Models for Estimation of Lightweight Deflectometer Moduli for Unbound Materials

Aria Fathi, S.M.ASCE,[1] Cesar Tirado, Ph.D.,[2] Mehran Mazari, Ph.D., A.M.ASCE,[3] and Soheil Nazarian, Ph.D., P.E., F.ASCE[4]

[1]Center for Transportation Infrastructure Systems (CTIS), The University of Texas at El Paso, 500 W. University Ave., El Paso, TX 79968; e-mail: afathi@miners.utep.edu
[2]Center for Transportation Infrastructure Systems (CTIS), The University of Texas at El Paso, 500 W. University Ave., El Paso, TX 79968; e-mail: ctirado@utep.edu
[3]Department of Civil Engineering, California State University Los Angeles, 5151 State University Drive, Los Angeles, CA 90032; e-mail: mmazari2@calstatela.edu
[4]Center for Transportation Infrastructure Systems (CTIS), The University of Texas at El Paso, 500 W. University Ave., El Paso, TX 79968; e-mail: nazarian@utep.edu

ABSTRACT

The use of lightweight deflectometer (LWD) to estimate the moduli of geomaterials for quality control (QC) of earthworks has gained attention among departments of transportation. The conventional method of estimating the LWD modulus is based on the assumption of a homogeneous linear-elastic half-space and a uniform stress distribution under the LWD plate. To account for the nonlinear behavior of geomaterials and soil-plate interaction, the results obtained from a dynamic finite element (FE) model was used to generate a comprehensive database containing the responses of a wide range of single- and two-layer geosystems with different nonlinear layer properties and top-layer thickness. An artificial neural network (ANN) model was trained to estimate the LWD moduli more accurately than the traditional layered elastic models. The proposed model improved the process of estimating the target modulus for compacted geomaterials with less simplifying assumptions and without the computational expense associated with the FE models.

Keywords: Lightweight deflectometer (LWD), Pavement modulus, Artificial neural network (ANN), Finite element modeling (FEM), LWD modulus, Quality Control, Subgrade and Base Layers.

INTRODUCTION

The quality control/quality assurance (QC/QA) of transportation infrastructure, and more specifically during highway construction, is conventionally based on the estimation of in-situ density (Nazarian et al. 1999; Burati et al. 2003; Schmitt et al. 2006; Chang et al. 2014; Nazarian et al. 2014; and Sullivan et al. 2017). In that approach, the link between the parameters used in the design and quality management is missing since the moduli of geomaterials are one of the main design parameters in the mechanistic-empirical pavement design approaches. To provide a reasonable connection between the design parameters and field quality control measures, stiffness-based quality management through nondestructive testing (NDT) has been under continuous development (Mooney et al. 2010; and Nazarian et al. 2014).

Lightweight deflectometer (LWD), a portable device that is based on the same principles used in the falling weight deflectometer (FWD), is an alternative to the plate load test (PLT). LWD consists of three main components: (1) a loading device that produces a defined load pulse, (2) a loading plate, and (3) one or more displacement sensors to measure the center deflection or a deflection bowl (see Figure 1). Similar to FWD, the LWD estimates the modulus of the pavement system by measuring the response under the impact of a load with a known magnitude, dropped from a known height. Many departments of transportation (DOTs) have moved away from PLT as it is costly and time consuming. On the other hand, the logistics of the statewide implementation of FWD, in terms of availability and calibration, may be challenging. As a result, the use of faster and more portable devices is gaining attraction among state highway agencies.

