Improving Freight Train Wheel Monitoring with Smart Sensors

Igor Makienko[1], Michael Grebshtein[1], and Eli Gildish[1]

[1]*RSL Electronics LTD, Migdal Ha'Emek, 23100, Israel*
igor@rsl-electronics.com

ABSTRACT

Onboard monitoring of freight car axleboxes enhances safety, reduces maintenance costs, and improves track conditions by preventing secondary damage. Installing wireless sensors on freight cars without a nearby power source should be cost-effective, given the large quantities involved. To address this, a new wireless smart sensor node has been deployed. The sensor automatically recognizes stable operating conditions, detects wheel rotational speed from vibrations, performs real-time condition monitoring, and transmits the results to the cloud. This study outlines the smart sensor concept and the pilot field test conducted with real freight cars. The results demonstrate the ability to estimate wheel rotational speed from vibrations and the potential for detecting wheel out-of-roundness (OOR) using a newly developed condition indicator for low-power real-time operations.

1. INTRODUCTION

1.1. Condition Monitoring of Freight Car Axlebox

Railway transport is gaining popularity among land-based options due to its low energy consumption. Technological efforts are being made to increase speed and load per axle, thereby boosting investments in safety improvements, as described by Viana et al. (2021). There are two potential solutions: wayside and vehicle-side (or onboard). Wayside solutions are cost-effective and can monitor the condition of axlebox bearings and wheels, as noted by Guedes et al. (2023) and Fu et al. (2023). However, they detect failures at very late stages, which does not prevent catastrophic derailments caused by axlebox bearing failures in the U.S., as described by Cohen et al. (2023), or by flat wheel failures in the UK, as mentioned by BBC et al. (2023). Onboard condition monitoring can be used for axlebox condition monitoring if it is cost-effective and wireless, considering the high deployment and operational costs. The new smart sensor system architecture, discussed in the next section, can offer a viable solution.

1.2. Smart Sensors Concept

The smart sensor is a wireless sensor node comprising the following modules: power source, sensing module, memory, data processing, and communication modules. The smart sensors conduct condition monitoring directly on the sensor, transmitting only the results to the cloud or nearby devices. This approach enables fast deployment and cost-effective operations and maintenance by eliminating the need for expensive data transmission, processing, and storage infrastructure. The schematic of the smart sensor is shown in Figure 1:

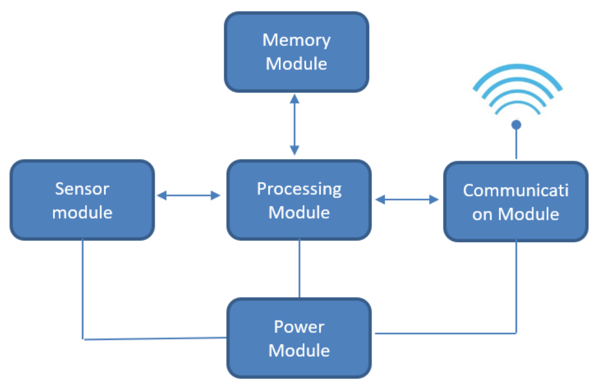

Figure 1. Schematic architecture of smart sensors

The sensor module includes two vibration sensors and one temperature sensor. The first vibration sensor has a low bandwidth and is used for wake-up and detection of stable train states, avoiding accelerations, decelerations, and curves. The second sensor is wideband and used for condition monitoring. The sensor module operates in two main modes: initial data acquisition and operational mode. During the initial mode, data is accumulated for learning purposes, and then the sensor is configured for operational use. The power module utilizes energy harvesting during operations and relies on the battery source during the data accumulation period. The installation of the sensor on the axlebox is shown in Figure 2.

