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A Mechanistic Approach to Utilize Traffic Speed Deflectometer (TSD) Measurements into Backcalculation Analysis

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Backcalculation analysis of pavement layer moduli is typically conducted based on the Falling Weight Deflectometer (FWD) measurements; however, the stationary nature of FWD requires lane closure and traffic control. To overcome these limitations, a number of continuous deflection devices were introduced in recent years including the Traffic Speed Deflectometer (TSD). In this study, a mechanistic-based approach was developed to utilize TSD deflection measurements in the backcalculation analysis. The proposed approach is based on the 3D-Move software to calculate the theoretical deflection bowls corresponding to FWD and TSD loading configurations. Since 3D-Move requires the definition of the constitutive behavior of the pavement layers, cores were extracted from 13 sections in Louisiana and were tested in the laboratory to estimate the dynamic complex modulus of Asphalt Concrete (AC). Afterwards, 3D-Move generated deflection bowls were field-validated with an acceptable accuracy. The 3D-Move models were then used in a parametric study consisting of pavement designs of varying thicknesses and material properties and their corresponding FWD and TSD surface deflections were calculated. The results obtained from the parametric study were incorporated into a Windows-based software application, which uses Artificial Neural Network (ANN) as the regression algorithm to convert TSD deflections to the corresponding FWD deflections. This conversion would allow backcalculation of layer moduli using TSD measured deflections, as equivalent FWD deflections can be used with readily available tools to backcalculate the layer moduli.</td></tr>
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A Mechanistic Approach to Utilize Traffic Speed Deflectometer (TSD) Measurements into Backcalculation Analysis

by

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ABSTRACT

Backcalculation analysis of pavement layer moduli is typically conducted using the Falling Weight Deflectometer (FWD) deflection measurements; however, the stationary nature of FWD requires lane closure and traffic control. To overcome these limitations, a number of continuous deflection devices were introduced in recent years including the Traffic Speed Deflectometer (TSD). The main difference between TSD and FWD is that a moving load is used in case of TSD and a stationary impact load is used in case of FWD. Recent findings suggest that TSD is a promising device for pavement evaluation at the network level because it can measure deflections at traffic speeds, which enable large spatial coverage and can generate continuous deflection profiles rather than measuring pavement deflection at discrete points as it is the case with FWD. Currently available tools to backcalculate layer moduli use FWD deflection measurements as the main input.

In this study, a mechanistic-based approach was developed to utilize TSD deflection measurements in the backcalculation analysis. The proposed approach is based on the 3D-Move software to calculate the theoretical deflection bowls corresponding to FWD and TSD loading configurations. Since 3D-Move requires the definition of the constitutive behavior of the pavement layers, cores were extracted from 13 sections in Louisiana and were tested in the laboratory to estimate the dynamic complex modulus of asphalt concrete (AC). Afterwards, 3D-Move generated deflection bowls were field-validated with an acceptable accuracy. The 3D-Move models were then used in a parametric study consisting of pavement sections of varying thicknesses and material properties and their corresponding FWD and TSD surface deflections were calculated. The results obtained from the parametric study were incorporated into a Windows-based software application, which uses artificial neural network (ANN) as the regression algorithm to convert TSD deflections to the corresponding FWD deflections. This conversion would allow backcalculation of layer moduli using TSD measured deflections, as equivalent FWD deflections can be easily used with readily available tools to backcalculate layer moduli.

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IMPLEMENTATION STATEMENT

This report is a supplemental report to LTRC Final Reports 581 and 590. Based on the findings and the results of this project, the developed Windows-based software application is implementation-ready. It can be easily used to convert TSD deflection to the corresponding FWD deflections. The converted deflections can then be used with regular backcalculation tools such as ELMOD to backcalculate the layer moduli from TSD measurements.

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INTRODUCTION

To assess the structural capacity of in-service roads, state agencies may elect to assess pavement layer moduli as an indicator of pavement structural conditions. Through an online survey, it was reported that about 69% of the agencies commonly backcalculate pavement layer moduli from surface deflections *[1]*. Backcalculation analysis of pavement layer moduli is typically conducted based on Falling Weight Deflectometer (FWD) measurements; however, the stationary nature of FWD requires lane closure and traffic control. To overcome these limitations, a number of continuous deflection devices were introduced in recent years including the Traffic Speed Deflectometer (TSD) *[2, 3]*.

The main difference between TSD and FWD is how the load is applied to induce surface deflections. TSD is a moving deflection-measuring device; whereas, FWD is stationary. Therefore, TSD measured-deflections can be influenced by surface irregularities such as roughness and other distresses at the pavement surface. Furthermore, the load configuration is different between a moving load in case of TSD and a stationary impact load in case of FWD *[4]*.

Recent studies conducted in Louisiana and elsewhere suggest that TSD is a promising device for pavement evaluation at the network level because it can measure deflection at traffic speeds, which enable large spatial coverage and can provide continuous deflection profile rather than measuring pavement deflection at discrete points, which is the case with FWD *[5, 6]*. Currently available tools to backcalculate pavement layer moduli uses FWD deflection measurements as the main input *[7]*. The main difference between TSD and FWD deflection measurements can be attributed to the different loading characteristics and dissimilar material responses to different loading configurations, which do not allow the direct incorporation of TSD deflections in these backcalculation tools *[8, 9]*. Therefore, a sound methodology is needed to allow backcalculation of layer moduli from TSD measurements.

As part of the experimental program conducted in this study, a TSD device operated by the Australian Road Research Board (ARRB) was used to measure the vertical surface deflection velocity in 13 sections located in six parishes of District 05 in Louisiana. Additional measurements were conducted to collect the speed of the vehicle, applied tire load, air temperature, and pavement surface temperature during testing. Field measurements were collected for 13 control sections at 0.01-mile interval. FWD measurements were also conducted for the same control sections at 0.1-mile intervals in order to evaluate TSD measurements as compared to FWD.

In this study, a mechanistic-based approach was developed to incorporate TSD deflection measurements in backcalculation analysis. The proposed approach is based on the 3D-Move software to calculate the theoretical deflection bowls corresponding to FWD and TSD loading configurations. Since 3D-Move requires the definition of the constitutive behavior of the pavement layers, cores were extracted from the 13 sections and were tested in the laboratory to estimate the dynamic complex modulus of asphalt concrete (AC). The moduli of the granular and subgrade layers were backcalculated by trial and error as part of the 3D-Move analysis. 3D-Move generated deflection bowls for TSD and FWD compared satisfactorily to field deflection measurements.

Upon validation, the 3D-Move models were then used to conduct a parametric study simulating 250 pavement designs of varying layer thicknesses and moduli and to calculate the corresponding TSD and FWD deflection bowls. To ensure validity of the analysis, a wide range of thicknesses and moduli were considered. Based on the results of the parametric study, an Artificial Neural Network (ANN) model was formulated and was incorporated in a Windows-based software application developed using Visual Basic. The application uses the ANN model as the regression algorithm. The Windows software developed in this study can be used to convert TSD measurements into an equivalent FWD deflection bowl, which can then be used in regular backcalculation tools.

Literature Review

Past studies showed that there could be significant differences between the TSD and FWD measured deflections. This difference may be attributed to the discrepancy in deflection measuring technique between the two devices, surface irregularities affecting TSD measurements, and/or the difference in load application on the pavement surface *[10]*. Typical backcalculation tools adopt only FWD loading characteristics to compute pavement responses and generally assume linear elastic behavior of the pavement layers. Therefore, these conventional programs may not be appropriate for direct use with TSD data due to the aforementioned differences between FWD and TSD *[11]*. However, limited research studies have been conducted to address this issue and the proposed approaches were not computationally practical for regular use by state agencies.

Deflection Measuring Techniques of FWD and TSD Devices

The deflection measuring techniques for FWD and TSD are quite different. Even if both devices apply the same load magnitude, the measured deflection is conceptually different. The stationary FWD device applies an impact load on the pavement surface and measures the deflection at the center of the applied load and at varying distances from the center of the load. The FWD uses a circular plate to load the pavement as shown in Figure 1(a). In contrast, the TSD operates at a traffic speed of up to 60 mph and loads the pavement through its rear axle. Over the right wheel, Doppler lasers are mounted to measure the deflection velocity between the dual tires. Doppler lasers measure the deflection velocity at the midpoint between the tires as shown in Figure 1(b).

(a) FWD testing using a circular plate

(b) TSD measuring deflection velocity between the dual tires

Figure 1
Deflection measuring techniques of FWD and TSD *[9, 11]*

While FWD applies a circular loading with a uniform contact pressure, TSD applies an elliptical-shape loading using regular tires with non-uniform contact pressure. Hence, pavement responses are expected to be different due to the different loading mechanisms for TSD and FWD *[11]*. It is also noted that a dynamic load of a five-axle truck-semitrailer can vary by almost 33% of the load of that truck when measured in a static scale *[13]*. Another difference is that TSD measurements are reported as deflection slopes (calculated by dividing the vertical deflection velocity by the horizontal velocity of TSD); whereas, FWD measures the actual vertical deflections.

TSD and FWD Comparisons

As previously noted, there are major differences between the TSD and FWD loading mechanisms, which could lead to notable differences in the measured deflection values obtained from these two devices. With respect to loading operations, TSD operates with a moving load at traffic speeds; whereas, the FWD load is stationary. Furthermore, TSD measured deflections could be highly influenced by the irregularities in the surface such as roughness and other pavement distresses *[8, 11]*. Previous studies compared the Structural Condition Index (SCI) and Base Damage Index (BDI) derived from TSD slope measurements and FWD deflection measurements *[14]*. The study found significant bias between these two devices and recommended using the Limit of Agreement (LOA) method to compare the measurements from the two devices *[14]*. In Australia and New Zealand, a research study found a strong correlation between TSD and FWD deflection measurements *[15]*. Another study compared between the TSD and FWD measured deflections in Virginia *[16]*. The comparison indicated a similar trend in deflections between the two devices. Furthermore, the study suggested that the structural conditions along the tested road was successfully reflected in the measurements of the two devices; see Figure 2. Similar findings were reported in Louisiana, which concluded that the deflections reported by both FWD and TSD for the same locations were statistically different *[4]*.

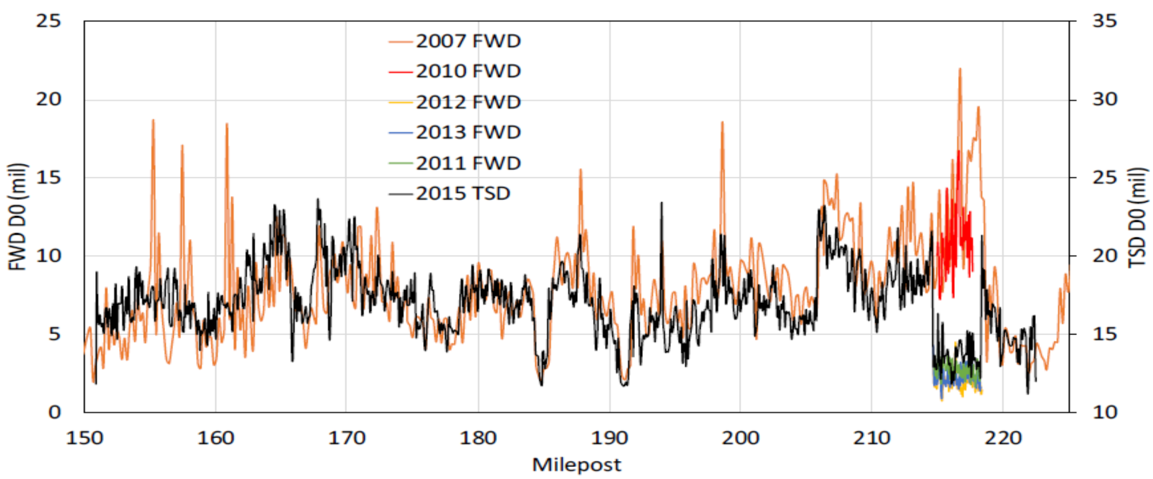


Figure 2
Comparison of TSD and FWD D0 on I81 South in Virginia *[4]*

Overview of 3D-Move Analysis Tool

Mechanistic procedures for estimating pavement responses due to traffic load were introduced in the early 1960s and have been evolving since then. For different performance models, the Strategic Highway Research Program (SHRP) has used the critical inputs such as the applied stresses due to traffic load and the resulting pavement response in terms of strain and deflections. Mechanistic procedures allow pavement engineers to incorporate vital factors such as material properties and loading characteristics in computing pavement responses more accurately. The 3D-Move model has been recognized as an efficient tool to simulate moving loads as compared to the more complicated finite-element method *[17]*. The 3D-Move program uses a finite layer approach and Fourier Transform Technique for estimating pavement responses. The outputs from 3D-Move have been validated using field-measured responses in previously conducted studies. In addition, 3D-Move is capable of incorporating the viscoelastic properties of AC layers, non-uniform contact pressure, and vehicle speed, while conventional backcalculation programs consider only stationary FWD loading configurations. An illustration of 3D-Move theoretical assumptions are shown in Figure 3.

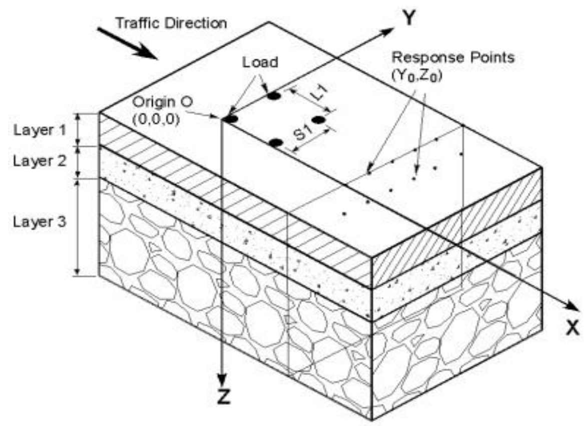


Figure 3
3D-Move pavement response measuring mechanism

Tire-Pavement Interaction. 3D-Move uses tire-pavement interaction-induced loading to model pavement responses. This is a critical factor considering that the noncircular loaded area and non-uniform contact stress induced from the tires can significantly affect pavement responses computation. In addition, the tire-induced load varies with the speed of the vehicle as it travels through the pavement. To ensure the success of mechanistic modeling, tire-pavement interaction, loading characteristics, and material behavior need to be incorporated in a realistic manner. Conventional multi-layer programs such as ELSYM5 and BISAR are simple to use, but they do not accurately consider the mechanisms associated with moving tire-induced loading on the pavement. Most of them are limited to defining static uniform circular loads while moving loads need to be modeled as dynamic and non-uniform. The 3D-Move model can consider tire-pavement interaction more efficiently and realistically. It also allows incorporation of the dynamic nature of traffic loading and can adopt multiple loads and non-uniform nature of contact stresses between the tire and the pavement *[18]*; see Figure 4 and Figure 5.

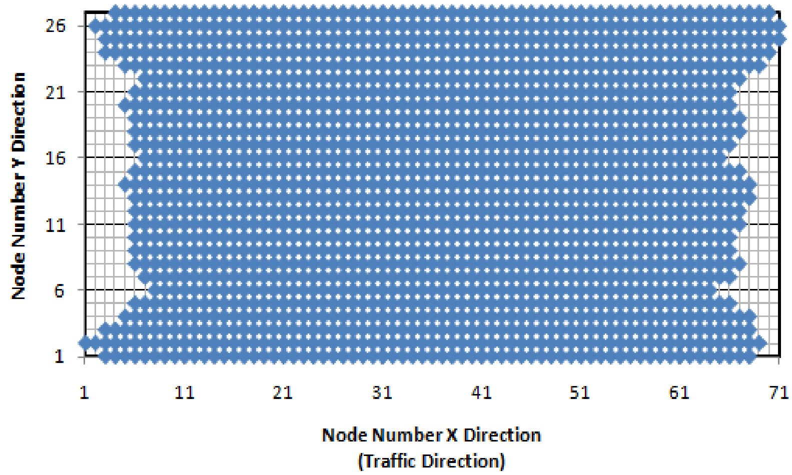


Figure 4
3D-Move model considering non-uniform tire foot print

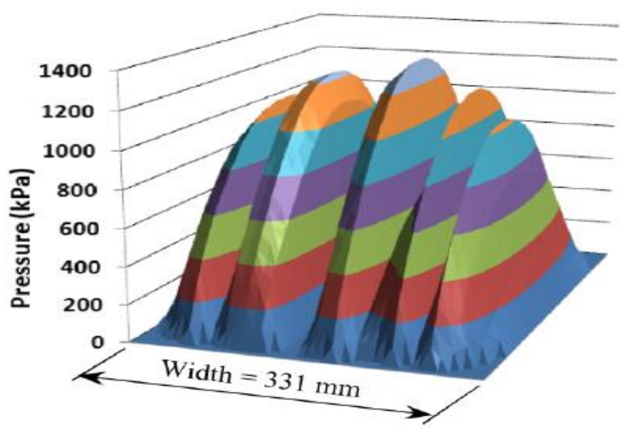


Figure 5
Contact stress distribution in 3D-Move

Defining Loading Characteristics in 3D-Move. The load applied by a moving vehicle varies with its traveling speed and pavement surface characteristics. This variation in moving load is typically disregarded by conventional response analysis tools. Furthermore, experimental studies suggest that vehicle speed influences pavement responses' computation such as strain and deflection *[19, 20]*. Many procedures do not consider these variations while modeling such a response due to multiple loading with different loaded areas, loading time history, and frequency-dependent pavement material properties. Moreover, modeling vehicle with a circular area could be somewhat questionable since tire loading area does not perfectly resemble a circular shaped area. For flexible pavement, the issue of the shape of the tire loading area is important *[18]*.

Defining Material Properties in 3D-Move. Studies have recognized the effects of stress- and frequency-dependent material properties on pavement responses *[21-23]*. The dynamic response of a viscoelastic layered system subjected to stationary circular loads can be simulated by a computer program such as SAPSI *[22, 24]*. This approach was later advanced by Papagiannakis et al., which considered multiple horizontal layers *[25]*. This program is capable of combining frequency-dependent properties of AC layer while treating base course and subgrade layers as linear elastic materials. Any number of layers can be handled by the program with any type of load distributions at the surface; yet, the computational time is greater for larger number of layers.

3D-Move allows incorporation of viscoelastic properties in pavement modeling. In 3D-Move, the AC layer can be simulated as either a linear elastic or a viscoelastic material. Deflections measured by Traffic Speed Deflection Devices (TSDDs) is significantly affected by the viscoelastic nature of AC layer. To characterize the viscoelastic behavior of AC layers, the dynamic modulus, |E*|, needs to be defined in 3D-Move.

Dynamic Modulus Definition in 3D-Move. When viscoelastic materials are subjected to sinusoidal loading, the stress and strain relationship due to the sinusoidal loading is characterized by a complex number called the Dynamic Complex Modulus, E* *[26]*.

The real and imaginary portion of the complex number as shown in equation (1) denotes two different properties of the material. The real portion of the complex modulus represents the elastic component and the imaginary portion represents the viscous component:

$$E^* = E' + iE'' \qquad (1)$$

where,
E' = Elastic Modulus portion of the complex number;
E'' = Viscous Modulus portion of the complex number.

