TECHNOLOGY DIGEST

Timely Technology Transfer — 99-022

NEURAL NETWORK MODELING: RESPONSES OF A LOADED, COVERED HOPPER CAR TO TRACK GEOMETRY

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Summary

Engineers with the Transportation Technology Center, Inc. (TTCI) have successfully applied the neural network modeling technique in establishing relationships between track geometry and vehicle responses for a typical 100-ton, loaded, covered hopper, a car type sensitive to geometry perturbations. By using the pattern-recognition power of the neural-network technique, an analysis system (leading to a "black box") has been developed to predict excessive vehicle responses related to deviations in track geometry for the loaded covered hopper.

Track renewal and maintenance is vital to ensure that track meets safety and quality standards. One of the main components of track maintenance is detection and correction of sub-standard track geometry. However, considering approximately 126,000 miles of class 1 railroad trackage in North America, a more cost-effective resource allocation would be of added benefit to railroads. In other words, a prioritization of track that may cause more severe vehicle responses is desired.

This Technology Digest describes the application of the neural-network approach in detecting track geometry that may cause excessive vehicle responses. Herein, neural networks are utilized as a powerful pattern recognition tool to build models for the covered hopper based on extensive test data including both track-geometry and vehicle responses. The data was obtained from a revenue-service test, performed on the CSXT railroad in July and August 1998.[1] More than 400 miles of track and vehicle test data were reduced and analyzed to develop the neural networks for the covered hopper.

Suggested Distribution:
- ☐ Mechanical
- ☐ Planning & Analysis
- ☐ Track Maintenance
- ☐ Safety

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INTRODUCTION

Under the "Performance-Based Track Geometry" project, funded by the Association of American Railroads, extensive work has been performed by the Transportation Technology Center, Inc. (TTCI) to develop an expert system (or black box) for predicting vehicle responses based on track-geometry inputs only. Such an expert system will help railroads focus track-geometry exceptions that excite poor vehicle responses.

Currently, track-geometry maintenance is based on exception criteria set by the Federal Railroad Administration (FRA). A track-geometry vehicle flags track segments that exceed FRA classifications, and maintenance is scheduled accordingly. However, to improve efficiency of track maintenance and to understand the response of certain vehicle types to repeated and/or combined track-shape deviations (perhaps within FRA standards), an expert system could be helpful.

Such an expert system basically incorporates one (or more) neural network model trained on vehicle/track interaction test data. This Technology Digest describes the successful application of this technique in predicting the response of a typical loaded covered hopper based on geometry measurements. To date, satisfactory results have been obtained in prediction of lateral wheel loads, vertical wheel loads and L/V ratios, using neural networks trained with extensive vehicle/track interaction test results.[1]

NEURAL NETWORK TECHNIQUE

The neural-network technique, enabled by the computing revolution of the 1990's, has emerged as a powerful modeling and classification tool. High-speed computation capabilities have resulted in successful imitations of biological systems such as neurons, leading to tools that can model complex problems. For our scope, this technique has been found very effective in recognizing patterns and relationships between a set of track-geometry inputs and vehicle-response outputs.

The key steps in obtaining a neural-network model, as shown in Exhibit 1, include extracting pertinent features for input and output parameters, training of the neural network, and validation and final application of the neural network model. The data set used in training must be diverse and include most possible cases. Otherwise, a neural network cannot accurately predict situations that were not encountered during training. For the covered hopper, the training data was preprocessed track-geometry features together with the corresponding vehicle responses. Once trained, the network or model can then be used in predicting potential vehicle responses from new geometry data (not seen during the training phase). This can lead to a "black box" for track-maintenance needs, which will be addressed in the next phase of this project.

