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Development of a Methodology to Backcalculate Pavement Layer Moduli Using the Traffic Speed Deflectometer

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ABSTRACT: 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. The objective of this study was to develop a methodology to incorporate Traffic Speed Deflectometer (TSD) measurements in the backcalculation analysis. To achieve this objective, TSD and FWD measurements were used to train and to validate an Artificial Neural Network (ANN) model that would convert TSD deflection measurements to FWD deflection measurements. The ANN model showed acceptable accuracy with a coefficient of determination of 0.81 and a good agreement between the backcalculated moduli from FWD and TSD measurements. Evaluation of the model showed that the backcalculated layer moduli from TSD could be used in pavement analysis and in structural health monitoring with a reasonable level of accuracy.

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Keywords: Traffic Speed Deflectometer, backcalculation, Falling Weight Deflectometer, 3D Move, deflection velocity

INTRODUCTION

Backcalculation of pavement layer moduli using Non-Destructive Testing (NDT) measurements is a commonly accepted procedure for evaluating pavement structural conditions (Saltan and Terzi 2008). Structural conditions evaluation of in-service pavements is essential to estimate pavement Remaining Service Life (RSL) and to select the most appropriate maintenance and rehabilitation activities (Goktepe et al. 2006). Backcalculation of pavement layer moduli is also necessary to calculate pavement responses under traffic loads (i.e., stresses, strains, and deflections) through both the layered elastic theory and the finite element method. In addition, overlay design in the new American Association of State Highway and Transportation Officials (AASHTO) Pavement Mechanistic-Empirical (ME) design guide requires defining the backcalculated layer moduli of in-service pavements (Haider et al. 2014). The backcalculated layer moduli can also be used in structural health monitoring of in-service pavement structures (Elbagalati et al. 2016).

The Falling Weight Deflectometer (FWD) is the most widely used NDT device for evaluating the structural conditions of in-situ pavements and in conducting backcalculation analysis; however, the stationary nature of the device limits its production rate, which reduces its applicability at the network level (Leiva-Villacorta and Timm 2013; Rada et al. 2011). The static nature of FWD disturbs traffic, requires traffic control, and increases accidents risk (Flintsch et al. 2013). To overcome these limitations, a number of continuous deflection measurement devices were introduced in

recent years. A recent Strategic Highway Research Program 2 (SHRP2) study identified the Traffic Speed Deflectometer (TSD) and the Rolling Wheel Deflectometer (RWD) as the most promising continuous deflection measurement devices (Flintsch et al. 2013). TSD allows the measurement of the complete deflection basin; therefore, it could be used in backcalculation analysis (Muller and Roberts 2013).

OBJECTIVES

The objective of this study was to develop a methodology to incorporate TSD measurements in the backcalculation analysis of flexible pavements. TSD and FWD measurements were obtained from two testing programs conducted in District 05 of Louisiana and at the MnROAD test facility in Minnesota. These measurements were used to develop and validate an Artificial Neural Network (ANN) model for predicting the corresponding FWD deflection basin (TSD*) from TSD measurements. ELMOD6 software was then used to conduct the backcalculation analysis based on TSD and FWD measurements. Evaluation and validation of the proposed methodology was conducted by comparing the critical pavement responses and structural health conditions based on the backcalculated moduli from FWD and TSD measurements.

BACKGROUND

Traffic Speed Deflectometer

The traffic speed deflectometer is a continuous deflection measurement device mounted on an articulated truck that uses a rear axle of 100 kN (22,000 lbs.) to load the pavement structure. The operational speed of the device is up to 80 km/h (50 mph); the TSD concept is based on the measurement of the deflection velocity rather than the absolute

deflection of the road surface (Flintsch et al. 2013; Rada et al. 2011). The TSD utilizes Doppler lasers to measure the vertical surface deflection velocity at six points along the midline of the rear right dual tires and in front of the axle at 100, 200, 300, 600, 900, and 1500 mm (Nasimifar et al. 2016; Zofka et al. 2014). Various testing programs have been conducted recently to evaluate TSD measurements in comparison to the FWD in Australia, Denmark, France, South Africa, UK, and the United States (Kannemeyer et al. 2014; Krarup et al. 2006; Soren et al. 2008; Roberts et al. 2014; Sivaneswaran 2014; Katicha and Flintsch 2014).

