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Neural Network Approach for Vehicle/Track Interaction Prediction

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Summary

A revenue service test was conducted by Class I member railroad in conjunction with Transportation Technology Center, Inc. (TTCI) to collect vehicle/track interaction (VTI) and track geometry data. The objective of TTCI was to examine the relationship between accelerations experienced by a locomotive and those on freight cars and determine the suitability of neural net models to make accurate predictions about this relationship. The test train consisted of an instrumented SD70 locomotive, six different aluminum-bodied instrumented freight cars (IFCs), and a track geometry car. The VTI and track geometry data was collected simultaneously and continuously.

About 700 miles of revenue service test data was selected and processed to build a synchronized locomotive-IFC database. The optimized database consisted of the dynamic response of the locomotive VTI system (i.e., vertical carbody acceleration) and six different aluminum-bodied instrumented freight cars (i.e., vertical carbody acceleration, suspension travel, and top chord stresses). Data from the different systems was shifted and overlaid at the same point on the track using GPS coordinates. The data was comprised of dynamic responses to wide-ranging track and operating conditions. The database was used to build neural network algorithms that relate VTI data obtained from a VTI-equipped locomotive to the likely response of freight cars.

TTCI analyzed the data to determine whether neural computing models could accurately predict IFC long wavelength exception responses. Such response types could lead to potential derailments or damage to track and car components. By feeding the neural net models vertical carbody accelerations (front and rear) and operating speed from a locomotive-based VTI system, it was determined that neural net model predictions of freight car response were adequate. Many neural net models were built, and a select number of them are shown in this digest. The correlation coefficients that measured the strength of association between neural net predictions and actual responses ranged from 0.65 to 0.77. Such a range is quite acceptable, because the validation datasets included not only target peak values, but also random data noise that neural net models tend not to recognize.

Neural network models were developed for a typical 286,000-pound gross rail load aluminium-bodied freight car equipped with wide wedge constant-damped trucks. The datasets used to build the models were selected from the revenue service database. They were selected based on diverse car dynamic response, operating speeds, and various track geometry conditions and features. The revenue service validation data that the neural net models were deployed over was not used in the training process of the neural net models.

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INTRODUCTION

Class I member railroads are increasingly using locomotive-based VTI monitoring systems. These onboard systems, unattended and monitoring track conditions in real time, allow more frequent track inspections without having to allocate work windows normally needed for conventional track inspection. Given the fact that locomotive suspensions differ from those of freight cars, some long wavelength track deviations may go undetected by locomotive-based VTI systems. The aim of this project was to develop neural net models capable of identifying such track deviations by predicting the likely freight car response from the locomotive inputs. These models would complement already-in-use VTI systems.

The neural net models were developed using revenue service data. The data was obtained from a VTI revenue service test conducted by an Association of American Railroads' (AAR) member railroad in which TTCI participated. The test consist was composed of an instrumented SD70 locomotive, six 286,000-pound aluminum-bodied instrumented freight cars similar to TTCI's IFC[1] and a track geometry car. Figure 1 shows the six IFCs as well as the geometry car at the end of the consist during testing in revenue service.

Figure 1. Six Instrumented Freight Cars and the Track Geometry Car

The revenue service test results have helped provide "real-world" data needed for building reliable neural net models. Different track classes were traveled and wide-ranging track conditions and features were present.

THE NEURAL NET TECHNIQUE

Locomotive response to track and operating conditions differs from that experienced by freight vehicles. Figure 2 shows an example of a locomotive and freight car response generated at the same track location. At 47 mph, an IFC A-end vertical acceleration reached about -1.0 g, whereas a locomotive's front acceleration was recorded at a value below -0.3 g.

The response amplitude of such an event is significantly different (locomotive versus freight car) and so will be performance exceptions experienced by both systems. However, complex and nonlinear relationships do exist between these acceleration signals, and they have potential to be captured with an appropriate tool, such as the neural computing technique.

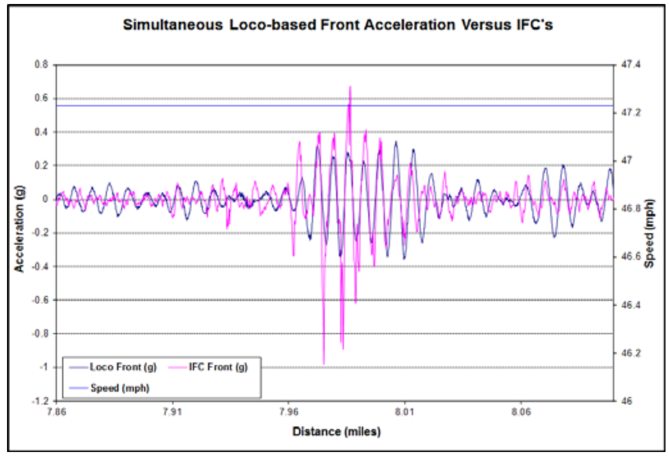

Figure 2. Vertical Carbody Response, Locomotive versus IFC

A neural net model is a pattern and complex relationship recognizer. It is a network of artificial nodes composed of several input paths and one output path.