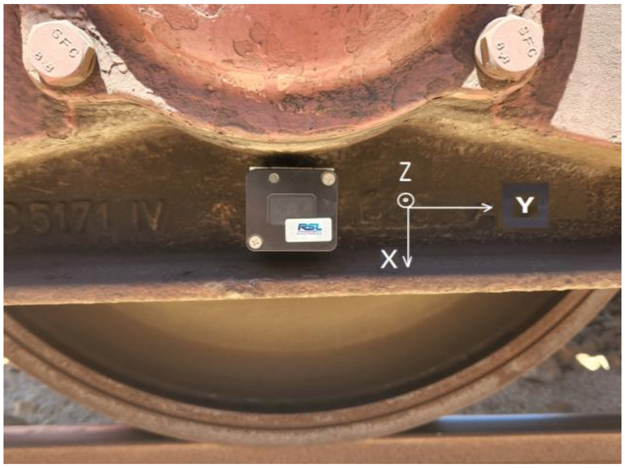

Figure 2. Smart sensor installation example

The smart sensor is designed to provide onboard condition monitoring of the following axlebox components:

- Bearing health conditions
- Wheel OOR: wheel flat, polygonization, and roughness
- Locked wheel detection

To achieve this functionality, several research challenges must be addressed. This study focuses on the initial evaluation of the sensor's capability for wheel health monitoring:

1. Evaluation of the sensor's ability to differentiate between healthy wheels and those with early signs of OOR
2. Automatic on-sensor estimation of wheel rotation speed using vibrations for wheel and bearing condition monitoring

A pilot field experiment was conducted on a test freight train with a wheel with OOR problem to address these challenges.

1.3. Related Works

The condition monitoring scope of smart sensors covers the health conditions of bearings and wheels in the axlebox. This study focuses on wheel health monitoring, based on the requirements of the pilot field test. Defective wheels can disrupt railway operations, cause significant track damage, increase maintenance costs, and potentially lead to derailments. Therefore, early defect detection is crucial, resulting in long-term cost savings and safety improvements.

Wheel defects are primarily characterized by OOR, which refers to any deviation from a perfectly round wheel. These deviations can be discrete, periodic, or random, leading to defects such as wheel flats, polygonization, and wheel roughness, respectively. A comprehensive review of wheel defects is provided by Iwnicki et al. (2023). Most wheel defect detection technologies fall into two categories: onboard monitoring systems, as noted by Bernal et al. (2018) and Bosso et al. (2019), and wayside monitoring systems, reviewed comprehensively by Shaikh et al. (2023). Current onboard monitoring systems are mainly deployed on passenger trains and locomotives, utilizing vibration, acoustic, image detection, and ultrasonic technologies, as seen in Bosso et al. (2018) and Cavuto et al. (2016). The high cost is the primary reason for the limited use of onboard wheel condition monitoring in freight trains, due to the significant volumes involved, as described by Cohen et al. (2023). The proposed smart sensor concept may help improve this situation by eliminating the need for high-cost data transmission, storage, and processing in the cloud.

A comprehensive review of existing methods for detecting wheel OOR using vibrations can be found in Gonçalves et al. (2023) and Wang et al. (2020), as applied to high-speed trains. These methods employ envelope-based analysis and wavelet transform, as suggested by Mosleh et al. (2023). Envelope analysis emphasizes peaks in time or spectrum resulting from local damage or modulation caused by distributed damage. The challenge is to filter the correct frequency band before using the envelope, utilizing system resonance frequencies to improve the signal-to-noise ratio. Methods like spectral kurtosis are used to identify the right frequency bands, as seen in Mosleh et al. (2021), where kurtosis measures the "peakedness" of the spectrum in different bands. The disadvantage of using kurtosis is its sensitivity to noise and random spikes, which means it does not focus on the repetitive peaks typically associated with the wheel OOR problem.

The issue of rotational speed estimation from vibrations in industrial IoT has been discussed by Gildish et al. (2023) and Gildish et al. (2024). Existing methods rely on identifying dominant gear vibrations with peaks in the spectrum, which is not applicable to healthy wheels. The use of cepstrum may enhance rotation-related signals by consolidating wheel harmonics, as proposed by Baasch et al. (2021), which may represent an algorithm for wheel speed estimation.

The literature review clearly indicates that existing systems and methods for onboard wheel health monitoring in freight trains require improvement. The new cost-effective smart sensor concept and new OOR condition indicator will be further presented.