The absolute value of the complex modulus is known as the dynamic modulus, expressed as |E*|. The mathematical representation of the dynamic modulus is shown in equation (2) where the peak dynamic stress is divided by the maximum recoverable strain:

$$|E^*| = \frac{\sigma_0}{\varepsilon_0} \qquad (2)$$

where,

|E*| = Dynamic modulus;
σ_0 = Peak dynamic stress; and
ε_0 = Maximum recoverable strain.

Asphaltic material properties can be defined using the dynamic modulus data in 3D-Move. 3D-Move incorporates the master curve, which enables the input of dynamic modulus at any selected pavement temperature in the analysis. The program uses an optimization tool to construct the master curve from the laboratory test data.

3D-Move can also develop master curves using the Witczak equation as demonstrated in Figure 6. This equation has the ability to predict the dynamic modulus of asphalt mixtures over a range of temperature, rates of loading, and aging conditions from information that is readily available from material specifications and from the volumetric design of the mixture *[26]*.

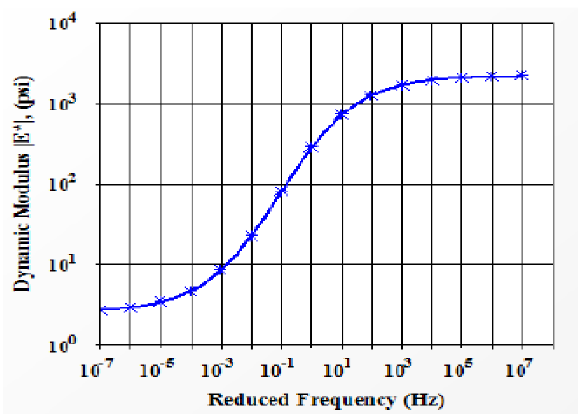


Figure 6
Dynamic modulus master curve

3D-Move Output. Critical pavement responses under traffic load can be estimated by 3D-Move such as normal stress, normal strain, shear stress, shear strain, displacement, principal stress, and principal strain. These pavement responses can be obtained in all three directions (X, Y, and Z). Surface deflection is the only response type of interest in this study. For static analysis, 3D-Move calculates the displacements at the specified locations. For dynamic analysis, 3D-Move can produce continuous displacement profile with time at each specified location as illustrated in Figure 7. The far distant deflections from the load can be extracted from the time-deflection history at the specified points by multiplying time by the speed of the vehicle *[27]*.

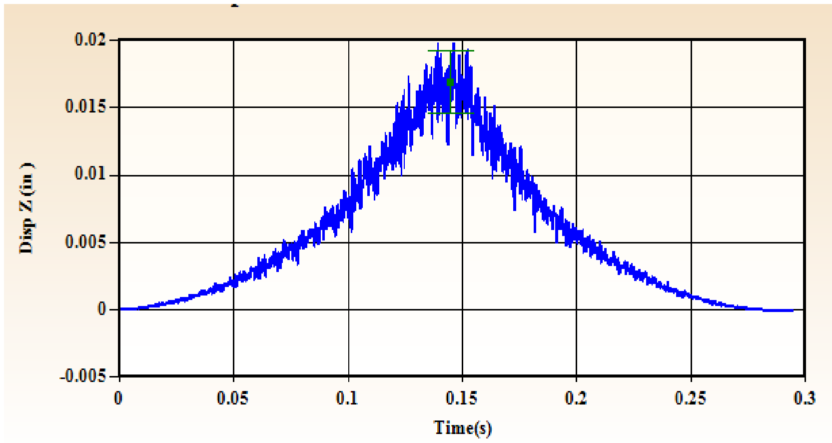


Figure 7
Displacement profile from 3D-Move output

Backcalculation of Layer Moduli Using 3D-Move
A study by Nasimifar et. al. used 3D-Move for the backcalculation of layer moduli from TSD measurements, but the proposed approaches were not computationally practical for regular use by state agencies *[9]*. Yet, these studies are informative and useful to support further research on this issue; hence, they are described in this section.

Using TSD Deflection Velocities. In this approach, 3D-Move simulation was conducted to calculate the TSD deflection velocities. Important TSD testing features were incorporated in 3D-Move such as the dynamic loading nature of TSD; i.e., non-uniform contact pressure distribution of tires, non-circular loaded area; vehicle speed, and viscoelastic properties of AC layer. 3D-Move uses layer moduli as an input in the simulation. In this approach, the inputs were altered by trial-error to match the 3D-Move output deflections to the TSD measured deflections. The trial-and-error process is certainly tedious especially for network level pavement evaluation. However, with a tire pressure of 116 psi, TSD loading characteristics were defined and simulated in this approach as shown in Figure 8 *[9]*.

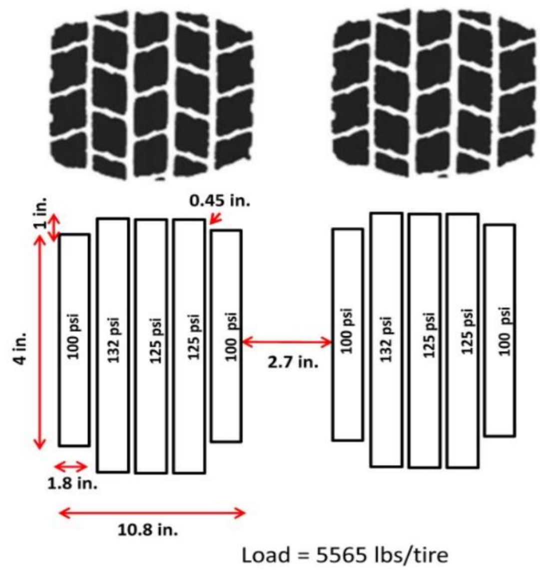


Figure 8
TSD tire simulated in 3D-Move *[9]*

The key benefit of this method is using TSD deflection velocities, which can be directly obtained from TSD measurements. This approach did not require the use of an algorithm to calculate the surface deflections and was independent of the error associated with the conversion. However, the error associated with the calculation of surface deflection is generally small. The results of this approach are shown in Table 1.

Table 1
Backcalculated layer moduli using deflection velocity method *[9]*

Pavement Section ID	Layer	Backcalculated moduli from TSD deflection velocities (ksi)	Backcalculated moduli from FWD deflections (ksi)
MnROAD Cell 19	AC	70-112*	178
	Base	16	17.3
	Subgrade	36	35.8
	Stiff Layer	Fixed	1000
MnROAD Cell 34	AC	211-305*	525
	Base	7	5.1
	Subgrade	16	17.3
	Stiff Layer	Fixed	1000

** Dynamic modulus at 75ºF for frequencies ranging between 5 and 45 Hz.*

Linear Elastic Analysis Approach. Another method was suggested by Nasimifar et al. using Linear Elastic Approach (LEA), which uses TSD surface deflection instead of deflection velocities *[9]*. This approach was conducted using 3D-Move but with more simplified assumptions of TSD characteristics such as circular loaded area and AC materials simulated as linear elastic. However, dual circular loads were used to simulate the TSD tires and non-uniform contact stress distribution. The results obtained with this approach were considered satisfactory by the authors. The advantage of this approach is that the computational effort was significantly reduced as compared to the first approach. The backcalculated moduli obtained from this approach are shown in Table 2.

Table 2
Backcalculated layer moduli using LEA approach *[9]*

Pavement Section ID	Layer	Backcalculated moduli using LEA approach (ksi)	Backcalculated moduli from FWD deflections (ksi)
MnROAD Cell 19	AC	133	178
	Base	14.7	17.3
	Subgrade	34.2	35.8
	Stiff Layer	1000	1000
MnROAD Cell 34	AC	364	525
	Base	5.9	5.1
	Subgrade	24.9	17.3
	Stiff Layer	1000	1000

The referenced study also compared the aforementioned two approaches by backcalculating the layer moduli of two additional pavement sections from Pennsylvania and Idaho. The results using both approaches are presented in Table 3. The study recommended using the LEA approach rather than the deflection velocity method because of the computational requirements of using trial and error using 3D-Move for network level pavement evaluation.

Table 3
Further validation of the two approaches on Pennsylvania and Idaho sections *[9]*

Pavement Section ID	Layer	Backcalculated moduli using deflection velocity method (ksi)	Backcalculated moduli using LEA approach (ksi)
Penn Route 144	Asphalt	181-267*	270
	Base	43	41
	Subgrade	22	20.5
	Stiff Layer	1000	1000
Idaho State Highway 22	Asphalt	325-480*	416
	Base	31	39
	Subgrade	12	11
	Stiff Layer	1000	1000

** Dynamic modulus at 75ºF for frequencies ranging between 5 and 45 Hz.*

In the present study, a mechanistic-based approach was developed to backcalculate the layer moduli from TSD measurements. TSD measured deflections were converted to the corresponding FWD deflections using an ANN algorithm. The ANN model output could then be used in the already established and easily available backcalculation tools for predicting the layer moduli. An overview of the ANN method is presented.

Artificial Neural Networks (ANNs)

ANNs are widely used as computational modelling tools; these networks work similar to the mechanism of the human biological nature of neurons to model practical complex world problems. It is globally accepted and is widely used because of its unique features such as non-linearity, which allows fitting complex data, noise tolerance in the input data, adaptability with complicated data patterns, and ability to generalize data, which facilitates the implementation of the model to unlearned data. Moreover, there are several types of ANNs, which can solve problems with various characteristics *[28]*. An ANN consists of a genetic flexible training algorithm that learns how to make decisions based on given information *[29]*. The use of ANN has increased tremendously in solving complex civil engineering problems in the last three decades *[30]*. They can be very generic, accurate, and convenient mathematical models with high capability in simulating numerical model components *[31]*. ANNs are useful with either small or large database; yet, large databases are preferable when modelling with ANNs. Furthermore, ANN models can be continuously updated with the addition of new data *[32]*.

The Feed-Forward ANN. The feed-forward ANN is mostly used for regression analysis and function approximation. This type of ANN consists of an input layer (i), one or more hidden layers (j), and an output layer. In the input layer, multiple independent variables can be defined; similarly, the output layer known as the target layer can be fed with one or more dependent variables. The hidden layers adjust and update the weights to process the data until the desired output is produced *[29]*. Each of these layers may contain multiple processing units, which are known as "neurons," and the neurons in a layer are linked with all other previous neurons layers *[33]*. A "weight" is assigned to each connection among these neurons and a "bias" is assigned to each of these neurons. Each neuron uses a transfer function, or activation function, to convert the collection of inputs to the neuron into an output value from the neuron, which is passed to neurons in the next layer. There is no recursion or cycles in a feed-forward ANN. A general layout of a feed-forward ANN is demonstrated in Figure 9.

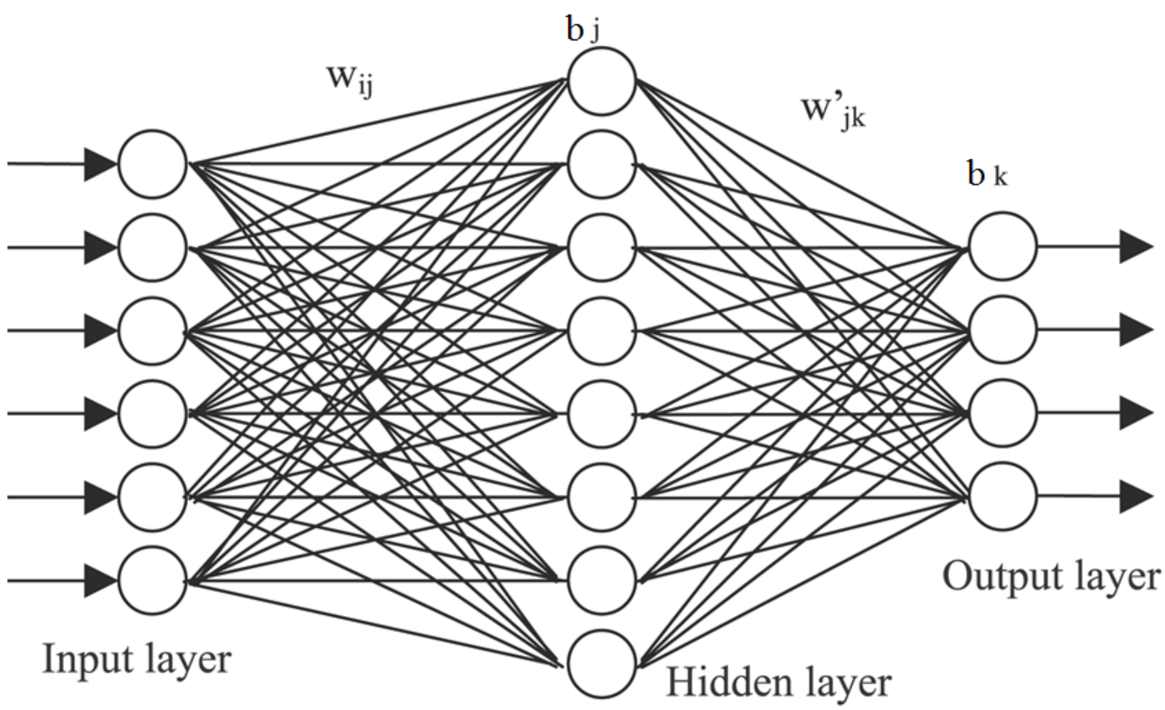


Figure 9
Example of feed-forward neural network structures *[34]*

ANN Back-Propagation. Learning or training of input data in ANN is the process where biases and weights are calculated to match the desired output data. Back-propagation is the most common algorithm for error optimization in the learning and training phases of

ANN. Back-propagation algorithm typically uses the feed-forward algorithm to calculate the output. The error is calculated by comparing the calculated output to the target values. The calculated error for each output neuron is then passed backwards through the ANN layers to update weights and biases. This algorithm minimizes the error by changing the weights and biases in small increments using a learning rate and generates the output with the least possible errors depending on the training and transfer functions considered in ANN *[34]*. An ANN may take several thousands of iterations to minimize the error. The mechanism of back-propagation algorithm is shown in Figure 10. Equation (3) illustrates the function used to calculate the error from the network output.

$$E = y * (1 - y) * (t - y) \tag{3}$$

where,
E= error function;
y = network output;
t = target value.

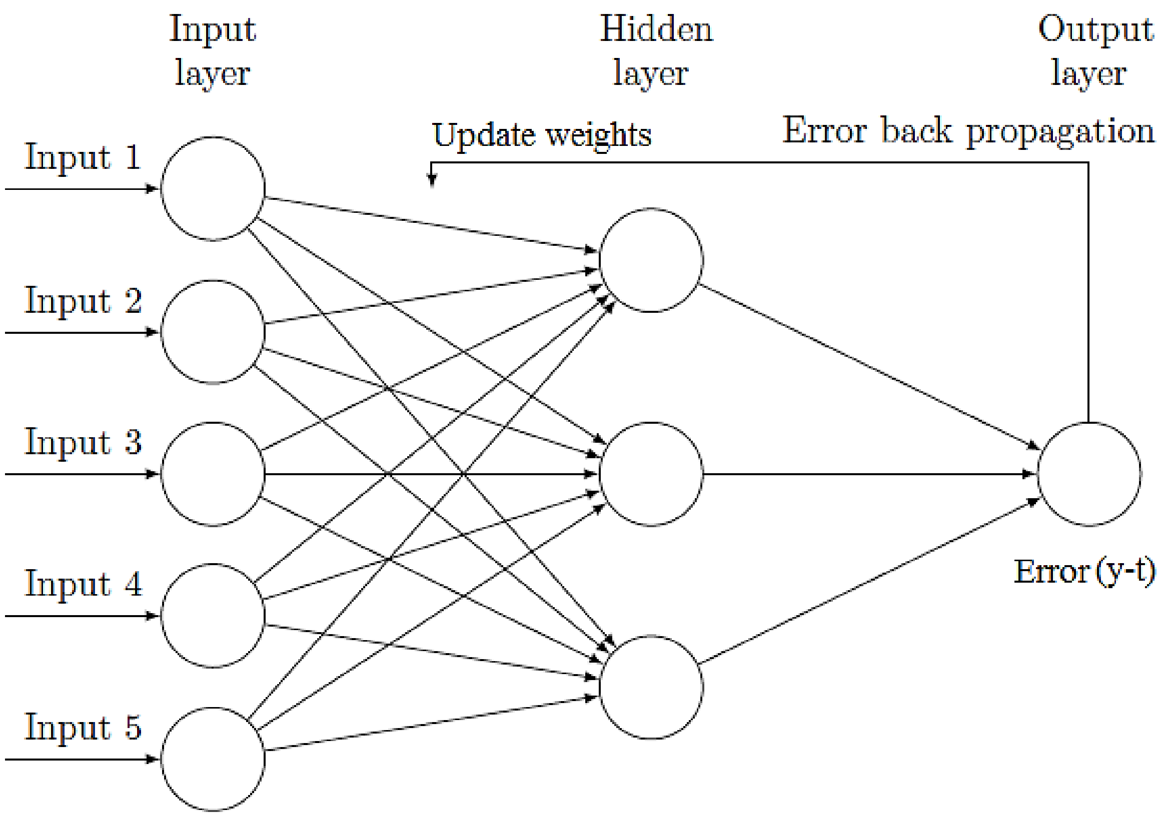


Figure 10
Back-propagation algorithm *[34]*

Back-propagation procedure uses different training algorithms. Each training algorithm has their individual characteristics of learning the data. Training algorithms also have different data learning rate, storage requirements, and computational time. The selection of training function depends on the type of problem to be modeled and input sample characteristics.

Transfer functions, or activation functions, are used to convert the collection of input values to each neuron into an output value from the neuron, which is passed to neurons in the next layer. Three commonly used transfer functions are logistic sigmoidal function (logsig), tan sigmoidal function (tansig), and "hardlim" transfer functions. The output for each transfer function has different properties. For example, logsig produces output between zero to +1, tansig function produces outputs between -1 to +1 and hardlim function is used to make decision and classification of input sample data. Equations (4) and (5) define the ANN logsig and tansig transfer functions, where x represents the independent variables.

$$\mathrm{logsig}(x) = \frac{1}{1+e^{-x}} \tag{4}$$

$$\mathrm{tansig}\ (x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{5}$$

The activation function used in this study is shown in equation (6):

$$A = \frac{1}{1+e^{-x}} \tag{6}$$

OBJECTIVES

The research objective of this study was to develop and to validate a mechanistic-based methodology using 3D-Move in order to utilize TSD deflection measurements in backcalculation analysis.

SCOPE

The objective of the study was achieved through a comprehensive analysis of TSD and FWD deflection data collected in Louisiana. The study also required laboratory testing of in-situ material properties at the tested sites. 3D-Move software was used to model TSD and FWD loading configurations and to calculate pavement deflections from these two devices. Surface deflections calculated from 3D-Move were validated with field measurements. The 3D-Move models were then used in a parametric study simulating pavement sections with varying structures and material properties and their corresponding FWD and TSD surface deflections were calculated. The results obtained from the parametric study were utilized to develop a Windows-based application, which uses artificial neural network as the regression algorithm to convert TSD deflections to the corresponding FWD deflections. The converted deflections may then be used in regular backcalculation analysis software to backcalculate the pavement layer moduli.

