

NEURAL NETWORK MODELING : RESPONSES OF A TANK CAR TO TRACK GEOMETRY

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Summary

A second test funded by the Association of American Railroads to develop an expert system to better prioritize track renewal and maintenance has supported the successful application of the neural-network modeling technique in understanding the complex interaction between a vehicle and mainline track.

This vehicle/track interaction test was conducted on a Burlington Northern Santa Fe (BNSF) revenue route between Topeka, Kansas and Fort Madison, Iowa in August 1999. Engineers with Transportation Technology Center, Inc., simultaneously measured track-geometry conditions and the resulting vehicle performance of a typical tank car. Approximately 470 miles of both track-geometry and vehicle-response data were collected. The same methodology used for modeling a covered hopper car in earlier tests² was utilized for the tank car modeling. Given various groupings of operation conditions, the neural network models of the tank car showed significant correlation under high-speed and curved-track operating conditions. This is consistent with covered hopper car neural-network modeling.

A long-term goal of this research is to develop an improved method of prioritizing track geometry maintenance to supplement the current inspection methods. A third revenue-service test with a coal gondola, a car type also sensitive to track geometry, is planned soon. The neural-network models from these three car types (covered hopper, tank, and gondola) will constitute the basis of an expert system, that can be used in predicting track segments likely to cause undesired vehicle performance. Thus, safer and more cost-effective prioritization of track maintenance can be achieved.

Suggested Distribution:

- Maintenance of Way
- Planning & Analysis
- Track Maintenance
- Safety



TTCI
Transportation
Technology Center, Inc.

Work performed by
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December 1999[©]



INTRODUCTION AND CONCLUSIONS

Track inspection and maintenance is vital to ensure that track meets safety and quality standards. Every year, significant railroad resources are dedicated to maintenance and correction of track-geometry defects. These resources are limited, therefore, a more cost-effective resource allocation is desired. Also, considering the added costs and revenue loss for the track time lost during maintenance, the importance of effective resource allocation increases significantly. This research project, funded by the AAR, aims at developing an expert system for optimal resource allocation and cost-effective track-maintenance schedules.

Currently, substandard track is flagged based on the Federal Railroad Administration (FRA) track-safety standards, or the standards of the railroads, which can be more restrictive due to economic considerations. These standards do not explicitly consider the complex nature of vehicle/track interaction. However, an improved track-geometry inspection system would not only indicate non-conforming locations, but also provide guidance as to the nature of possible vehicle behaviors. Such a system would augment the railroad's track maintenance standards by taking into account the response sensitivity of certain vehicles. This expert system is basically one (or more) neural network models trained on empirical data.

BACKGROUND

The first vehicle/track interaction tests and analyses were performed using a loaded covered hopper through 400 miles of CSX Transportation revenue-service operations.¹ Similar to the covered hopper car test, the tank car was instrumented with a non-contact, inertial system to collect track geometry data. The car responses (i.e., wheel loads, L/V ratios, etc.) were recorded by TTCI's load measuring wheelsets. The tank car was also instrumented with eight accelerometers to be able to account for car body motions which will be discussed in later report. Similarly, data processing included extraction of statistical features (average, min., max., 95th percentile, 50th percentile, 5th percentile and standard deviation) for each 0.1 mile of track. These statistical features from basic inputs (track geometry) and basic outputs (wheel loads, accelerations) are then used in neural network training and identification of track geometry patterns that may produce undesired vehicle responses.

The key steps in obtaining the neural-network

models are:

- Extracting pertinent features.
- Training of the neural network.
- Validation of the neural-network model.

The results illustrated here should be considered along with results of AAR *Technology Digests* TD99-013 and TD99-022.

BNSF REVENUE-SERVICE TEST AND RESULTS

The tank car and TTCI's instrumentation car were operated near the head-end of a revenue train during the week of August 23, 1999. This tank car, with a truck spacing of 46.25 feet was selected. It was installed with Barber S-2 trucks (variable damping). It weighed 71,000 pounds empty and 241,000 pounds loaded. During this test, track geometry and tank car responses (both forces and accelerations) were recorded continuously and analyzed.

As an initial examination of the track recordings from Kansas City to Fort Madison, various curve designs were examined. Peak superelevation in each curve was examined and plotted versus the curvature as shown in the railroad's track charts. Exhibit 1 shows the results of this exercise, with each data point indicating one curve, and several lines of constant balance design for curves at various train speeds. As shown, some of this territory is designed for balance near 80 mph. This is expected since daily Amtrak runs of the Southwest Chief use the line. Since spiral transitions were of historical interest on this line, five high-speed 1.5-degree curves with more than 5 inches of superelevation were closely examined (lower far right on the figure). For these curves the spiral length was found to be 550 to 700 feet, and showed a maximum rate of superelevation change in 62 feet of under 0.5 inch. This is well under the FRA Class 5 specification of 1.5-inch allowable cross level difference in 62 feet..

