RAIL-WEB MOUNTED PITCH-CATCH PIEZOELECTRIC SETUP FOR DETECTION OF HEAD CHECKS USING SURFACE ACOUSTIC WAVES

Mohsen Rezaei[1], David Künstner[2], Sven Eck[1], Hans-Peter Gänser[1]
[1]Materials Center Leoben Forschung GmbH, Roseggerstrasse 12, 8700 Leoben, Austria
[2]voestalpine Rail Technology GmbH, Kerpelystraße 199, 8700 Leoben, Austria

Abstract

Detecting early indications of head checks in rail systems is paramount for effective service and maintenance, presenting substantial cost savings through the anticipation of crack growth behaviour. Current methodologies, such as wayside monitoring employing equipment like laser vibrometers or specialized test trains, have been in operation for several years. However, these approaches often prove cost-prohibitive, overly complex, or overly sensitive to environmental variations. This creates a critical void in the availability of an affordable and resilient sensor network specifically designed for installation in crucial rail locations.
Piezoelectric sensors emerge as promising candidates due to their cost-effectiveness and versatility. While existing literature introduces some piezo-based systems, they frequently grapple with the intricacies of signal complexity or impractical installation locations on the rail profile, such as the sides of the head. The current project aims at addressing these issues by implementing a pitch-catch network of permanently installed piezo sensors, presenting an affordable solution for rail network operators. Positioned on the web of the rail, these sensors avoid collision with passing wheels, enhancing practicality. A dedicated hardware/software setup is designed to excite, collect, and analyze signals, overcoming the limitations of passive systems. To validate the setup's performance, a pearlite rail sample underwent artificial loading designed to provoke head checks at a special wheel-rail test rig. Surface acoustic waves generated and collected by the piezo sensors every 10,000 cycles were analyzed. The results demonstrate the promising potential of the proposed setup for field applications, providing a reliable and cost-effective solution for early head check detection in rail systems.

Keywords: surface acoustic waves, piezo electric sensors, signal processing, rail condition monitoring

1 Introduction

The rail industry has seen a significant surge in attention towards condition monitoring systems, driven by the imperative to detect defects early and mitigate potential failures and consequential costs [1]. One critical area of focus within this domain is the identification of surface cracks near the gauge corner of rails, commonly referred to as head checks [2]. Detecting and addressing these cracks is vital for the safety of rail systems and the reduction of maintenance expenses. Various methodologies, both destructive and non-destructive, have been explored in literature for defect detection, including dye penetration, eddy-current, microscopic testing, vibration and acceleration measurement, thermography, laser and image processing, and acoustic and ultrasonic waves [2-5].

DOI: https://doi.org/10.5592/CO/CETRA.2024.1715

Of particular interest in this research is the utilization of ultrasonic waves, specifically surface acoustic waves (SAW). These waves, typically generated by laser [6], electromagnetic transducers (EMAT) [7], or piezoelectric transducers [8, 9], offer promise due to their ability to interact with cracks, resulting in reflection and transmission effects that can provide insights into crack depth [10].
While laser-based devices offer precision, they are prohibitively expensive and susceptible to environmental factors, making them unsuitable for permanent wayside monitoring. Conversely, piezoelectric actuators present a more cost-effective and robust solution for continuous monitoring applications. However, practical implementation is hindered by challenges such as sensor placement to avoid collision with the wheel and signal complexity due to rail geometry.
This research endeavours to address these challenges by proposing a web-mounted setup accompanied by a tailored signal processing pipeline capable of extracting relevant features for predictive maintenance. The paper proceeds to present the configuration of the setup in section 2, followed by the signal processing methodology in section 3. Section 4 presents the findings, and conclusions are drawn in section 5, outlining the contributions and implications of the research.