In Denmark, the TSD showed productivity as high as 3,300 km of the road network in 10 working days. In addition, a methodology was developed to calculate the structure curvature index (SCI_{300}) and the maximum deflection under the center of the load (Krarup et al. 2006; Soren et al. 2008). In Australia, the ability of the TSD to distinguish between damaged and sound pavements was demonstrated, and the measurements showed good correlation between the TSD and the FWD center deflection with a coefficient of determination (R^2) of 0.7 (Roberts et al. 2014). Recent testing programs conducted in the United States found acceptable repeatability of TSD measurements (Sivaneswaran 2014; Katicha and Flintsch 2014). In addition, the TSD was identified along with the RWD as the most promising continuous deflection measurement devices (Flintsch et al. 2013).

Differences between TSD and FWD

In a recent study conducted by Katicha et al., it was concluded that the differences between the TSD and FWD measurements could be significant (Katicha et al. 2013). The effect of surface irregularities on the TSD measurements, the difference in the load

contact area between the two devices, and the difference in materials transferring the load (rubber plate for the FWD and dual-tire assembly for the TSD), are all factors which may have led to the aforementioned differences (Katicha et al. 2013; Rada and Nazarian 2011).

3D Move Software

The University of Nevada at Reno (UNR) developed a software for the analysis of pavement structures known as 3D Move (Siddharthan et al. 2000). The software is based on continuum mechanics and utilizes Fourier transformation technique (Fakhri et al. 2013). Several studies have been conducted to evaluate the applicability of the software in calculating pavement responses (Siddharthan et al. 1996; Siddharthan et al. 2002, Siddharthan et al. 2002). Recently, the software was adopted by researchers in various applications in the field of pavement analysis and design (Leiva-Villacorta and Timm 2013; Sivaneswaran 2014).

Artificial Neural Networks (ANN)

An ANN consists of a genetic flexible training algorithm that learns how to make decisions based on given information (Kim et al. 2014). ANNs provide robust models that can be continuously updated as new data become available. In addition, they can be used in databases with either large or relatively small amount of data (Plati et al. 2015). ANNs' use has increased tremendously in solving complex civil engineering problems in the last three decades (Ceylan et al. 2014). They can be very generic, accurate, and convenient mathematical models with high capability in simulating numerical model components (Karlaftis and Vlahogianni 2011). However, ANN's limitations include the

need for large data set for fitting and validation, they are considered by some researchers as a black box with no explanatory power, and they can be misused when linear regression can be more suited for simpler problems.

DATA DESCRIPTION

Louisiana

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 on 13 control sections (each section was approximately 1.5-mile-long) at 0.01-mile interval. FWD measurements were simultaneously collected for the same control sections at 0.1-mile interval for the evaluation and comparison with TSD measurements. The difference between the TSD and the FWD sampling rates is due to the fact that TSD measurements are continuous while FWD measurements are discrete.

Minnesota

FWD and TSD measurements were collected at the MnROAD test facility in Minnesota (Sivaneswaran 2014). The surveyed road network consisted of a 3.5-mile (5.6-km) mainline roadway (ML) with 45 sections and with “live traffic” as part of Interstate 94 near Albertville, Minnesota. In addition, a 2.5-mile (4-km) closed-loop low volume roadway (LVR) consisting of 28 sections was surveyed; the section lengths were typically about 500 ft. (150 m). Furthermore, an 18-mile (29-km) segment in Wright

County was tested. This segment was located about 20 miles (32 km) from the MnROAD facility and was divided into nine sections.

Tested sections varied between flexible pavements, rigid pavements, and composite pavement sections. Yet, the present study focused on the use of TSD measurements in conducting backcalculation analysis of flexible pavements. Therefore, only TSD and FWD data collected on flexible pavements were considered. The flexible pavement test segments in which both FWD and TSD measurements were conducted consisted of 16 sections. Table 1 provides the layer thicknesses of the pavement segments analyzed in the study.