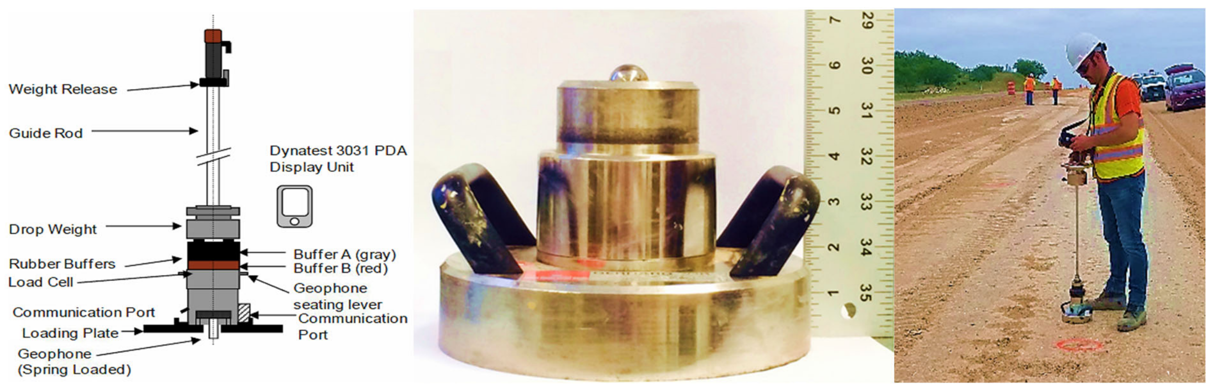

Figure 1. Lightweight deflectometer (LWD).

Alshibli et al. (2005) and Fleming et al. (2007) assessed the potential use of LWD for QC/QA of subgrades, base courses, and compacted soil layers. Both studies concluded that LWD was a useful field quality control and pavement investigation tool if the users have an understanding of the device limitations. Vennapusa and White (2009) evaluated key features of eight commonly used LWD devices and found that their modulus values were affected by the size of the loading plate, plate contact stresses, type and location of deflection sensor(s), plate rigidity, loading rate, and buffer stiffness.

The simplest way to simulate a geomaterial's behavior under LWD is to utilize the theory of elasticity. Even though pragmatic and straightforward, this approach is unable to take the nonlinear behavior of the layered geomaterials and the soil-plate interaction into consideration (Mazari et al. 2016; Tirado et al., 2017 and 2018). Several studies have attempted to address those drawbacks of the LWD analysis. For example, Tirado et al. (2015) developed an FE model to show that the variation of LWD response was related to the characteristics of the device. They concluded that the nonlinear parameters of geomaterials could affect the LWD responses. Tirado et al. (2017) studied the depth of influence of LWD for a wide range of geomaterials for single and two-layer systems using static and dynamic FE models. They indicated that the depth of influence under dynamic loading seemed to be deeper compared to the same condition with static loading.

Even though the FE methods for the evaluation of pavement related problems in general, and simulation of LWD in particular, are versatile, the nonlinear analysis of such problems is time-consuming and requires an extensive computational effort. One solution to overcome this problem is the use of complex nonlinear predictive models. These models have been developed to forecast the performance and quality of the compacted layered geomaterials. The conventional regression analysis has been employed for prediction of the moduli of pavement layers in several studies. For instance, Asli et al. (2012) backcalculated the elastic modulus of subgrade layer under a LWD using an equivalent spring-mass-dashpot system. However, there is a consensus among the researchers that the models developed through the conventional regression analysis may not be as accurate owing to the level of complexity of the relationships between the output and the input variables (Choi et al., 2004).

Soft-computing techniques, such as the artificial neural network (ANN), have been widely deployed to predict the moduli of flexible pavement layers. The application of ANN in solving complex nonlinear models and supervised learning problems in pavement related projects have been extensively documented in the literature (e.g., Meier and Rix, 1995; Kim and Kim, 1998; and Abdallah et al. 2000). Although there is an extensive literature on the models for estimation of moduli of unbound materials, most of them are either based on the application of FWD or employment of linear elastic theory (e.g., Kim and Kim, 1998; Sharma and Das, 2008; and Zaman et al., 2010).