Figure 3 shows a simplified neural net representation relating locomotive-based VTI carbody acceleration and vehicle operating speed to freight car dynamic response. The input nodes take locomotive acceleration and operation speed. The hidden nodes store the weighed correlations between locomotive and freight car responses, as established in the neural net training process. The output nodes give vehicle response features such as carbody acceleration or top chord stresses.

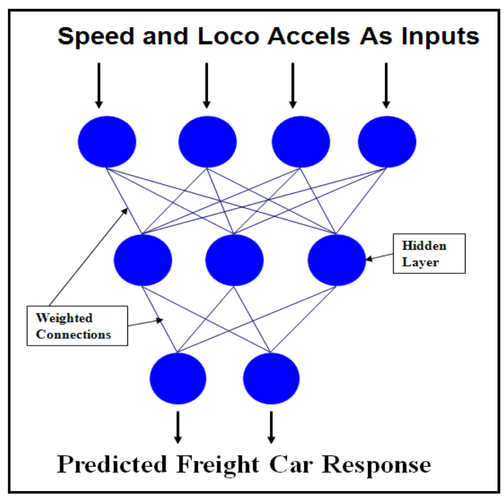

Figure 3. A Simplified Neural Net Representation

NEURAL NET TRAINING DATA

The neural net models were built to predict dynamic response based on a 1-foot increment (point to point). To achieve such granularity and ensure good neural net predictions, data from VTI systems installed on different vehicles was shifted to the same point on the track using GPS coordinates and measured distances between the GPS antennas and their associated sensors.

Figure 4 displays some of the IFC and locomotive VTI channels as well as some track geometry parameters after they were synchronized. The track geometry data was not used to build the neural net models. After it was aligned with the VTI data, track geometry was used as a means to help select informative datasets used to train the neural net models. The three top plots show freight car suspension travel, top chord stresses, and carbody acceleration, respectively. The fourth plot shows locomotive vertical acceleration. The last three plots show track curvature, and left and right track surface as measured by the track geometry car.

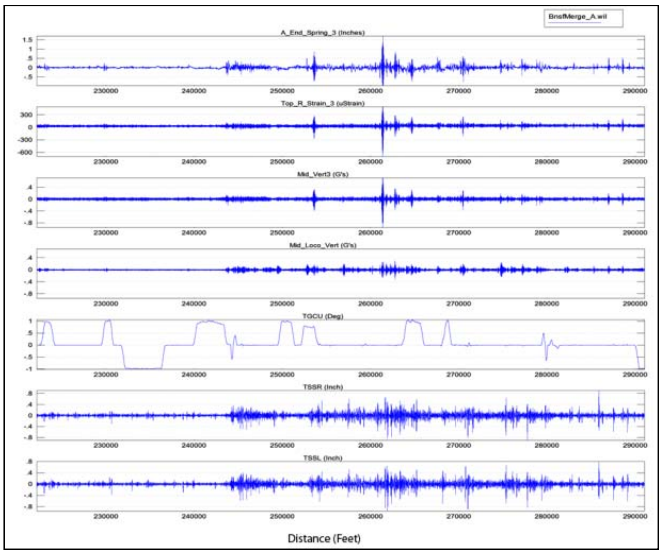

Figure 4. Synchronized Data

THE NEURAL NET MODEL RESULTS

The input variables to build and validate the neural net models were as follows:

- The front and rear vertical acceleration out of the locomotive-based VTI system
- Vertical acceleration at the locomotive center (synthetic channel computed from averaging front and rear vertical acceleration)
- Operating speed from the locomotive's GPS unit.

Freight car output variables predicted were as follows:

- Freight car top chord compressive stresses
- Carbody vertical acceleration at both ends
- Vertical acceleration at carbody center (synthetic channel computed from averaging A-end and B-end vertical accelerations)

Adding the locomotive vertical acceleration at the locomotive center as a synthetic input variable was found to have improved the correlation by 9 percent in some models compared to the same models without the synthetic input variable. The neural net models learned to predict better with the synthetic variable added to the model inputs.

