AN ARTIFICIAL NEURAL NETWORK SPEED PROFILE MODEL FOR HIGH-SPEED HIGHWAY CONSTRUCTION WORK ZONES

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ABSTRACT
Speed profile models can be used by highway engineers to assess the adequacy of a design. Previous work has investigated relationships between operating speed and geometric roadway elements for permanent roadway conditions, mostly two-lane rural roads. No research of this type has been done for construction work zones. For this reason, a speed profile model for high-speed highway construction work zones was successfully developed using artificial neural networks (ANN) and implemented into an EXCEL spreadsheet. The model inputs include geometric features of the road as well as variables specific to construction work zones. The output of the model is a speed versus distance plot for cars, trucks and all vehicles.

INTRODUCTION

One of the most complex issues related to roadway design is vehicle operating speed. This issue is even further complicated in construction work zones due to speed reduction from pre-project conditions and transitions into the work zone. Construction work zones also typically contain additional design features such as temporary traffic barriers, reduced lane widths, and crossover sections that may influence vehicle speed.

The Manual on Uniform Traffic Control Devices (MUTCD) states, "[a] Temporary Traffic Control (TTC) plan should be designed so that vehicles can reasonably and safely travel through the TTC zone with a speed limit reduction of no more than 10 mph." Although this may be a sensible recommendation, it is difficult for the designer to know what speed a driver would consider reasonable and safe given the work zone geometry. It is also made clear in the MUTCD that "reduced speed zoning [lowering the regulatory speed limit] should be avoided as much as practical because drivers will reduce their speeds only if they clearly perceive a need to do so" (*1*). In other words, a reduced posted speed limit may not be effective or appropriate if the visible roadway environment and posted speed are not complementary. .

It is well known that vehicle operating speed is affected by road features and geometry. Predicting highway operating speeds under various scenarios is a useful precursor to appropriate regulatory and design decisions. However, reliable mathematical and statistical speed models have proven elusive.

This paper presents the development of such a speed profile model using ANN methodology. It has only been recently that Artifical Neural Networks (ANNs) have found their way into the area of transportation data analysis, and it seems that this modeling technique is well suited for such applications. First, the data collection is presented. This is followed by the model development and results.

DATA COLLECTION

Speed and geometric data were collected from high-speed highway construction work zones. A high-speed highway was defined as "roads and highways with free-flow operating speeds of 50 mph and higher" (*1*). A construction work zone is defined as "an area occupied for three or more days for the purpose of constructing, reconstructing, rehabilitating or performing preventive maintenance" (*1*). All sites were four-lane divided freeways and typically interstate facilities; however, interstate look-alike facilities were also used.

This study was limited to two typical work zone configurations: lane closures and median crossovers. The following are definitions of these two work zone types taken from (*2*).

Median crossover: "a construction work zone strategy used on expressways (which include freeways) where:

- the number of lanes in both directions are reduced,
- at both ends, traffic in one direction is routed across the median to the opposite-direction roadway on a temporary roadway constructed for that purpose,

- bi-directional traffic is maintained on one roadway while the opposite direction roadway is closed."

Lane closure: "a construction work zone technique for which one or more travel lanes and any adjacent shoulders are closed to traffic. This technique is often employed as part of a reduction *in* number of lanes work zone strategy." Although median crossovers and lane closures may have different lane configurations, the data collection and modeling apply only to facilities meeting these definitions.

Data were collected from 10 different construction work zone sites throughout the state of Pennsylvania and 7 sites throughout the state of Texas. All sites were carefully selected so that they represented standard and typical configurations. Work zones with an excessive number of interchanges were avoided because interchange presence may involve vehicle interaction modeling which was not the goal of this research.

The speed profile of a traveling vehicle is continuous in nature; therefore, an ideal model would involve using a continuous representation of this profile. Such an approach would require tracking the speed of many vehicles through the entire length of a work zone with each vehicle having its own unique profile for the particular site. Available methods of data collection, however, make it difficult to capture this profile as a continuous function. Therefore, measured speeds were captured only at particular locations or "points" throughout a work zone site.