METHODOLOGY

Figure 11 presents the research methodology used to achieve the objective of this study. As detailed in a previous report, TSD and FWD testing was conducted on 13 road sections of District 05, Louisiana. The TSD device recorded the GPS coordinates of the locations of measurements. GPS coordinates were referenced to extract cores from these locations. The extracted cores were tested in the laboratory to measure material properties needed to predict the dynamic modulus (E*) of the mixture, which are the binder complex shear modulus (G*), phase angle (δ), aggregate gradation, and other volumetric properties (i.e., effective binder content (%, by volume), air voids (%), and unit weight (lb./in^3). The data obtained from laboratory testing were then used in 3D-Move software to calculate pavement responses under a moving load. TSD loading and viscoelastic material properties were simulated in 3D-Move to predict pavement surface deflections. Pavement response was also simulated under a static load to simulate FWD using 3D-Move. For FWD simulation in 3D-Move, the elastic material properties of the AC layer was incorporated in the analysis.

The 3D-Move models simulating TSD and FWD were validated by comparing pavement responses (surface deflections) from 3D-Move to field measurements. Validation of these 3D-Move models was followed by a parametric study, which consisted of using 3D-Move models to simulate a wide range of pavement designs. In this parametric study, 162 pavement designs were simulated with varying layer thicknesses and moduli. These cases were run by 3D-Move to calculate pavement surface deflections for TSD and FWD. The theoretical surface deflections obtained from both TSD and FWD were then used to develop an ANN model. The ANN model correlated the theoretical TSD deflections to the theoretical FWD deflections. The ANN model can be used to estimate the corresponding FWD deflections if the TSD deflections are known. Therefore, the ANN model would facilitate the backcalculation of layer moduli from TSD measurements.

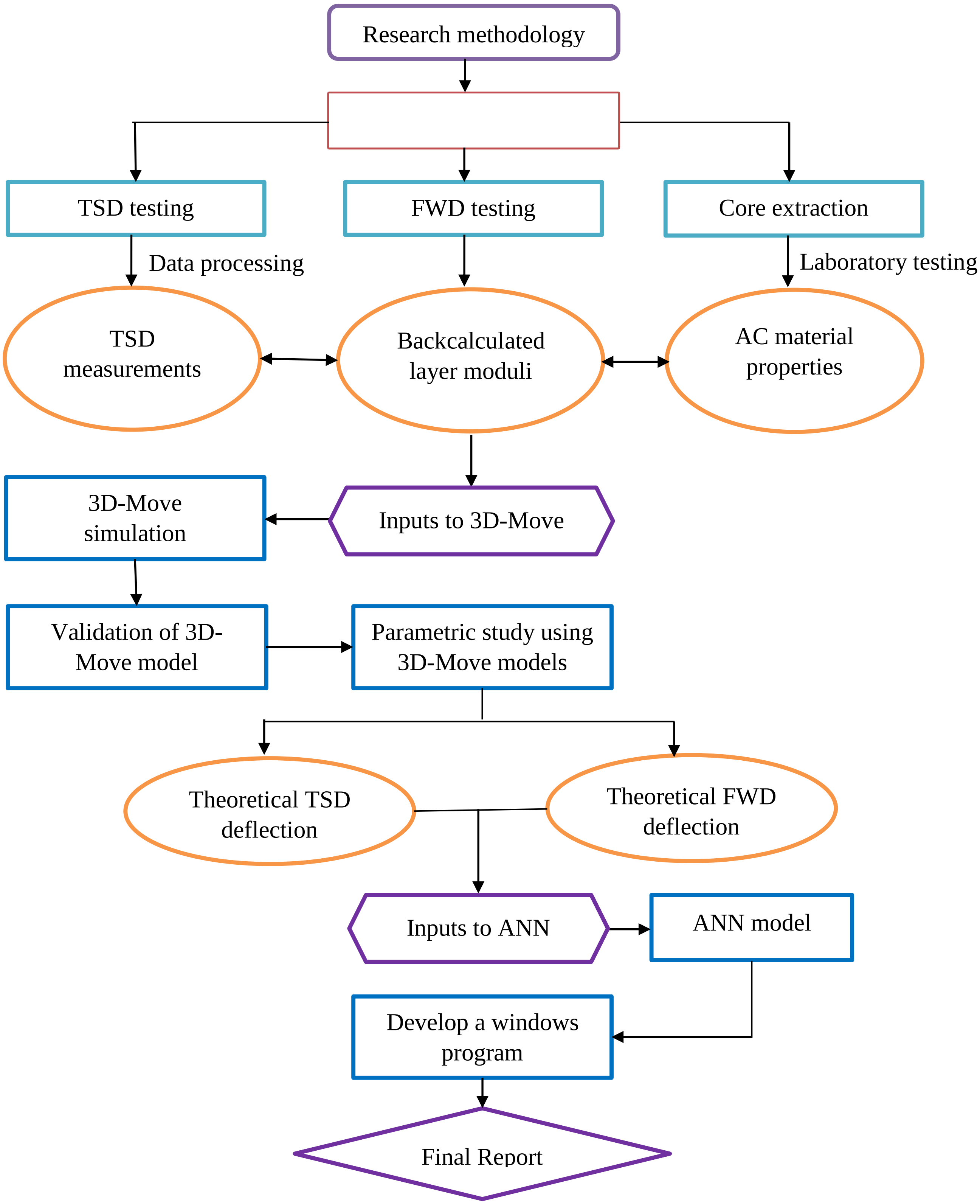


Figure 11
General layout of research methodology

Data Description

FWD and TSD measurements were conducted successfully in Louisiana in May 2016 with no significant problems to report. The tested sites were further characterized to measure the in-situ material properties. Data processing and evaluation was conducted on the raw measurements obtained from field testing and laboratory testing.

TSD and FWD Test Measurements

In 2016, a TSD device operated by the Australian Road Research Board (ARRB) was used to measure vertical deflection velocity, horizontal speed of the vehicle, air temperature, and pavement surface temperature in six parishes of District 05 in Louisiana. Measurements were conducted for 13 control sections at 0.01-mile intervals. FWD measurements were also collected for the same control sections at 0.1-mile intervals and normalized to a load of 9,000 lbs. *[4]*.

Collected raw measurements (vertical deflection velocity and actual horizontal speed) of the TSD device were used to calculate the deflection basin at each milepost according to the methodology known as "Area under the Curve (AUTC)" developed by Muller and Roberts *[35]*. According to this method, the vertical deflection velocity is divided by the actual speed of the vehicle to get the deflection slope; slopes are then plotted against TSD sensor locations. Afterward, the plotted curve is numerically integrated assuming the deflection slope is zero at locations 0 and 137.8 in. from the load. The deflection value was then calculated at the selected locations with adequate curve fitting using the Piecewise Cubic Hermite function as suggested by the AUTC method. Surface deflections were calculated at nine locations (i.e., 0, 8, 12, 18, 24, 36, 48, 60, 72 in. from the center of the load). Temperature corrections for both TSD and FWD surface deflections were conducted to a reference temperature of 20°C according to the methodology developed by Kim and Park *[36]* and asphalt mid-depth temperature was calculated using Bell's equation *[37]*.

In summary, the dataset consisted of corresponding FWD and TSD deflections, magnitude of the applied load, temperature at the time of testing, GPS coordinates of measurement locations, TSD speed, etc. These measurements were utilized as an input in 3D-Move for simulation of TSD and FWD testing configurations.

Laboratory Tests of Extracted Cores

To accurately assess the in-service conditions of pavement materials, cores were collected from the TSD and FWD test sites. Core extraction locations were selected as referenced to the GPS coordinates recorded by TSD. Two cores were extracted from the wheel path of each pavement section since TSD measures deflection under the right wheel tires. The extracted cores were saw-cut to separate the AC layer and core thicknesses were recorded.

Afterward, the cores were subjected to laboratory testing to estimate the viscoelastic asphalt concrete properties and to construct the dynamic modulus master curves based on the Witczak model. To characterize the viscoelastic properties, the following properties were estimated (Table 4):

1. Asphalt mix properties

a. Aggregate Gradation
   (i) Cumulative % retained in ¾-in. sieve
   (ii) Cumulative % retained in $^{3}/_{8}$-in. sieve
   (iii) Cumulative % retained #4 sieve
   (iv) % passing #200 sieve

b. Volumetric Properties
   (i) Effective Binder Content, % (by volume)
   (ii) Air voids, %
   (iii) Unit Weight, lbs/in^3

2. Asphalt binder properties

a. Dynamic Shear Modulus (G*), psi
b. Phase Angles (associated with G*), degree
c. Binder viscosity at a temperature of interest

Table 4
Tests conducted on extracted cores

Type of tests	Parameter determined	Remarks
Bulk Specific Gravity (G_{mb}) Test	*Specific gravity*, which was used to determine the *unit weight* of each sample core	Unit weight = Specific gravity × Acceleration of gravity
Theoretical Maximum Specific Gravity (G_{mm}) Test	*Percentage air void content* in the sample specimen	Air void content (%) = $(1 - \frac{Gmb}{Gmm})$ *100 where, G_{mb} = Bulk Specific Gravity G_{mm} = Theo. Sp. Gravity
Extraction	Recovery of *Asphalt binder* & *aggregate* from sample core specimen	Recovered binder and aggregates were subjected to further testing
Aggregate Gradation	To determine the cumulative percentage aggregate retained on the sieves.	Used as an input in 3D-Move
DSR (Dynamic Shear Rheometer)	To determine *Dynamic Shear Modulus (G*)*, *Phase Angles (associated with G*)*, *Binder viscosity* at temperature of interest	Used in the Witczak model to determine dynamic modulus (E*) of AC mixture

3D-Move Simulation

The loading mechanisms associated with the TSD and FWD were simulated using 3D-Move. The objective was to develop 3D-Move models, which can produce theoretical TSD and FWD deflection bowls. In order to achieve this objective, loading characteristics of TSD and FWD, material properties of pavement layers, and other necessary parameters were defined in 3D-Move. The noteworthy inputs in 3D-Move are discussed below.

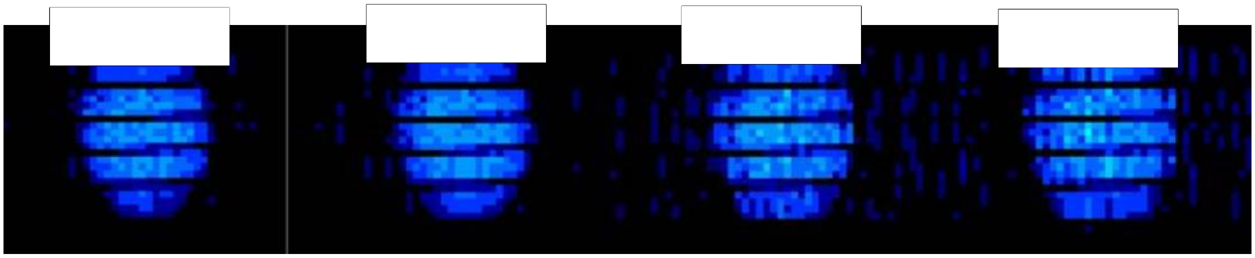
Type of Analysis

At first, the type of analysis (i.e., static or dynamic) needs to be specified in 3D-Move. For FWD, the analysis type would be static, while for simulation of TSD, a dynamic analysis was conducted. In dynamic analysis, the operating speed of TSD during testing was defined in 3D-Move. Since the speed of deflection measuring device has been shown to affect the measurements, 3D-Move uses TSD speed as an important variable in calculating the resulting deflections. During TSD testing, the operating speed was recorded at each measurement location and was defined in 3D-Move.

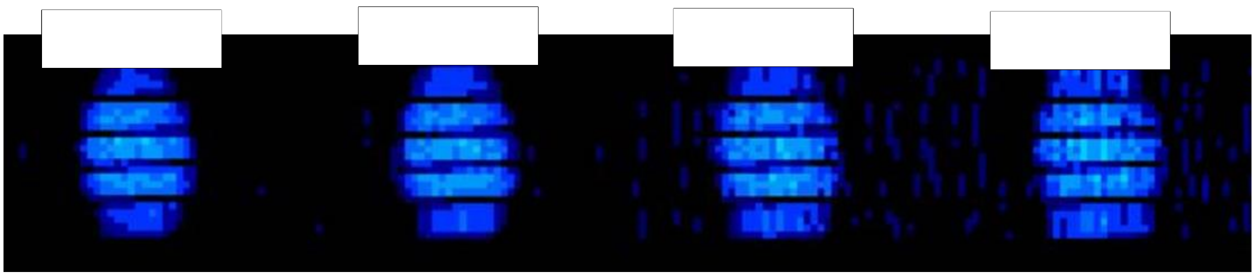
Loading Characteristics Simulation

TSD. Traveling at traffic speed, TSD loads the pavement using its rear axle tires. The articulated Doppler lasers over the right wheel of the rear axles measure the deflection velocity along the midline between these dual tires. Since 3D-Move can incorporate moving load characteristics with the non-uniform contact stress, accurate simulation of TSD was achievable. Loading variation was defined in 3D-Move using the Dynamic Load Coefficient (DLC). It was shown in earlier studies that a dynamic load of a five-axle truck-semitrailer can vary by almost 33% of the load of that truck when measured on a static scale *[10]*. However, loading measurements are measured continuously by the TSD at the time of testing, which was considered in the simulation.

To measure the exact loading area is challenging as it requires pressure plates and slowing down the TSD during testing. The SANRAL (South African National Roads Agency Limited) measured the varying loading area under moving TSD as shown in Figure 12 *[38]*. As shown in this figure, the contact area varied between 52 to 89 in.^{2} for each tire on the inner and outer side of the dual tire assembly. During TSD testing, the contact area will vary due to the dynamics of the tire itself, suspension, wheel camber, and tire wear.



(a) Trail inner tire



(b) Trail outer tire

Figure 12

Varying loading contact area of TSD *[38]*

Measurements of the loaded area and tire dimensions were obtained by measuring the footprint of the outside tire as shown in Figure 13 and Figure 14. Tire longitudinal dimension (travel direction) was measured at 7.48 in. and at 9.45 in. in the transverse direction. The spacing between the two tires was measured at 4.33 in.

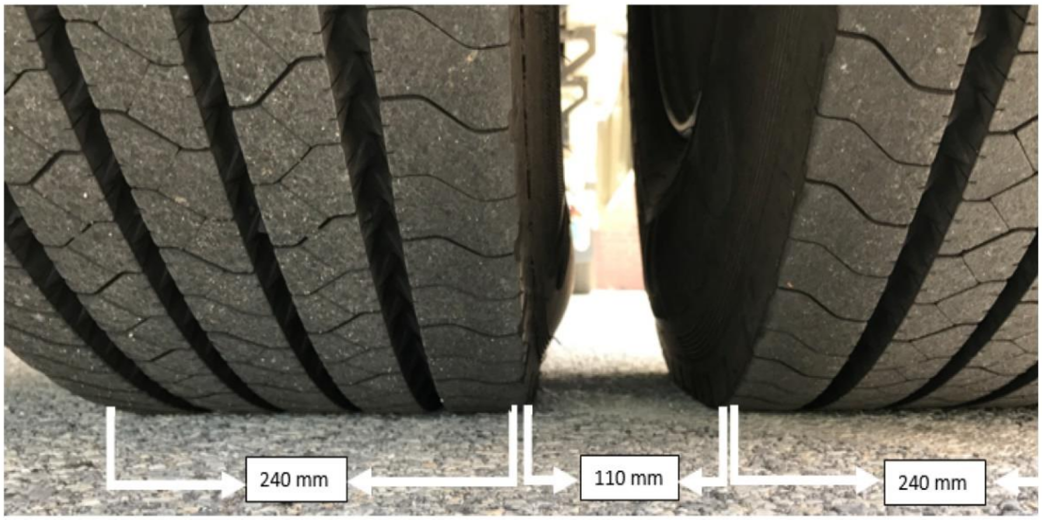


Figure 13
TSD tire dimensions in the transverse direction

Figure 14
TSD tire dimensions in longitudinal (traffic) direction

Under static conditions, the measurement of the contact tire pressure was reported at 115 psi. It is to be noted that the ARRB TSD used in the testing program was intentionally slightly biased towards the right dual tire with a greater load to increase the deflection since it measures the deflection along the midline between the right dual tires.

3D-Move is able to incorporate both uniform and non-uniform pressure distributions over any shape of loading area. To accurately simulate the loading characteristics of TSD, a non-uniform contact pressure was incorporated with measured TSD tire configurations. The specified tire shape and imprinted tire area (70.1 in^2) were in agreement with the shape and range of loading area (52 to 89 in^2) demonstrated by the SARNAL; see Figure 15 *[38]*. As shown in Figure 16, the tire threads were defined and varying pressures were simulated for each thread to account for the non-uniform distribution reported by Nasimifar et al. *[9]*.

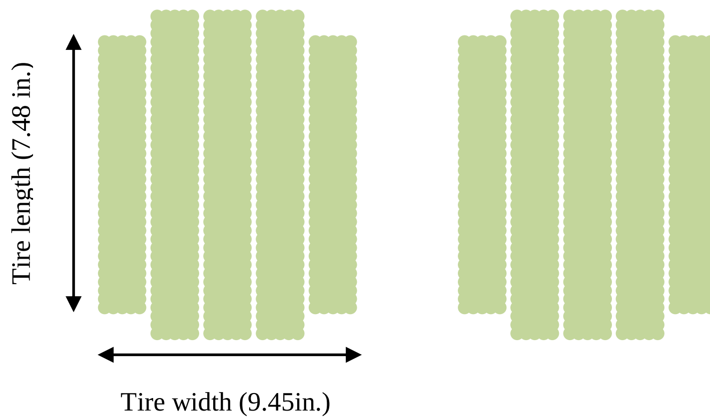


Figure 15
Right wheel dual tire imprint

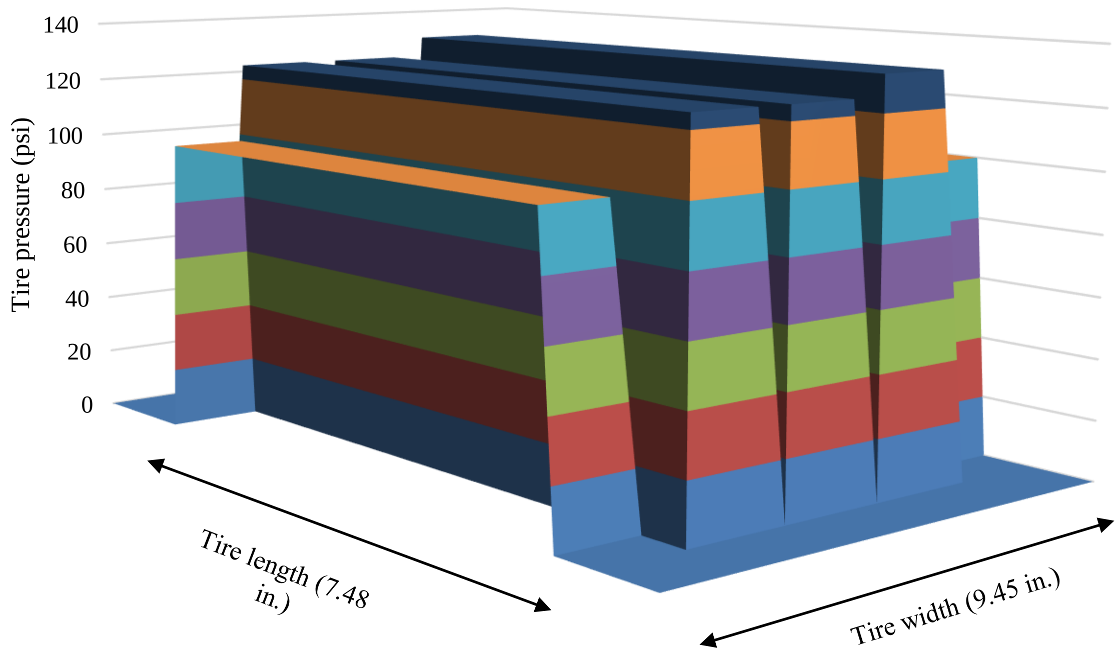


Figure 16
Non-uniform pressure distribution

FWD. The static impulse load applied by FWD was defined in Move-3D as a circular shape tire with radius of 5.904 in. and with a load of 9,000 lbs., which generates a uniform pressure of 82.2 psi on the pavement surface.