1.4. Contribution

The new smart sensor concept and OOR condition indicator were developed and validated through pilot field tests with freight trains. This study introduces the new condition indicator for wheel OOR monitoring and presents experimental results using smart sensors for onboard condition monitoring of axlebox components in freight trains.

The recorded vibrations demonstrated the sensor's capability to differentiate between healthy wheels and those with OOR using the new condition indicator.

The evaluation dataset was limited to a one-hour run of a single train. Further evaluation of the method will be conducted using a larger dataset. Additionally, the method was evaluated using only stable operating conditions. Testing the method under non-stationary conditions will be necessary.

This paper is structured as follows: Section 2 describes the methods used for detecting wheel out-of-roundness and estimating wheel speed from vibrations. Sections 3 and 4 present the experimental results. Conclusions and future work are summarized in Section 5.

2. METHODS

The study focuses on two tasks: detecting early-stage OOR wheel problems and estimating wheel speed using vibration signals. The analysis assumes stable operating conditions, defining a stationary signal environment.

2.1. Detecting Wheel OOR

As discussed in the literature review, the envelope spectrum is a well-known method for detecting OOR. This study compares OOR detection in both time and frequency domains to determine the necessity of spectrum calculation, considering the importance of power saving for on-sensor operations. The signal envelope can be computed using the Hilbert transform or the method described by Gonçalves et al. (2023), which involves band-pass filtering, shifting the filtered band to zero through complex signal multiplication, and low-pass filtering the resultant complex signal, as described by Hasan et al. (1983):

$$y(t) = h_{LP} * (x(t) * h_{BP}) exp\,(2\pi i f_0 t) \qquad (1)$$

where $x(t)$ represents the raw vibration data, h_{BP} and h_{LP} denote the band-pass and low-pass filters respectively, and f_0 is the center frequency of the filtered band. In this study, the filter band is selected to maximize spectral kurtosis, as suggested by Mosleh et al. (2021). For low-power real-time operations, the filter remains constant for each sensor, and decimation may be applied after low-pass filtering to reduce computational load.

Both the signal $y(t)$ and its spectrum $s(f)$ can be utilized in OOR monitoring, with the latter potentially enhancing signal-to-noise ratio (SNR) and accuracy. Due to low-power constraints, minimal calculations are required. Two condition indicators (CIs) will be evaluated, focusing on signal peakedness: Kurtosis and the newly proposed Peakindness-by-Spread (PBS).

Kurtosis, applicable to both time and frequency domains, is computed as:

$$Kurtosis = \frac{\sum_{t=0}^{T}(y(t) - \mu)^4}{\sigma^4} - 3 \qquad (2)$$

where μ and σ represent the mean and standard deviation of the time series $y(t)$.

Kurtosis is sensitive to noise, random spikes, and does not specifically target repetitive peaks typical of OOR wheel issues. In contrast, the new PBS indicator is designed to enhance robustness against noise and random spikes by focusing on repetitive peaks, making it suitable for low-power real-time calculations.

The Peakindness-by-Spread (PBS) CI increases when repetitive peaks appear in the signal, causing its distribution to develop a long-tail shape. In distributions with long tails, the mean increases relative to the median. Therefore, PBS is defined as the difference between the mean and median, normalized to be unitless and independent of train operating conditions:

$$PBS = \frac{\overline{|y(t)|} - median(|y(t)|)}{median(|y(t)|)} \qquad (3)$$

where $\overline{|y(t)|}$ refers to the mean of $|y(t)|$.

Both CIs are evaluated by applying them to both the envelope and its spectrum, using data from the pilot field test. A schematic view of the method is presented in Figure 3.