2 Test setup

A practical experiment was conducted at the voestalpine R&D site in Donawitz, Austria, to test the proposed configuration. The experiment utilized a test rig consisting of a bogie, which holds the rail specimen, and a train wheel connected to a heavy hydraulic press. Some details on the corresponding rail wheel test rig and how it is used to achieve RCF damage in the lab within a much shorter time than in real tracks have been published in [11]. The entire setup is controlled by a PLC system programmed by the operator. During the test, the bogie moves reciprocally, with the wheel pressed firmly down by the hydraulic press when moving forward to simulate train running. The hydraulic press can apply a vertical and lateral force equivalent to up to 50 and 10 tons, respectively. When moving backward, the press lifts to allow the rail to return to its initial position. The rail is 1.3 meters long, with half in contact with the wheel, experiencing head checks, and the other half-untouched.
Four piezo sensors are attached to the rail web on both sides, as shown in Figures 1a and 1b: inside (I) and outside (O). A pair of sensors is placed under the damaged (D) section in contact with the rail and another pair under the undamaged (U) section, which is known as pitch-catch configuration (a sender and a receiver). Thus, the sensors are labelled OD, ID, OU, and IU for clarity and convenience.
The experiment ran for 310,000 rolling cycles, spanning approximately three weeks. Measurements were automatically initiated by the laptop every 10,000 cycles following a trigger signal from the PLC after the system stopped (Figure 1c).
Two types of excitation signals, wavelet and burst signals, were employed. The excitation frequency ranged from 500 kHz to 2 MHz in steps of 100 kHz, totaling 16 different frequencies.
An in-house designed switch box, labeled OptiSwitch (Operating Piezo Toggling Switch), facilitates the automatic switching between pairs of sensors, allowing for various combinations of sender and receiver. The primary signal paths of interest are ID -> OD or vice versa, providing valuable information about head checks because that is the path where the surface wave interacts with the gauge corner cracks evolving during the lifetime experiment. Additionally, other paths like ID -> IU or OU -> OD are explored for different purposes, such as assessing sound speed in the material and ensuring signal stability and calibration.

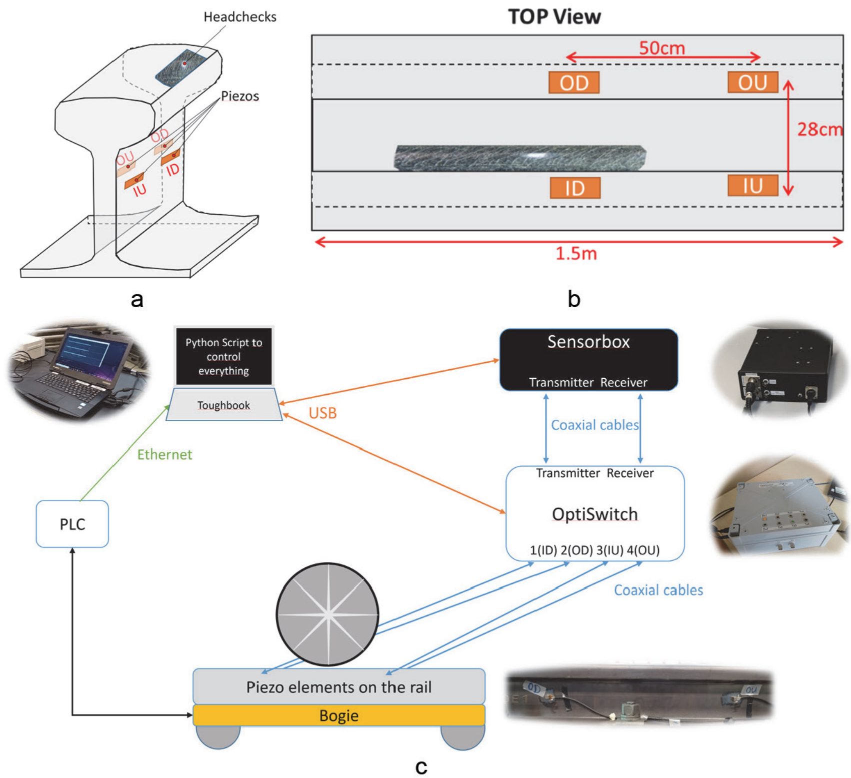

Figure 1 Test setup: a) Piezo locations on the web of the rail, b) Piezo locations from top view, c) Overall setup configuration

In total, 8 meaningful signal paths are included in the measurements. Considering the signal type, frequency selection, and signal path, there are 256 different measurements for every 10,000 cycles. Each of these 256 measurements itself is repeated 32 times, and the average of the measurements, along with the raw data, is saved to mitigate the effects of disturbances and noises. This results in 8192 measurements after each stop, taking around 15 minutes to complete before the new cycle set commences. It has to be noted, that the recorded data during the experiment is much more than will be needed later for the application in track – the excessive data has been used to develop the signal processing pipeline described in the following section.

