection problem. It detects the change in the level of the signal under test. It is possible to apply this approach to the Fourier transform, thus capturing changes in frequency.

Initialization. Set the values of the signal y_t, θ_0, and θ_1 – means, σ – standard deviation of the data set.

Signal observation. The signal y_t is sampled in K, where K is the sequence number of the large period of sampling. In addition, each large period is divided into N small periods, as indicated in Figure 1.

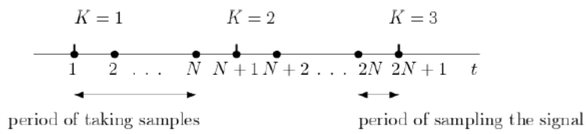

FIGURE 1. Illustration of the signal divided into K intervals [9].

Compute and update statistics. Calculate the likelihood ratio for y_t on N-th small interval, and update statistics over small intervals using the alpha coefficient in Eq. (2). The closer α is to 1, the more weight is given to the value of S_{t-1}:

$$S_t = \alpha \cdot S_{t-1} + \frac{(\theta_1 - \theta_2)}{\sigma^2} \left[y_t - \frac{\theta_1 + \theta_2}{2} \right], \tag{2}$$

where S_t is the current value of the statistic, y_t is the current observed value, and α is the coefficient of forgetting where $0 < \alpha < 1$.

After obtaining the result on the small interval N, the value of $S_1^N(K)$ big interval is computed, as shown in Eq. (3), where $S_1^N(K)$ is the value of the statistic on the K-th interval.

$$S_1^N(K) = \tfrac{(\theta_1 - \theta_0)}{\sigma^2} \textstyle\sum_{t=N(K-1)+1}^{N} K \left[y_t - \tfrac{\theta_1 + \theta_0}{2} \right]. \tag{3}$$

Threshold test. Compare $S_1^N(K)$ with a predetermined threshold h. The decision rule is:

$$d = \begin{cases} 0, & \text{if } S_1^N(K) < h, \\ 1, & \text{if } S_i^N(K) > h, \end{cases} \tag{4}$$

where $S_1^N(K) = S_{N(K-1)+1}^{NK}$ [10].

If $S_1^N(K) > h$, it is considered that there was a change in the distribution from θ_0 to θ_1.

3. Railway noise data

The purpose of the experiment part is to find intervals where noise significantly and rapidly changes using the likelihood ratio method. Within the framework of the HLUKOS research project, data collection is carried out by means of microphones placed symmetrically on the wheelset of the diagnostic vehicle MVŽSv2 (owned and operated by Czech rail infrastructure manager: Technology and Diagnostics Centre, Railway Administration, State organisation), in such a reference position (see Figure 2), which is closest to the measured wheel and, according to further technical analysis and listening to the sound recording, shows the lowest level of interference by air flow and other ambient phenomena.

The key is the choice and correct configuration of the sound analyser, whose function is to process the data recorded by the measuring microphones in real time and convert them into specific acoustic parameters. The problem lies in the combination of the high speed of the diagnostic vehicle (currently max. 160 km h^{-1}, in the near future up to 200 km h^{-1}) and the requirement for very fine sampling of the track parameters. For the solution of this project, a specially designed sensor-acoustic system developed by the project team – EKOLA group, spol. s r.o., and CTU in Prague, Faculty of Transportation Sciences – was used. This system enables the collection of acoustic data with an accuracy comparable to conventional sound measurement technology at a sampling frequency of up to 48 kHz, which corresponds to a sampling duration of 0.02 ms [11].

The study was conducted in a station throat section with three single rail switches running against the switch blades at a low speed, within the range of 35.6 to 36.8 km h^{-1}. The data set used of 1 001 observations contained two key variables: ID and railway noise values. The ID variable is dimensionless and indicates the order of observations, with measurements taken every 0.25 m of track. The ID range is from 0 to 1 000, which means that the measured track sample is 250 m long. The next variable is the noise in dB. These values reflect the amplitude of the Z-network (unweighted) equivalent sound pressure level recorded at corresponding ID points. The range of noise values is from 87.5 to 118.4 dB.

