US Department
of Transportation
**Federal Railroad
Administration**

Research Results

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Computer Model Developed to Predict Rail Passenger Car Response to Track Geometry

SUMMARY

The Federal Railroad Administration sponsored research to develop a computer model to predict the interaction between vehicle and track as a railroad passenger car travels over track with known geometry. This computer model is capable of identifying potentially hazardous sections of track when given the track geometry and the vehicle speed. These predictions will improve safety of railroad operations by helping to determine the maintenance needs for tracks.

This computer model, known as a neural network system, estimates the vertical and lateral forces on the wheel/rail interface as a function of the geometry of the track and the operating characteristics of the vehicle. Unlike conventional computer models, a neural network simulates the analytical workings of the human brain. A series of computer models of a railroad passenger car were developed to evaluate the effectiveness of the neural network. This series of computer models accurately represents the dynamic response of an actual railroad passenger car. In Figure 1, the neural network output closely predicts the series of computer models. In the future, the fully developed system will be used to identify track locations where the estimated lateral and vertical forces exceed the limits recommended for safe operations. Only the track geometry and train speed, which are routinely and easily measured parameters, need to be known in order to identify the potentially hazardous locations.

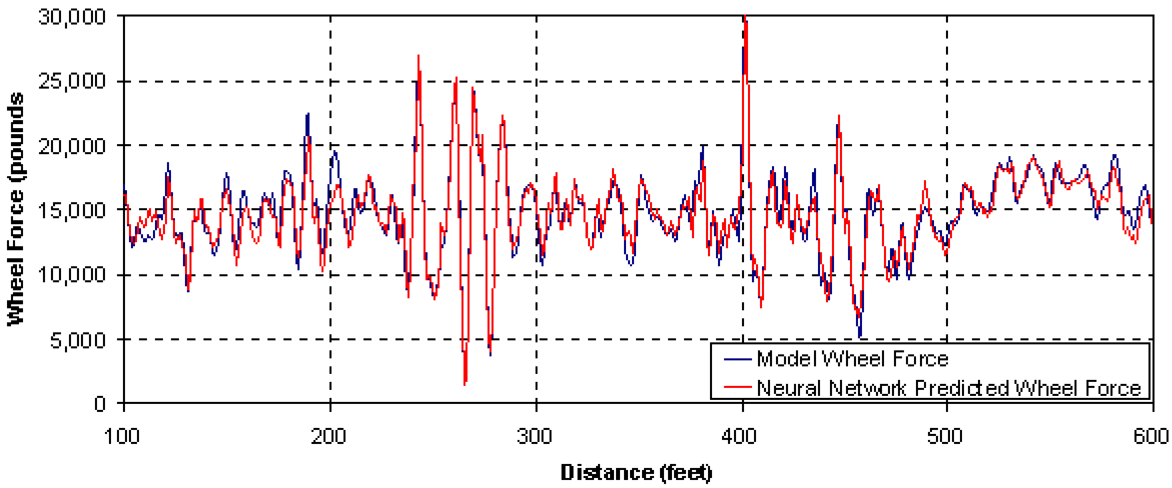

Figure 1. Wheel Force Comparison of the Neural Network and Model.

BACKGROUND

Artificial neural networks, an emerging technology that frequently performs better than conventional technologies, is increasingly being used in both commercial and military applications. This investigation analyses the application of neural network technology for predicting wheel and rail interaction forces generated from a railroad passenger car traveling over track with known geometry. Once properly trained on the operating characteristics of a vehicle, a neural network should be able to estimate the vertical and lateral forces on the wheel/rail interface as a function of the geometry of the track. The neural network technology has the ability to learn relationships between a mechanical system's input and output. When given the track geometry and the vehicle speed, a neural network should be capable of identifying potentially hazardous sections of track.

NEURAL NETWORK SELECTION AND CONFIGURATION

Of the numerous types of neural networks available, four types were considered for this investigation: the perceptron, feedforward, Jordan and Elman, and recurrent network. The recurrent neural network was chosen because it is the most powerful of the four networks, having multiple input layers and an infinite memory depth which enables it to extract temporal information needed for studying a dynamic mechanical system.