METHODOLOGY

Figure 1 presents a general overview of the proposed methodology to utilize TSD measurements in backcalculation analysis. First, the TSD deflection velocity measurements were used to calculate the deflection basins through numerical integration. Then, both TSD and the FWD deflections were shifted to a reference temperature of 20°C. An ANN model with a topology of 9-5-9 was developed to establish a correlation between FWD and TSD deflection basins. Based on this correlation, the corresponding FWD deflection basin (TSD*) was calculated using the corrected TSD deflection basin. TSD* could be regarded as the deflection basin that would have been measured if FWD was used instead of the TSD in the survey process. TSD* obtained from the ANN model was then used to conduct the backcalculation analysis using ELMOD-6 software. For validation purpose, the developed procedure was evaluated by utilizing the backcalculated layer moduli in stress-strain analysis, fatigue life prediction, and structural health monitoring.

Calculation of TSD Deflection Basin

The TSD device measures the pavement surface deflection velocity at six points in front of the rear axle at 100, 200, 300, 600, 900, and 1500 mm. Muller and Roberts developed a methodology, referred to as the Area under the Curve (AUTC), to numerically integrate the deflection velocity measurements and to calculate pavement surface deflections (Muller and Roberts 2013). First, the deflection velocity is divided by the horizontal travel speed of the vehicle to get the deflection slope. Second, the correlation between the deflection slope and the offset distance from the rear axle is plotted. Third, a curve is fitted through the six points assuming the slope at distance 0 is equal to 0 and the slope at a distance of 3500 mm is equal to 0. Finally, the deflection basin is produced by incrementally adding up the area under the curve as shown in Figure 2. In the present study, the deflection values were calculated at distances of 0, 203, 305, 457, 610, 914, 1219, 1524, and 1829 mm from the rear axle, to match the radial offsets of the FWD geophones.

The aforementioned method was adopted by Australia and New Zealand for TSD analysis (Muller and Roberts 2013). Developing a multiple parameter model to calculate the TSD deflections from the TSD deflection slopes, would allow more accurate calculation of the TSD deflection basin (Zofka et al. 2014). The current methodology assumes that the pavement deflection at a distance of 3500mm to be equal to zero, which may not always be true especially for pavement structures on very soft soils.

Temperature Correction

The FWD and TSD deflections were corrected to a reference temperature of 20°C. The Bells equation was used to calculate the pavement temperature at asphalt mid-depth (Lukanen et al. 2000). Kim and Park concluded that no influence of the load level was found on the temperature correction procedure; therefore, their methodology was assumed to be valid for correcting both TSD and FWD measurements. Pavement surface deflections at radial offsets were then corrected using the methodology described in Equations (1) to (3) based on the approach proposed by Kim and Park as follows (Kim and park 2002):

$$\lambda_w = \frac{w_{T0}}{w_T} \tag{1}$$

where,
 w_{T0} = the deflection corrected to temperature T_0 ;
 w_T = the deflection at temperature T ; and
 λ_w = the deflection correction factor calculated as follows:

$$\lambda_w = 10^{-C(H_{ac})(T-T_0)} \tag{2}$$

where,
 H_{ac} = Asphalt Concrete (AC) layer thickness; and
 C = Regression constant calculated as follows:

$$C = -Ar + C_0 \tag{3}$$

where,
 r = the radial distance from the center of the load; and
 $A = -5.26 \times 10^{-8}$ for U.S. Central Region; and
 $C_0 = 5.80 \times 10^{-5}$ for U.S. Central Region.

RESULTS AND ANALYSIS

Artificial Neural Network Model

There are clear differences between TSD and FWD such as in the loading mechanisms and dynamics. Furthermore, backcalculation programs (e.g., Modulus and ELMOD) assume the load to be applied through a circular plate, which is not the case with the TSD. Therefore, the use of the TSD deflection “as is” in a backcalculation software would not be accurate. In the present study, an ANN model was developed to convert the TSD deflection basin to a corresponding FWD deflection basin (TSD*).

A multilayered feed-forward ANN using a back-propagation error algorithm was selected with a tan-sigmoid transfer function. The network architecture consisted of three layers; an input layer of 9 neurons; a hidden layer of 5 neurons; and a target layer of 9 neurons. The input layer was fed with the TSD deflections at the nine aforementioned radial distances while the target layer was fed with the FWD measurements normalized to a load level of 40 kN (9,000 lbs.), as shown in Figure 3. A total of 1,467 data points were used in the model development phase. The data were divided into 70% for training, 15% for validation, and 15% for testing. Training was halted when the validation set error stopped decreasing to avoid overfitting and to increase the generalization ability of the network. The testing data set had no effect on the training so it was used to provide an independent measure of the network performance.