4. Results and discussion

A model was defined with the parameters $\theta_0 = 90$ and $\theta_1 = 107$. These values represent the mean values obtained from the measured signal, which was segmented into two distinct models. The signal was divided into K samples to determine the moment of signal change.

Figure 2. Position of the microphone for measuring the contact noise between the rail wheel and the rail on the MVŽSv2 diagnostic vehicle [12].

Table 1 presents the number of samples on which $S_1^N(K)$ changes from θ_0 to θ_1 for different values of N, where N is 5, 10, 20, 40. The threshold h was established at 4.58.

N	5	10	20	40
Total	15	9	5	3

Table 1. Demonstration of the relationship between segment length N and detection sensitivity h.

Figures 3–6 presents a comprehensive chart detailing the detection of changes in railway noise. The top graph displays the raw signal data, the middle graph illustrates the values of the S_t statistic on the K-th sample, and the bottom graph visualizes the decision-making process for detecting changes in the signal, based on the analysis of $S_1^N(K)$ and h.

The coefficient α was applied during calculations over small periods, preserving $\alpha = 0.95$ when $N = 5$ and $N = 10$, and $\alpha = 1.0$ when N is 20 and 40.

For each combination of parameters N and h, the results have shown the number of detected changes were obtained:

- at $N = 5$ and $h = 4.58$, changes were identified due to the high sensitivity of the threshold,
- at $N = 10$ and $h = 4.58$, the sensitivity decreased and the number of false alarms decreased,
- at $N = 20$ and $h = 4.58$, the lowest number of false alarms and the most accurate detection of changes were recorded,
- at $N= 40$ and $h = 4.58$, three samples exhibited a change in the signal, and no other notable peaks were identified. This suggests that this specific combination of segment length and threshold might limit the detection of additional signal changes.

5. Conclusions

Listening to the sound recording, three clear sound perceptions can be heard in the analysed section of track (at ID = 81, 251 and 834). The abrupt change at ID = 81 was only detected at $N = 5$; at IDs = 251 and 834 at ID = 834 at all N values examined.

