Predicting Axial Stress in Continuous Welded Rails Using Machine Learning

MATTHEW BELDING, ALI ENSHAEIAN
and PIERVINCENZO RIZZO

ABSTRACT

Buckling is a major contributor to derailments on continuous welded rails (CWRs) and is caused by extreme compression due to high temperatures. Thus, the determination of the axial stress is necessary to gauge when buckling may occur. As many techniques are often invasive, this study focuses on the latest advancements of an ongoing non-invasive technique based on the use of low-frequency vibrations using machine learning (ML). Based on the theory seen in guitar strings, the relationship between the frequency of vibration and tension/compression is used to associate spectral features to axial stress. This in turn enables the determination of the rail neutral temperature (RNT), which is the point at which the net longitudinal force is zero. As the RNT is not only a function of the stress but also varying boundary conditions associated with the ballast, fasteners, and ties, the RNT can change frequently over time. This stresses the need for a system that is also flexible to this variability. In order to capture some of this, field data was captured twice in Pueblo Colorado using several accelerometers where vibrations were induced with an instrumented hammer. Both a wood-tie and concrete-tie rail section were experimented on with the latter having a 5^o curve. The accelerometers consisted of both wired and wireless sensors, with the wireless counterpart being used to prove the replacement of the wired in the second field test. Using the power spectral densities (PSDs) associated with the lateral and vertical direction as input to an artificial neural network (ANN), the RNTs were predicted and compared to those determined by an independent third party. Our predictions showed very good agreement with the RNT captured by conventional strain-gage rosettes. In this paper, an analysis of our two field tests as well as the impact of boundary conditions data on ML predictions is explored.

Matthew Belding, PhD Student, Email: mtb60@pitt.edu. Department of Electrical and Computer Engineering, University of Pittsburgh, Pittsburgh, PA, USA
Alireza Enshaeian, PhD Student, Email: ale69@pitt.edu. Laboratory for Nondestructive Evaluation and Structural Health Monitoring Studies, Department of Civil and Environmental Engineering, University of Pittsburgh, Pittsburgh, PA, USA
Piervincenzo Rizzo, Professor, Email: pir3@pitt.edu. Laboratory for Nondestructive Evaluation and Structural Health Monitoring Studies, Department of Civil and Environmental Engineering, University of Pittsburgh, Pittsburgh, PA, USA

INTRODUCTION

Rail buckling (or sun kink in the U.S.) remains one of the most expensive causes of damage in the U.S. rail network. This phenomenon occurs when axial stress in the form of compression builds up significantly in the rail and can no longer be countered. Continuous welded rails (CWR) are in compression when the temperature of the rail is above the rail neutral temperature (RNT) or point at which the axial stress is zero. CWRs are typically pre-tensioned when laid to compensate for thermal expansion with RNT being set between 32°C and 43°C. However, over time a rail experiences degradation and with it boundary condition changes that cause the RNT to decrease, making it easier for a CWR to buckle. Thus a method capable of determining RNT is of great importance.

Several methods have been used over the years but are often invasive. These include the use of strain gauges which requires rail cutting or the lift method (commercially known as VERSE®) that unfastens 30 meters of rail [1,2]. Not all methods are invasive, however, such as digital image correlation, hole-drilling, and ultrasound just to name a few [3–7]. Although a brief overview of several RNT methods is provided here, a more comprehensive review can be found in [8].

This work provides some of the continued developments of a low-frequency vibration-based approach to estimate the RNT of a CWR. Spectral information from several sensors in the field is utilized as the input to an artifical neural network (ANN) to extract and associate features with changes in the axial stress. The stress is then associated to the RNT via the ideal column equation. A comparison between the predicted and actual stress is performed on both a wood and concrete cross-tie section. The developments provided here are a continuation of previous work seen in [9–11] as well as part from [12].