Data were collected from a total of 119 locations or points (excluding 17 upstream points) in 17 work zones, with an average of 7 data points per site. Points were selected in an effort to cover the range of all predictor variables. This was accomplished through the following steps. First a video log was created for each work zone. Then the video was reviewed and the work zone was divided into uniform sections with regards to the predictor variables. Depending on the length of the work zone, this resulted in anywhere from 4 to 50 uniform sections. Finally, selection of these uniform sections was made to best represent the range of geometric and roadside conditions present in the work zone.

Upstream speed data was collected from all work zones. This was typically 2-3 miles upstream from the lane taper outside of the influence of any traffic control devices in the advanced warning area. It is important to note that the upstream speed was used as an input to the model rather than an additional point. Speed measurements were also taken at the center of the lane taper for all work zones.

Both geometric and speed data were collected from the locations described above. Descriptions of all variables used in the model can be seen in Table 1. Speed data was collected using LIDAR and radar guns. Approximately 200 vehicle speeds were measured at each data collection point. In order to ensure that speed measurements represented a driver's response to the input variables and not a response to vehicle interactions, only "free-flow" speed measurements were taken. This was defined, for the purpose of this research, as vehicles with time headway greater than 4 seconds from the vehicle ahead. For each vehicle speed measured, it was noted whether the vehicle was a passenger car or truck. Trucks were defined as vehicles having more than two wheel axels. Summary statistics for all variables can be seen in the Tables 1 through 5 below.

TABLE 1 Input Variable Descriptions

Variable	Description
WZ Configuration	Lane closure; Median crossover
WZ Location	Taper; Within Work Zone
Length	Distance from Beginning of Work Zone (Measured from the Lane Taper)
Posted Speed	Posted Speed Limit
Roadway Type	Permanent; Temporary
R	Radius of Horizontal Curve
VA	Flat; Upgrade; Downgrade; Crest Curve; Sag Curve
TWW	Traveled Way Width
RSW	Right Shoulder Width
LSW	Left Shoulder Width
TPW	Total Paved Width
RSDL	Roadside Device on Left (None; Drum; Vertical Panel; Other Soft; Guardrail; Barrier; Opposing Traffic w/ No Separation)
Loffset	Offset from Traveled Way of Roadside Device on Left
RSDR	Roadside Device on Right (None; Drum; Vertical Panel; Other Soft; Guardrail; Barrier; Opposing Traffic w/ No Separation)
Roffset	Offset from Traveled Way of Roadside Device on Right
Upstream Speed	Speed Upstream from Advanced Warning Area
Previous Speed	Previous Measured (or Predicted) Speed
Previous Length	Distance from Previous Measured (or Predicted) Speed

TABLE 2 Categorical Variables

Work Zone Configuration	Closure	Crossover					
	42.9%	57.1%					
Work Zone Location	Taper	Within WZ					
	19.3%	80.7%					
Roadway Type	Permanent	Temporary					
	74.8%	25.2%					
Vertical Alignment	Flat	Upgrade	Downgrade	Crest	Sag		
	37.8%	21.8%	26.1%	9.2%	5.0%		
Roadside Device Left	None	Drum	Vertical Panel	Other Soft	Guardrail	Barrier	Opposing Traffic
	38.7%	11.8%	1.7%	0.0%	3.4%	42.9%	1.7%
Roadside Device Right	None	Drum	Vertical Panel	Other Soft	Guardrail	Barrier	Opposing Traffic
	36.1%	21.0%	8.4%	7.6%	7.6%	19.3%	0.0%

TABLE 3 Continuous Variables

Variable	Mean	Standard Deviation	Minimum	Maximum	Number of Samples
Length (mi)	2.46	2.96	0	10.64	119
Posted Speed (mph)	59.96	7.09	50	70	119
Radius (ft)	5599.34	3158.15	1911	11480	48
TWW (ft)	13.33	2.93	11	24	119
RSW (ft)	3.93	4.2	0	16	119
LSW (ft)	3.33	4.15	0	36	119
TPW (ft)	19.89	5.18	12	48	119
Loffset (ft)	3.6	8.96	0	48	73
Roffset (ft)	2.47	3.47	0	24	76