A typical recurrent neural network configuration was used in this investigation. Two neural networks were developed utilizing the same basic layout consisting of one input layer, one hidden layer, and one output layer. The number of nodes in each layer differs. A node is a processing element which receives input, performs a function on this input, and then passes it to the next layer. Figure 2 shows the schematic layout of a smaller version of the recurrent neural network. The actual network developed in this study has more nodes in the input layer and hidden layer. Both models used a single output node for a vertical force at a single location.

Most neural networks process data in a similar manner. Each input layer node passes the current input value straight through to the hidden layer. In this study, the track surface was used for this input. The surface is sometimes referred to as profile, which is the vertical displacement of a rail relative to a reference plane. Each node in the hidden layer performs three functions. First, the outputs of all the nodes from the input layer and the recurrent nodes are multiplied by their corresponding weights, W_{ij}. Second, the summation of these products plus a bias factor, B_i, is computed. The bias factor simply shifts the output up or down. Third, this summation is passed through an activation function, which in this case is a hyperbolic tangent. The output from the activation function is passed to the output layer and the recurrent node. The recurrent node is represented by z^{-1} since it delays and stores one sample of the hidden layer output before it is sent back to the hidden layer. The output layer is similar to the hidden layer except that it uses a linear activation function without a recurrent node. The output from the output layer is the vertical force in this study. Although a detailed analysis could be done on choosing the ideal activation function, the hyperbolic tangent on the hidden layer and linear on the output layer produced the best initial results.

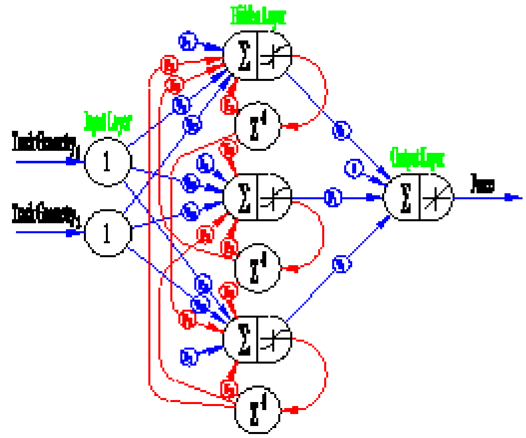

Figure 2. Recurrent Neural Network Layout.

ANALYTICAL MODELS DEVELOPED

Two analytical models were developed to generate the relationships between the geometry input and the vertical force output used to teach the neural network. Analytical models were used instead of actual force measurements in order to avoid the complexity of measurement errors. The models were the two degree-of-freedom (2DOF) and the multiple degree-of-freedom (MDOF).

The neural network used to simulate the 2DOF analytical model has two input nodes, corresponding to the vertical surface displacements in the track. The hidden layer consists of ten nodes with a feedback delay of one sample corresponding to one foot. The output layer is comprised of one node, which generates a vertical force at one location.

The neural network used to simulate the MDOF analytical model has four input nodes, corresponding to the left and right surface and the left and right alignment. The hidden layer consists of thirty nodes with a feedback delay of one sample. The output layer is comprised of one node, which generates the left vertical force.

TWO DEGREE-OF-FREEDOM (2DOF) ANALYTICAL MODEL

A simplified linear 2DOF model of a rail car was generated to evaluate the effectiveness of the neural network. The input for the 2DOF model was a cosine wave with varying wavelengths representing an artificial track geometry surface. The technique used allowed for the development of both a balanced training dataset and a cross-validation dataset. The neural network learned and mimicked the model's structure-in-time while only being given the track geometry in distance and a constant traveling speed.

Results of the 2DOF Model

The simple 2DOF model was primarily used to highlight the issues of trying to develop a network that operates over a full range of speeds and track wavelengths. Despite some problems, the network produced very reasonable results with a training error standard deviation of 200 pounds and cross-validation error standard deviation of 170 pounds. (The nominal vertical wheel load is around 15,000.) However, this model could not train the neural network to match the full model dynamic characteristics exactly.

MULTIPLE DEGREE-OF-FREEDOM (MDOF) ANALYTICAL MODEL

The neural network was further refined with the development of a more complex vehicle model called the MDOF model. The MDOF model consisted of a computer simulation program which was used to predict the dynamic behavior of a standard passenger coach used in intercity operation. A rigid vehicle model, developed and refined for several previous investigations, was used. This vehicle model is comprised of 11 rigid bodies having a total of 53 degrees of freedom, and is interconnected by a total of 40 linear and nonlinear force elements, such as springs, dampers, and friction sliders. The equations used in this system's model are derived from the multi-body dynamics software and integrated into the simulation to solve for forces and displacements in response to track input.