PUEBLO FIELD TEST

The experiments were conducted in May 2021 and May 2022 at the Transportation Technology Center in Pueblo (CO), a testing facility owned by the Federal Railroad Administration, previously managed by MxV Rail. Across the days, experiments were performed on a tangent RE 136 rail on wooden ties (Figure 1) as well as a 5° curved RE 141 rail on concrete (Figure 2). The field side of the rail head was hit laterally in alternation at the midspan and above the tie, where both accelerometers were placed respectively, as seen in Figure 1. In 2021, two wired tri-axial accelerometers were used and the signals were sampled at 10 kHz using a signal conditioner and an oscilloscope. One year later, two LORD G-Link-200-40G wireless tri-axial accelerometers were added to the same setup (Figure 1). Magnetic bases were used to deploy rapidly all the sensors and the time waveforms from the wireless sensors were sampled at 4.096 kHz. In order to maintain the 0.1 Hz resolution zero of the wired counterpart, the wireless signals were zero padded. A dual type K/J input thermometer controlled by the authors of this study was also utilized. One probe was taped to the rail head whereas the other was taped to the field side of the web, which was mostly in the shade. To validate our findings, the rail contained strain-gauge rosettes bonded to the web of the rail and a temperature sensor, both operated independently by MxV.

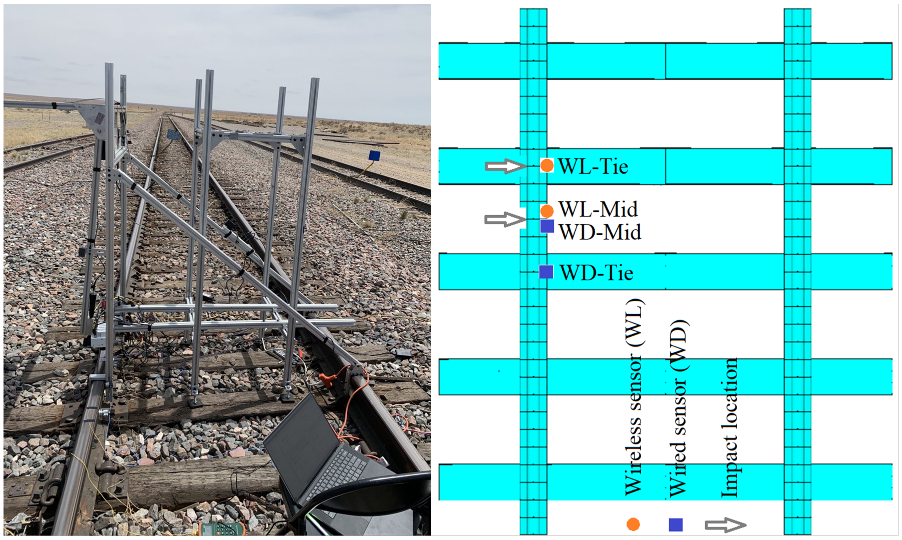

Figure 1. (left) The field setup on wood ties. (right) An overview of the accelerometer placements for both wood and concrete tie days in 2022. **Note:** May 21' did *not* include wireless accelerometers denoted by WL.

Figure 2. The field setup for concrete ties.

FIELD TEST FINDINGS

Throughout our experiments, three days of wood tie testing were achieved, one of which was from 2021 and two 2022, respectively. For concrete, four days were collected, with two in 2021 and two in 2022.

48 and 61 samples were collected on concrete in 2021 while in 2022, 415 and 531 were. The temperature readings from 9AM-2PM via our K/J input thermometer on the web and head as well as MxV's system can be seen in Figure 3. As expected, the head temperature is typically above that of the web due to direct exposure to the sun. Also