The output of the ANN model is the corresponding corrected and normalized at 40 kN FWD deflection basin based on the TSD measurements, which were referred to as TSD*. The regression plots of the ANN model for the training, validation, testing, and

overall sets are shown in Figure 4. All data processing was performed off-line using a commercial software package (MATLAB R2013a, The MathWorks, Inc.). Table 2 shows the root mean square error (RMSE %) values at each radial offset, which were calculated as follows:

$$RMSE = 100 * \sqrt{\frac{\sum_1^n [\text{Predicted value (TSD*)} - \text{measured value (FWD)}]^2}{n}} / \frac{\sum_1^n \text{measured value}}{n} \quad (4)$$

An example of the correlation between FWD, TSD, and TSD* deflections (all corrected to 20°C) is presented in Figure 5. As shown in this figure, the ANN model was successful in converting the TSD deflection basin to a corresponding FWD deflection basin.

Model Validation

The generalization ability of the presented ANN model was tested and validated using measurements obtained from the testing program conducted at MnROAD. TSD data from 16 flexible pavement testing cells were used as inputs to predict TSD* using the proposed ANN model. The resulted TSD* basin values were then compared with the measured FWD deflections. As shown in Figure 6, the model showed acceptable accuracy with a coefficient of determination (R^2) of 0.9.

Backcalculation Analysis

The Dynatest software ELMOD 6 was used in this study to perform the backcalculation analysis. The ELMOD 6 program provides three methods for conducting the backcalculation of layer moduli (radius of curvature, deflection basin fit, and finite element based method). For the present study, the deflection basin method was used in

the backcalculation analysis. The iterative analysis procedure was conducted until an RMSE of 2% or less was achieved.

The backcalculation analyses were conducted using the FWD measurements and the TSD* deflection values. These analyses were conducted for the entire experimental data set (i.e., 13 sections tested in Louisiana and 16 tested in Minnesota). Figure 7 shows the correlation between the backcalculated moduli using the FWD and the TSD*. As shown in this figure, there was a good agreement between the backcalculated moduli from FWD and TSD deflection measurements. The RMSE was 12.5%, 13.2%, and 10.2% for the AC moduli, base moduli, and subgrade moduli, respectively.

Evaluation and Validation of the Proposed Backcalculation Methodology

The use of the TSD-based backcalculated moduli was evaluated by conducting a comparison with the FWD-based backcalculated moduli in the following pavement analysis applications using the MnROAD testing data:

- Calculating critical pavement responses (stress-strain analysis);
- Pavement fatigue life prediction; and
- Structural health monitoring.

Comparison of Critical Pavement Responses

To investigate the proposed approach, critical pavement responses were calculated using 3D Move software for the 16 road segments tested in Minnesota. These responses included the horizontal tensile strain at the bottom of the AC layer (ϵ_t) and the vertical compressive strain on the top of the subgrade (ϵ_v). These calculations were conducted

using the backcalculated moduli based on FWD measurements and using the backcalculated moduli based on the predicted TSD* values. A static load of 80 kN (18,000 lbs.) was applied on a single axle dual-tire assembly. While the tire pressure was assumed 689 kPa (100 psi), the contact area was considered circular, and the distance between the two tires, center to center, was assumed 370 mm (14.57 in.). Critical pavement responses (ϵ_t and ϵ_v) were calculated at three radial offsets; under the center of the tire, under the mid-distance between the tires, and under the tire edge in the Y-Z plane as shown in Figure 8. In the X-Z plane, ϵ_t and ϵ_v were calculated under the center of the tire.

From the 3D Move analysis, critical pavement responses calculated based on the FWD measurements, showed good correlation with responses calculated based on the predicted TSD* values. Figure 9 presents these correlations for ϵ_t at the bottom of the AC layer and for ϵ_v on the top of the subgrade, both calculated under the center of the tire. Table 3 summarizes the error and the correlation between the pavement responses obtained from the 3D Move analysis.