Dynamic Load Coefficient

This input segment is only applicable to the dynamic analysis for TSD. While traveling on the pavement surface, the moving load induced by the vehicle tires changes with time and varies about its mean loading magnitude. This load variation was quantified by a number of studies through field tests and various tire-pavement interaction analytical models. This variation in tire loads was described by the coefficient of variation (std. deviation/mean load), which is also known as the Dynamic Load Coefficient (DLC) and is largely dependent on the surface roughness, the speed of the vehicle, and the suspension system of the truck. In the present analysis, DLC was defined as a function of vehicle suspension type and surface roughness using the analytical model developed by Sweatman, which also take into consideration the vehicle speed *[27]*.

Material Characteristics

Strength and stiffness of paving materials are important key factors in the estimation of pavement responses to an applied load. The material properties were obtained from laboratory testing conducted on extracted cores and from the backcalculation of layer moduli from FWD measurements. The pavement structure was divided into three layers (i.e., AC, base, and subgrade layers) and each layer was defined in 3D-Move. The thickness of these layers were obtained from the extracted cores and a constant Poisson's ratio was assumed for each layer (i.e., 0.30, 0.35, and 0.40 for the AC, base and subgrade layers, respectively).

Asphalt Concrete Layer. In the static analysis for FWD, linear elastic material properties were assumed (i.e., elastic modulus). As discussed earlier, the viscoelastic properties of AC layer only need to be defined while estimating pavement responses for a dynamic analysis. In 3D-Move, the viscoelastic properties can be defined using three methods used to construct the dynamic modulus master curve (i.e., using dynamic modulus data, using Witczak model, or user-defined viscoelastic properties).

In the present study, the Witczak model was used to describe the viscoelastic properties of the AC layer. The parameters needed in the Witczak model were obtained from laboratory testing. The analysis temperature was set to 20˚C since all TSD measurements were temperature-corrected to the same temperature. The Witczak model is presented in equation (7):

$$\log E^* = 3.750063 + 0.02932 * (\rho_{200})^2 - 0.002841 * \rho_4 - 0.05809 * V_a - 0.802208 * \left(\frac{V_{beff}}{V_{beff}+V_a}\right) + \frac{3.871977 - 0.0021*\rho_4 + 0.003958*\rho_{38} - 0.000017*(\rho_{38})^2 + 0.005470*\rho_{34}}{1+e^{(-0.603313-0.313351\log(f)-0.393532\log(\eta))}} \quad (7)$$

where,

E^* = Dynamic Modulus, in 10^5 psi;

η = Bitumen viscosity, 10^6 Poise;

f = Loading frequency, Hz;

V_a = Air void content, %;

V_{beff} = Effective bitumen content, % by volume;

ρ_{34} = Cumulative % retained on the 3/4 sieve;

ρ_{38} = Cumulative % retained on the 3/8 sieve;

ρ_4 = Cumulative % retained on the No. 4 sieve; and

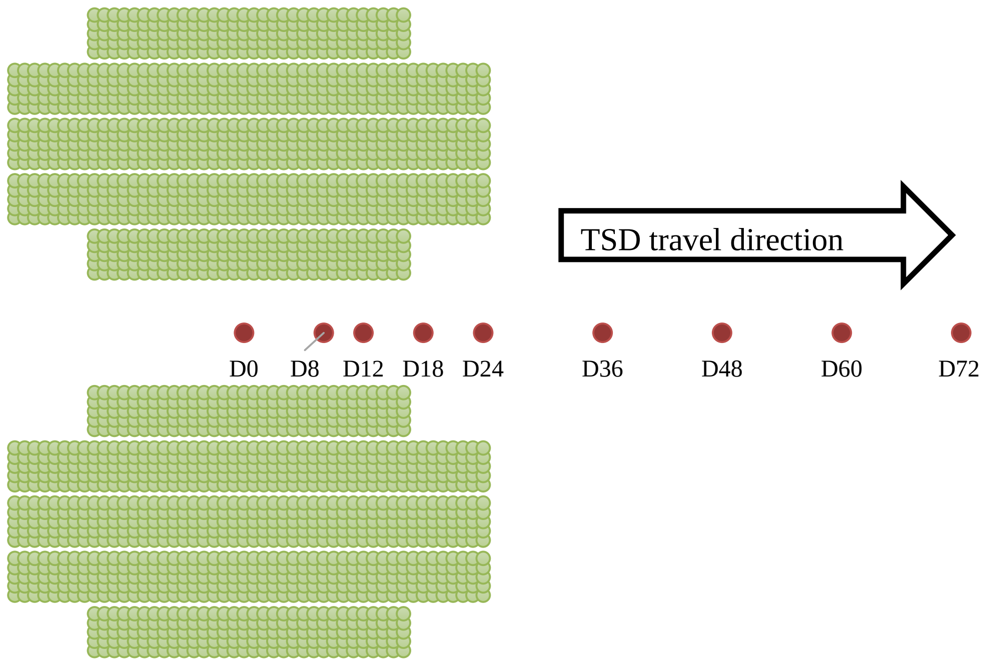
ρ_{200} = % passed the No. 200 sieve.

Base and Subgrade Layer. To characterize the base and subgrade layers both for TSD and FWD, the elastic moduli of these layers were defined in 3D-Move. Moduli were obtained by trial and error to achieve acceptable fitting between measured and calculated deflections. A constant Poisson's ratio and damping ratio were specified for these layers.

Deflection Locations

The locations where pavement responses need to be calculated were specified. For dynamic analysis as in TSD, 3D-Move produces a time-deflection history as an output. Therefore, defining only one response point is sufficient to obtain deflection measurements different distances from the applied load. The far distant deflections from the load can be extracted from the time-deflection history at the specified points of deflection measurements. The time is multiplied by the speed of the vehicle to calculate the distance and thus their corresponding deflections can be obtained from one response point. As shown in Figure 17(a), TSD measures deflections at the midline of the tires and D_0 is the maximum deflection caused by the loaded tires. It is to be noted that past studies have showed that the maximum deflection occurs just behind the mid-point between the tires along the dual-tire-midline.

For the static analysis for FWD, the required number of response points needed to be defined as shown in Figure 17(b). The maximum deflection is assumed to occur at center of the loaded plate, which is noted as D_0.



(a) Response points specified for TSD

(b) Response points specified for FWD

Figure 17
Illustration of response points in 3D-Move

DISCUSSION OF RESULTS

3D-Move models simulating the TSD were developed for the tested sections. Each input was fed into 3D-Move as per the description presented in the methodology section to calculate the corresponding pavement responses. The GPS coordinates of the extracted core locations were used as a reference to compare the 3D-Move outputs to the field measured deflection bowls. Laboratory-measured AC properties are presented in Tables 5 and 6 for two of the test sections. Results for the other sections are presented in Appendix A.

Table 5

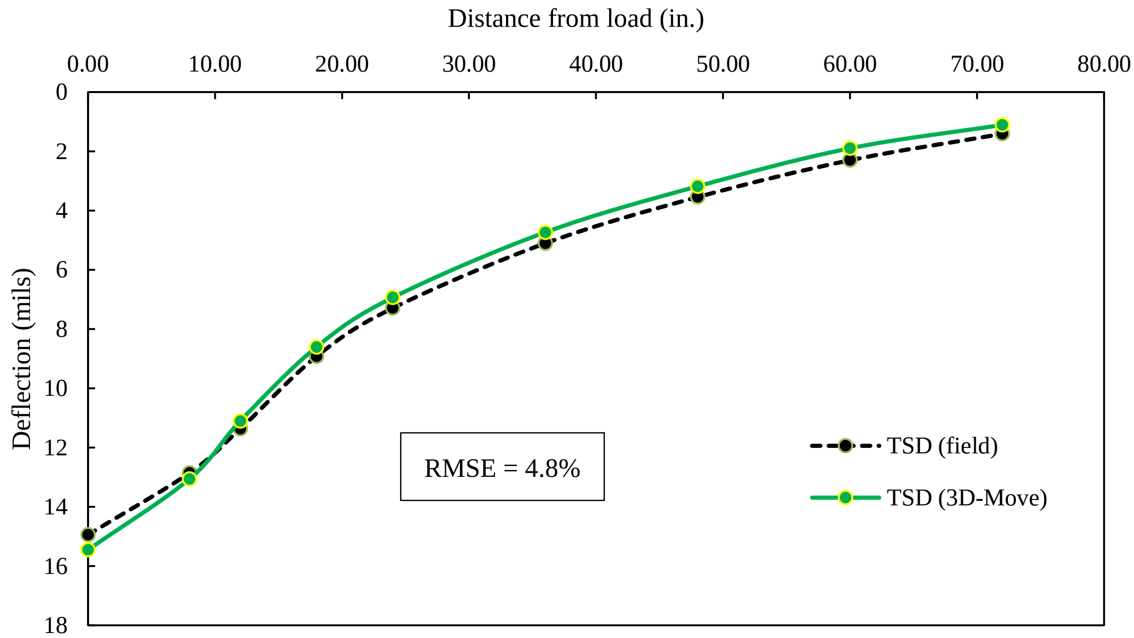
3D-Move inputs for control section 326-01 (LA 594-2)

Control Section 326-01 (LA 594-2) (3D-Move inputs)	TSD speed (mph)		46.4		
	DLC		0.05		
	Thickness (in.)	AC	4.0		
		Base	7.5		
	Moduli (psi)	Base	110000		
		Subgrade	18500		
	AC layer properties	Aggregate gradation	Sieve 3/4 (% retained)		9.6
			Sieve 3/8 (% retained)		27.2
			Sieve 4 (% retained)		47.7
			Sieve 200 (% passed)		5.8
		Effective bitumen content (%)			4.04
		Air void content (%)			6.7
		Unit weight (lbs./in^3)			0.08491
		Superpave binder test data	Temperature (˚F)	G* (psi)	Phase angle (˚)
			39.9	1989.5	35.3
			100.0	37.5	55.4
			129.2	4.2	61.4

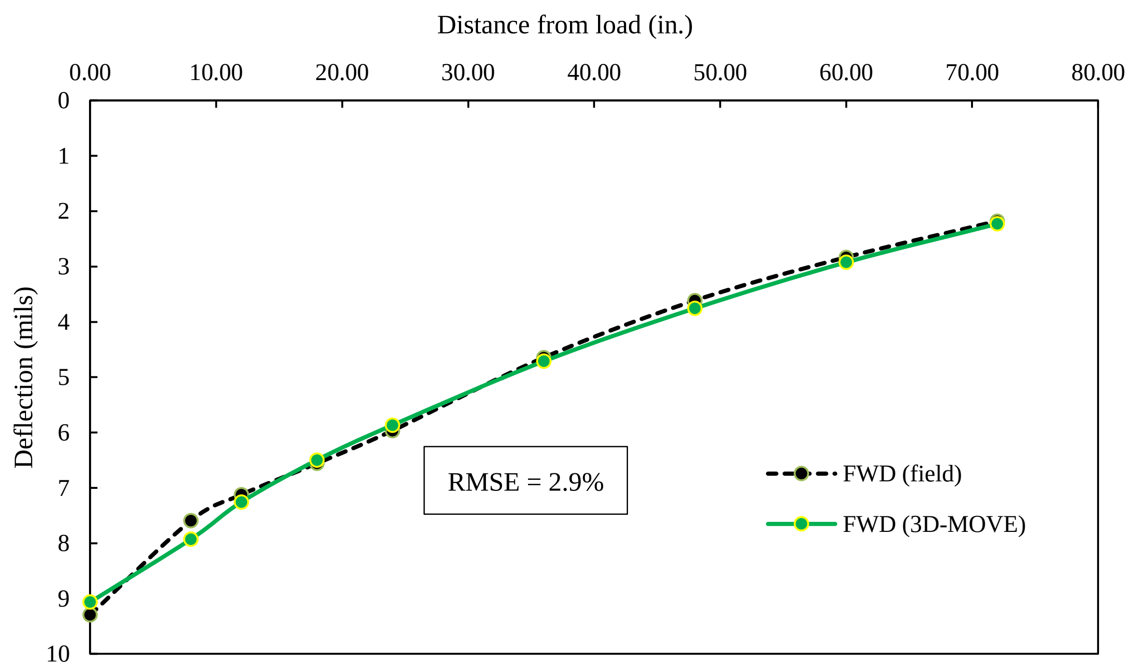
Table 6
3D-Move inputs for control section 069-03 (LA 33)

<table>
<tr><td rowspan="17">Control Section 069-03 (LA 33) (3D-Move inputs)</td><td colspan="2">TSD speed (mph)</td><td colspan="3">45.2</td></tr>
<tr><td colspan="2">DLC</td><td colspan="3">0.085</td></tr>
<tr><td rowspan="2">Thickness (in.)</td><td>AC</td><td colspan="3">6</td></tr>
<tr><td>Base</td><td colspan="3">11</td></tr>
<tr><td rowspan="2">Moduli (psi)</td><td>Base</td><td colspan="3">75000</td></tr>
<tr><td>Subgrade</td><td colspan="3">7200</td></tr>
<tr><td rowspan="11">AC layer properties</td><td rowspan="4">Aggregate gradation</td><td colspan="2">Sieve 3/4 (% retained)</td><td>1.79</td></tr>
<tr><td colspan="2">Sieve 3/8 (% retained)</td><td>12.79</td></tr>
<tr><td colspan="2">Sieve 4 (% retained)</td><td>44.64</td></tr>
<tr><td colspan="2">Sieve 200 (% passed)</td><td>5.3</td></tr>
<tr><td colspan="3">Effective bitumen content (%)</td><td>5.13</td></tr>
<tr><td colspan="3">Air void content (%)</td><td>7.6</td></tr>
<tr><td colspan="3">Unit weight (lbs./in^3)</td><td>0.08298</td></tr>
<tr><td rowspan="4">Superpave binder test data</td><td>Temperature (˚F)</td><td>G* (psi)</td><td>Phase angle (˚)</td></tr>
<tr><td>114.8</td><td>41.11</td><td>69.7</td></tr>
<tr><td>125.6</td><td>23.20</td><td>70.6</td></tr>
<tr><td>136.4</td><td>9.71</td><td>74.1</td></tr>
</table>

As shown in Figures 18(a) and 19(a), 3D-Move produced reasonable results for TSD as compared to the field measurements. When FWD loading was simulated in 3D-Move, the AC layer was assumed to respond elastically to the applied load since the deformation caused by FWD loading is deemed recoverable given the instantaneous nature of FWD loading *[38, 39]*. Thus, throughout the short period of FWD loading, the AC layer was assumed to exhibit an elastic behavior. As shown in Figures 18(b) and 19(b), the comparison between FWD-measured deflections and 3D-Move calculated deflections was acceptable in terms of a Root Mean Square Error (RMSE) less than 5%. Results for the other test sections are presented in Appendix A.

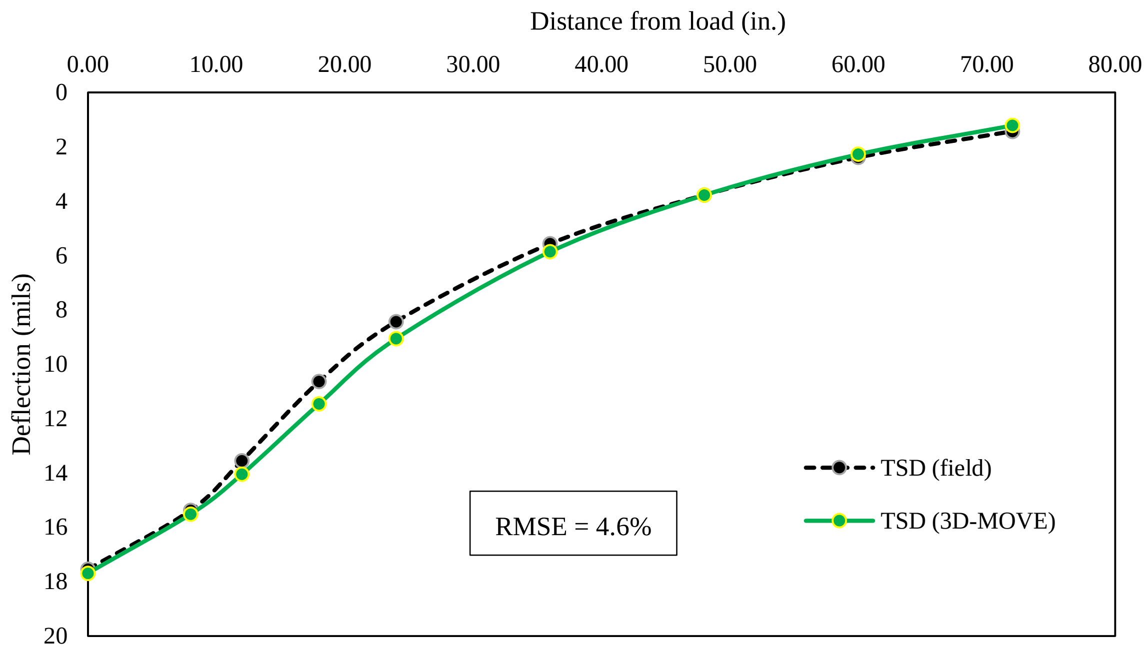


(a) TSD

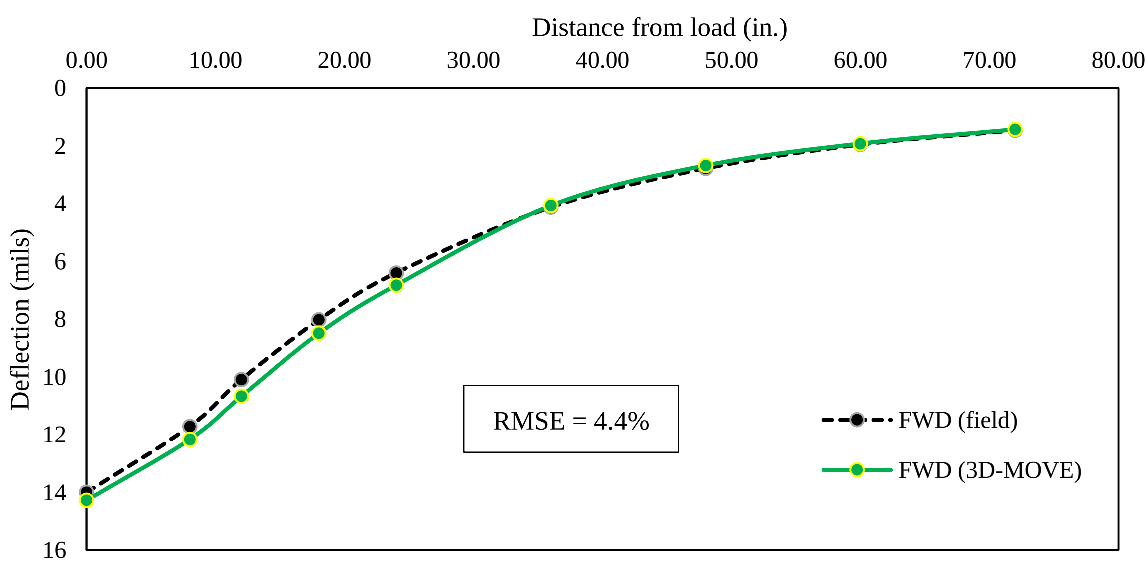


(b) FWD

Figure 18
3D-Move generated deflection bowl validation on section 326-01 (LA 594-2)