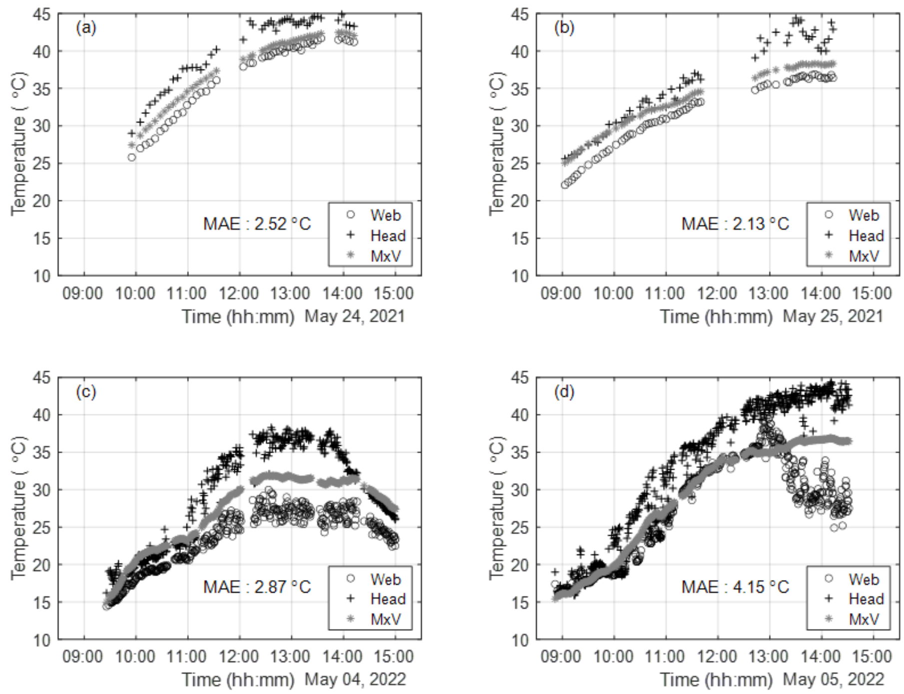

Figure 3. Temperature readings for concrete.

noted, the MxV readings coincide closely with the rail head readings in the morning and diverge later. Day 4's extreme divergence can be attributed to a loose sensor.

For the wood section, 70 measurements were collected in 2021 whereas 181 and 332 were collected in 2022. In Figure 4, the temperature readings via our system show similar trends to those of the concrete section, with most of the scattering seen in the head caused by cloudy weather. The mean absolute error (MAE) is provided on both figures to show the difference in readings between the head thermocouple (ours) and MxV's on the web.

Contrary to what is expected of the RNT with regards to staying relatively constant, it changes frequently not only throughout the day but day-to-day making the problem particularly difficult to solve. Such changes are caused by variability in the boundary conditions i.e lateral resistance in the fasteners and ties. This is seen in the left figure (wood) and right (concrete) in Figure 5. As a result, RNT cannot be estimated accurately using one day of data unless the boundary conditions are very similar. This is validated in our previous study using one day or all days to train a model [9].

DATA PREPROCESSING AND MACHINE LEARNING DESIGN

To reliably capture the underlying governing function of a system, machine learning not only relies on an abundance of data typically but also maintaining the same distribution it was trained on when testing. Owing to the RNT variability captured over several days of data and validation via our previous study on the difficulties of determining stress with one day of training data, stratified splits are obtained across days for both ties [9]. Two datasets were created containing the combined days for concrete and wood

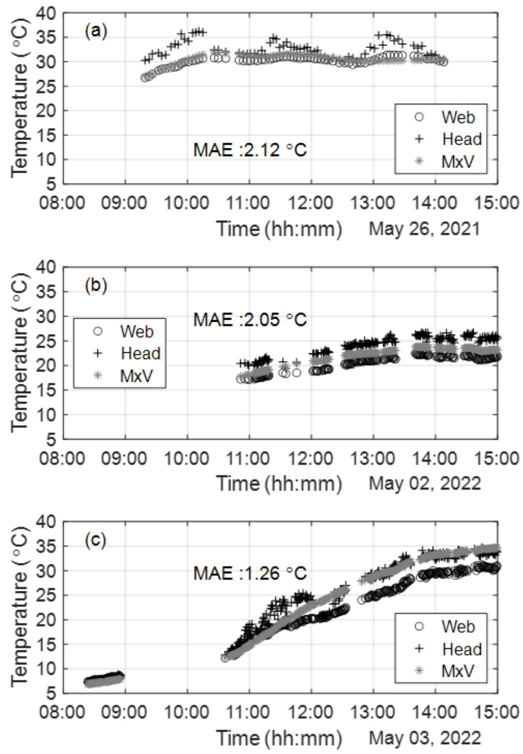

Figure 4. Temperature readings for wood via our system and MxV.