Comparison of Number of Cycles for Fatigue Failure

The calculated tensile strain at the bottom of the AC layer (ϵ_t) and the backcalculated AC moduli (E_{AC}) were incorporated in the bottom-up fatigue model adopted in Pavement ME (NCHRP 2004):

$$N_f = K_{f1} C_H \beta_{f1} \left(\frac{1}{\epsilon_t} \right)^{k_{f2} \beta_{f2}} \left(\frac{1}{E_{AC}} \right)^{k_{f3} \beta_{f3}} \quad (5)$$

$$C = 10^M \quad (6)$$

$$M=4.84 \left(\frac{V_b}{V_a V_b} - 0.69 \right) \quad (7)$$

$$C_H = \frac{1}{0.000398 + \frac{0.003602}{1 + e^{11.02 - 3.49 h_{ac}}}} \quad (8)$$

where,

N_f = Number of cycles for fatigue failure;

K_{f1} , K_{f2} , K_{f3} = Global calibration coefficients ($K_{f1} = 0.007566$, $K_{f2} = 3.9492$, $K_{f3} = 1.281$);

B_{f1} , β_{f2} , β_{f3} = Local calibration factors (set to 1.0);

V_b = Effective binder content by volume (assumed to be 10%);

V_a = Air voids after construction (assumed to be 7%); and

h_{ac} = thickness of AC layers.

Equation (5) was used to calculate the number of cycles for fatigue failure considering the results obtained from FWD measurements and the results from TSD* values. The comparison showed an RMSE of 16.0% and an R^2 of 0.99. A comparison between N_f based on FWD measurements and TSD* values is shown in Figure 10.

Structural Health Index Comparison

A recent study conducted by the authors introduced the Structural Health Index (SHI) calculated based on pavement backcalculated layer moduli (Elbagalati et al. 2016). The SHI was defined based on the estimated loss in SN; it was scaled logistically from zero to 100. A sigmodal function was selected to represent the correlation between the loss in SN (%) and the SHI:

$$SHI = \frac{100}{1 + e^{0.15 (SN \text{ loss } \% - 30)}} \quad (9)$$

316

317 Fitting parameters in the sigmodal model were selected such that pavement sections with
318 loss in SN greater than 50% would have an SHI value close to zero, and sections with
319 minimal or no loss in SN will have an SHI value near 100. The SHI evaluation and
320 validation demonstrated that it responded realistically to sections in poor and in good
321 structural conditions. More details about the development and validation of the SHI have
322 been presented elsewhere (Elbagalati et al. 2016). In the present study, the SHI was
323 calculated for the MnROAD 16 Road segments based on both FWD measurements and
324 the TSD* values; and the resulting average RMSE was found to be 4.6%. Figure 11
325 presents a comparison between the SHI values for segments tested in the MnROAD
326 Facility. As shown in this figure, both approaches agreed reasonably well in predicting
327 the SHI.

328 SUMMARY AND CONCLUSIONS

329 The objective of this study was to develop a methodology to incorporate TSD
330 measurements in the backcalculation analysis of flexible pavements. TSD and FWD
331 measurements were obtained from two testing programs conducted in Louisiana and at
332 the MnROAD facility in Minnesota. These measurements were used to develop and
333 validate an ANN model for predicting FWD deflection basins from TSD measurements.
334 The ANN model showed acceptable accuracy with a coefficient of determination of 0.9
335 in the validation phase. Furthermore, there was a good agreement between the
336 backcalculated moduli from FWD and TSD deflection measurements. The RMSE was
337 12.5%, 13.2%, and 10.2% for the AC moduli, base moduli, and subgrade moduli,
338 respectively. Evaluation and validation of the proposed methodology was successful and

showed that the backcalculated moduli from TSD measurements can be successfully used in pavement analysis and in structural health monitoring with a reasonable level of accuracy.

Conducting additional TSD and FWD testing will allow feeding the developed ANN with more data, which will assist in creating a more robust network with greater generalization ability. In addition, testing of pavement sections with various surface conditions will allow a better understanding of the effect of surface irregularities on TSD measurements.