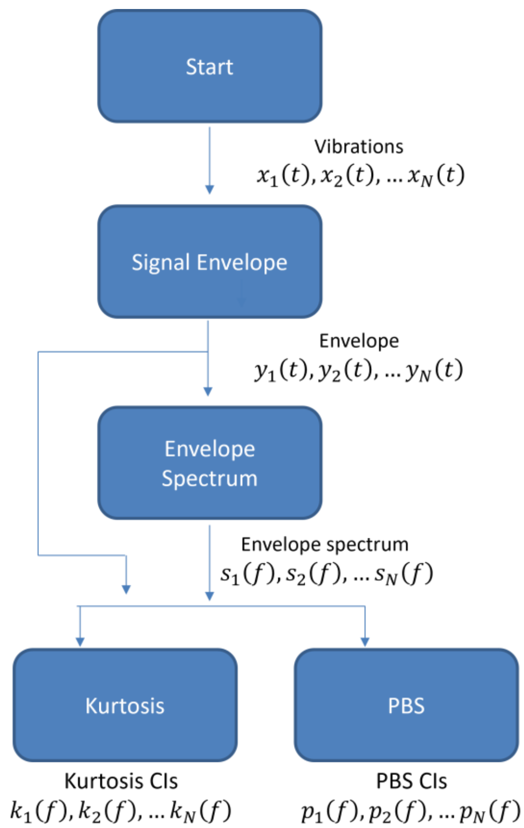

Figure 3. Wheel OOR monitoring method

2.2. Wheel Speed Estimation

Estimating wheel speed using vibrations becomes challenging in healthy wheels without OOR issues, as vibration spectrum analysis fails to provide reliable results. The cepstrum power transform, detailed by Baasch et al. (2021), offers a solution by accentuating peaks at quefrencies (in contrast to frequencies) correlated with inverse of wheel speed. The power cepstrum is applied to raw vibration data and defined as the power spectrum of the logarithm of the power spectrum:

$$C(q) = |F^{-1}\{log(|F\{x(t)\}|^2)\}|^2 \qquad (4)$$

where $F\{\}$denotes the FFT transform, and q represents the quefrency axis of the cepstrum. Wheel speed is then calculated as the inverse of the distance between peaks in the quefrency domain of the power cepstrum. The following section details the experimental results of applying this methodology to vibration data collected during field tests on real freight trains.

3. EXPERIMENTAL SETUP

3.1. Goals

- Evaluation of the proposed condition indicators (CIs) for monitoring wheel OOR when one wheel exhibits OOR problem.
- Testing the capability to estimate wheel speed from vibration signals by correlating with the train's speed.
- Investigating the sensor's dynamic range across diverse operating conditions.

3.2. Wagons and Sensors Setup

The pilot study utilized a freight train consisting of 8 wagons. A total of 18 smart sensors were installed and distributed across the wagons, detailed in Table **1**, which indicates that the right wheel of Bogie 1 in Wagon 2 exhibited an OOR issue.

Table 1. Installation of Smart Sensors.

Wagon #	Weight, ton	Sensors #
1	65	1
2	65	3
3	60	6
4	60	1
6	0 (empty)	2
8	0 (empty)	5

The empty wagons used in the test demonstrate that the method is effective for wagons of any weight. Two sensors were installed on the wheelset with the OOR problem. The distribution of sensors among wagons was not uniform due to mechanical considerations of the bogies during installation. For simplicity in comparison, only bogies of the same type were selected for the pilot. Sensor locations are denoted as follows: W1B1A1-L, indicating Wagon 1, Bogie 1, Axle 1, left wheel.

3.3. Train Speed Recording

Estimating the wheel rotation speed is required for detecting bearing faults and identifying consistent operational conditions. Smart sensors must estimate rotation speed from vibration signals alone, without requiring additional measurements. To validate the algorithm for estimating wheel rotation speed from vibrations, the average train speed was recorded using GPS loggers on two separate phones and used as a reference. It was assumed that no wheel slipping occurred during the experiment.

The test involved approximately one hour of driving, including stops, conducted in both directions. The recorded train velocity profile is illustrated in in Figure 4.