TABLE 4 Data points in work zone (including taper)

85th Percentile Speed Summary Statistics (MPH)				
Variable	Mean	Standard Deviation	Minimum	Maximum
All Vehicles	62.06	5.55	44	74
Cars	62.70	5.71	43	76
Trucks	60.69	5.09	44	70

TABLE 5 Upstream Speeds

85th Percentile Upstream Speed Statistics (MPH)				
Variable	Mean	Standard Deviation	Minimum	Maximum
All Vehicles	73	4.20	59	78
Cars	72.16	6.97	51	79
Trucks	70.88	3.41	60	75

MODEL DEVELOPMENT

Artificial neural networks (ANNs) have successfully been employed by researchers over the past 25 years in solving a wide variety of engineering problems. However, it has only been recently that ANNs have found their way into the area of transportation data analysis. ANN structure and methodology is loosely based on the biological nervous system which consists of many interconnected neurons (*3*). ANNs operate on a much smaller scale but use the same basic principles. As with the biological nervous system, ANNs consist of many interconnected but “artificial” neurons which weight, sum and threshold incoming signals to produce an output. Information is stored within the strengths of the interconnections or weights. Figure 1 depicts a typical ANN architecture.

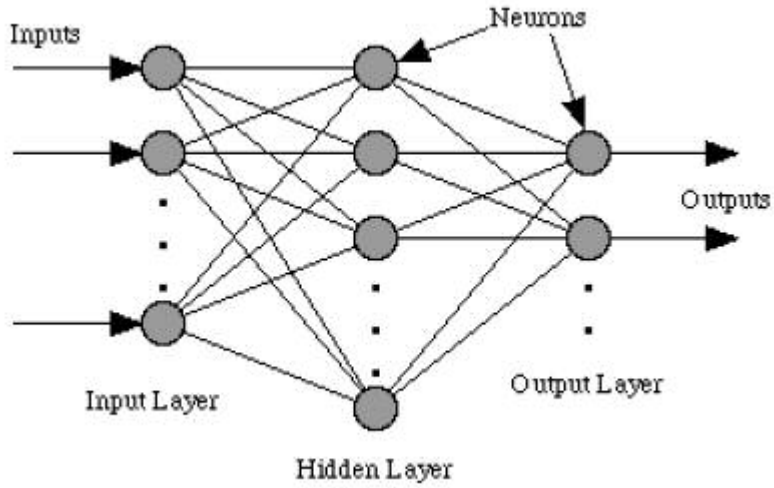

FIGURE 1 General Structure of a Feed-forward ANN.

Just as new memories are formed in biological neural systems through adjustments in the synaptic connection strengths, new memories are formed in ANNs by adjusting the weighted connections between neurons. This is typically done through well established training procedures wherein the network is presented pairs of input/output data and an attempt is made to search for a global minimum on the error surface over the space of the network parameters or weight values. Figure 2 demonstrates the basic training process.

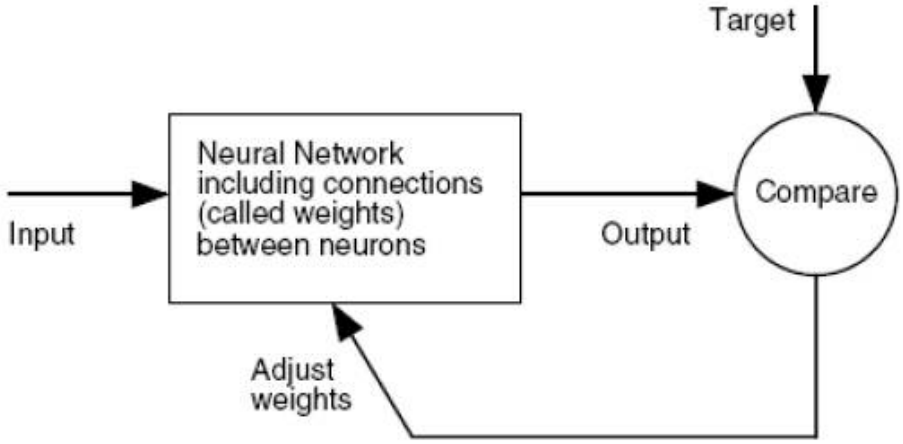

FIGURE 2 Network Training (*4*).