(a) TSD



(b) FWD

Figure 19

3D-Move generated deflection bowl validation on section 069-03 (LA 33)

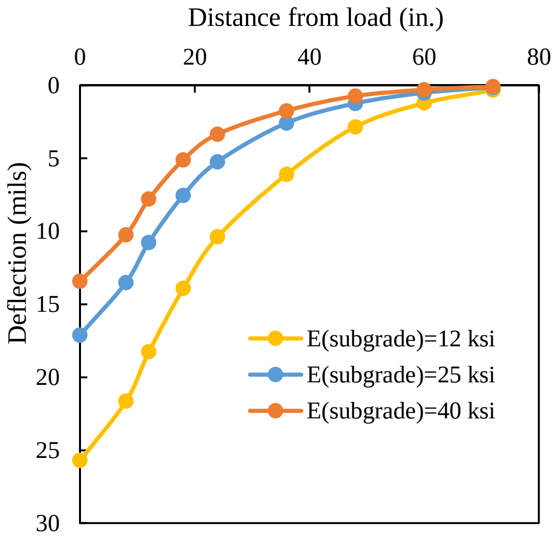
Parametric Study

After the field validation of the 3D-Move models, these models were used to conduct the parametric study. The parametric study included 162 pavement designs of varying layer thicknesses and moduli. Typical pavement design structures used in Louisiana were selected. The cases represent the designs typically used in low-volume and high-volume roads. Each parameter was varied between three different levels; see Table 7.

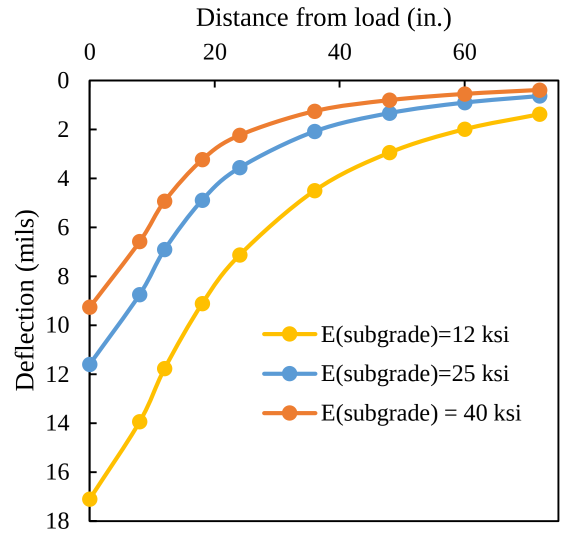
Table 7
Design factors in the parametric study

Thickness (in.)		**Moduli (ksi)**		
AC	Base	AC	Base	Subgrade
3.5	8.5	Dynamic modulus with varying traffic levels, NMAS, and PG grading	50	12
6.0	14		100	25
10	16		200	40

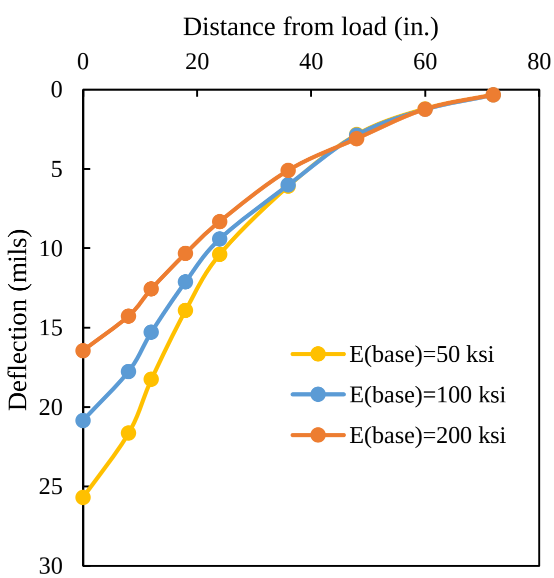
To incorporate the viscoelastic properties of the AC layer, a dynamic modulus dataset developed for typical Louisiana asphalt mixtures by Mohammad et al. was used in this study *[40]*. The dataset consisted of dynamic modulus and phase angle data for different mixtures with varying nominal maximum aggregate size and PG grading under three different traffic levels (i.e., traffic Level 1, Level 2, and Level 3). The mixtures under traffic Level 1 had the lowest PG grade binder and Level 3 had the highest PG grade binder. Three different nominal maximum aggregate sizes (12.5 mm, 19.0 mm, and 25.0 mm) were considered for the AC layers. Since 25.0 mm HMA mix is not recommended as the wearing course in design specifications for Louisiana, the AC layers had a NMAS of 12.5 or 19.0 mm in these cases. For cases with TSD loading, the dynamic modulus data were used to characterize the viscoelastic properties of AC; whereas, for FWD, the elastic modulus of the AC layer was assumed. The modulus at the highest frequency was used as the elastic modulus in the FWD analysis. An illustration of 3D-Move outputs is shown in Figure 20.



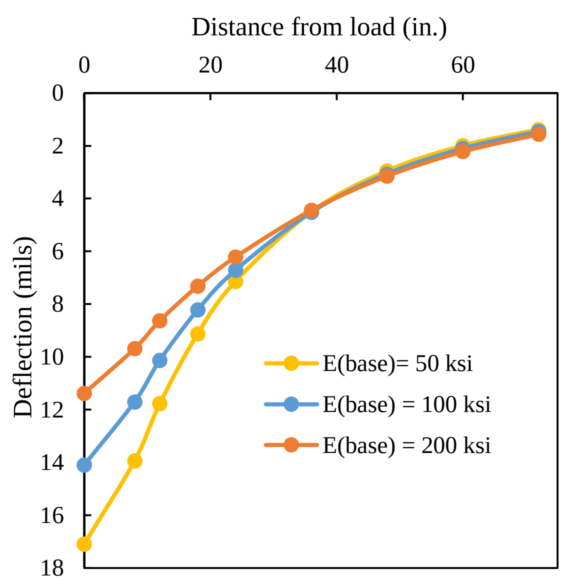
(a) Subgrade Variation (TSD)



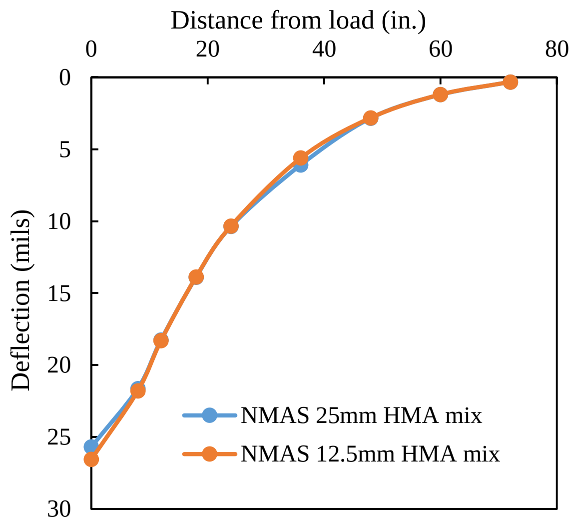
(b) Subgrade Variation (FWD)



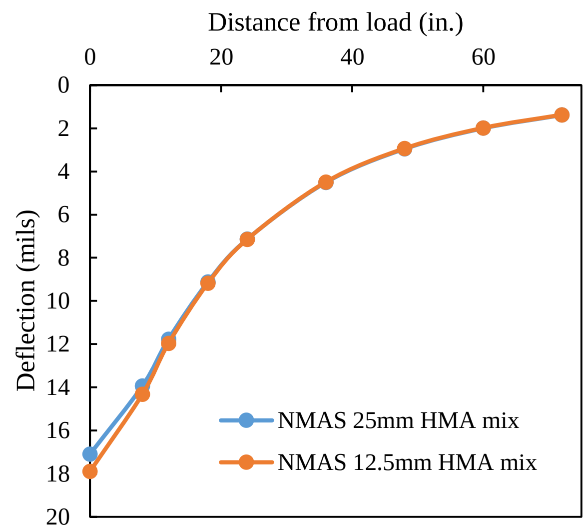
(c) Base variation (TSD)



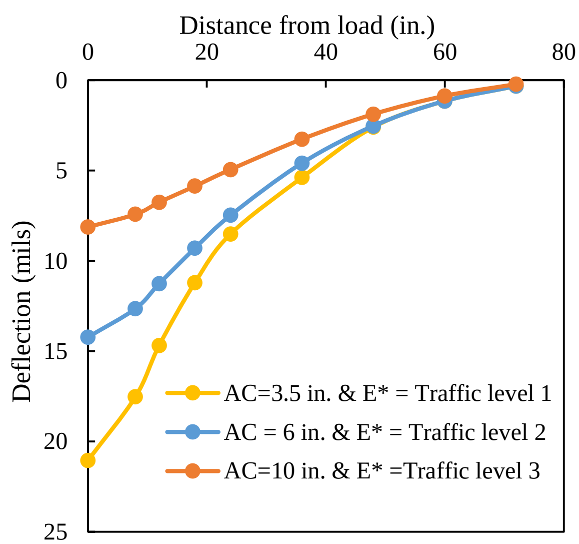
(d) Base variation (FWD)



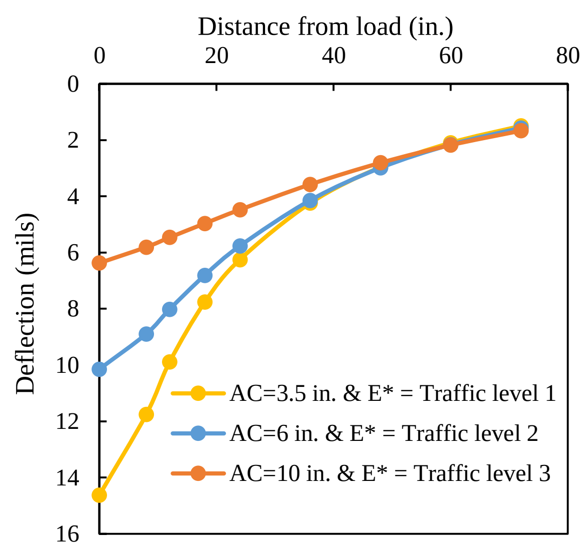
(e) NMAS HMA variation (TSD)



(f) NMAS HMA variation (FWD)



(g) AC thickness & E* variation (TSD)



(h) AC thickness & E* variation (FWD)

Figure 20
3D-Move output for varying pavement conditions

Development of an ANN based Windows Application

An application to convert TSD deflections into FWD deflections was created as a Windows Form application using Visual Basic .Net Framework 4.6.1; see Figure 21. The application uses an artificial neural network as the regression algorithm. The neural network consists of 16 input values: TSD deflections (D_0 to D_{72}), two asphalt pavement thickness, base thickness, two asphalt layer types, base modulus, and subgrade modulus. The neural network has 9 output values: FWD deflections (D_0 to D_{72}). The neural network also contains one hidden layer with 10 nodes. The main interface of the application is structured with fields for all required inputs and all outputs. The “Run Single” option loads the current ANN weights from file, executes a feed-forward ANN analysis on the inputs, and displays the computed outputs. The training portion of the application will generate MS Excel files that store the neural network weights, which must be included in the same directory as the application.

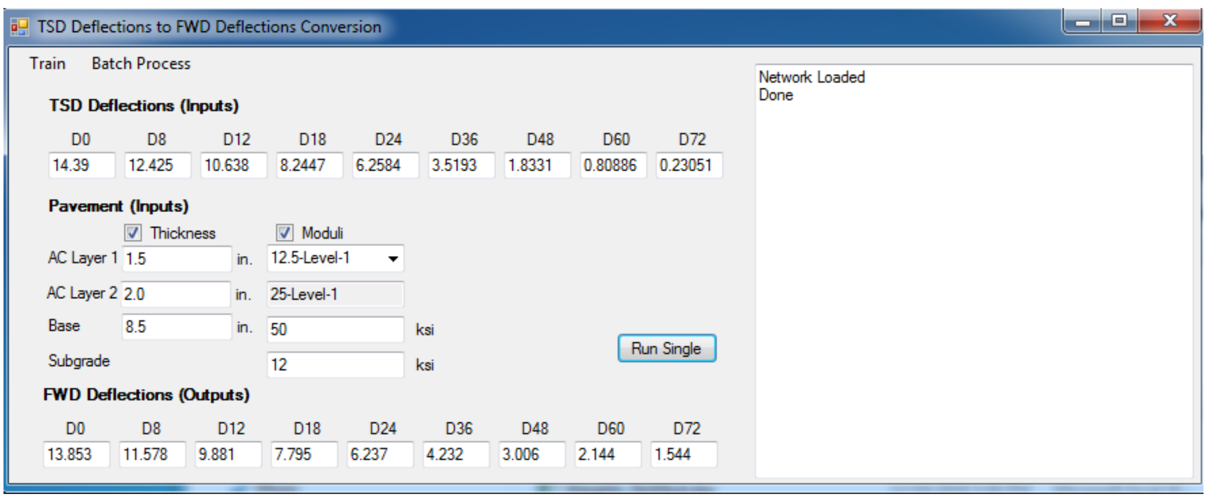


Figure 21
ANN interface – Windows form

The ANN is a feed-forward neural network, which uses the back-propagation algorithm during training. This ANN uses the logistic sigmoidal function as the activation function for all nodes in the ANN. In order to better accommodate for the logistic sigmoidal function outputs between 0 and 1, all input data were divided by 50 during the ANN computations. The ANN outputs were then multiplied by 50 to generate the FWD deflection outputs. The application handles all numeric conversions automatically.

The application allows three different options of analysis: no pavement inputs (the nine input deflections only), only layer thicknesses as pavement inputs, or all pavement inputs (layer thicknesses and layer moduli). A separate weights file can be used for training with each option. The accuracy increases with the additional pavement parameters. Layer thicknesses are often known during typical section design.

The asphalt, base, and subgrade layer thickness and moduli are optional inputs. The asphalt moduli were aggregated into the categories shown in Table 8. A numeric value was assigned to each type in each layer; the meaning of the value assigned is irrelevant to the neural network, as long as the same value is assigned for layers of the same type. The learning algorithm of the ANN accounts for the different types accordingly. The input TSD deflection values are divided by a factor of 50 to normalize for use with the sigmoidal activation function, similarly, the output ANN values are multiplied by 50 to scale back to FWD deflection values. If TSD or FWD values are measured in excess of 50 mils, which is unlikely, the normalization factor may need to be adjusted.

The application includes a feature for training the ANN with the three options listed above. This feature allows for modification or continued training from the existing weights or allows for new weights to be established by seeding random numbers as the initial weights. Figure 22 shows the training window; users can browse to select the desired file for training and specify the number of repetitions that the ANN will perform to establish weights. The application expects the training file to be an MS Excel file with a tab named “Inputs” and a tab named “Outputs” containing the TSD deflections and pavement information as inputs and FWD deflections as outputs respectively. Once training is complete, the application will store the weights in an MS Excel file located in the same directory as the application.

Table 8
Asphalt, base, and subgrade types

Layer	**Type**	**ANN Value**
Asphalt Layer 1	12.5 mm Nominal Aggregate Size – Design Level 1	0.1
Asphalt Layer 1	19.0 mm Nominal Aggregate Size – Design Level 2	0.5
Asphalt Layer 1	19.0 mm Nominal Aggregate Size – Design Level 3	0.9
Asphalt Layer 2	25.0 mm Nominal Aggregate Size – Design Level 1	0.1
Asphalt Layer 2	25.0 mm Nominal Aggregate Size – Design Level 2	0.5
Asphalt Layer 2	25.0 mm Nominal Aggregate Size – Design Level 3	0.9

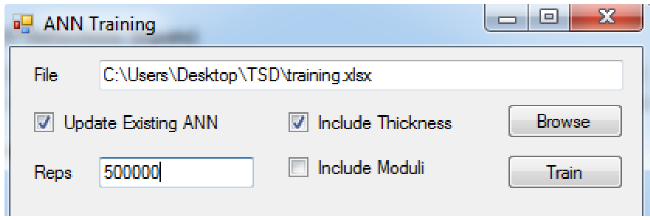


Figure 22
ANN training window

The application has also a feature to process a spreadsheet of TSD results at one time, shown in Figure 23. The batch process form allows users to specify the input file and output file. The input file must be an MS Excel file with a tab named “Inputs” containing the TSD deflections and pavement information. The batch process will output the FWD deflections into the specified output file. If “Output .mdb file” is checked, an additional MS Access database file will be created in the format of a typical FWD file from ELMOD software.