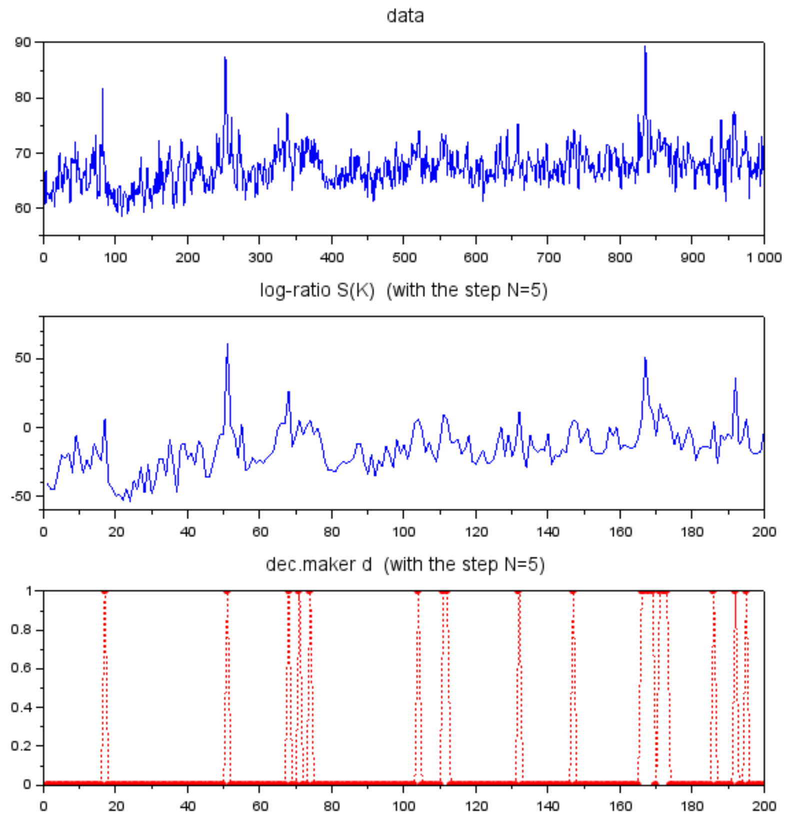

FIGURE 3. Abrupt change the visualization of railway noise using likelihood ratio detection: Graph of signal detection with the sample length $N = 5$.

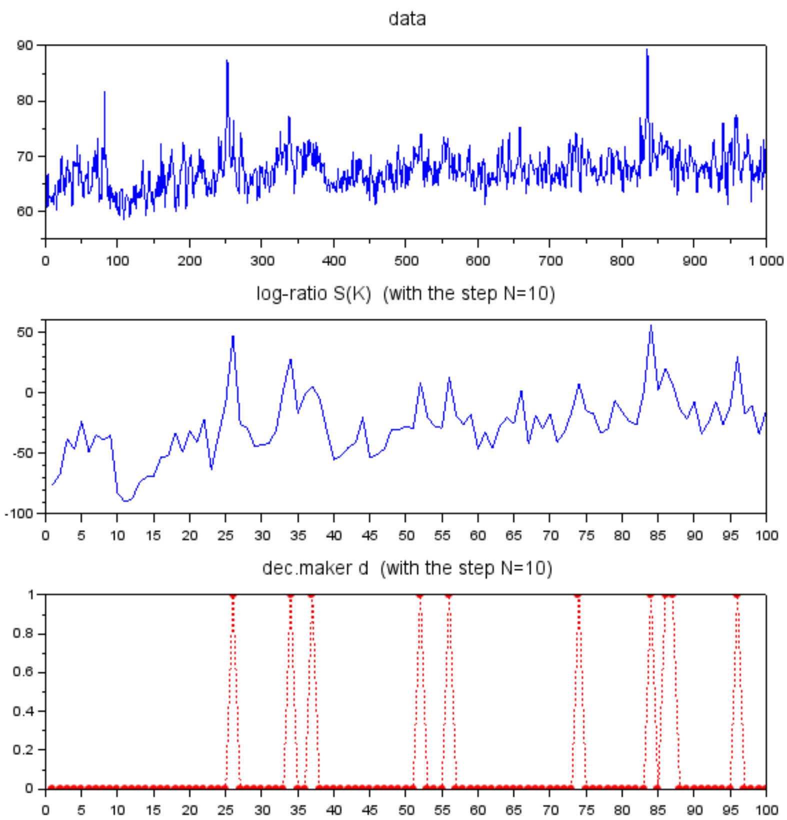

FIGURE 4. Abrupt change the visualization of railway noise using likelihood ratio detection: Graph of signal detection with the sample length $N = 10$.

