Trackside Installation System for Rail Neutral Temperature Estimation

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ABSTRACT

This short article describes one of the latest advancements of a monitoring/inspection technique for the estimation of localized longitudinal stress in continuous welded rails (CWR). The technique is based on the use of vibration measurements and machine learning (ML). A finite element analysis is conducted to model the relationship between the boundary conditions and the longitudinal stress of any given CWR to the vibration characteristics of the rail. The results of the numerical analysis are used to train a ML algorithm that is then tested using field data obtained by an array of accelerometers polled on the track of interest. The proposed technique was tested in the field. A commercial FEM software was used to model the rail track as a short rail segment repeated indefinitely and under varying boundary conditions and stress. A ML model was developed to infer the rail neutral temperature and the local resistance of rails to vertical and lateral displacement. The results of the experiments demonstrated that the success of the technique is dependent on the accuracy of the model and the ability to properly label the modes of the detected frequencies. This study builds upon previous research conducted at the University of Pittsburgh and the interested reader is referred to previous publications from the authors for more details about the proposed technique.

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INTRODUCTION

With the advent of high-speed rail and the increase of tonnage moved by freight transportation, the use of continuous welded rails (CWR) has increased significantly worldwide. The mechanical and dynamic behavior of a CWR is a function of the track resistance, rail temperature, misalignment, as well as other secondary variables. When the temperature T_R of a given rail is above the so-called rail neutral temperature (RNT) T_N, defined as the temperature at which the longitudinal stress is zero, the rail is subject to longitudinal compression. When the compressive stress become extreme, buckle may occur. This leads to the need for reliable ways to estimate longitudinal stress and RNT. Current state-of-the-art methods are mostly invasive and target the measurement of longitudinal stress from which the RNT is estimated using a simplified well-known relationship.

The rail cutting method consists of cutting the rail at cold temperatures and measuring the gap (the rail opening) between the opposite faces at the cut [6]. The longitudinal stress is zero at the cut and progressively increases to the pre-cut stress values at a location that can be hundreds of meters away. Such force difference is denoted as the longitudinal force profile and the length of the rail having reduced internal longitudinal force is referred to as the influence zone. VERSE® [7] is a static semi-invasive method that links the axial force to the vertical force required to lift 30 meters of unanchored rail by a certain amount.

Over the last three decades nondestructive evaluation (NDE) methods based on electromagnetism, ultrasounds, acoustics, high-frequency vibration, and optics have emerged, and most of these methods were thoroughly reviewed by Enshaeian and Rizzo [1] and Huang et al. [2].

Vibration-based methods are one of the earliest approaches ever proposed. They are based on the physical evidence that longitudinal stress alters the natural vibration frequencies and modal characteristics of beams and beam-like structures, including CWR. However, any vibration-based monitoring system faces a critical challenge: the effect of the boundary conditions. In CWR, the vibrations are not solely influenced by axial loads but by other factors, such as fasteners, sleepers' materials, distance between consecutive crossties, and environmental variability. These factors add complexity to an already challenging problem.

To address these challenges, Machine Learning (ML) has emerged as a powerful tool to identify the complex patterns and relationships within data, making them well-suited to account for the multifactorial influences on rail vibrations. Over the last few years, our team has developed a NDE technique based on the measurement of low-frequency (< 1 kHz) rail vibrations, and the computation of the corresponding power spectral densities (PSD) to train a machine learning algorithm (MLA) to predict the RNT [3-10] Those works focused on the experimental verification of the research hypotheses in the laboratory and in the field, as well as on the development of the MLA trained and tested with the experimental data.

The study presented in this article summarizes latest developments especially related with the development of a wayside installation system designed and tested to allow for frequent measurements and monitoring of any railroad track without interfering with normal train operation or maintenance activities. In this study, the deep learning strategy was validated by using data collected during three field visits and 11 days of testing at two controlled loop facilities in Pueblo (CO) in 2021, 2022, and 2024, and then blindly tested at three revenue service lines. Finally, the experimental campaign conducted in Pueblo and at the revenue service lines in 2024 are reported in this paper for the first time.

EXPERIMENTAL SETUP

This section briefly describes the three test setups deployed in Colorado. More insights about the field visits in 2021 and 2022 are available in [4,5,7-10].

Three test days were conducted in May 2021 at the FRA Transportation Technology Center (TTC). The first two days were on a 5° curved RE 141 rail on concrete ties while the third day was on a tangent RE 136 wood-based section. Two tri-axial PCB 356B08 wired accelerometers were bonded to the gage side of the rail head on the midspan and above the crosstie. The accelerometers were sampled at 10 kHz and triggered manually with an instrumented hammer used to induce a lateral impact on the field side. Two K-type thermocouples were attached to the head and web of the rail. The setup required a signal conditioner, an oscilloscope, and a power supply. TTCI instrumented the rails with strain gauge rosettes and temperature sensors to provide the true RNT.