In addition to extraction of features to train neural networks, the test data was sorted for events of higher L/V ratios (greater than 0.8). These events were examined in detail. Exhibit 2 shows perturbations evident in track space curves for such an event on Class 4 track near De Soto, Kansas. Although not shown here, the geometry data showed minor superelevation (.75 inch) and curvature (0.5 degree) at this segment where the track chart showed tangent track only. The geometry recording also showed peak 0.9-inch alignment and 0.85-inch profile transients (62-foot mid-chord offset). These are well within FRA-specified mid-chord alignment and profile allowances (of 1.5 and 2.0 inches respec-

tively). The track gage was a minimum of 56.1 inches (-0.4 inch tight) in this zone. Empty (westbound) operations within this zone at 46 mph resulted in a transient trailing L/V ratio (single wheel) of 2.9 with no impact on train operations. The overall time of L/V greater than 1.0 was 40 milliseconds. Previous controlled axle flange climb tests have shown that L/V can exceed 1.0 with no detrimental effects when conditions are favorable (e.g., operating with low angles of attack at lower speeds³).

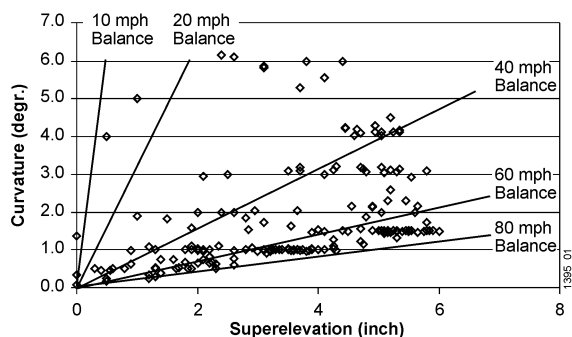


Exhibit 1. BNSF Curvature & Superelevation for Many Curves Between Kansas City and Ft. Madison, Iowa

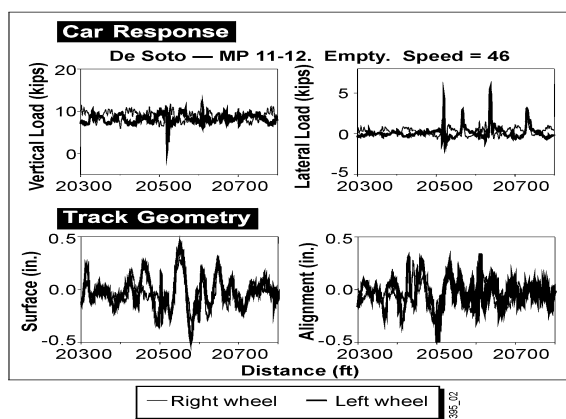


Exhibit 2. Surface and Alignment Perturbations Corresponding to Wheel Unloading (Empty Tank Car)

NEURAL-NETWORK MODELING AND RESULTS

Neural network technology is an effective tool for modeling complex relationships and recognizing patterns. However, its successful utilization is dependent on accurately defining the network objectives, problem parameters (i.e., inputs and outputs), and the problem itself. For a successful model, the analyst should have a good idea of important input conditions that are likely to relate to the changes in the system output. The basic idea of predicting vehicle responses² from track geometry is applied here. The vehicle responses induced by track geometry are highly dependent on speed and curvature. Vehicle response patterns can vary more significantly in curves than in tangents, and can vary with speed change (15 to 50 mph). Therefore, data grouping based on train-operation parameters is suggested such that similar segments of track are grouped and analyzed together. This significantly homogenized the data based on vehicle responses. Exhibit 3 shows the resulting data distribution after such categorization.

The preliminary modeling focus has been on the high-speed and curve categories. It should be noted that the best modeling results have been observed in these groups (both for covered hopper car and tank car). However, successful modeling in the other categories (i.e., low-speed, tangent) is highly dependent on the strength of correlation between track geometry and vehicle responses. Therefore, the most relevant group for our purpose is the higher-speed and higher-curvature group.

As an example of neural network modeling, Exhibit 4 illustrates the comparison of the actual and predicted results for vertical wheel loads in chronological order. From 30 miles of track, 15 miles of track-geometry data was used to train the neural network and the last 15 miles for validation (checking) of the network. The predictions for the last 15 miles (that was not seen during neural network training) closely matches with the actual values.