3 Signal processing pipeline

As previously mentioned, the sensors in this setup are mounted on the web of the rail rather than on or under the head (as shown in [8]), which reflects a more realistic scenario. However, this setup introduces challenges. The longer signal path results in increased attenuation, and the complex geometry of the path leads to multiple reflections and mode conversions during propagation, as illustrated in literature (e.g., in [8], Figure 7). Consequently, the received signal exhibits a complex and noisy form, posing challenges for analysis. An example of such a signal from the experiment is depicted in Figure 2.

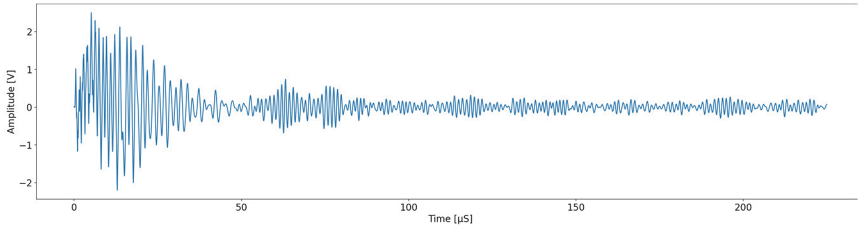

Figure 2 A typical signal (amplitude versus time) received by the receiver piezo (direction = ID2OD; cycle = 20,000; frequency = 0.9 MHz)

In response to the realistic scenario described earlier, a customized signal processing pipeline has been devised and implemented to extract the part of the signal that corresponds to the interaction of the SAW with the gauge corner damage. The pipeline comprises six main blocks, each playing a role in ensuring signal integrity and extracting pertinent information. These steps are illustrated in Figure 3.
Traditionally, in similar signal processing workflows, parameters such as the type, order, and frequencies of low or band-pass filters must be fine-tuned. This tuning process is subjective and heavily reliant on the user's expertise and opinion, often leading to subjective and conflicting results. The proposed pipeline offers the advantage of having no tunable parameters, thereby reducing reliance on user input. The only step where users are required to make a selection, consistent across all similar algorithms, is the initial step where the expected arrival time window is chosen.

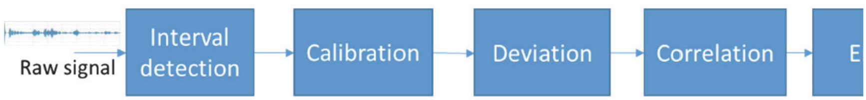

Figure 3 The proposed signal processing pipeline

3.1 Interval detection

The initial and crucial step in signal processing involves selecting the appropriate time window within which the arrival of the surface acoustic wave (SAW) is expected. Figure 2 illustrates several peaks observed in the received signal, including bulk waves, which are not in the focus of the analysis because they do not interact with the surface damage. To accurately select the time window, a time of flight (TOF) analysis was conducted, examining the most likely signal paths and their reflections, as depicted in Figure 4. This figure showcases some of the most plausible paths, each identified with a specific code representing its travel distance and wave type.

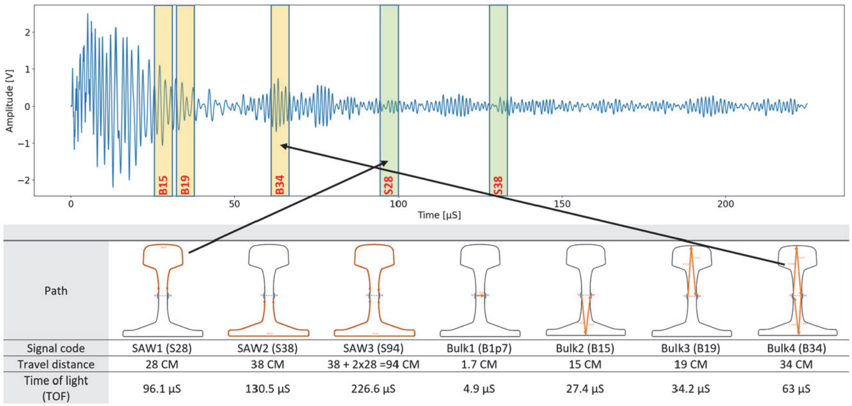

Figure 4 Interval detection in the recorded signal. The plot of the amplitude versus the arrival time has been analyzed; bulk waves are indicated by yellow time intervals and surface waves by green time intervals

3.2 Calibration

This section deals with the challenges posed by changes in raw recorded signals over cycles, which are influenced by factors like aging of the couplant and environmental conditions, rather than crack development. To address this, a calibration method is proposed. Bulk waves, largely unaffected by surface conditions, are utilized for monitoring these effects over time. The calibration factor is the ratio of signal power in a given cycle to that in the initial cycle. An example of this normalization process is provided in Figures 5a and 5b, illustrating the trends before and after normalization.