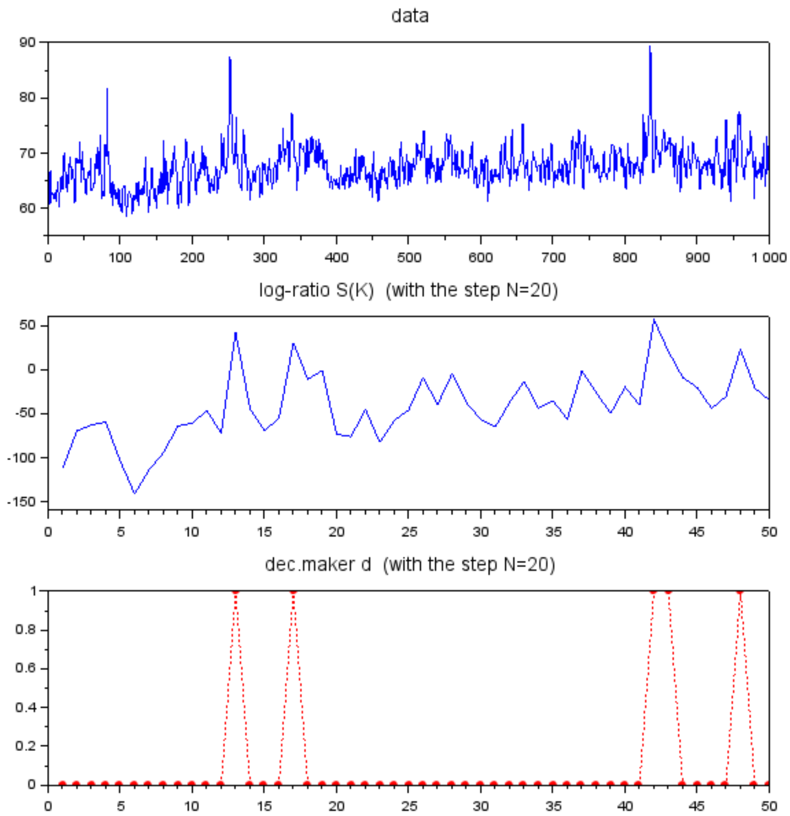

FIGURE 5. Abrupt change the visualization of railway noise using likelihood ratio detection: Graph of signal detection with the sample length $N = 20$.

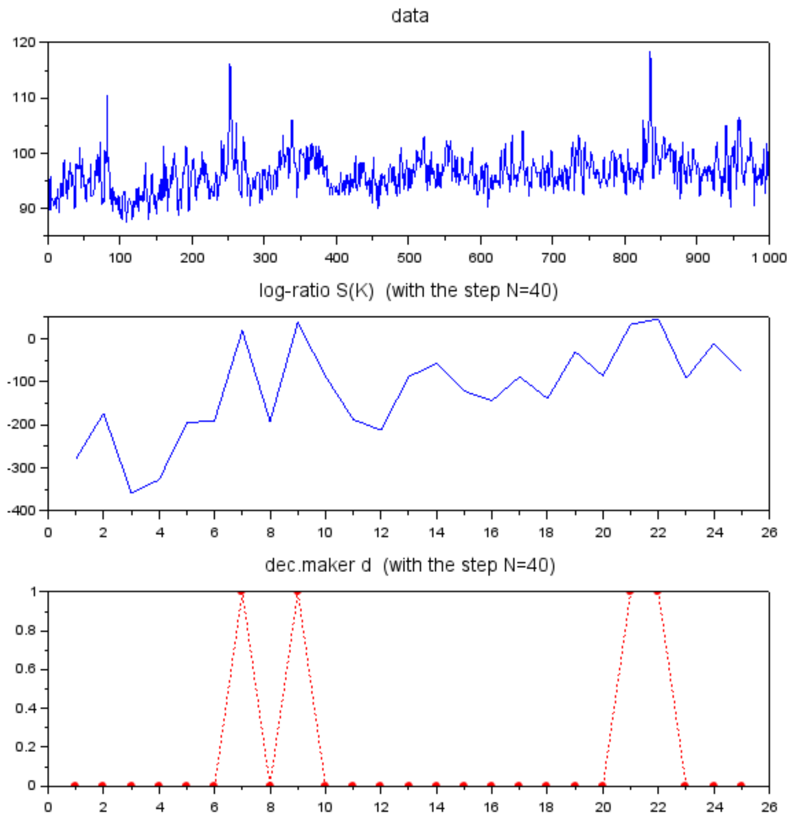

FIGURE 6. Abrupt change the visualization of railway noise using likelihood ratio detection: Graph of signal detection with the sample length $N = 40$.