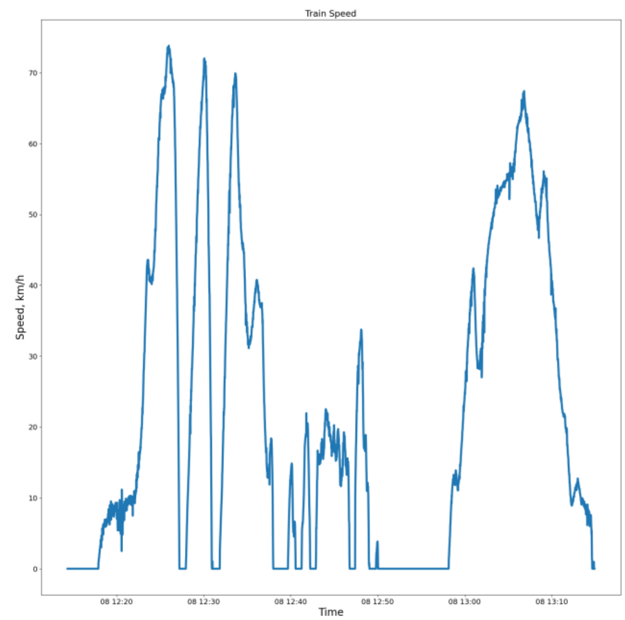

Figure 4. Train Velocity Profile

The driving profile included accelerations, decelerations, and track curves. The timing of each maneuver was recorded and subsequently analyzed.

3.4. Vibration Data Acquisition

After the smart sensors were installed and activated, 10-second recordings were stored periodically. Each recording included vibrations from two types of accelerometers, acquired simultaneously:

- A 3-axis accelerometer with a 1,200Hz bandwidth, sampled at a 3,200Hz rate, and a ±64G range for condition monitoring.

- A 3-axis accelerometer with a 50Hz bandwidth, sampled at a 100Hz rate, and a ±8G range for sensor wake-up and detection of train operating conditions.

The measurement directions were set as follows: Y in the longitudinal direction, X oriented towards the ground, and Z in the lateral direction, as demonstrated in Figure 2.

4. EXPERIMENT RESULTS

4.1. Evaluation of OOR Condition Indicators

As expected, peaks related to wheel rotations were detected in the envelope of the suspected wheel compared to the other wheels. The envelopes of the wheel with OOR and a healthy wheel are demonstrated in Figure 5.

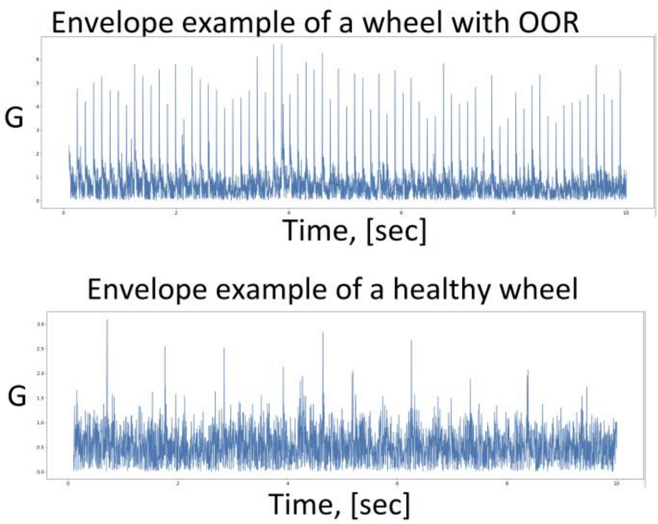

Figure 5. Envelope examples of a wheel with OOR (top) and a healthy wheel (bottom).

The periodic peaks series indicates uneven wear or a wheel flat on the specific wheel. Two CIs described in Section 2.1 are evaluated using the envelope and envelope spectrum. The results are shown in Figure 6 and Figure 7.

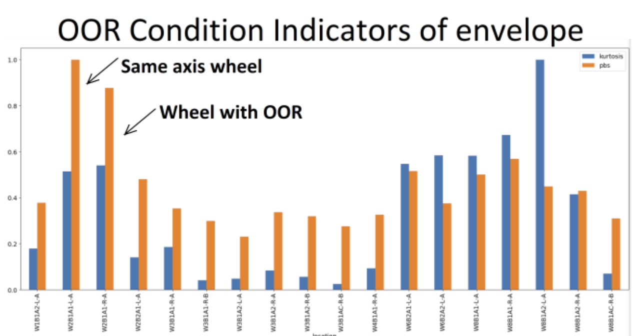

Figure 6. Kurtosis (blue) vs. PBS (orange) OOR indicators applied to the envelope for all wheels