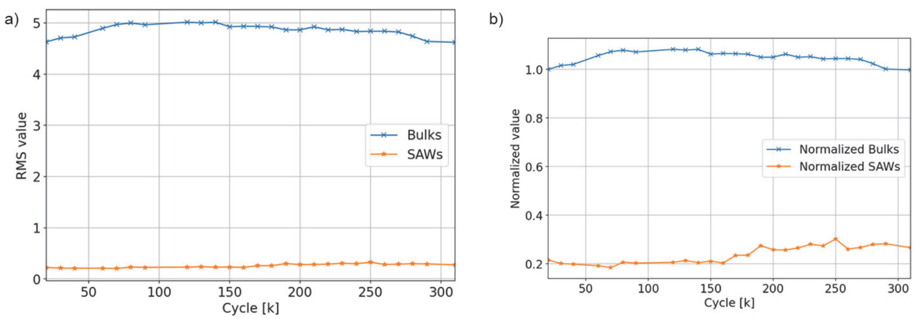

Figure 5 Calibration of the signals: a) raw bulk and SAW RMS values, b) calibrated bulk and SAW values

3.3 Deviation

This step focuses on the reduction of unwanted signals alongside the desired surface acoustic wave (SAW) component in the calibrated signals. It proposes a simplified relation where the signal comprises the SAW, bulk, noise, and other undesired signals (signal = SAW + bulk + noise + other undesired signals). While the bulk and noise components remain relatively constant across rolling cycles, electronic noise from measurement devices also remains stable. By subtracting the signal at cycle n from the signal at cycle 0, the major contributor, the SAW part, can be isolated ($signal_0 - signal_n = SAW_n$). This initial deduction aims to remove unwanted effects from the signal. Further refinement is achieved by calculating the cross-correlation of the sent and received signals in the subsequent step.

3.4 Correlation

In the next step, to further refine the signal and remove remaining unwanted components like harmonics, the cross-correlation operation is employed. This operation measures the similarity between two signals and helps identify and align corresponding features. Defined as the integral of the product of the two signals over a desired interval and time shift, the cross-correlation determines the optimal shift where the signals are most similar. This process, akin to a "matched filter" enhances the signal-to-noise ratio (SNR) by identifying and aligning relevant features, commonly used in fields like RADAR and communications. Unlike using filters, which require parameter adjustments and may lack generalizability, cross-correlation offers a robust approach to signal refinement. This is because, the matched filters are optimal filters which can maximize the signal to noise ratio (SNR), when the signal is highly mixed with white gaussian noise [12].

3.5 Energy

The conventional view of piezos as point sources or sinks is challenged by their dimensions (approximately 1 cm), which are comparable to the wavelength of excitation signals (a few mm for MHz signals). This leads to complex behaviour, where vibrations experienced across the sensor result in superimposed equivalent vibrations and electrical signals at the terminals, as depicted in Fig. 6a. Consequently, received signals may not always exhibit sharp wavelet forms, complicating peak amplitude extraction using traditional methods.
In this study, an alternative approach is proposed, focusing on energy or power rather than peak amplitude alone. By considering the duration of wave reception by the sensor, the energy or power experienced within this window can be calculated, encompassing various effects. This is achieved by cross-correlating the excitation and received signals within the expected arrival time window and selecting the maximum value, corresponding to the signal power. This technique enhances signal clarity, as illustrated in Figure 6b, making peak amplitude selection easier compared to raw signals with indefinite forms.