Some advantages of using ANN that are particularly relevant to modeling complex relationships are:

1. No assumptions need to be made on the form of the model
2. It is capable of extracting non-linear variable interactions

3. It is able to generalize from small training dataset

In this research, the ANN model was developed using the input variables and measured 85th percentile speeds. ANN was used to find an appropriate functional mapping between the inputs (geometric variables) and the output (85th percentile operating speed). A block diagram of the model developed can be seen in Figure 3.

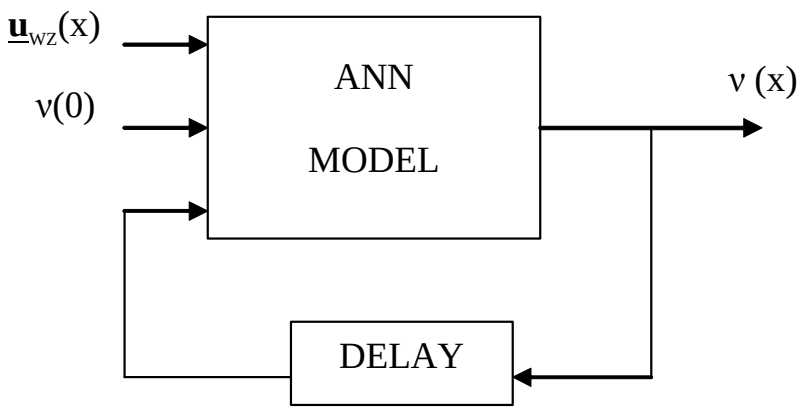

FIGURE 3 Block Diagram of Speed Profile Model.

The output of the model is the speed of a vehicle, ν, as a function of distance, x, measured from the beginning of the work zone or lane taper. The model predicts speeds only for locations of x for which an input vector is defined. The ANN model predicts vehicle speed based on three inputs.

The first input, $\underline{\mathbf{u}}_{WZ}(x)$, is a vector containing the geometric variables at the particular location. Some of these variables, like work zone type, are constant for a particular site, while most variables change depending on the particular point within the site. The second input, $\nu(0)$, is upstream speed. This is the estimated speed of a vehicle prior to entering the work zone and is typically 2-3 miles upstream from the lane taper and outside of the influence of the work zone traffic control. The upstream speed is used in predicting all other speeds within the work zone. The final input is the previous predicted speed which is fed back from the model output through a distance delay block. For the first speed predicted in a work zone, the previous predicted speed is the upstream speed, $\nu(0)$. It is important to note that distance to the previous predicted speed is included in $\underline{\mathbf{u}}_{\mathbf{wz}}$ (x). It is necessary to include this variable since data collection points were not equally spaced.

Before developing an ANN model, input variables were transformed through a variable encoding process. Categorical variables were encoded using a binary representation which is typical in neural network implementation. For example, a variable containing N categories was represented using N separate binary inputs. This is a common technique which avoids the ordering of inputs and keeps categories independent from one another. Variables with only two categories were represented with a single binary input.

In addition to the variable encoding, both radius of curvature and the distance to the previous speed measurement were inverted in order to represent these quantities

within a finite range. The variables Loffset and Roffset were set to an arbitrary large value in cases where there was no roadside device on that side of the roadway. Inputs were normalized in a manner that the mean was zero and the standard deviation was one. Such normalization techniques are commonly employed to increase learning rates and reduce training time.