The experiment demonstrated that the parameter N is essential for the accurate detection of signal changes. Shorter segments ($N = 5$) enhance sensitivity but increase the likelihood of false alarms. The threshold h must be selected to achieve an optimal balance between sensitivity and accuracy. With a chosen threshold of $h = 4.58$, a value of N in the range 20–40 seems to be optimal.

This research paper advances the knowledge base and capabilities for identifying railway noise, paving the way for more effective monitoring and maintenance strategies. Ultimately, this research contributes to the enhancement of railway safety and reliability.

Acknowledgements

This paper has been financed with the state support of the Technology Agency of the Czech Republic and the Ministry of Transport of the Czech Republic within the project CK03000099 Dynamic opto-acoustic method for railway superstructure emission noise assessment within the TRANSPORT 2020+ Programme.

References

[1] J. Kruntorád, L. Týfa. Vision Zero application on Czech railways. *Acta Polytechnica CTU Proceedings* **41**:15–19, 2023. `https://doi.org/10.14311/APP.2023.41.0015`

[2] A. Ukil, R. Živanović. Adjusted Haar wavelet for application in the power systems disturbance analysis. *Digital Signal Processing* **18**(2):103–115, 2008. `https://doi.org/10.1016/j.dsp.2007.04.001`

[3] J.-P. Qi, J. Qi, Q. Zhang. A fast framework for abrupt change detection based on binary search trees and Kolmogorov statistic. *Computational Intelligence and Neuroscience* **2016**(1):8343187, 2016. `https://doi.org/10.1155/2016/8343187`

[4] M. F. R. Chowdhury, S.-A. Selouani, D. O'Shaughnessy. Bayesian on-line spectral change point detection: a soft computing approach for on-line ASR. *International Journal of Speech Technology* **15**(1):5–23, 2012. `https://doi.org/10.1007/s10772-011-9116-2`

[5] Q. Liu, S. Wan, B. Gu. A review of the detection methods for climate regime shifts. *Discrete Dynamics in Nature and Society* **2016**(1):3536183, 2016. `https://doi.org/10.1155/2016/3536183`

[6] M. Quade, M. Abel, J. Nathan Kutz, S. L. Brunton. Sparse identification of nonlinear dynamics for rapid model recovery. *Chaos: An Interdisciplinary Journal of Nonlinear Science* **28**(6):063116, 2018. `https://doi.org/10.1063/1.5027470`

[7] H. Zhuang, Z. Tan, K. Deng, G. Yao. Adaptive generalized likelihood ratio test for change detection in SAR images. *IEEE Geoscience and Remote Sensing Letters* **17**(3):416–420, 2020. `https://doi.org/10.1109/LGRS.2019.2922198`

[8] S. Mariani, P. Cawley. Change detection using the generalized likelihood ratio method to improve the sensitivity of guided wave structural health monitoring systems. *Structural Health Monitoring* **20**(6):3201–3226, 2021. `https://doi.org/10.1177/1475921720981831`

[9] M. Basseville, I. V. Nikiforov. *Detection of Abrupt Changes: Theory and Application*. Prentice-Hall, New Jersey, 1993. ISBN 978-0-13-126780-0.

[10] K. S. Riedel. Detection of abrupt changes: Theory and application. *Technometrics* **36**(3):326–327, 1994. `https://doi.org/10.1080/00401706.1994.10485821`

[11] J. Kruntorád, L. Týfa, O. Simon. Analysis of noise emissions at wheel-rail contact. In O. Prentkovskis, I. Yatskiv (Jackiva), P. Skačkauskas, et al. (eds.), *TRANSBALTICA XV: Transportation Science and Technology*, pp. 502–511. Springer Nature Switzerland, Cham, 2025. ISBN 978-3-031-85390-6. `https://doi.org/10.1007/978-3-031-85390-6_47`

[12] L. Ládyš, O. Simon, M. Ládyš, et al. CK03000099 Dynamická opto-akustická metoda hodnocení emisní hlučnosti železničního svršku. Interim report 2023, EKOLA group, Prague, 2024.