The improved prediction capability for the model using the synthetic input variable versus a model without it shows a statistically significant reduced prediction error. Two tests were used for comparison, Wilcoxon Matched Pair and Sign Test, and both indicated a highly significant statistical difference. The quantile-quantile plot in Figure 5 shows the error, or residuals, from the carbody acceleration model using the synthetic input (in blue) to be distinctly smaller compared with the model not using the synthetic input (in red). The most significant error reduction is at the highest level of accelerations.

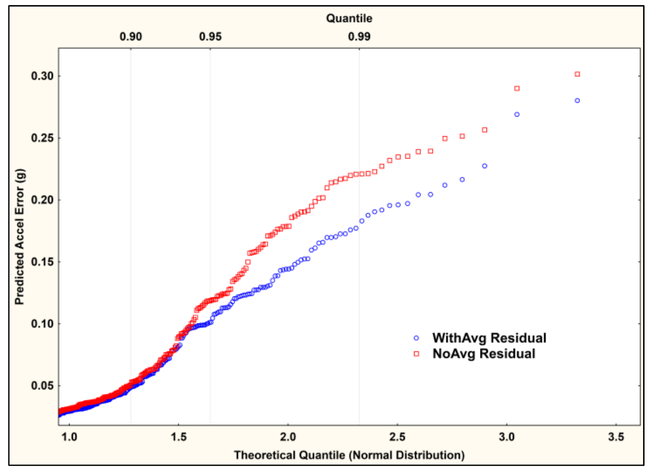

Figure 5. Less Prediction Error in Model with Additional Input Variable (in Blue) Versus Model without (in Red)

Figure 6 shows an example of a predicted B-end car vertical acceleration (in red) versus actual test result (in blue). The validation data was not used during training of the neural net model. The test peak acceleration was 1.13 Gs and predicted value was 0.98 Gs. Correlation coefficient was 0.67 for this example recorded at an operating speed of 47 mph over a track surface deviation of 0.8 inch.

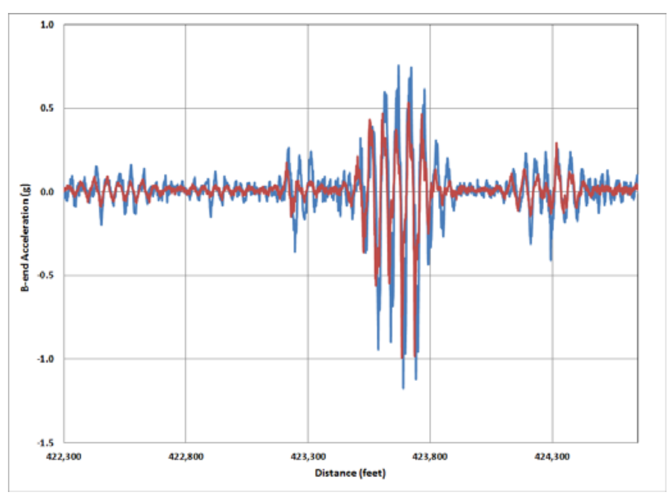

Figure 6. Predicted B-end Acceleration (in Red) versus Actual Acceleration (in Blue)

Figures 7 and 8 show predicted top chord stress and carbody acceleration versus the actual test output over a distance of 1,300 feet at 50 mph. Figure 9 shows the left and right rail surface data from the track at this location. The correlation coefficient is 0.75 for the top chord model and 0.72 for the carbody acceleration at the center of the car.

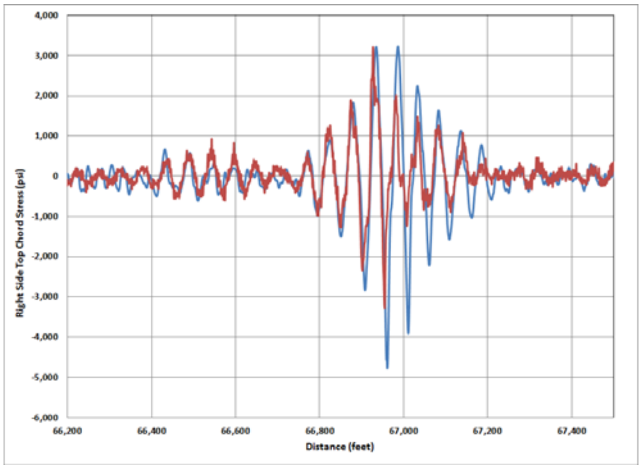

Figure 7. Predicted Top Chord Stress (in Red) versus Actual Output (in Blue)