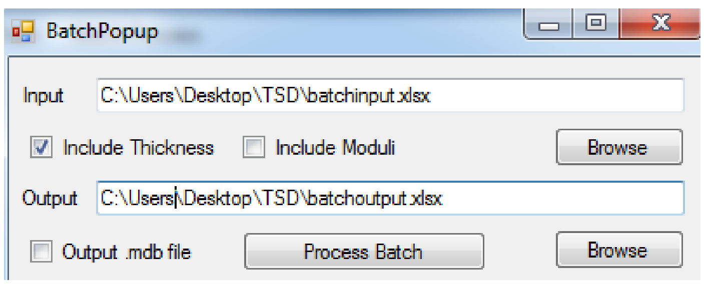
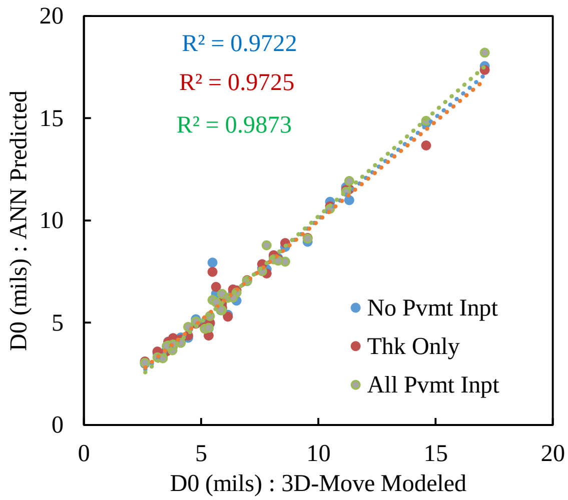


Figure 23
Batch process window

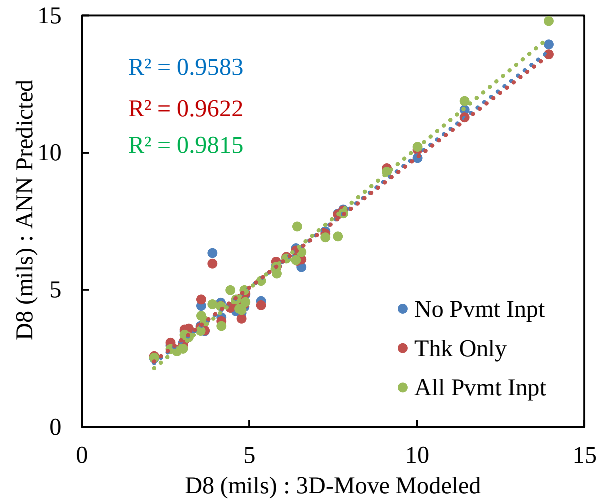
ANN Training

The neural network was trained using cases based on the models developed with 3D-Move. A total of 163 cases were created, 80% of which were randomly selected and used for training the ANN. The remaining cases were used for validation of the ANN model. The training file took about 9 minutes to process 500,000 iterations on a 3.20 GHz Intel Core i7 with 16.0 GB of RAM.

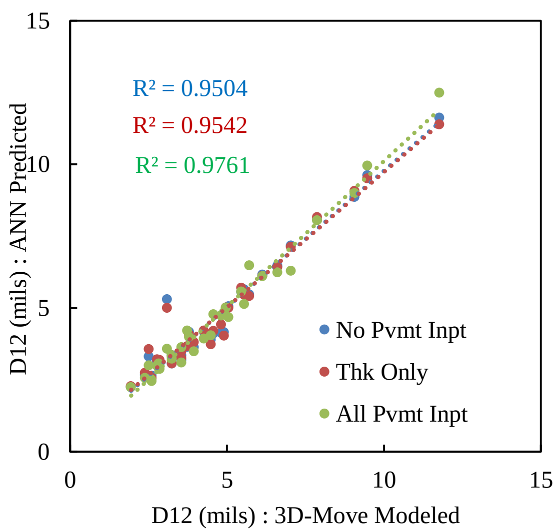
Figure 24 shows the validation results of the ANN predicted FWD deflections plotted against the 3D-Move modeled FWD deflections for the same TSD input cases. Using no pavement inputs (the nine input deflections), all deflection comparisons showed a coefficient of determination (R^2) of 0.85 or greater. Using only the layer thickness as pavement inputs, all deflection comparisons showed a coefficient of determination (R^2) of 0.88 or greater. Using both layer thickness and layer moduli as pavement inputs, all deflection comparisons showed a coefficient of determination (R^2) of 0.97 or greater. The MATLAB code is provided in Appendix B for future use of this model.



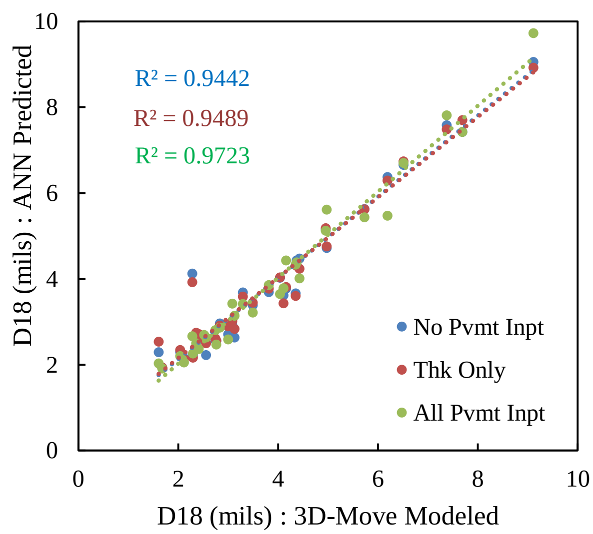
(a) D_0 prediction



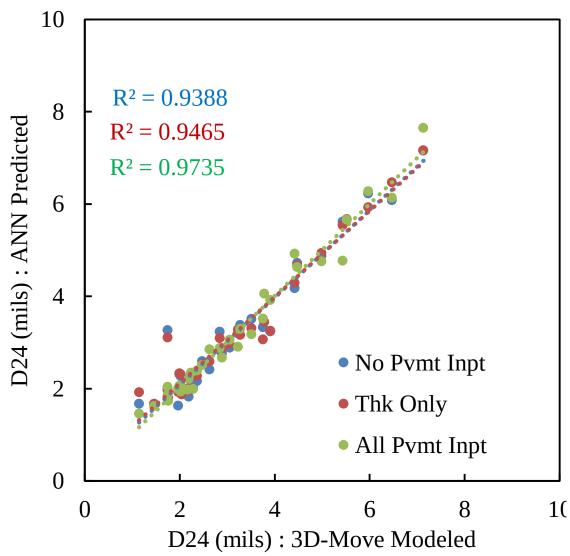
(b) D_8 prediction



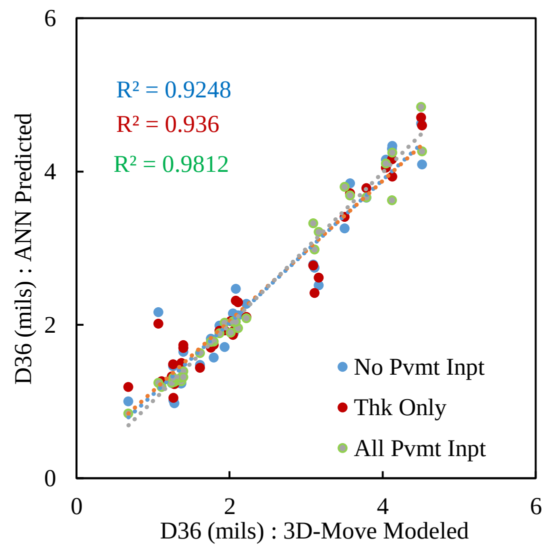
(c) D_{12} prediction



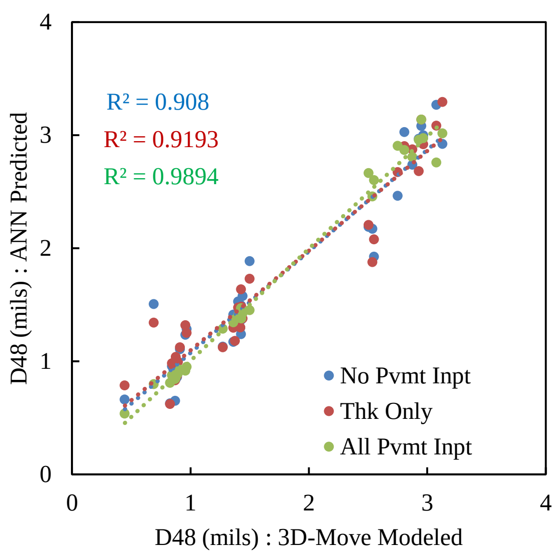
(d) D_{18} prediction



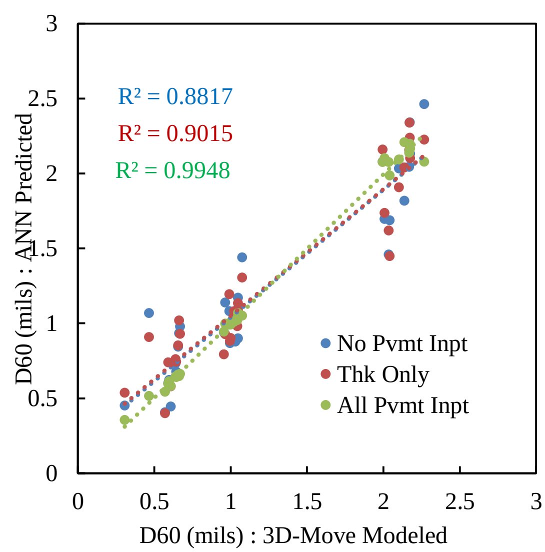
(e) D_{24} prediction



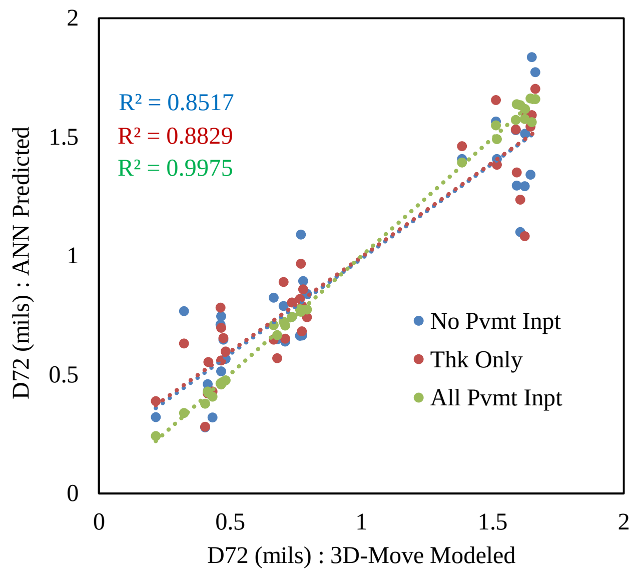
(f) D_{36} prediction



(g) D_{48} prediction



(h) D_{60} prediction



(i) D_{72} prediction

Figure 24

ANN predicted deflections evaluation

CONCLUSIONS

This study presented the development of a comprehensive mechanistic methodology that can incorporate TSD measured deflections into backcalculation analysis of layer moduli. The analysis was based on the use of 3D-Move into estimating the pavement response under traffic loading, which was supported by field testing program of FWD and TSD as well as the laboratory testing of in-situ material properties. The developed methodology is mechanistic-based as it considers the realistic representation of moving load and material characteristics in 3D-Move. The conclusions of the study are as follows:

- 3D-Move models for FWD and TSD were developed such that they can accurately estimate the surface deflections when compared to field measurements. Since 3D-Move is mainly developed for simulating tire loading, it was generally more accurate to model the TSD loading than the impulse nature of FWD loading.

- 3D-Move estimation of surface deflection bowls under TSD loading was in good agreement with field measurements. In general, 3D-Move can successfully predict the surface deflections under the load if the layer moduli are properly defined both for TSD and FWD loading.

- A Windows-based software application was developed using ANN as the regression algorithm to convert TSD deflection to the corresponding FWD deflections. This tool will greatly reduce the computational effort to backcalculate layer moduli from TSD measurements.

RECOMMENDATIONS

Based on the results and findings of this project, the study recommends the following future studies:

- A backcalculation tool should be developed to directly utilize TSD measurements into the backcalculation analysis without the need for conversion.
- Research should develop a methodology to incorporate TSD measurements into PMS decision-making processes and in pavement design.
- Cost-effectiveness of TSD measurements should be investigated in future studies.

ACRONYMS, ABBREVIATIONS, AND SYMBOLS

AC	Asphalt Concrete
ANN	Artificial Neural Network
ARRB	Australian Road Research Board
COV	Co-efficient of Variation
D_0	Maximum Surface Deflection
DOTD	Louisiana Department of Transportation and Development
FHWA	Federal Highway Administration
ft.	foot (feet)
FWD	Falling Weight Deflectometer
HMA	Hot Mix Asphalt
in.	in.(es)
ksi	Kilo pounds per square in.
lbs.	pound(s)
LTRC	Louisiana Transportation Research Center
LVR	Low Volume Road
NHS	National Highway of Significance
PMS	Pavement Management System
psi	Pounds per square in.
RMSE	Root Mean Square Error
RWD	Rolling Wheel Deflectometer
SHRP	Strategic Highway Research Program
SHS	State Highway of Significance
TSD	Traffic Speed Deflectometer
TSDD	Traffic Speed Deflection Devices

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APPENDIX A

Table 9

3D-Move inputs for control section 324-02 (LA 616)

<table>
<tr><td rowspan="16">Control Section 324-02 (LA 616)
(3D-Move inputs)</td><td colspan="2">TSD speed (mph)</td><td colspan="3">45.3</td></tr>
<tr><td colspan="2">DLC</td><td colspan="3">0.086</td></tr>
<tr><td rowspan="2">Thickness (in.)</td><td>AC</td><td colspan="3">5</td></tr>
<tr><td>Base</td><td colspan="3">5</td></tr>
<tr><td rowspan="2">Moduli (psi)</td><td>Base</td><td colspan="3">57000</td></tr>
<tr><td>Subgrade</td><td colspan="3">15400</td></tr>
<tr><td rowspan="10">AC layer properties</td><td rowspan="4">Aggregate gradation</td><td colspan="2">Sieve 3/4 (% retained)</td><td>0.73</td></tr>
<tr><td colspan="2">Sieve 3/8 (% retained)</td><td>9.71</td></tr>
<tr><td colspan="2">Sieve 4 (% retained)</td><td>37.13</td></tr>
<tr><td colspan="2">Sieve 200 (% passed)</td><td>7.4</td></tr>
<tr><td colspan="3">Effective bitumen content (%)</td><td>3.90023116</td></tr>
<tr><td colspan="3">Air void content (%)</td><td>2.3</td></tr>
<tr><td colspan="3">Unit weight (lbs./in^3)</td><td>0.0885365</td></tr>
<tr><td rowspan="4">Superpave binder test data</td><td>Temperature (˚F)</td><td>G*, (psi)</td><td>Phase angle, (˚)</td></tr>
<tr><td>39.92</td><td>5163.83</td><td>29.21</td></tr>
<tr><td>100.04</td><td>72.3196</td><td>66.04</td></tr>
<tr><td></td><td></td><td>129.2</td><td>4.52922</td><td>76.35</td></tr>
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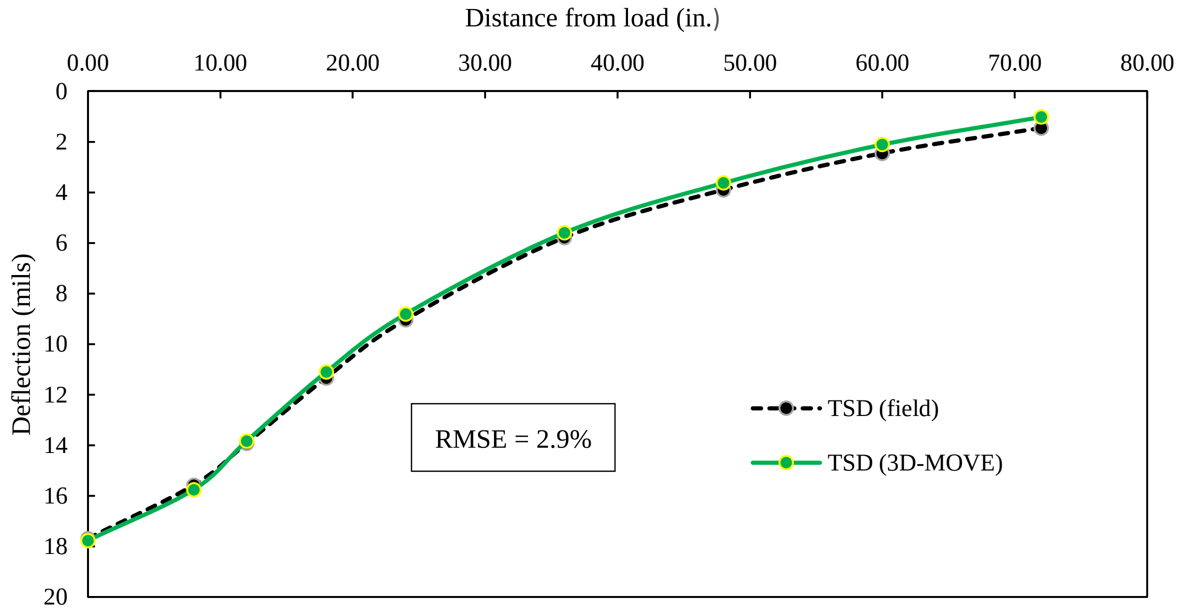
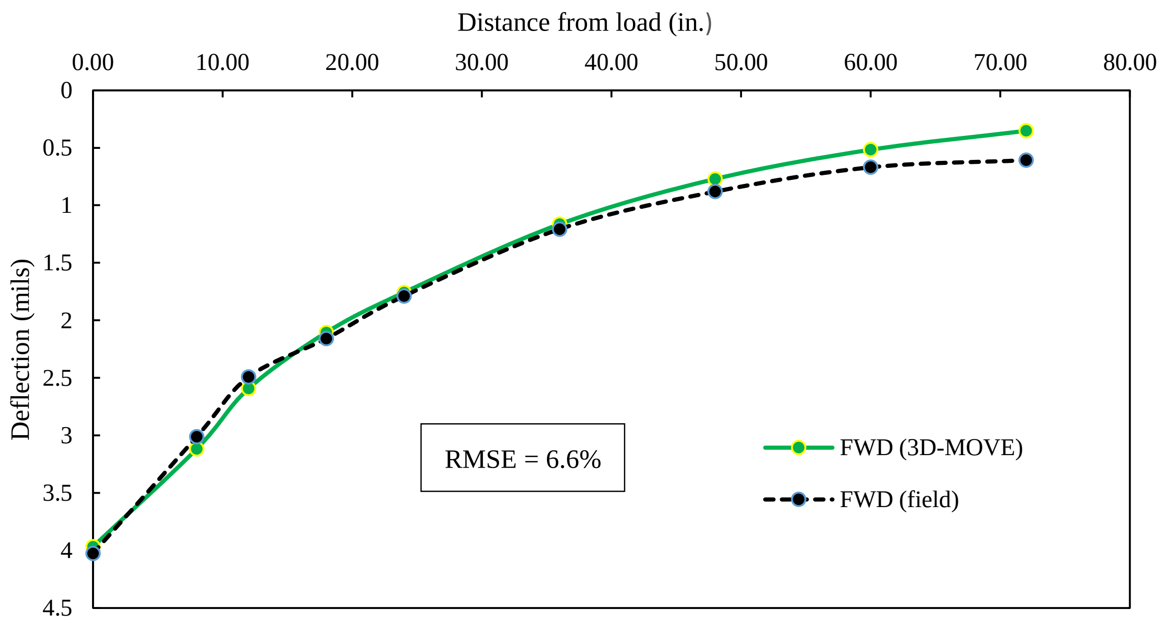


(a) TSD



(b) FWD

Figure 25
3D-Move generated deflection bowl validation on section 324-02 (LA 616)

Table 10
3D-Move inputs for control section 862-14 (LA 589)