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458 Fig. 8. Selected Locations for Pavement Response Analysis in the Y-Z Plan

459 Fig. 9. Correlation between Pavement Responses calculated under the Center of the Tire

460 Based on FWD Measurements and TSD* (a) ϵ_t (b) ϵ_v

461 Fig. 10. Comparison between N_f Calculated based on FWD and TSD* Deflection

462 Measurements

463 Fig. 11. SHI Comparison for MnROAD Segments

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TABLE 1. Structural Description of Pavement Segments

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Site	Route	Segment #	AC Thickness (mm)	Base Thickness (mm)	Subbase Thickness (mm)
Louisiana	LA 34	067-08	215.9	228.6	-
Louisiana	LA 34	067-09	254.0	203.2	127.0
Louisiana	LA 33	069-03	177.8	279.4	304.8
Louisiana	US 425	071-02	215.9	215.9	-
Louisiana	LA 143	315-02	254.0	127.0	-
Louisiana	LA 616	324-02	127.0	127.0	-
Louisiana	LA 594	326-01 A	101.6	190.5	-
Louisiana	LA 594	326-01 B	177.8	152.4	228.6
Louisiana	LA 821	831-05	190.5	355.6	-
Louisiana	LA 589	862-14	38.1	177.8	-
Louisiana	LA 582	333-03	241.3	215.9	-
Louisiana	LA 139	038-01	241.3	304.8	-
Louisiana	I20 EB	451-05	101.6	330.2	241.3
MnROAD	ML	15ML	406.4	0.0	-
MnROAD	ML	16ML	127.0	304.8	-
MnROAD	ML	17ML	127.0	304.8	-
MnROAD	ML	19ML	127.0	304.8	-
MnROAD	ML	3ML	76.2	152.4	-
MnROAD	ML	4ML	76.2	152.4	-
MnROAD	ML	70ML	76.2	203.2	-
MnROAD	LVR	24LVR	76.2	101.6	-
MnROAD	LVR	27LVR	101.6	152.4	-
MnROAD	LVR	28LVR	152.4	101.6	-
MnROAD	LVR	33LVR	101.6	304.8	-
MnROAD	LVR	34LVR	101.6	304.8	-
MnROAD	LVR	35 LVR	101.6	304.8	-
MnROAD	LVR	78LVR	101.6	203.2	-
MnROAD	LVR	79LVR	101.6	203.2	-
MnROAD	LVR	86LVR	127.0	101.6	-

TABLE 2. RMSE (%) between FWD and TSD*

Offset Distance, mm	0	203.2	304.8	457.2	609.6	914.4	1219.2	1524	1828.8
RMSE, %	5.4	5.1	4.9	4.7	3.8	5.3	5.3	5.3	5.2

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TABLE 3. Statistics of Predicted Pavement Response

Criterion	Location					
	Tire Center		Tire Edge		Between Tires	
Response	ϵ_t	ϵ_v	ϵ_t	ϵ_v	ϵ_t	ϵ_v
R^2	0.91	0.96	0.85	0.96	0.88	0.96
RMSE %	13.8	5.6	18.9	5.3	19.3	5.4

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Fig. 1. General Overview of the Research Methodology

Fig. 2. AUTC Method for Calculating TSD Deflections (Muller and Roberts 2013)

D_0 to D_8 are deflections at the predefined FWD offsets

Fig. 3. General Layout of the Artificial Neural Network Model

Fig. 4. Regression Plots of the TSD* vs the FWD Deflection

Fig. 5. Deflection Basins of the FWD, TSD, and TSD* at Station (0+00) Section 67-08

Fig. 6. Validation of the ANN model using MnROAD data

(a)

(b)

(c)

Fig. 7. Correlation between Backcalculated Layer Moduli Using FWD Measurements and TSD* for (a) AC Layer (b) Base Layer (c) Subgrade

Fig. 8. Selected Locations for Pavement Response Analysis in the Y-Z Plan

(a)

(b)

Fig. 9. Correlation between Pavement Responses calculated under the Center of the Tire Based on FWD Measurements and TSD* (a) ϵ_t (b) ϵ_v

Fig. 10. Comparison between N_f Calculated based on FWD and TSD* Deflection Measurements

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Fig. 11. SHI Comparison for MnROAD segments

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