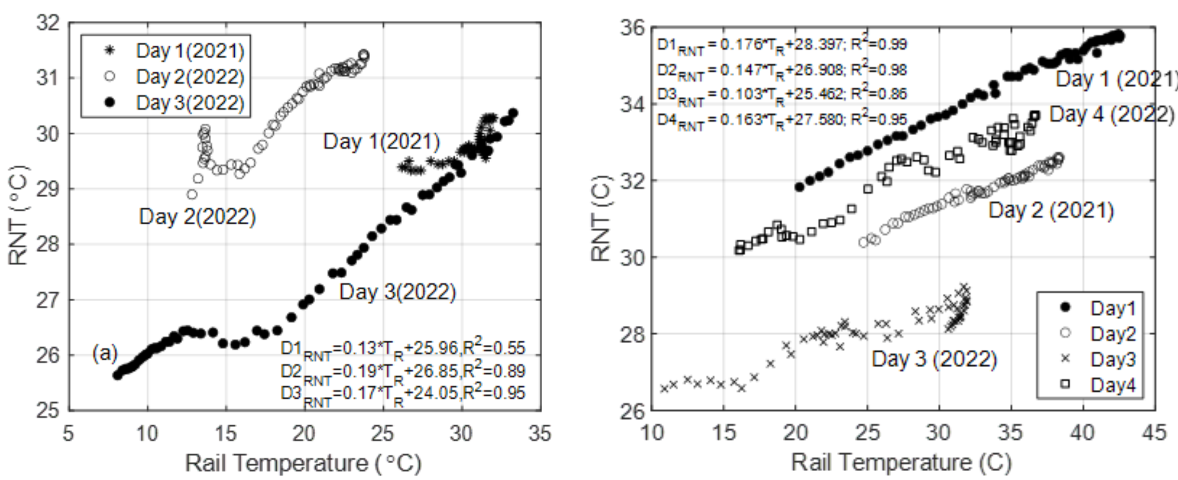

Figure 5. (left) RNT readings for wood independently estimated by MxV. (right) RNT readings for concrete independently estimated by MxV.

ties. This in turn enables an accurate representation of data that's been seen in training across varying boundary conditions. Although train/validation/test splits of 50-25-25 and 70-15-15 were analyzed as well, this study will provide the results of the worst case scenario, 35-15-50.

The ANN in this study considered four parameters in the input to determine axial stress and thus RNT: the power spectral density (PSD) of the lateral vibration, PSD of vertical vibration, frequency, and the rail head temperature. PSDs were limited to the 0-700 Hz range and min-max normalization was performed on the them in order to remove inherent bias associated with impact strength. Due to multiple sensors being used and in turn multiple vibration signals being provided in each direction, frequency domain decomposition (FDD) was used to combine sensor information in both directions [13]. The frequency vector is used to maintain spatial information once reshaped in the network. The head temperature is used as opposed to the web due to it's distribution likely being closer to that of the whole cross-section along with the web often being exposed to shade. Hyperparameter tuning via KerasTuner was used to obtain the number of nodes, hidden layers, and activation function in the network [14]. A node range of 96 to 512 with a 32 step size was considered, in addition to up to 4 hidden layers, and relu or tanh activation functions, respectively. As this is a regression problem, a node size of 1 with a linear activation is used on the output of the network. Up to 200 epochs were considered with overfit protection using early stopping mechanisms and dropout layers between subsequent hidden layers. Mean squared error (MSE) is used as the loss function to protect against outliers and MAE is used alongside it in evaluation.