Approximately one year later, four days were spent at the same facility with several improvements to the setup. The same PCB accelerometers sampling at 10 kHz were paired with two wireless (WL) LORD G-Link-200-40G sensors sampling at 4096 Hz. The wireless signals were zero-padded to match the frequency resolution of 0.1 Hz. The wired and the WL sensors wireless counterparts were attached to the rail using permanent magnets. The instrumented hammer was secured to a motor-operated arm, which acted as a pendulum, to improve the repeatability of the impacts.

Figure 1 – Close-up view of the new wayside system.

The newest field test at a controlled facility was conducted at the FAST Loop, a new site built and operated by MxV Rail. Our setup consisted of a non-intrusive wayside system (Fig. 1) designed to enhance repeatability, increase the number of hourly measurements, reduce footprint, allow for remote operation, minimize cost, and to limit track closure to the time needed for installation and removal. In the study presented here, three hits per minutes, i.e., 180 impacts per hour, was selected. Four days were spent onsite. Two wayside units were deployed about 5.6 m (220 in.) apart on the field side of the track, and each unit was paired to two WL sensors identical to those used in 2022. The setup included a power generator, a laptop to communicate with the sensors and to receive the signals from them, and two thermocouples attached to the head and web to measure rail temperature.

The rail temperature and the RNT estimated by MxV across the four days of our field visits. Based on such readings, the rail was nearly always in tension as T_R was below T_N. The only exception occurred in the early afternoon hours during the second day of testing when $T_R > T_N$ (strain gage #3).

Table 1 summarizes the test conditions including the number of signals collected during the three field visits and the 11 days of testing. One of the most evident improvements over the years, has been the number of waveforms collected (see rightmost column of the table). The first time 179 signals were collected. One year later, the samples were 1,457, whereas the most recent setup configuration enabled the acquisition of 4,454 signals. The other significant transformation is the simplification of the setup and the deployment of a truly non-intrusive monitoring system that would not interfere with and would not be affected by regular passenger or freight train operation.

Year	**# of days**	**Alignment**	**RE**	**Tie material**	**Sensor type**	**Impact locations**	**Site**	**# of signals**
2021	1	Tangent	136	Wood	Wired	One (manual)	TTC	70
2021	2	5° curve	141	Concrete	Wired	One (manual)	TTC	109
2022	2	Tangent	136	Wood	Wired and WL	One (pendulum)	TTC	512
2022	2	5° curve	141	Concrete	Wired and WL	One (pendulum)	TTC	945
2024	3	Tangent	136	Wood	WL	Two (impactor)	FAST	3075
2024	1	Tangent	136	Wood	WL	Two (impactor)	FAST	1379

Table 1 – Summary table of the instrumented rails tested in Pueblo (CO) in years 2021, 2022, and 2024. Note: WL = wireless.

RESULTS

The use of the wireless accelerometers and the automatic nature of the impact mechanism bring the potential risk of false positives/negatives. In the present context, false positives are waveforms accidentally recorded by the sensors and unrelated to any individual strike of the rod. False negatives represent vibrations triggered by the rod but not recorded by the sensor(s). As such, the raw waveforms were post-processed (data cleansing) to remove false positives, and to identify and eventually remove outliers generated by unwanted interferences. Details about such filtering procedures were presented in [11] and are not repeated here for the sake of space.

The developed MLA architecture consisted of a 1DCNN designed to use only the normalized frequency spectrum of the vertical and lateral components of the vibrations. The deep learning approach benefits from the ability of the convolution operation to automatically extract relevant spatial features in the frequency domain when mapping to a target value, in this case rail neutral temperature, which is contrary to which utilized the entire PSDs for the feature space. This hierarchical approach is commonly used in computer vision and large language applications to learn relative features for systems that cannot be modelled easily. Additionally, removal of the rail temperature allows for one less measurement for this technique. Details about such filtering procedures were also presented in [11] and are not repeated here for the sake of space.

To avoid overfitting, the best validation loss was monitored using the Mean Squared Error (MSE), defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{1}$$

where, Y_i is the true RNT, $\hat{Y}_i$ is the predicted RNT, and n represents the number of samples. MSE calculates the mean square residual error between the predicted value and target, where the square assists in penalizing larger residual predictions. A period of 200 epochs was used to train alongside a validation split of 15% and test split of 50%. MSE was used as the loss function for training while the Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{2}$$

was used for validating the model because this value measures the mean absolute residual error between the predicted value and target without penalizing outliers like the MSE.