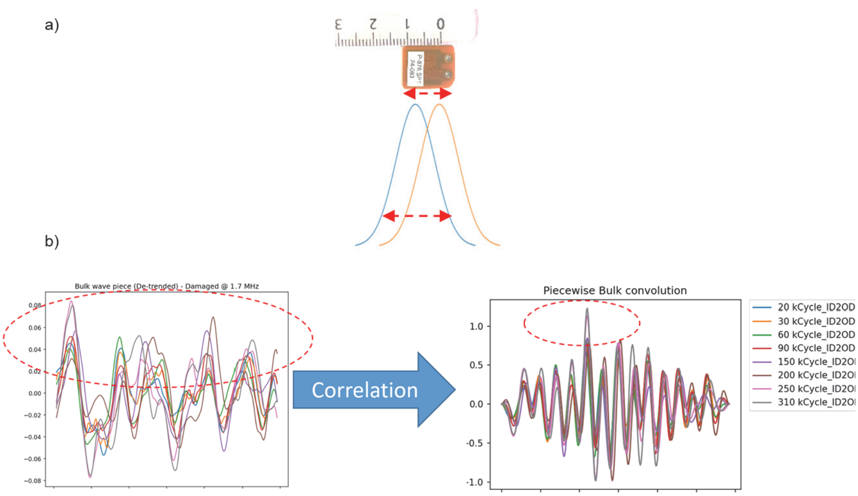

Figure 6 The concept of energy instead of the peak amplitude: a) The effect of dimension of the sensor on detected waveform, b) the result of calculating cross-correlation on the raw signals and then taking the highest peak (power of the original signal)

3.6 Normalization

The peak value of the cross-correlation or the energy obtained from the previous step is an absolute value influenced by experimental conditions like the voltage amplitude applied on the piezos. To ensure comparability across experiments, normalization is necessary. One approach is to use the root mean square (RMS) value of the non-deviated signal or the first cycle as the reference and divide the RMS of the current cycle deviation by it. This normalization process yields a damage index value ranging ideally between 0 (no deviation from the initial signal) and 1 (full deviation from the initial signal, indicating zero amplitude). In principle, it may even exceed 1 due to additional noise and disturbances in different cycles. Nonetheless, it serves as a useful indicator of head check development trend.

4 Results

The experiment is conducted following the test setup outlined in section 2. Figure 7a displays the micrograph of the specimen at the end of the last cycle, revealing the formation of head-checks up to 398 µm. Subsequently, the signal processing pipeline described in Section 3 was applied to the raw signals recorded during the test. Figure 7b illustrates the results for frequencies of 1.3, 1.4, 1.6, and 1.7 MHz, selected among 16 frequencies for reasons to be explained in the discussion section.
All frequencies exhibit a similar trend: an initial increase until around 150,000 cycles, correlated with the emergence and deepening of head-checks, consistent with empirical rail track measurements. This is followed by a period of steady behaviour between 150,000 and 200,000 cycles, possibly due to head-check polishing by further wheel passage. Finally, there is another slow increase in the index until the end of the experiment. Thus, the signal's development can serve as a feature to trigger maintenance measures when it surpasses a predefined threshold.
It is notable that higher frequencies generally have a higher deviation index, indicating lower signal amplitudes compared to lower frequencies. This aligns with literature expectations that higher frequencies or shorter wavelengths experience lower transmission coefficients [10].

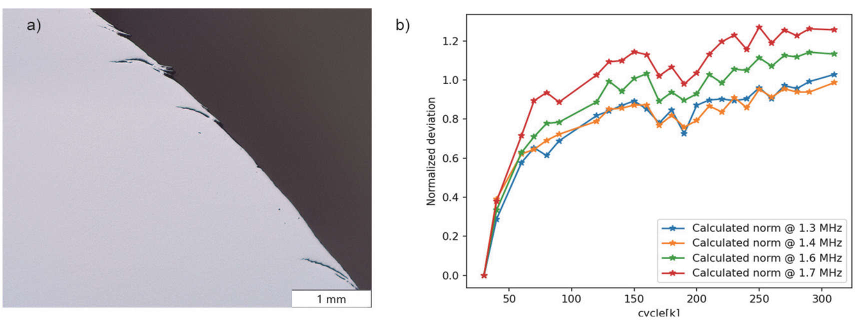

Figure 7 a) Micrograph of the specimen with 310,000 cycles roll-over, b) Deviation norm (damage index) calculated for various frequencies vs over-rolling cycles

Discussion: The selection of only four frequencies (1.3, 1.4, 1.6, and 1.7 MHz) for analysis among the 16 frequencies ranging from 500 kHz to 2 MHz is justified for several reasons:

- Overlap at lower frequencies: Frequencies lower than 1.3 MHz exhibited substantial overlap of nearby signals due to longer signal periods. This overlapping increased the possibility of errors, hence these frequencies were avoided.

- Low amplitude at higher frequencies: Frequencies higher than 1.7 MHz resulted in received signals with low amplitudes, which did not provide sufficient resolution to the Analog to Digital Converter (ADC) of the sensor box. Consequently, these frequencies were not considered suitable for analysis.
- Persistent electronic noise: Persistent electronic noise was observed in the data at harmonics of 300 kHz (e.g., 600, 900, 1200 kHz), which coincided with excitation signals of the same frequencies. This overlapping made it difficult to distinguish between noise and signal.