RAIL NEUTRAL TEMPERATURE PREDICTIONS

As mentioned prior, the days were combined for their respective type of tie, using stratified sampling to conduct train/validation/test splits. The splits consisted of 70-15-15, 50-25-25, and 35-15-50 with the latter being considered in this study for the worst case scenario. The test split is the most important consideration in these splits as it is unseen to the network during training and therefore can adequately evaluate the performance overall of the model. The results of the wood tie section using the 35-15-50 split can be seen in Figure 6 where the MxV rail RNT (ground truth) is plotted against our predicted RNT. The 45° line represents a perfect prediction to the ground truth (MxV). As such, it can be seen that the predictions provided by our model remain well within the ±2.78 °C (or ±5 °F) requirement despite the data never being seen by the model, showing promise for future developments with this method. Figure 7 shows the complementing concrete tie, where the horizontal axis is Pitt's predictions for RNT and the vertical axis is MxV's. Again, the ANN manages to maintain all predictions not only within the criteria of ±2.78 °C but also achieves very small errors within the day-to-day predictions regardless of the boundary condition changes.

CONCLUDING REMARKS

This study presented the results on two types of rail ties of a low-frequency vibration-based method to determine axial stress in rails and in turn, the rail neutral temperature. The method is based on the relationship between shifts in frequency and stress as often seen in guitar strings. The normalized power spectral densities of the lateral and vertical directions are fed into a neural network alonside their corresponding frequencies and rail head temperatures. The models are trained across all days using stratified sampling in order to compensate for the changes in boundary conditions day-to-day. The data the ANNs are trained on represents two field tests performed on the same tracks one year

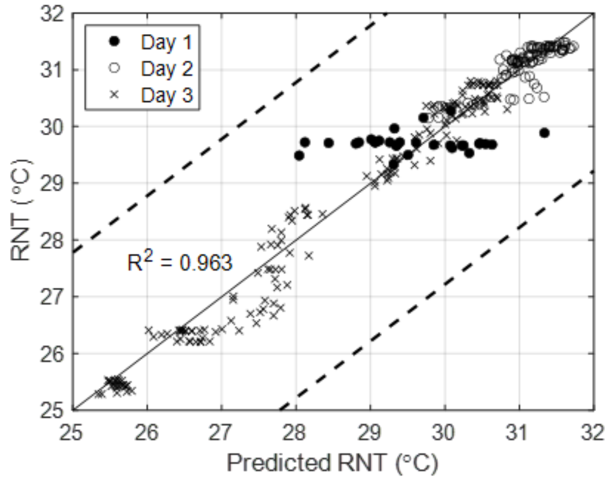

Figure 6. Wood neutral temperature predictions from MLA and estimated by MxV Rail.

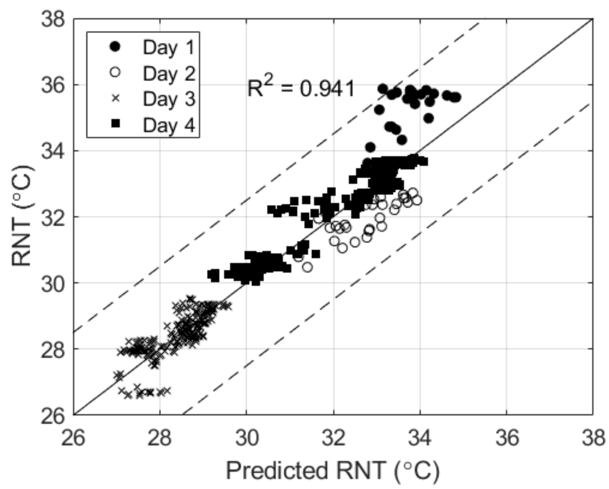

Figure 7. Concrete neutral temperature predictions from ML and estimated by MxV Rail.

apart. Using the models, the predicted RNTs were compared to those determined by an independent third party using a strain-gauge based approach. The resulting comparison showed good agreement that met the desired criteria of accuracy within ±2.78 °C (or ±5 °F), showing promise for the method. Although the data collected in this study represents hours of consecutive measurements, the device will only require a few measurements in order to adequately determine RNT once fully proven. This is representative of the limited data needed to represent several days of testing with varying boundary conditions.