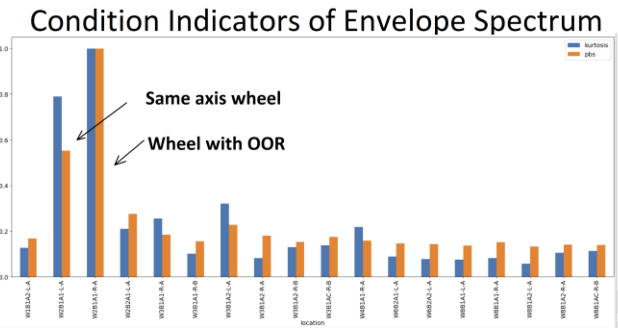

Figure 7. Kurtosis (blue) vs. PBS (orange) OOR indicators applied to the envelope spectrum for all wheels

The figures depict the average CIs per sensor location, calculated using the entire dataset that includes various operating conditions of the train. The new PBS indicator is more robust to noise and random spikes compared to Kurtosis, and it can operate on both the envelope and its spectrum. The spectrum-based results demonstrate improved performance, as the transform reduces the impact of random spikes in the envelope. High PBS values are observed not only in a wheel with OOR but also in the corresponding wheel on the same axle, due to their shared axis location.

4.2. Wheel Speed Estimation

The evaluation of the capability to estimate wheel rotation speed from vibrations was performed using train speed data as a reference, assuming no wheel slipping due to bearing or brake faults. An example of the spectrum and the power cepstrum, detailed in section 2.2, from a sensor installed on the wheel with OOR, driving at 56 km/h, is shown in Figure 8.

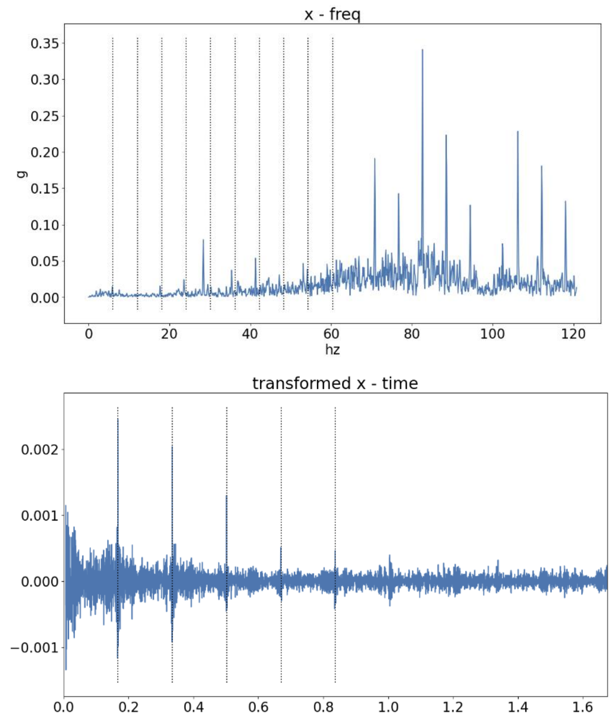

Figure 8. Vibration spectrum (top) and its cepstrum transform (bottom) of a wheel with OOR

The vibration spectrum up to 120 Hz, with vertical lines indicating potential harmonics of the wheel rotation speed, is shown in the bottom graph. Recognizing the corresponding harmonics of the wheel rotation speed proves challenging. The use of cepstrum for wheel speed estimation is demonstrated in the bottom graph, compared to reference vertical lines calculated based on the train's speed. The cepstrum-based algorithm helps highlight the harmonics associated with wheel rotation speed, assuming no wheel slipping due to bearing or brake faults. Further investigation is needed to quantitatively evaluate the algorithm's accuracy across wheels of varying health conditions and compare it with other existing methods.

4.3. Dynamic Range Estimation

To assess the sensors' dynamic range, the peak-to-peak (P2P) values of recorded vibrations were plotted against driving time. A clear correlation emerged between the train's accelerations, decelerations, and the variations in P2P values. In loaded cars, the P2P values were lower compared to empty cars, as depicted in the example figure. Only a few sensors on the empty cars, under specific travel conditions, reached the maximum dynamic range of ±64G. For the remaining sensors, the range was lower. This example is illustrated in Figure 9.