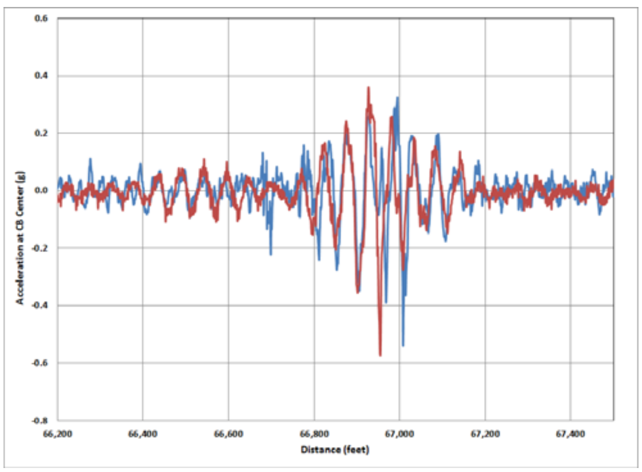

Figure 8. Predicted Acceleration at Carbody Center (in Red) versus Test Output (in Blue)

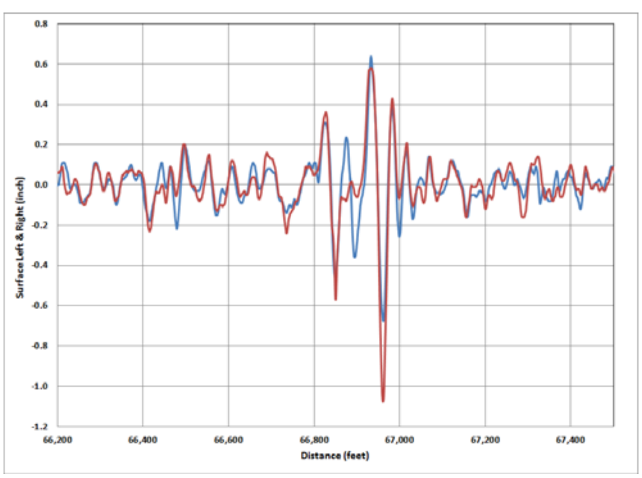

Figure 9. Space Curve Track Surface Left and Right

The training and validation data was collected on separate days during the revenue service testing. Six miles of training data was used to build the model, and 90 miles of data was used for validation. Just one single neural net model was deployed for all the validation dataset. None of the validation data was used during the neural net model training. Figure 10 shows an example of predicted carbody vertical acceleration at the car center (in red) versus test acceleration for the entire validation data set. The amplitude of peak events predicted by the model were mostly satisfactory and in phase with the actual test data.

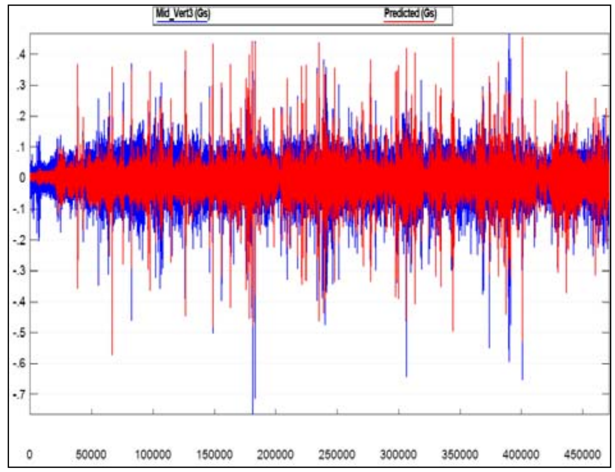

Figure 10. Predicted Carbody Center Acceleration (in Red) versus Actual Output (in Blue)

CONCLUSION

The neural net models built capture the essential relationships between a set of VTI system input response and loaded coal car outputs. The predictions of the neural net models were mostly adequate, and correlation coefficients ranged from 0.65 to 0.77. Such a range is quite acceptable, because the validation datasets included not only target peak values, but also random data noise that neural net models tend not to recognize.

It should be noted that in order for the neural net models to perform acceptably on unseen data (i.e., deployment data), it is important that the training data be statistically representative of the deployment data. The latter should be generated from a locomotive-based VTI system with continuous data streaming capabilities, and it should preferably be equipped with front and rear vertical carbody acceleration.

ACKNOWLEDGMENT

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1. Li, D, A. Meddah, and W. Lundberg. July 2008. "Instrumented Freight Car for Performance-based Track Inspection," *Technology Digest* TD-08-028, Association of American Railroads, Transportation Technology Center, Inc., Pueblo, CO