RESULTS

The Neural Network Toolbox in MATLAB® was used to develop the ANN model. Network inputs and targets were first normalized using the "PRESTD" command in MATLAB®. The first step in training the network is separating the dataset into two groups; one for training the network, and the other for testing the network. Because of the limited number of data points available, the testing dataset needed to be carefully selected such that it was representative set. A total of 5 sample points out of the total of 119 was chosen for testing.

The top two plots in Figures 4 to 6 display results for the training dataset in a slightly different manner. The plot on the left has predicted speed on the vertical axis and measured speed on the horizontal axis. If the predictions were perfect, these data points should be located along the dashed line that has a slope equal to one. Regression was performed for the actual data points and correlation coefficients were calculated. The plot on the right shows measured speed and predicted speed for each training data point. The results were sorted in ascending order (increasing values) of measured speed. A mean squared error (MSE) for the training data set is also displayed in the plot. The testing data results are displayed in a similar manner below the training results. The results obtained using the 85th percentile datasets for cars, trucks and all vehicles are shown in Figures 4 to 6.

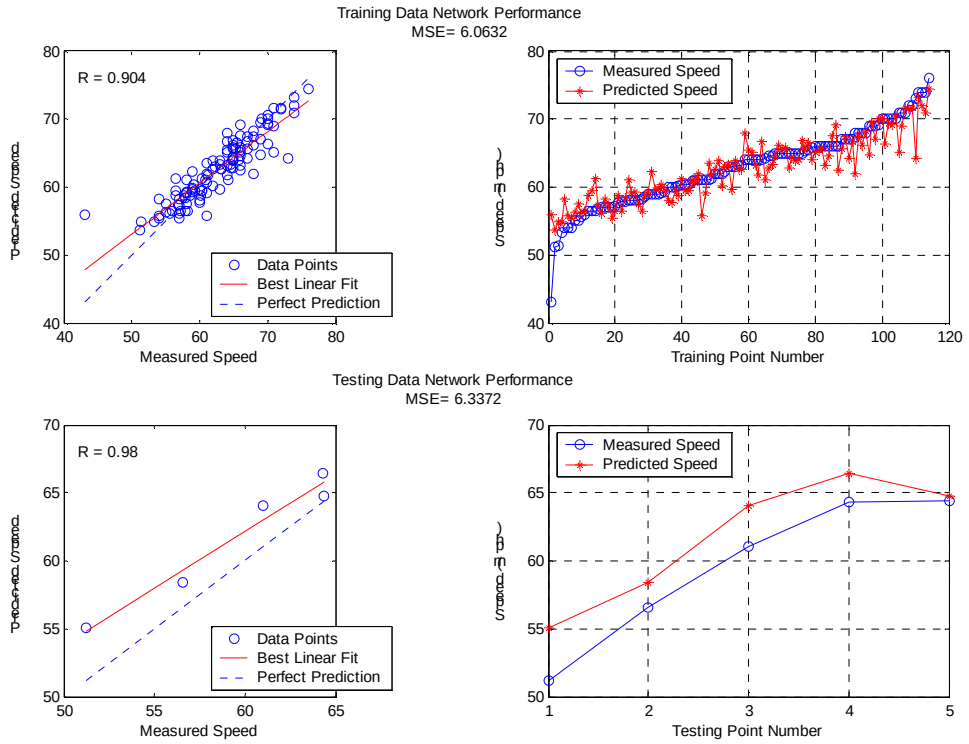

FIGURE 4 ANN Results for Car Model

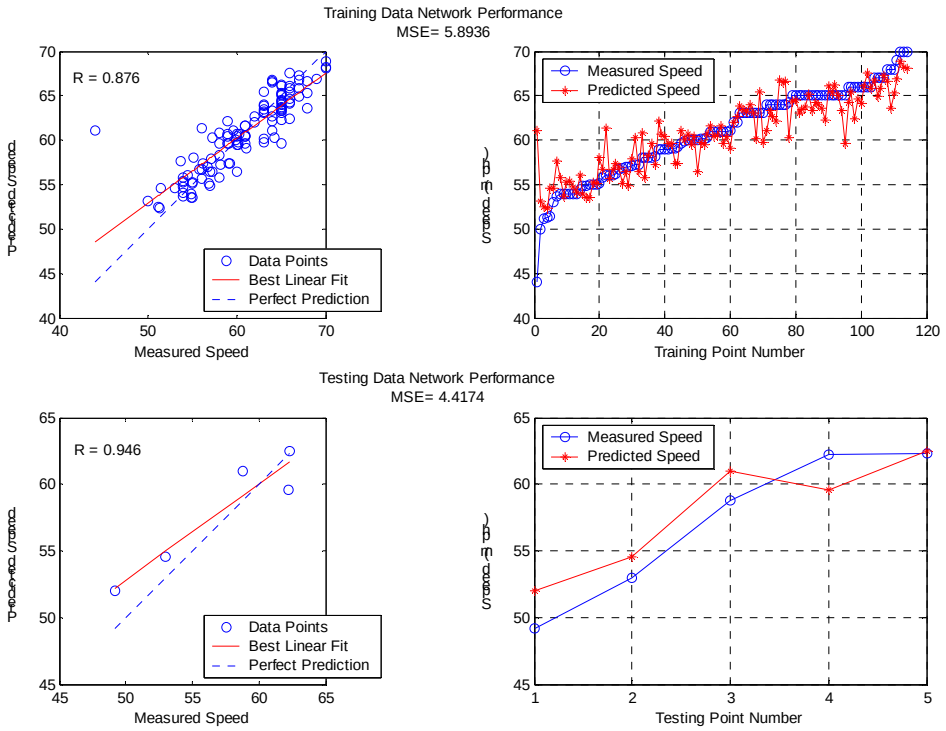

FIGURE 5 ANN Results for Truck Model

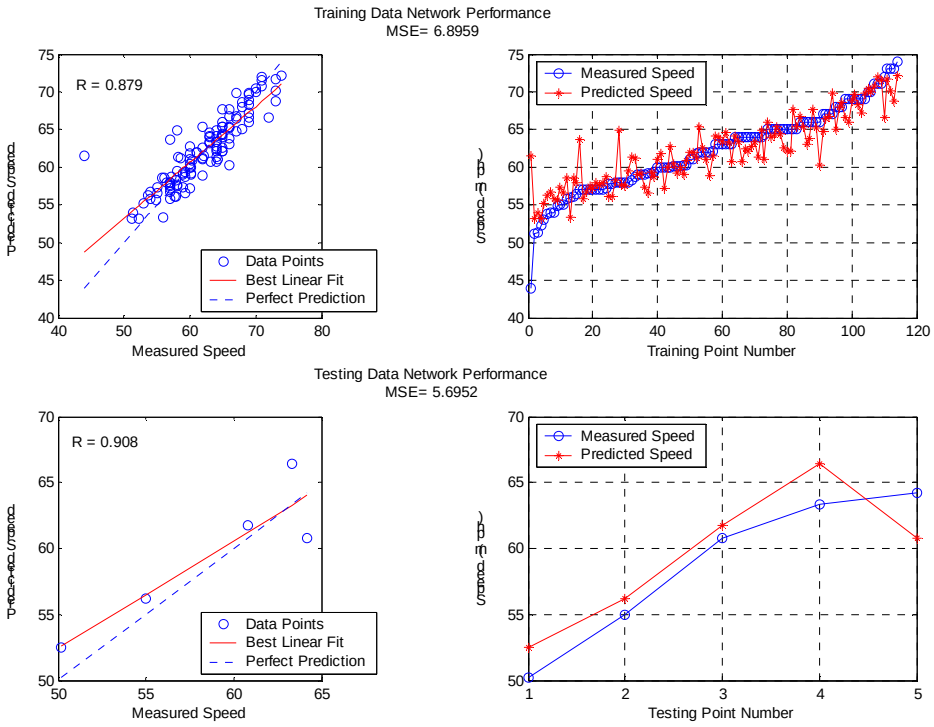

FIGURE 6 ANN Results for Model with All Vehicles