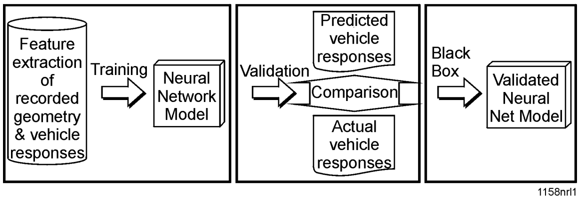

Exhibit 1. Simplified Neural Network Modeling Steps

FEATURE EXTRACTION OF TEST DATA

As mentioned earlier, a neural network for predicting responses of a specific vehicle must be trained using extensive test data. This test data for this study was collected in CSXT revenue service between Cincinnati and South Eastern Kentucky in 1998, for a typical loaded covered hopper. During this test, more then 400 miles track-geometry and vehicle responses were recorded.[1]

Although major vehicle responses and track-geometry conditions were measured during this test, there were other factors that were not accounted for, such as wheel/rail friction, wheel profile, in-train forces, etc. Consequently, the input (geometry) and output (responses) must be treated in a stochastic rather than deterministic nature. In other words, the features used for input and output parameters should be of statistical nature, based on finite track segments.

For this purpose, all the input and output parameters have been characterized using their statistical values (mean, maximum, minimum, standard deviation, upper 95th percentile, 50th percentile and lower 5th percentile). The obtained statistical features were selected such that the important information in the raw data could be represented.

Exhibit 2 shows an example of several statistical features (maximum, upper 95th percentile, mean, lower 5th percentile and minimum). These features were computed for 528-foot segments based on the time history of a measured lateral wheel force.

The preprocessing of the raw test data into pertinent values is also referred to as “feature extraction” for neural-network modeling. For the covered hopper, the “feature extraction” of test data was accomplished through two major steps:

- Reducing redundant channels and removing problem data such as noise and spiking. To better account for wavelength information, additional synthetic channels such as first and second derivatives for track-space curves were added.
- Transforming the test data such that neural networks can handle it. To do so, the continuously recorded data were segmented, with each segment being characterized by the statistical parameters for each geometry- and vehicle-response measurement. As to the segment length, it was found that track segment lengths of 264 and 528 feet produced similar results. However, a shorter segment of 132 feet was not as successful.

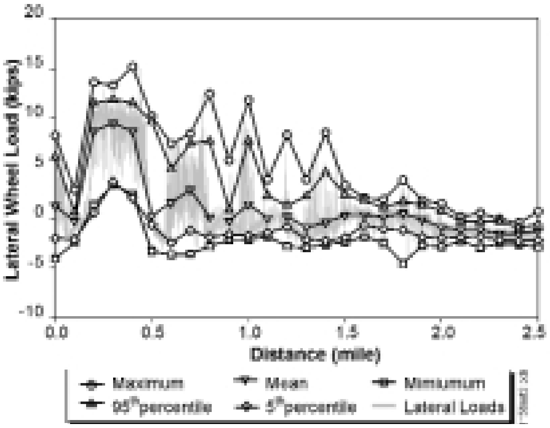

Exhibit 2. Example Segment Features Based on Time History of Lateral Wheel Loads

NEURAL NETWORK MODELING RESULTS

Speed and curvature are two first-order parameters affecting the correlation between vehicle responses and track geometry. Therefore, for the loaded covered hopper, separate networks were trained in each of several speed and curvature groups. This significantly homogenized the data within groups based on vehicle responses. For the test data of the covered hopper, Exhibit 3 shows the resulting test-data distribution after such categorization. Thus far, the greater analysis effort among these groups has been on higher speed, for both tangent and curve categories. As indicated in Exhibit 3, only 108 miles of the test data were used (out of 400 miles worth of raw test data). This was due to either invalid data, or low vehicle-response level (over smooth track).

Exhibits 4-6 show example comparisons of predicted and actual results for several vehicle-response parameters (lateral and vertical wheel loads and L/V ratios). The actual results were obtained from the covered-hopper response transducers on the CSXT track. The predicted results were obtained using the neural-network models based only on the measured geometry conditions as inputs. For all three examples, the neural networks shown are those corresponding to the curve tracks above 2 degrees and for the speed range from 35 to 50 mph. Therefore, these results cover approximately 18 miles of tracks, based on the distribution shown in Exhibit 3.

In these three exhibits, however, the actual vehicle responses are plotted in rank-order track segments (increasing activity from left to right; e.g., active segments to the right, inactive segments to the left). The corresponding neural-network prediction is plotted directly with actual values. Each track segment is 528 feet in length.