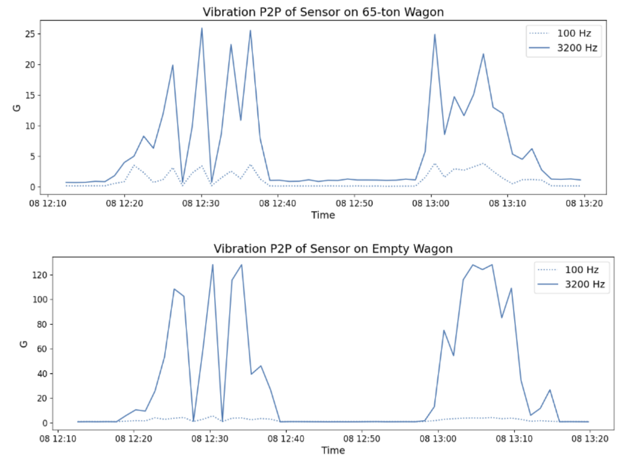

Figure 9. Example of Sensor dynamic range for a 65-ton wagon (top) and an empty wagon (bottom)

In the upper graph, the sensor was installed on a 65-ton loaded car, while in the lower graph, it was installed on the last empty car. Vibrations from both types of wagons are illustrated for two types of sensors: those with a 100 Hz sampling rate (dashed lines) and those with a 3200 Hz sampling rate (solid lines), across three axes with axis X oriented towards the ground. The maximum peak-to-peak (P2P) range of 125G was observed during train operations. In such cases, the sensor's range can be extended up to ±200G for further testing to prevent saturation in the event of failures.

5. CONCLUSION AND FUTURE WORK

The study illustrates that smart sensors have the potential to enhance onboard condition monitoring of axlebox components in freight cars. Their ease of deployment and cost-effective operation at scale are notable advantages. The newly proposed OOR monitoring condition indicator and pilot field test results demonstrate the ability to distinguish between healthy wheels and those with OOR. The robustness of the new CI to noise and random spikes suggests potential application in various other PHM (Prognostics and Health Management) applications, where kurtosis has traditionally been used to detect repetitive peaks in signals. The successful operation of wheel speed estimation from vibrations was demonstrated on wheels with OOR, but not on healthy wheels, indicating the need for further research in this area.

To ensure accurate monitoring and potentially reduce false alarm rates, further research should focus on developing methods to automatically detect stable train operating conditions and mitigate the influence of track irregularities on diagnostic decisions. Further investigation is necessary to validate the sensors' capability for axlebox condition monitoring in operational trains. The evaluation dataset should be significantly expanded, and further assessments should include non-stationary conditions.

REFERENCES

Baasch, B., Heusel, J., Roth, M., & Neumann, T. (2021). Train wheel condition monitoring via cepstral analysis of axle box accelerations. Applied Sciences, 11(4), 1432.

BBC,(2023) https://www.bbc.com/news/uk-england-cumbria-67064845

Bernal, E., Spiryagin, M., & Cole, C. (2018). Onboard condition monitoring sensors, systems and techniques for freight railway vehicles: a review. IEEE Sensors Journal, 19(1), 4-24.

Bosso, N., Gugliotta, A., & Zampieri, N. (2018). Wheel flat detection algorithm for onboard diagnostic. Measurement, 123, 193-202.

Bosso, N., Gugliotta, A., Magelli, M., & Zampieri, N. (2019). Monitoring of railway freight vehicles using onboard systems. Procedia Structural Integrity, 24, 692-705.

Cavuto, A., Martarelli, M., Pandarese, G., Revel, G. M., & Tomasini, E. P. (2016). Train wheel diagnostics by laser ultrasonics. Measurement, 80, 99-107.