<table>
<tr><td rowspan="19">Control Section 862-14 (LA 589) (3D-Move inputs)</td><td colspan="2">TSD speed (mph)</td><td colspan="3">49.9</td></tr>
<tr><td colspan="2">DLC</td><td colspan="3">0.127</td></tr>
<tr><td rowspan="2">Thickness (in.)</td><td>AC</td><td colspan="3">2.5</td></tr>
<tr><td>Base</td><td colspan="3">15.75</td></tr>
<tr><td rowspan="2">Moduli (psi)</td><td>Base</td><td colspan="3">125000</td></tr>
<tr><td>Subgrade</td><td colspan="3">26000</td></tr>
<tr><td rowspan="11">AC layer properties</td><td rowspan="4">Aggregate gradation</td><td colspan="2">Sieve 3/4 (% retained)</td><td>0.82</td></tr>
<tr><td colspan="2">Sieve 3/8 (% retained)</td><td>10.00</td></tr>
<tr><td colspan="2">Sieve 4 (% retained)</td><td>36.67</td></tr>
<tr><td colspan="2">Sieve 200 (% passed)</td><td>5.8</td></tr>
<tr><td colspan="3">Effective bitumen content (%)</td><td>4.32</td></tr>
<tr><td colspan="3">Air void content (%)</td><td>5.9</td></tr>
<tr><td colspan="3">Unit weight (lbs./in^3)</td><td>0.084663286</td></tr>
<tr><td rowspan="4">Superpave binder test data</td><td>Temperature (˚F)</td><td>G*, (psi)</td><td>Phase angle, (˚)</td></tr>
<tr><td>39.92</td><td>3044.89</td><td>19.92</td></tr>
<tr><td>100.04</td><td>78.16</td><td>36.06</td></tr>
<tr><td>129.2</td><td>6.02</td><td>62.65</td></tr>
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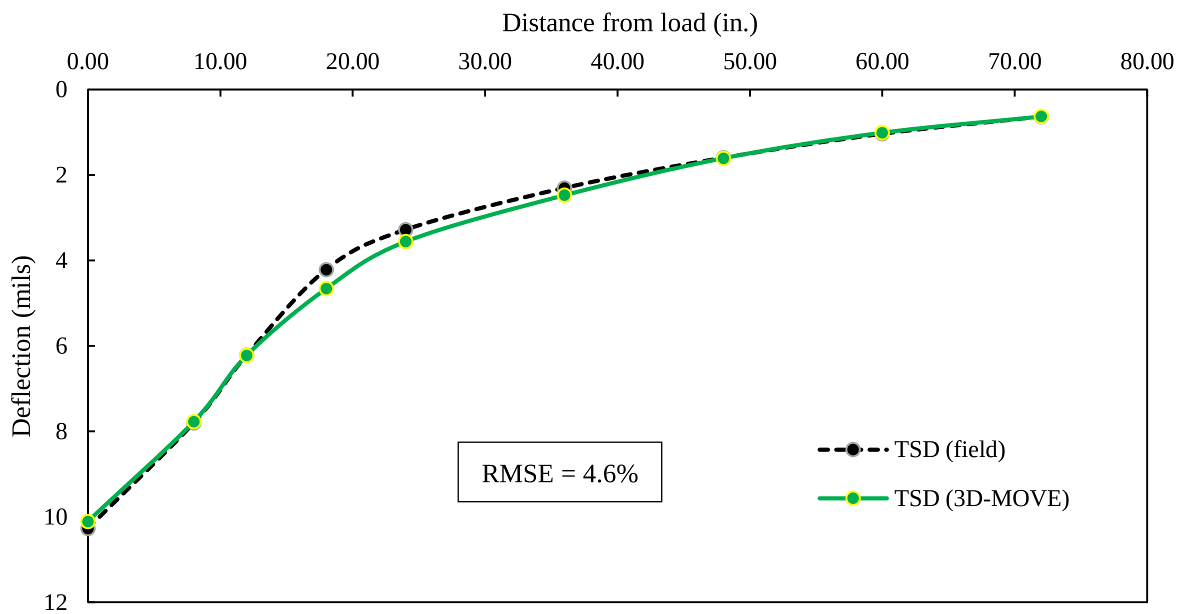
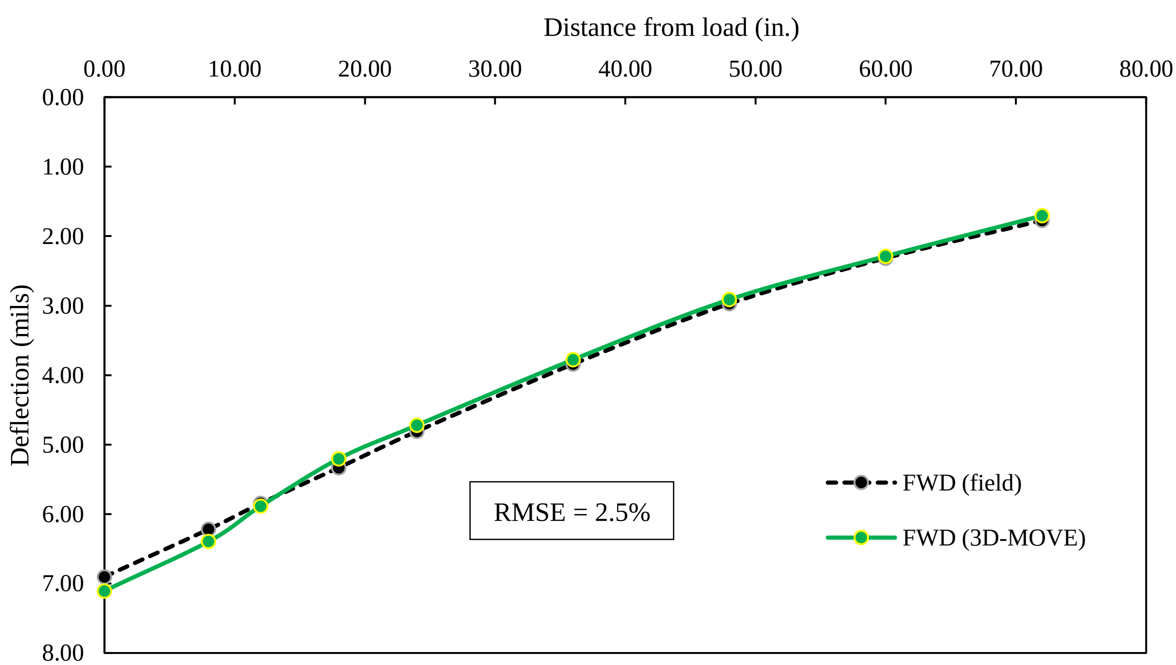


(a) TSD



(b) FWD

Figure 26

3D-Move generated deflection bowl validation on section 862-14 (LA 589)

Table 11

3D-Move inputs for control section 326-01 (LA 594-1)

<table>
<tr><td rowspan="19">Control Section 326-01 (LA 594-1) (3D-Move inputs)</td><td colspan="2">TSD speed (mph)</td><td colspan="3">31.1</td></tr>
<tr><td colspan="2">DLC</td><td colspan="3">0.040</td></tr>
<tr><td rowspan="3">Thickness (in.)</td><td>AC</td><td colspan="3">8.5</td></tr>
<tr><td>Base</td><td colspan="3">8</td></tr>
<tr><td>Sub-base</td><td colspan="3">19.5</td></tr>
<tr><td rowspan="3">Moduli (psi)</td><td>Base</td><td colspan="3">73000</td></tr>
<tr><td>Sub-base</td><td colspan="3">24500</td></tr>
<tr><td>Subgrade</td><td colspan="3">12700</td></tr>
<tr><td rowspan="11">AC layer properties</td><td rowspan="4">Aggregate gradation</td><td colspan="2">Sieve 3/4 (% retained)</td><td>2.0</td></tr>
<tr><td colspan="2">Sieve 3/8 (% retained)</td><td>17.15</td></tr>
<tr><td colspan="2">Sieve 4 (% retained)</td><td>56.57</td></tr>
<tr><td colspan="2">Sieve 200 (% passed)</td><td>7.5</td></tr>
<tr><td colspan="3">Effective bitumen content (%)</td><td>5.20</td></tr>
<tr><td colspan="3">Air void content (%)</td><td>8.0</td></tr>
<tr><td colspan="3">Unit weight (lbs./in^3)</td><td>0.0827788</td></tr>
<tr><td rowspan="4">Superpave binder test data</td><td>Temperature (˚F)</td><td>G*, (psi)</td><td>Phase angle, (˚)</td></tr>
<tr><td>39.92</td><td>4707.00</td><td>24.42</td></tr>
<tr><td>100.04</td><td>207.88</td><td>51.53</td></tr>
<tr><td>129.2</td><td>16.13</td><td>61.09</td></tr>
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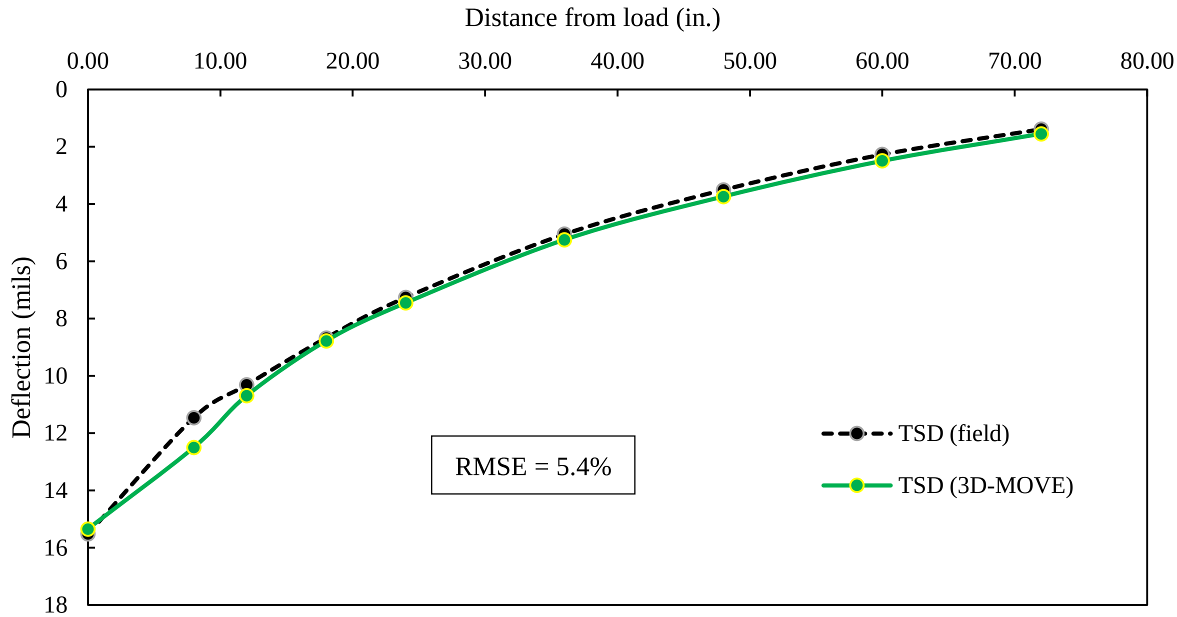
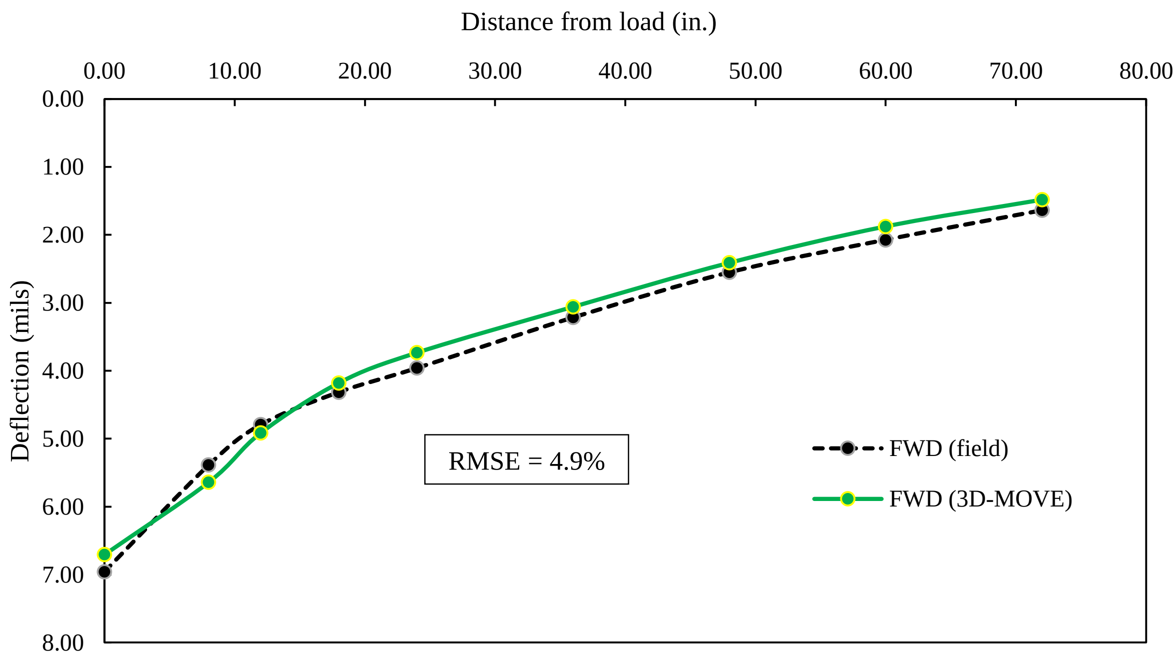


(a) TSD



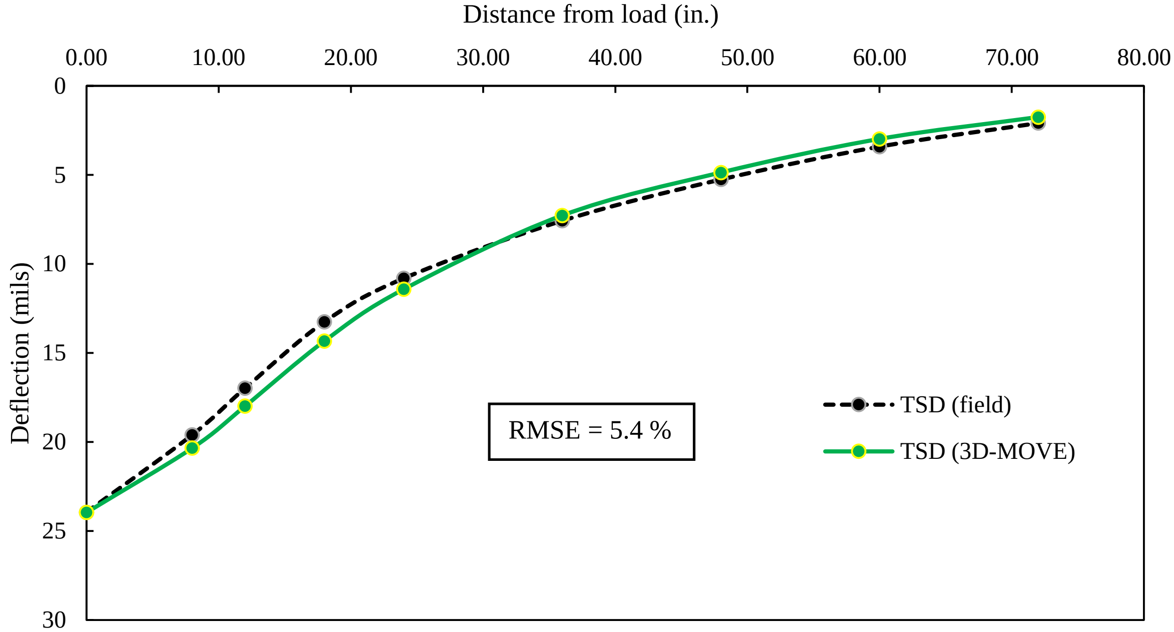
(b) FWD

Figure 27
3D-Move generated deflection bowl validation on section 326-01 (LA 594-1)

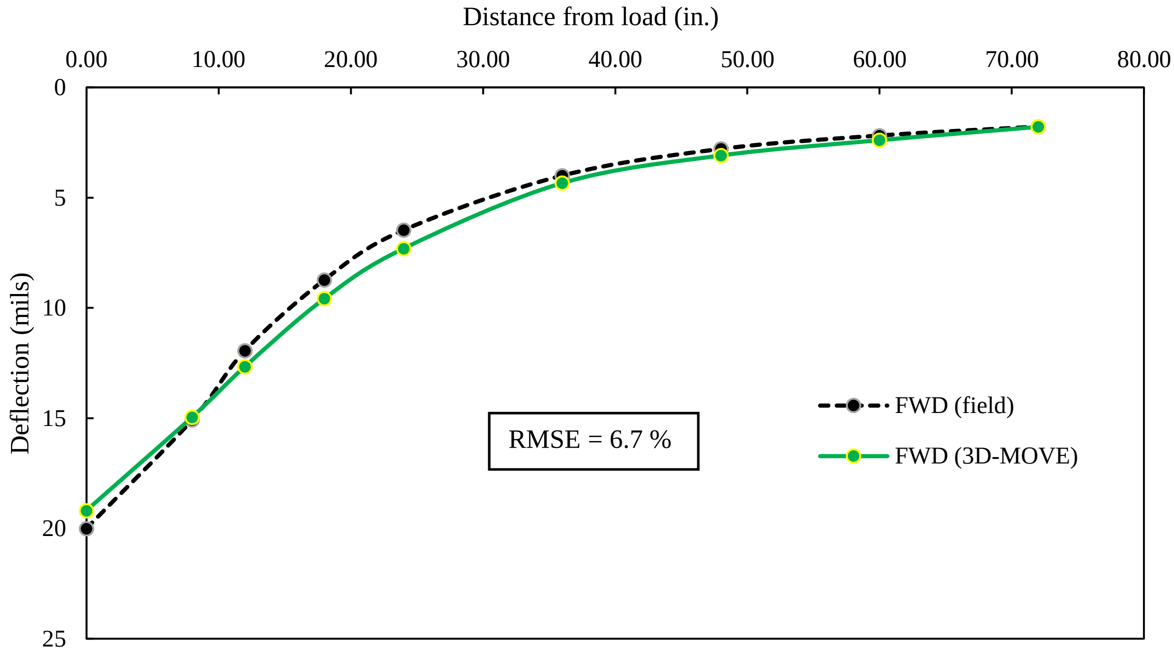
Table 12

3D-Move inputs for control section 333-03 (LA 582)