Adam was chosen as the optimizer with a learning rate of 0.01 given its adjustable learning rate and faster convergence [12]. Additionally, weights were adjusted every 64 signals by using a minibatch size of 64.

Three analyses were conducted. In the first analysis the deep learning model was trained using 2021 and 2022 data to estimate the RNT at the TTC tracks. The same trained model was then used to estimate the RNT of the MxV FAST loop track. In the third analysis the model was trained using data from all 11 days on the field to estimate the RNT at both field sites. The results from this latter analysis are presented here.

The deep learning model was trained by randomly selecting 50% of the data from each sensor and each of the 11 days in the field. The same validation split of 15% in the training set was used. The results are presented in Fig. 2 and shows the predicted RNT against the true RNT estimated with the strain gages. The bisector indicates the ideal case of a perfect match whereas the two dashed parallel lines are ±2.78 °C (or ±5 °F) distant from the ideal bisector and represent a desirable accuracy. The MAE associated with all the years is presented as well. The figure demonstrates how well the MLA was able to estimate the RNT.

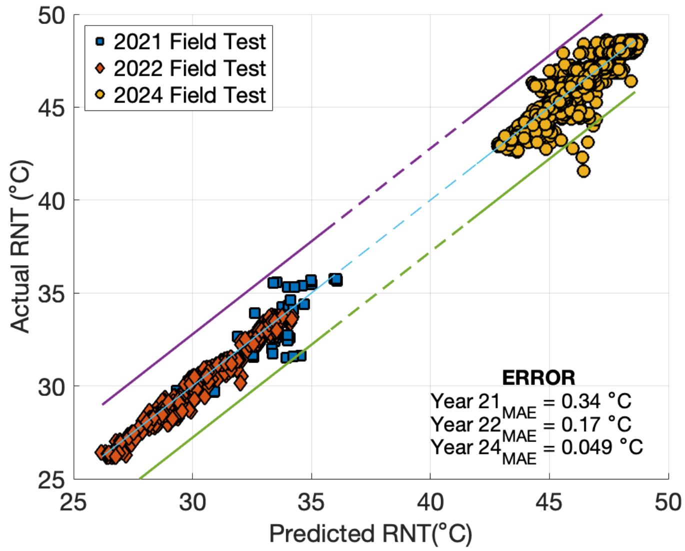

Figure 2 – RNT calculated from a strain gage rosette vs the RNT predicted with the MLA. The dashed lines indicate ±2.78 °C offsets from the bisector. 50% of the cleansed data from each day was used for training and the remaining 50% was used for testing. The mean absolute error (MAE) was calculated according to Eq. (2).

CONCLUSION

This brief article presents one of the latest advancements of a vibration-based method to monitor CWR with the purpose of estimating the RNT and then inferring the longitudinal stress. The principal novelty of the paper is the design and testing of a compact device for the excitation of local vibrations in the rail. The compact device allows for more repeatable results of several new field tests conducted using a novel NDT method to determine RNT. A newly designed impactor allows for conducting measurements at any location without closing the track for more than a few minutes and without requiring personnel on the track. Moreover, the device is entirely non-invasive, as demonstrated by active trains running over the track during revenue service field testing. The latest MLA based on deep learning eliminates the need to measure the rail temperature. However, it was still measured and collected for potential future developments as changes in RNT have been observed to be heavily influenced by rail temperature. This has further confirmed that the RNT can be measured with low frequency information but will require exposure to more track conditions to generalize. With the advent of significantly increased data collection from the new device, a new cleansing strategy was implemented to reject outliers, which will have positive implications for future applications involving moving vehicles.

Owing to the scope of this article, the interested readers are referred to paper [11] for more insights about the setup and results of the study briefly presented here.

ACKNOWLEDGEMENTS

The second author was supported by the Association of American Railroads (AAR) under the University Grand Challenge Master Contract No. 20-0701-007537, Modification 4, Task Order 01, PO 100034 (Dr. Anish Poudel as Technical Monitor). The field tests in years 2021 and 2022 were conducted under the support of the U.S. Federal Railroad Administration under contract FR19RPD3100000022 (Dr. Robert Wilson as Technical Monitor) as well. The authors acknowledge the logistic support of *MxV Rail* and Mr. Christopher Johnson, during the planning and execution of all field tests. The authors are also grateful to *MxV Rail* for sharing their strain gage data as well as the service line support under David Kress, Elliott Clakeley, and Daniel Stabile of Norfolk Southern and Brad Spencer of CSX.

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