Figure 7 displays the effect of posted speed and five geometric variables on predicted speed. The five geometric variables considered are work zone configuration, crest curve, sag curve, length and total paved width (TPW). Predicted speed in miles per hour is shown on the vertical axis and the variable values are shown on the horizontal axis. While studying the effect of one input variable, all other inputs were fixed at their average value. It is to be noted that for categorical variables only values 0 and 1 have a physical meaning.

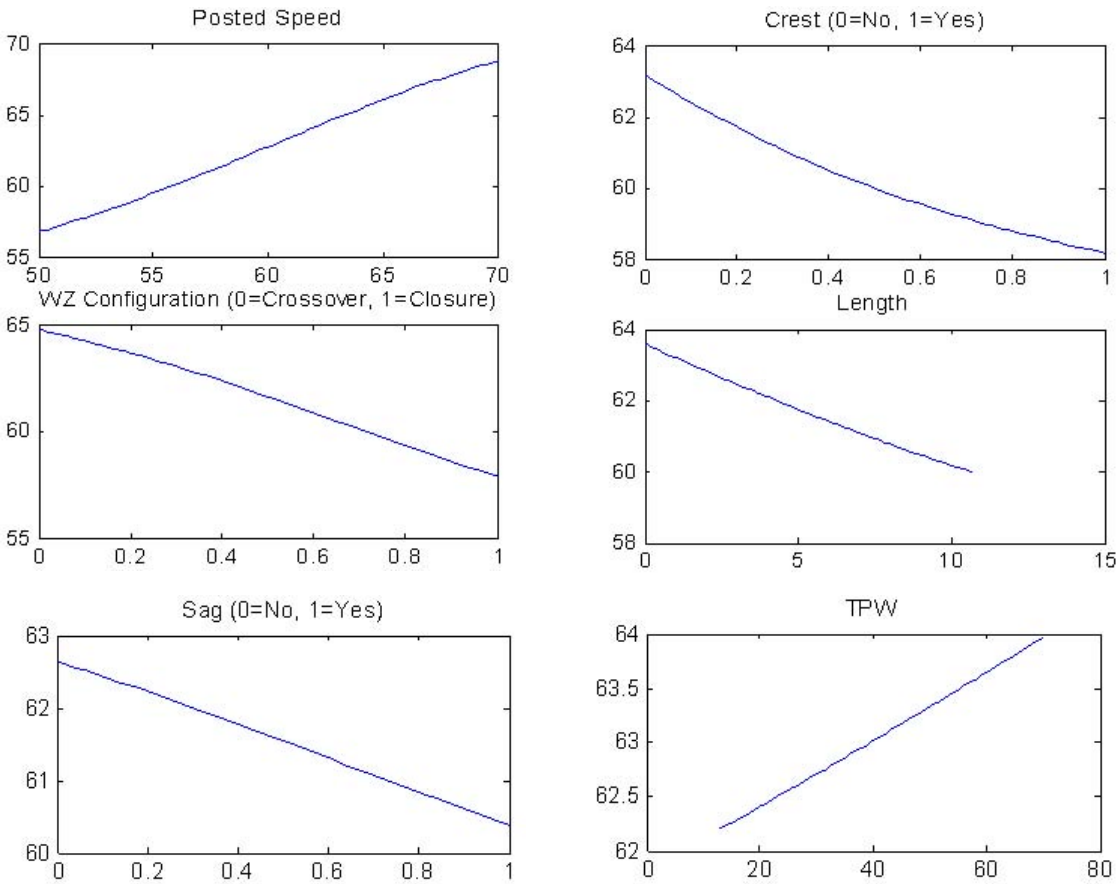

FIGURE 7 Influences of Some Input Variables on Predicted Speed

The trained ANN model was then implemented in an easy to use EXCEL® spreadsheet. The user can input the desired values for the input variables, and a speed vs. distance plot is simultaneously generated. A screenshot of the program is shown in Figure 8.