<table>
<tr><td rowspan="17">Control Section 333-03 (LA 582) (3D-Move inputs)</td><td colspan="2">TSD speed (mph)</td><td colspan="3">45.8</td></tr>
<tr><td colspan="2">DLC</td><td colspan="3">0.169</td></tr>
<tr><td rowspan="2">Thickness (in.)</td><td>AC</td><td colspan="3">4</td></tr>
<tr><td>Base</td><td colspan="3">8.5</td></tr>
<tr><td rowspan="2">Moduli (psi)</td><td>Base</td><td colspan="3">36500</td></tr>
<tr><td>Subgrade</td><td colspan="3">10300</td></tr>
<tr><td rowspan="11">AC layer properties</td><td rowspan="4">Aggregate gradation</td><td colspan="2">Sieve 3/4 (% retained)</td><td>1.2</td></tr>
<tr><td colspan="2">Sieve 3/8 (% retained)</td><td>10.87</td></tr>
<tr><td colspan="2">Sieve 4 (% retained)</td><td>36.54</td></tr>
<tr><td colspan="2">Sieve 200 (% passed)</td><td>6.8</td></tr>
<tr><td colspan="3">Effective bitumen content (%)</td><td>4.06</td></tr>
<tr><td colspan="3">Air void content (%)</td><td>5.5</td></tr>
<tr><td colspan="3">Unit weight (lbs./in^3)</td><td>0.08530839</td></tr>
<tr><td rowspan="4">Superpave binder test data</td><td>Temperature (˚F)</td><td>G*, (psi)</td><td>Phase angle, (˚)</td></tr>
<tr><td>39.92</td><td>6210.549351</td><td>24.245</td></tr>
<tr><td>100.04</td><td>249.9389598</td><td>51.84</td></tr>
<tr><td>129.2</td><td>21.78294684</td><td>63.715</td></tr>
</table>



(a) TSD

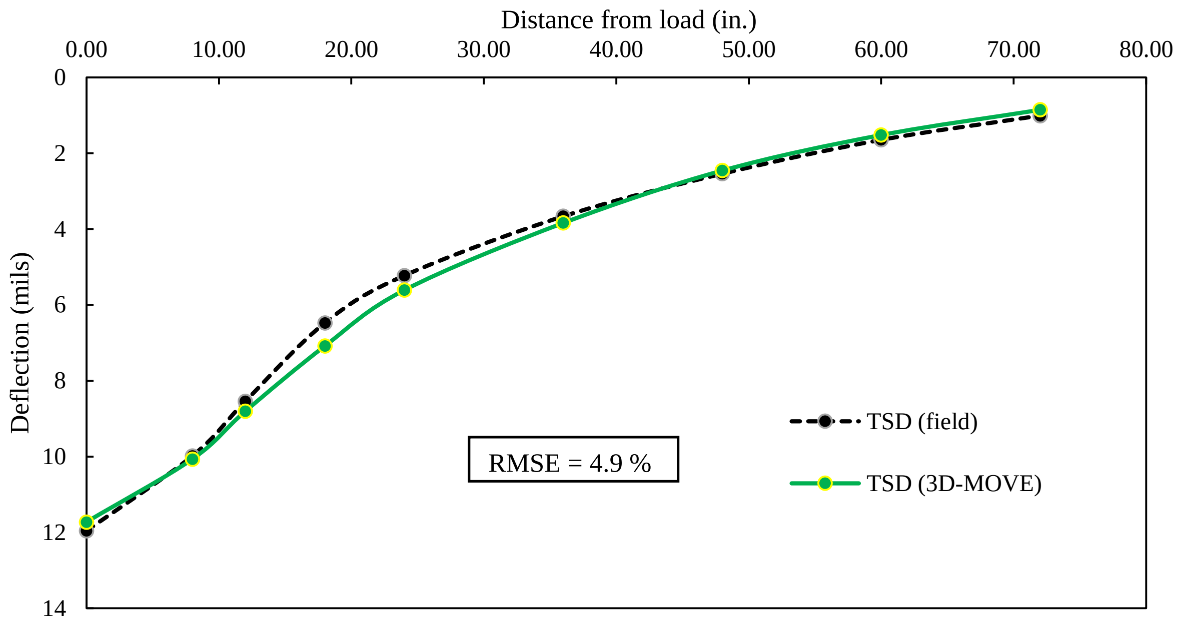


(b) FWD

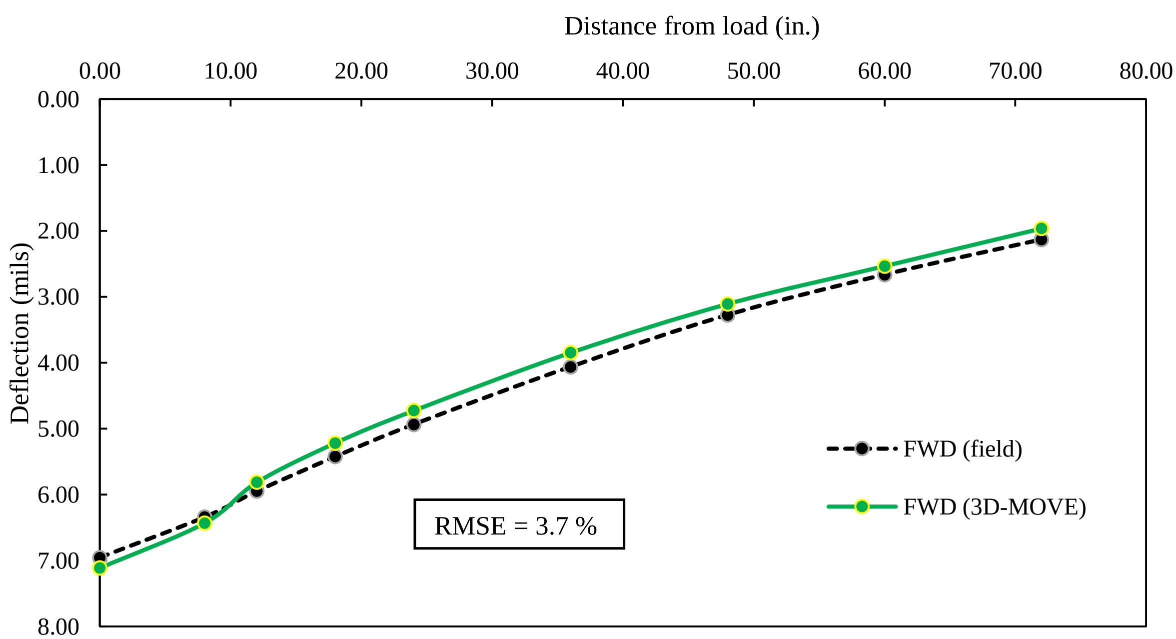
Figure 28
3D-Move generated deflection bowl validation on section 333-03 (LA 582)

Table 13
3D-Move inputs for control section 071-02 (US 425)

<table>
<tr><td rowspan="19">Control Section 071-02 (US 425)
(3D-Move inputs)</td><td colspan="2">TSD speed (mph)</td><td colspan="3">51.8</td></tr>
<tr><td colspan="2">DLC</td><td colspan="3">0.055</td></tr>
<tr><td rowspan="2">Thickness (in.)</td><td>AC</td><td colspan="3">8.5</td></tr>
<tr><td>Base</td><td colspan="3">8.5</td></tr>
<tr><td rowspan="2">Moduli (psi)</td><td>Base</td><td colspan="3">69200</td></tr>
<tr><td>Subgrade</td><td colspan="3">18800</td></tr>
<tr><td rowspan="13">AC layer properties</td><td rowspan="4">Aggregate gradation</td><td colspan="2">Sieve 3/4 (% retained)</td><td>3.1</td></tr>
<tr><td colspan="2">Sieve 3/8 (% retained)</td><td>17.18</td></tr>
<tr><td colspan="2">Sieve 4 (% retained)</td><td>41.11</td></tr>
<tr><td colspan="2">Sieve 200 (% passed)</td><td>6.4</td></tr>
<tr><td colspan="3">Effective bitumen content (%)</td><td>6.14</td></tr>
<tr><td colspan="3">Air void content (%)</td><td>5.6</td></tr>
<tr><td colspan="3">Unit weight (lbs./in^3)</td><td>0.08523783</td></tr>
<tr><td rowspan="4">Superpave binder test data</td><td>Temperature (˚F)</td><td>G*, (psi)</td><td>Phase angle, (˚)</td></tr>
<tr><td>114.8</td><td>44.96</td><td>69.9</td></tr>
<tr><td>125.6</td><td>37.93</td><td>63.9</td></tr>
<tr><td>136.4</td><td>22.26</td><td>62.8</td></tr>
</table>



(a) TSD



(b) FWD

Figure 29

3D-Move generated deflection bowl validation on section 071-02 (US 425)

APPENDIX B

MATLAB Code for the proposed ANN model

```
Public Class Dendrite

'Dendrite is the connection between neurons, this object is used to store the weight
between each neuron.

    Dim _weight As Double

    Property Weight As Double
        Get
            Return _weight
        End Get
        Set(value As Double)
            _weight = value
        End Set
    End Property

    Public Sub New()    'Assigns random value as initial weight
        Randomize
        Me.Weight = (Rnd * 2) - 1
    End Sub
End Class


Public Class Neuron

'Neuron is the nodes of each layer.  Neurons recieve input signals from layers above and
convert to output values that are passed to layers below.

    Dim _dendrites As New List(Of Dendrite)  'list of dendrites corresponding to layer
above
    Dim _dendriteCount As Integer
    Dim _bias As Double                      'weight applied as a bias
    Dim _value As Double                     'output value of the neuron
    Dim _delta As Double                     'error correction value used for back
propogation

    Public Property Dendrites As List(Of Dendrite)
        Get
            Return _dendrites
        End Get
        Set(value As List(Of Dendrite))
```

```vb
            _dendrites = value
        End Set
    End Property

    Public Property Bias As Double
        Get
            Return _bias
        End Get
        Set(value As Double)
            _bias = value
        End Set
    End Property

    Public Property Value As Double
        Get
            Return _value
        End Get
        Set(value As Double)
            _value = value
        End Set
    End Property

    Public Property Delta As Double
        Get
            Return _delta
        End Get
        Set(value As Double)
            _delta = value
        End Set
    End Property

    Public ReadOnly Property DendriteCount As Integer
        Get
            Return _dendrites.Count
        End Get
    End Property

    Public Sub New()  'Assigns random value as initial bias
        Randomize
        Me.Bias = (Rnd * 2) - 1
    End Sub
End Class
```

```
Public Class Layer
    'Layer is a collection of neurons

    Dim _neurons As New List(Of Neuron)
    Dim _neuronCount As Integer

    Public Property Neurons As List(Of Neuron)
        Get
            Return _neurons
        End Get
        Set(value As List(Of Neuron))
            _neurons = value
        End Set
    End Property

    Public ReadOnly Property NeuronCount As Integer
        Get
            Return _neurons.Count
        End Get
    End Property

    Public Sub New(neuronNum As Integer)
        _neuronCount = neuronNum
    End Sub
End Class

Public Class NeuralNetwork
    'Neural Network represents the ANN as a whole, a collection of layers

    Dim _layers As New List(Of Layer)
    Dim _learningRate As Double

    Public Property Layers As List(Of Layer)
        Get
            Return _layers
        End Get
        Set(value As List(Of Layer))
            _layers = value
        End Set
    End Property

    Public Property LearningRate As Double
        Get
            Return _learningRate
        End Get
```

```
        Set(value As Double)
            _learningRate = value
        End Set
    End Property

    Public ReadOnly Property LayerCount As Integer
        Get
            Return _layers.Count
        End Get
    End Property

    Sub New(LearningRate As Double, nLayers As List(Of Integer))
        'initializes with learning rate and number of nodes at each layer (including
input and output layers)

        If nLayers.Count < 2 Then Exit Sub

        Me.LearningRate = LearningRate

        For ii As Integer = 0 To nLayers.Count - 1

            Dim l As Layer = New Layer(nLayers(ii) - 1)
            Me.Layers.Add(l)

            For jj As Integer = 0 To nLayers(ii) - 1
                l.Neurons.Add(New Neuron())
            Next

            For Each n As Neuron In l.Neurons
                If ii = 0 Then n.Bias = 0

                If ii > 0 Then
                    For k As Integer = 0 To nLayers(ii - 1) - 1
                        n.Dendrites.Add(New Dendrite)
                    Next
                End If

            Next

        Next
    End Sub


    Private Function Activation(ByVal value As Double) As Double
```

```
        Return (1 / (1 + Math.Exp(Value * -1)))   'sigmoidal

    End Function

    Function Execute(inputs As List(Of Double)) As List(Of Double)
        'Forward feed algorithm, top down

        If inputs.Count <> Me.Layers(0).NeuronCount Then
            Return Nothing
        End If

        For ii As Integer = 0 To Me.LayerCount - 1
            Dim curLayer As Layer = Me.Layers(ii)

            For jj As Integer = 0 To curLayer.NeuronCount - 1
                Dim curNeuron As Neuron = curLayer.Neurons(jj)

                If ii = 0 Then
                    curNeuron.Value = inputs(jj)
                Else
                    curNeuron.Value = 0
                    For k = 0 To Me.Layers(ii - 1).NeuronCount - 1
                        curNeuron.Value = curNeuron.Value + Me.Layers(ii -
1).Neurons(k).Value * curNeuron.Dendrites(k).Weight
                    Next k

                    curNeuron.Value = Activation(curNeuron.Value + curNeuron.Bias)
                End If

            Next
        Next

        Dim outputs As New List(Of Double)
        Dim la As Layer = Me.Layers(Me.LayerCount - 1)
        For ii As Integer = 0 To la.NeuronCount - 1
            outputs.Add(la.Neurons(ii).Value)
        Next

        Return outputs
    End Function

    Public Function Train(inputs As List(Of Double), outputs As List(Of Double)) As
Boolean
        'Back propogation algorithm, bottom up
```

```
        If inputs.Count <> Me.Layers(0).NeuronCount Or outputs.Count <>
Me.Layers(Me.LayerCount - 1).NeuronCount Then
            Return False
        End If

        Execute(inputs) 'uses feed-forward to compute outputs

        'loop to compute deltas (error adjustments) for each neuron
        For ii = 0 To Me.Layers(Me.LayerCount - 1).NeuronCount - 1
            Dim curNeuron As Neuron = Me.Layers(Me.LayerCount - 1).Neurons(ii)

            curNeuron.Delta = curNeuron.Value * (1 - curNeuron.Value) * (outputs(ii) -
curNeuron.Value) 'error computation

            For jj = Me.LayerCount - 2 To 1 Step -1
                For kk = 0 To Me.Layers(jj).NeuronCount - 1
                    Dim iNeuron As Neuron = Me.Layers(jj).Neurons(kk)

                    iNeuron.Delta = iNeuron.Value *
                                    (1 - iNeuron.Value) * Me.Layers(jj +
1).Neurons(ii).Dendrites(kk).Weight *
                                    Me.Layers(jj + 1).Neurons(ii).Delta
                Next kk
            Next jj
        Next ii

        'loop to apply deltas (adjusted by learning rate) to each weight
        For ii = Me.LayerCount - 1 To 0 Step -1
            For jj = 0 To Me.Layers(ii).NeuronCount - 1
                Dim iNeuron As Neuron = Me.Layers(ii).Neurons(jj)
                iNeuron.Bias = iNeuron.Bias + (Me.LearningRate * iNeuron.Delta)

                For kk = 0 To iNeuron.DendriteCount - 1
                    iNeuron.Dendrites(kk).Weight = iNeuron.Dendrites(kk).Weight +
(Me.LearningRate * Me.Layers(ii - 1).Neurons(kk).Value * iNeuron.Delta)
                Next kk
            Next jj
        Next ii

        Return True
    End Function

    Public Sub SetInitialWeights(ByVal dt As DataTable)
```

```
        'Used to apply existing weights pulled from file

        Dim oANNFrameList As New List(Of ANNFrame)
        oANNFrameList = ANNFrame.ConvertDataTabletoANNFrame(dt)
        Dim f As Integer = 0

        For ii As Integer = 0 To Me.LayerCount - 1
            Dim curLayer As Layer = Me.Layers(ii)

            For jj As Integer = 0 To curLayer.NeuronCount - 1
                Dim curNeuron As Neuron = curLayer.Neurons(jj)

                If ii = 0 Then
                    'ignore input layer
                Else
                    curNeuron.Bias = oANNFrameList(f).Bias
                    For k = 0 To Me.Layers(ii - 1).NeuronCount - 1
                        curNeuron.Dendrites(k).Weight = oANNFrameList(f).Weight
                        f = f + 1
                    Next k
                End If
            Next
        Next
    End Sub

End Class


Private Sub btnRunSingle_Click(sender As Object, e As EventArgs) Handles
btnRunSingle.Click

        Dim network As NeuralNetwork

        Dim layerList As New List(Of Integer)
        With layerList
            .Add(14)
            .Add(10)
            .Add(9)
        End With

        network = New NeuralNetwork(0.5, layerList)

        Dim dt As DataTable = ExcelIO.ImportWeightsExcel(Directory.GetCurrentDirectory +
"\Weights.xlsx")
        network.SetInitialWeights(dt)
```

```
txtOutput.Text = txtOutput.Text + "Network Loaded" + vbCrLf

Dim oANNDataList As List(Of ANNData) = New List(Of ANNData)
Dim oANNData As New ANNData

oANNData.Inputs.Add(AsDouble(txtTSTD0.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD8.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD12.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD18.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD24.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD36.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD48.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD60.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtTSTD72.Text,0)/50)

oANNData.Inputs.Add(AsDouble(txtLayer1Thick.Text,0)/50)
oANNData.Inputs.Add(AsDouble(txtBaseThick.Text,0)/50)

Select Case ddlACModulus.SelectedItem
    Case "12.5 Level 1"
        oANNData.Inputs.Add(0.1)
    Case "19 Level 2"
        oANNData.Inputs.Add(0.3)
    Case "19 Level 3"
        oANNData.Inputs.Add(0.4)
    Case "25 Level 1"
        oANNData.Inputs.Add(0.6)
    Case "25 Level 2"
        oANNData.Inputs.Add(0.7)
    Case "25 Level 3"
        oANNData.Inputs.Add(0.8)
    Case Else
        oANNData.Inputs.Add(0)
End Select

Select Case ddlBase.SelectedItem
    Case "Cement-Stabilized"
        oANNData.Inputs.Add(0.1)
    Case "Stone"
        oANNData.Inputs.Add(0.5)
    Case "Cement-Treated"
        oANNData.Inputs.Add(0.9)
    Case Else
        oANNData.Inputs.Add(0)
```

```
        End Select

        Select Case ddlSubgrade.SelectedItem
            Case "Low"
                oANNData.Inputs.Add(0.2)
            Case "Medium"
                oANNData.Inputs.Add(0.4)
            Case "High"
                oANNData.Inputs.Add(0.6)
            Case "Very High"
                oANNData.Inputs.Add(0.8)
        End Select

        oANNData.Outputs = network.Execute(oANNData.Inputs)

        txtFWDD0.Text   = Math.Round(oANNData.Outputs(0) * 50,3)
        txtFWDD8.Text   = Math.Round(oANNData.Outputs(1) * 50,3)
        txtFWDD12.Text  = Math.Round(oANNData.Outputs(2) * 50,3)
        txtFWDD18.Text  = Math.Round(oANNData.Outputs(3) * 50,3)
        txtFWDD24.Text  = Math.Round(oANNData.Outputs(4) * 50,3)
        txtFWDD36.Text  = Math.Round(oANNData.Outputs(5) * 50,3)
        txtFWDD48.Text  = Math.Round(oANNData.Outputs(6) * 50,3)
        txtFWDD60.Text  = Math.Round(oANNData.Outputs(7) * 50,3)
        txtFWDD72.Text  = Math.Round(oANNData.Outputs(8) * 50,3)


    End Sub
```

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