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REFERENCES

1. Wang, P., K. Xie, L. Shao, L. Yan, J. Xu, and R. Chen. 2015. “Longitudinal force measurement in continuous welded rail with bi-directional FBG strain sensors,” *Smart Materials and Structures*, 25(1):015019, doi:10.1088/0964-1726/25/1/015019.
2. PANDROL. 2019, “VERSE® technical information pack,” https://railway-news.com/wp-content/uploads/2020/02/VERSE-253Technical-Information-Pack.pdf (accessed 10-29-2022).
3. Knopf, K., D. C. Rizos, Y. Qian, and M. Sutton. 2021. “A non-contacting system for rail neutral temperature and stress measurements: Concept development,” *Structural Health Monitoring*, 20(1):84–100, doi:10.1177/1475921720923116.
4. Zhu, X., F. Lanza di Scalea, and M. Fateh. 2016. “Thermal stress measurement in continuous welded rails using the hole-drilling method,” in J. P. Lynch, ed., *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2016*, vol. 9803 of *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, p. 98031C, doi:10.1117/12.2218664.
5. Nucera, C. and F. Lanza di Scalea. 2014. “Nondestructive measurement of neutral temperature in continuous welded rails by nonlinear ultrasonic guided waves,” *The Journal of the Acoustical Society of America*, 136(5):2561–2574, ISSN 0001-4966, doi:10.1121/1.4896463.
6. Nucera, C. and F. Lanza di Scalea. 2014. “Nonlinear wave propagation in constrained solids subjected to thermal loads,” *Journal of Sound and Vibration*, 333(2):541–554, ISSN 0022-460X, doi:https://doi.org/10.1016/j.jsv.2013.09.018.
7. Szelażek, J. 1992. “Ultrasonic measurement of thermal stresses in continuously welded rails,” *NDT E International*, 25(2):77–85, ISSN 0963-8695, doi:https://doi.org/10.1016/0963-8695(92)90497-5.
8. Enshaeian, A. and P. Rizzo. 2021. “Stability of continuous welded rails: A state-of-the-art review of structural modeling and nondestructive evaluation,” *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 235(10):1291–1311, doi:10.1177/0954409720986661.
9. Belding, M., A. Enshaeian, and P. Rizzo. 2023. “Nondestructive rail neutral temperature estimation based on low-frequency vibrations and machine learning,” *NDT E International*, 137:102840, ISSN 0963-8695, doi:https://doi.org/10.1016/j.ndteint.2023.102840.
10. Belding, M., A. Enshaeian, and P. Rizzo. 2023. “A Machine learning-based approach to determining stress in rails,” *Structural Health Monitoring*, 22(1):639–656, doi:10.1177/14759217221085658.
11. Belding, M., A. Enshaeian, and P. Rizzo. 2022. “Vibration-Based Approach to Measure Rail Stress: Modeling and First Field Test,” *Sensors*, 22(19), ISSN 1424-8220, doi:10.3390/s22197447.
12. Belding, M., A. Enshaeian, C. Hager, and P. Rizzo. 2023. “Machine Learning for the Nondestructive Prediction of Neutral Temperature in Continuous Welded Rails,” *Research in Nondestructive Evaluation*, under Review.
13. Brincker, R., L. Zhang, and P. Andersen. 2001. “Modal identification of output-only systems using frequency domain decomposition,” *Smart Materials and Structures*, 10(3):441, doi:10.1088/0964-1726/10/3/303.

14. O'Malley, T., E. Bursztein, J. Long, F. Chollet, H. Jin, L. Invernizzi, et al. 2019, "Keras-Tuner," https://github.com/keras-team/keras-tuner.