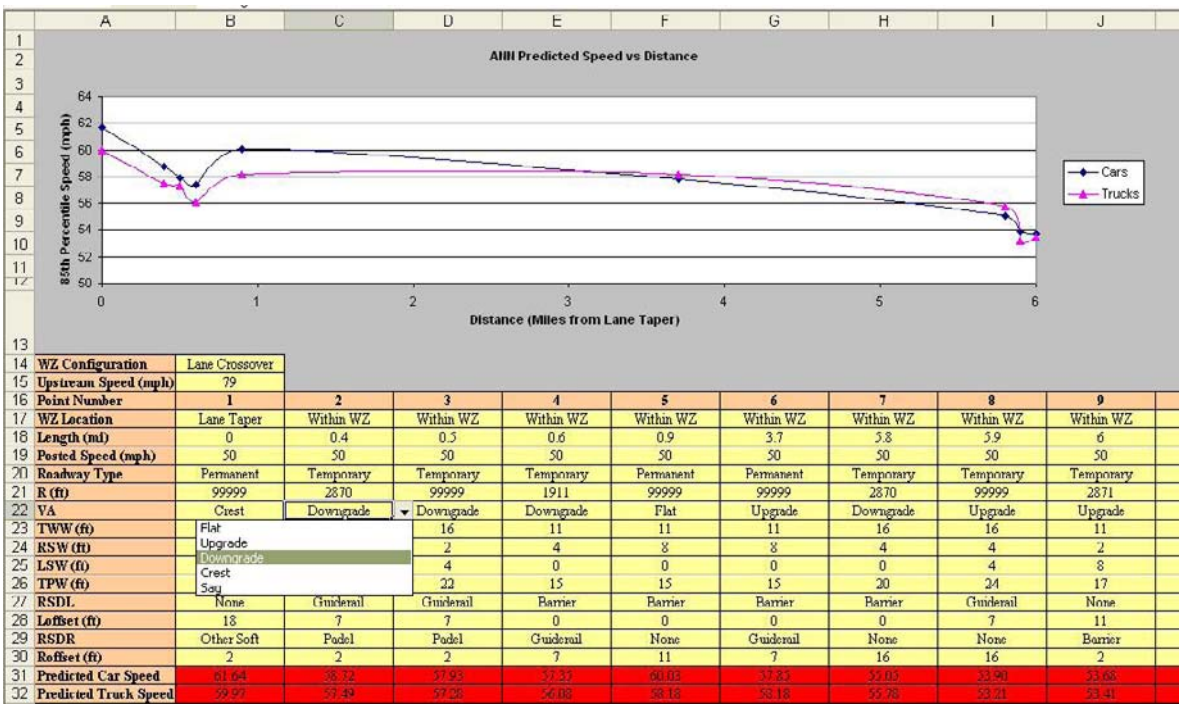

FIGURE 8 EXCEL® Speed Profile Model

CONCLUSIONS

Recent design consistency studies suggest that speed profiles can be used as a method for detecting safety problems with road features. It was the goal of this research to develop a speed profile model that will enable designers to detect design inconsistencies in high-speed highway construction work zone designs before implementation. An artificial neural network model was successfully developed for predicting 85th percentile speeds of cars and trucks separately. The models were developed using geometric data and speed data collected from ten different work zones throughout the state of Pennsylvania and seven work zones in the state of Texas. The final model was then implemented into an EXCEL spreadsheet.

Suggestions for future work include developing a larger dataset to improve model performance. Although the model performed well on this particular dataset, it is recommended that further testing be done to validate the model on a wide variety of work zones. It is possible that different mappings exist between geometric variables and 85th percentile speed depending on the particular samples used for training. In addition to more testing, future data collection methods should be more representative of a continuous speed profile. If more data points were

collected at closer intervals throughout the work zones, it is likely that a more accurate model could be developed.

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