Similarly, Exhibits 5 and 6 show the correlation of the actual and predicted values for vertical loads and lateral loads but in a different format. Here, the actual and predicted values are presented in a rank-ordered plot. Rank-ordered plots are better for visualization of the strength of correlation between actual and predicted values. Because of the sorted nature of the rank-ordered plots, the least-active segments (0.1 mile) are to the left and the most active segments are to the right. Exhibit 5 illustrates predictions for the lower 5th percentile of vertical

wheel loads (same as Exhibit 4 but for all 30 miles). Exhibit 6 illustrates the same phenomenon for the upper 95th percentile of the lateral loads. The correlation (actual vs. predicted) for each case is given as an inset on the plot.

Speed (mph)	15-25	25-35	35-50
Curves above 0.5°	4.9 miles	18.3 miles	33.0 miles
Tangent to 0.5°	15.1 miles	52.3 miles	117.8 miles

Loaded Operations

Speed (mph)	15-25	25-35	35-50
Curves above 0.5°	2.7 miles	5.7 miles	43.4 miles
Tangent to 0.5°	5.5 miles	17.9 miles	152.4 miles

Empty Operations

Exhibit 3. Test Data Distribution at Various Operating Conditions (miles of track, categorized by speed & curvature)

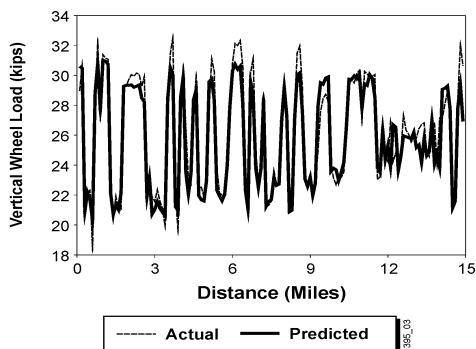


Exhibit 4. Comparison of Actual and Predicted Vertical Wheel Loads (Chronological Order)

REFERENCES

1. Shust, W., Li, D. and Salahifar, T., "Vehicle/Track Interaction: Revenue-Service Testing of an Instrumented Covered Hopper," *Technology Digest* 99-013, April 1999.
2. Salahifar, T., Li, D., Shust, W., "Neural Network Modeling: Responses of a Loaded Covered Hopper Car to Track Geometry," *Technology Digest* 99-022, June 1999.
3. Shust, W., Elkins, J., Kalay, S., El-Sibaie, M. "Wheel-Climb Derailment Tests Using AAR's Track Loading Vehicle," AAR Report No. R-910, December 1997.

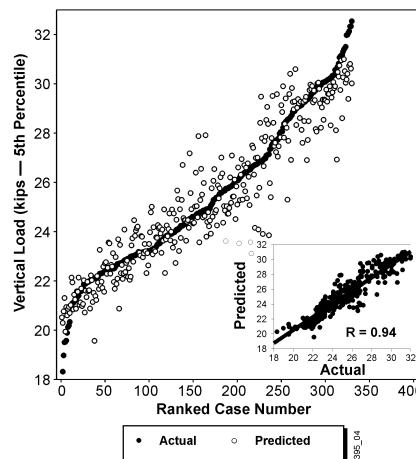


Exhibit 5. Comparison of Actual and Predicted Vertical Wheel Loads (Rank-Ordered Plot)

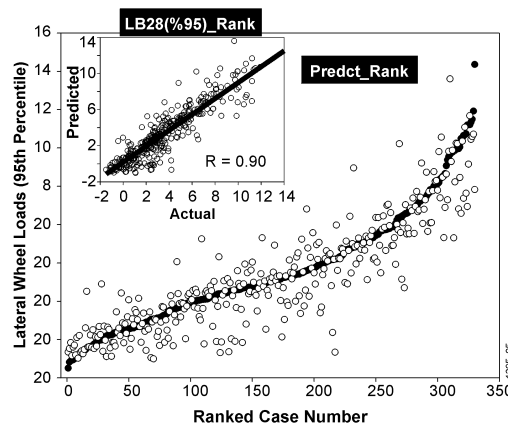


Exhibit 6. Comparison of Actual and Predicted Lateral Wheel Loads (Rank-Ordered Plot)

ACKNOWLEDGMENTS

TTCI would like to thank BNSF for providing the opportunity to gather data in revenue service. The assistance of Mr. Corey Wills, Mr. Robert Banister, and Mr. Geoffrey Dahlman of BNSF, is most appreciated.

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