Cohen G. (2023). Hot box detectors didn't stop the East Palestine derailment. Research shows another technology might have. *CNN* (https://edition.cnn.com/2023/02/25/us/ohio-train-derailment-bearing-vibration/index.html)

Fu, W., He, Q., Feng, Q., Li, J., Zheng, F., & Zhang, B. (2023). Recent advances in wayside railway wheel flat detection techniques: A review. Sensors, 23(8), 3916.

Gildish, E., Grebshtein, M., Aperstein, Y., & Makienko, I. (2023, May). Vibration-Based Estimation of Gearbox Operating Conditions: Machine Learning Approach. In 2023 International Conference on Control, Automation and Diagnosis (ICCAD) (pp. 1-6). IEEE.

Gildish, E., Grebshtein, M., & Makienko, I. (2024). Vibration-based rotation speed estimation for Industrial IoT. Internet of Things, 25, 101024.

Gonçalves, V., Mosleh, A., Vale, C., & Montenegro, P. A. (2023). Wheel out-of-roundness detection using an envelope spectrum analysis. Sensors, 23(4), 2138.

Guedes, A., Silva, R., Ribeiro, D., Vale, C., Mosleh, A., Montenegro, P., & Meixedo, A. (2023). Detection of wheel polygonization based on wayside monitoring and artificial intelligence. Sensors, 23(4), 2188.

Hasan, T. (1983). Complex demodulation: Some theory and applications. Handbook of Statistics, 3, 125-156.

Iwnicki, S., Nielsen, J. C., & Tao, G. (2023). Out-of-round railway wheels and polygonisation. Vehicle System Dynamics, 61(7), 1787-1830.

Mosleh, A., Meixedo, A., Ribeiro, D., Montenegro, P., & Calçada, R. (2023). Early wheel flat detection: An automatic data-driven wavelet-based approach for railways. Vehicle System Dynamics, 61(6), 1644-1673.

Mosleh, A., Montenegro, P. A., Costa, P. A., & Calçada, R. (2021). Railway vehicle wheel flat detection with multiple records using spectral kurtosis analysis. Applied Sciences, 11(9), 4002.

Shaikh, M. Z., Ahmed, Z., Chowdhry, B. S., Baro, E. N., Hussain, T., Uqaili, M. A., ... & Shah, A. A. (2023). State-of-the-art wayside condition monitoring systems for railway wheels: A comprehensive review. IEEE Access, 11, 13257-13279.

Viana, C. O., Carvalho, H., Correia, J., Montenegro, P. A., Heleno, R. P., Alencar, G. S., ... & Calçada, R. (2021). Fatigue assessment based on hot-spot stresses obtained from the global dynamic analysis and local static sub-model. International Journal of Structural Integrity, 12(1), 31-47.

Wang, R., Crosbee, D., Beven, A., Wang, Z., & Zhen, D. (2020). Vibration-Based Detection of Wheel Flat on a High-Speed Train. In Advances in Asset Management and Condition Monitoring: COMADEM 2019 (pp. 159-169). Cham: Springer International Publishing.

BIOGRAPHIES

Igor Makienko earned his B.Sc., and M.Sc. degrees from the Faculty of Electrical Engineering at the Technion – Israel Institute of Technology, specializing in Machine Learning and Signal Processing. Currently, he serves as the Head of the PHM group at RSL Electronics Ltd, where he has accumulated over 20 years of experience developing AI-powered Predictive Maintenance Platforms for Aerospace, Energy, Maritime, and Transportation sectors. His current research focuses on integrating edge AI into PHM applications, enabling processing at the sensor level.

Michael Grebshtein received his Ph.D. degree in Aerospase Engineering from the Technion – Israel Institute of Technology. He is currently Lead diagnostic expert in RSL Electronics Ltd working on innovative PHM solutions including AI-based data analysis and physical models development.

Eli Gildish is a data scientist with more than 15 years of experience in applied research, software and algorithm development in the fields of Machine Learning, Artificial Intelligence, Signal Processing and Computer Vision. He is a Senior Algorithm Developer at RSL Electronics and his current research focuses on application of deep learning to anomaly detection, condition monitoring, diagnostics, and prognostics. Eli studied M. Sc. in Applied Mathematics and B. Sc. in Aerospace Engineering at the Technion – Israel Institute of Technology.