Exhibit 4 shows the results of lateral wheel load in terms of its overall statistical features. As shown,

Speed (mph)	**15-25**	**25-35**	**35-50**
Curves above 2°	7 miles	13 miles	18 miles
Tangent to 2°	17 miles	26 miles	27 miles

Exhibit 3. Test Data Distribution

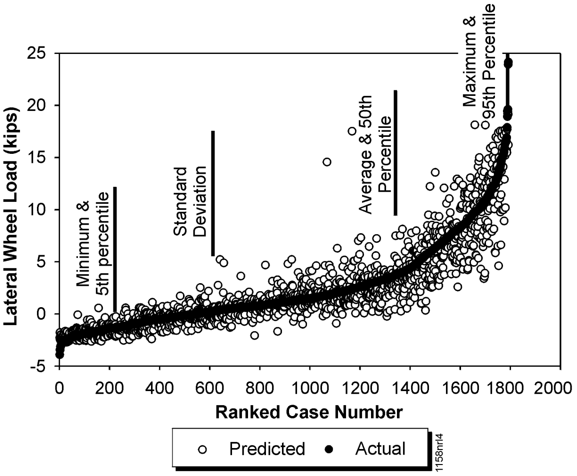

Exhibit 4. Comparison of Predicted and Actual Lateral Wheel Loads

for 18 miles of track, the predicted lateral wheel loads are consistent with the actual measured wheel loads.

Because small vertical wheel forces and larger L/V ratios should be avoided during operations, Exhibits 5-6 give predictions for the lower 5th percentile of vertical wheel loads and for the upper 95th percentile of L/V ratio. Also shown in these two exhibits as insets are the correlation results between the predicted and actual responses. As shown in the insets, the actual and predicted results are linearly correlated, indicating satisfactory modeling results. The correlation coefficient for upper 95th percentile of L/V ratios is 0.93. The correlation coefficient for lower 5th percentile of vertical loads is 0.81.

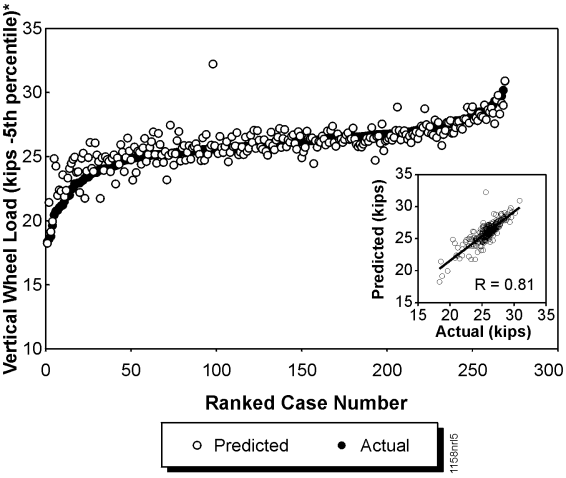

Exhibit 5. Comparison of Actual and Predicted Vertical Wheel Loads (5th Percentile)

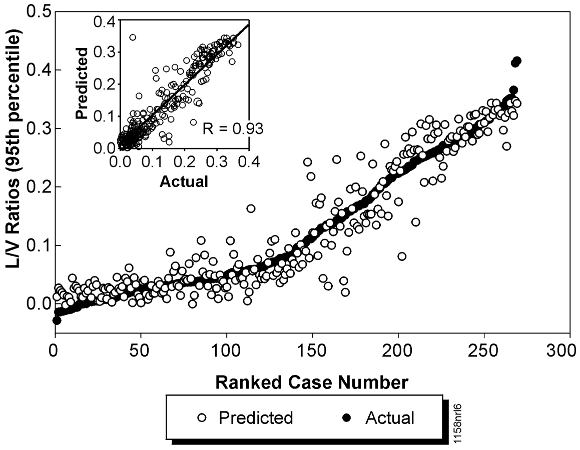

Exhibit 6. Comparison of Actual and Predicted L/V Ratios (95th Percentile)

REFERENCE

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.

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