Given these challenges with certain frequencies, the four frequencies mentioned were considered reliable for analysis after omitting the problematic frequencies. This selection aimed to ensure accurate and meaningful results by focusing on frequencies with clear signals and minimal interference.

5 Conclusion and future work

The following conclusions are drawn:
- The web-mounted pitch-catch piezo configuration provides a reliable and cheap measurement setup, which provides useful information regarding the head check development in the rail at a predefined cross-section.
- However, due to a complex signal, mixed with noise and other unwanted interferences, an advanced signal processing workflow is required to extract the required information.
- The proposed tailor-made signal processing pipeline can effectively extract the main component (surface acoustic wave) from the raw signal.
- There will be a follow-up to this research for improvements:
- Although the extracted signal feature shows a fair agreement with the trend of the crack growth over cycles, from the previous experiments, a new measurement will be conducted, in which this time every 50,000 or 100,000 cycles, a part of the rail will be delivered to metallographic analysis to determine the crack depth. In this way, a more precise correlation between the damage index and the real crack depth can be determined.
- A deeper analysis will be performed to determine and limit the electronic noise observed in the data, to have results that are more precise.

Acknowledgement

The authors gratefully acknowledge the financial support under the scope of the COMET program within the K2 Center “Integrated Computational Material, Process and Product Engineering (IC-MPPE)” (Project No 886385). This program is supported by the Austrian Federal Ministries for Climate Action, Environment, Energy, Mobility, Innovation and Technology (BMK) and for Labour and Economy (BMAW), represented by the Austrian Research Promotion Agency (FFG), and the federal states of Styria, Upper Austria and Tyrol.

References

[1] Kostrzewski, M., Melnik, R.: Condition Monitoring of Rail Transport Systems: A Bibliometric Performance Analysis and Systematic Literature Review, Sensors 21 (2021) 4710, DOI: 10.3390/s21144710

[2] Mátéé, T., Zwierczyk, P.T.: Comparison of Rail Head Checks Using Destructive and Non-Destructive Examination Methods, J Fail. Anal. and Preven, 22 (2022), pp. 1898–1904, DOI: 10.1007/s11668-022-01475-w

[3] Kou, L.: A Review of Research on Detection and Evaluation of the Rail Surface Defects, Acta Polytechnica Hungarica, 19 (2022) 3, DOI: 10.12700/APH.19.3.2022.3.14

[4] Chen, K., Fu, X., Dorantes-Gonzalez, D.J., Li, Y., Wu, S., Hu, X.: Laser-Generated Surface Acoustic Wave Technique for Crack Monitoring – A Review, International Journal of Automation Technology, 7 (2013), pp. 211-220

[5] Oßberger, U., Kollment, W., Eck, S.: Insights towards Condition Monitoring of Fixed Railway Crossings, Procedia Structural Integrity, 4 (2017), pp. 106-114, DOI: 10.1016/j.prostr.2017.07.00

[6] Tuschl, C., Oswald-Tranta, B., Eck, S.: Inductive Thermography as Non-Destructive Testing for Railway Rails, Applied Sciences, 11 (2021) 1003, DOI: 10.3390/app11031003

[7] Thompson, R.B.: Physical Principles of Measurements with EMAT Transducers, Physical Acoustics, 1990, pp. 157-200, DOI: 10.1016/B978-0-12-477919-8.50010-8

[8] Gruber, C., Hammer, R., Gänser, H. P., Künstner, D., Eck, S.: Use of Surface Acoustic Waves for Crack Detection on Railway Track Components – Laboratory Tests, Appl. Sci. 12 (2022) 6334, DOI: 10.3390/app12136334

[9] Aleksandrova, M., Badarov, D.: Recent Progress in the Topologies of the Surface Acoustic Wave Sensors and the Corresponding Electronic Processing Circuits, Sensors 22 (2022) 4917, DOI: 10.3390/s22134917

[10] Angel, Y.C., Achenbach, J.D.: Reflection and transmission of obliquely incident Rayleigh waves by a surface-breaking crack, The Journal of the Acoustical Society of America, 75 (1984) 313

[11] Stock, R., Pippan, R.: Rail grade dependent damage behaviour – Characteristics and damage formation hypothesis, Wear, 314 (2014) pp. 44-50, DOI: 10.1016/j.wear.2013.11.029

[12] Ziemer, R.E., Tranter, W.H.: Principles of Communications, John Wiley and Sons, 1988, pp. 465-468