The input for the MDOF model was measured track geometry data that was collected from Amtrak's 10002 test car, while traveling on the Northeast corridor between Washington, DC and New York City, NY. The main parameters recorded by the car include left and right surface (profile), left and right alignment, gage, curvature, and crosslevel. Only the left and right alignment and surface were used to train and evaluate the neural network (see Figures 3 and 4).

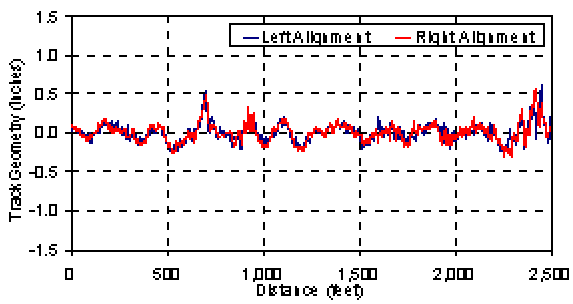

Figure 3. Track Geometry (Alignment) Inputs as a Function of Distance for MDOF Model and Neural Network Training Dataset.

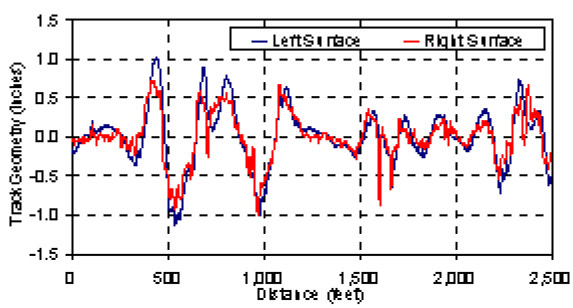

Figure 4. Track Geometry (Surface) Inputs as a Function of Distance of MDOF Model and Neural Network Training Dataset.

Results of the MDOF Model

The neural network trained very well using the MDOF model (see Figure 1). The neural network wheel force output and the MDOF force output for 2500 feet of the training dataset had a force error standard deviation of 850 pound and the mean values were nearly identical. The neural network produced similar results for the cross-validation dataset. The cross-validation data set presents the neural network with track geometry that has not been used to train the system to determine if the neural network has learned the actual system dynamics. The error for the cross-validation data had a standard deviation of 1,100 pounds. This shows that the recurrent neural network can predict the MDOF model wheel forces with reasonable accuracy. Unlike the network trained with the 2DOF model, the MDOF trained network predicted the lower forces with a higher level of accuracy than the higher forces on the cross-validation dataset.

These results can be improved by carefully designing a training dataset that contains more information on the relationship between the forces being generated and the track geometry. A quick review of a common training approach which uses a larger dataset containing almost all possible permutations could result in the network becoming "over trained on the average" and losing the transient response characteristics. To prevent this problem, a custom data filter that only passes a balanced amount of response data needs to be developed.

FUTURE RESEARCH

Future research on the development of the neural network to predict wheel forces will be conducted in four steps.

1. Selectively train the neural network using measured wheel forces instead of simulated forces.
2. Introduce curvature and crosslevel geometry parameters into the network design and training dataset.
3. Train the network using lateral force along with vertical force.
4. Train the network on car body and truck accelerations in order to have a more complete relationship between the track geometry and the vehicle dynamics.

CONCLUSIONS

This investigation showed that recurrent neural networks can successfully predict the vertical wheel forces produced by a complex MDOF model with a well-designed track geometry training dataset. Once a neural network is trained for a specific railroad vehicle, it can predict the dynamic response of that vehicle to a variety of track geometry. The purpose of the neural network system is to estimate the vertical and lateral forces on the wheel/rail interface as a function of the geometry of the track and the operating characteristics of the vehicle. In the future, the fully developed system will be used to identify track locations where the estimated lateral and vertical forces exceed the limits recommended for safe operations. Only the track geometry and train speed need to be known in order to identify the potentially hazardous sections of the track.

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