This paper employs a dynamic finite element model, developed by Tirado et al. (2017), to estimate the LWD target moduli for one- and two-layer geomaterial systems. That software contains a subroutine to simulate the constitutive material model that accounts for the nonlinear behavior of geosystems. A database consisting of more than 18,500 different pavement sections, including a wide range of single-layer (subgrade only) and two-layer geosystems (subgrade and base) with different nonlinear properties and base layer thickness was generated. This paper contains two sections. The first section is dedicated to explaining the finite element model and geomaterial properties used to assemble the database. The second section describes the process to develop the predictive models for determining moduli of single and two-layer pavement systems.

FINITE ELEMENT MODELING OF LIGHTWEGHT DEFLECTOMETER

Tirado et al. (2017) developed an axisymmetric dynamic nonlinear FE model to simulate an LWD on top of both single- and two-layer systems consisting of subgrade and base layers, as shown in Figure 2. That model deployed an automatic 2-D surface-to-surface contact model for simulating the soil-plate interaction. The geomaterial layer was 2.5 m (100 in.) thick and 2 m (80 in.) wide and was simulated using about 75,000 square elements. The LWD impulse load was applied through a 6.7 kN (1500 lb) simulated force with a pulse duration of 17 msec acting on a 25 mm (1 in.) diameter circular area corresponding to the ball protruding from the top of the unit. A more detailed explanation of the assembled models and discussion of the LWD analyses can be found in Tirado et al. (2017). For this study, that model was used to develop a database comprised of more than 18,500 FE scenarios.

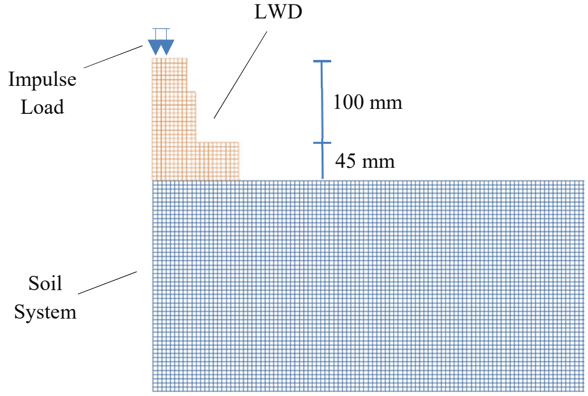

Figure 2. Simulated finite element model of soil system under the induced LWD impulse.

Nazarian et al. (2014) showed that the resilient modulus constitutive model proposed by Ooi et al. (2004) generated more realistic results in terms of estimating the nonlinear response of geomaterials. The proposed model is in the form of:

$$M_R = k_1' P_a \left(\frac{\theta}{P_a}+1\right)^{k_2'} \left(\frac{\tau_{oct}}{P_a}+1\right)^{k_3'} \quad (1)$$

where θ is the bulk stress, and τ_{oct} is the octahedral shear stress, P_a is the normalizing stress (atmospheric pressure) = 100 kPa (14.7 psi), k'_1, k'_2, and k'_3 are model parameters (determined form nonlinear regression model fitted to the laboratory data). The bulk normal stress and the octahedral shear stress are defined as:

$$\theta=\sigma_1+\sigma_2+\sigma_3 \quad (2)$$

$$\tau_{oct} = \frac{1}{3}\sqrt{(\sigma_1-\sigma_2)^2+(\sigma_2-\sigma_3)^2+(\sigma_1-\sigma_3)^2} \quad (3)$$

where σ_i is one of the principal stresses. The k-parameters represent the nonlinearity and stress sensitivity of the stiffness properties of unbound geomaterials. National Cooperative Highway Research Program (NCHRP) Project 1-28A recommended using θ = 210 kPa (31 psi) and τ_{oct} = 50 kPa (7.5 psi) for base and subbase materials, and θ = 85 kPa (12.4 psi) and τ_{oct} = 20 kPa (3 psi) for subgrade soils (Oh and Fernando, 2011).

Stress distribution under a plate depends on the plate rigidity and soil type. The LWD surface modulus, E_{LWD}, is calculated using Eq. 4, which is based on the Boussinesq's theory (Terzaghi and Peck, 1967):

$$E_{LWD} = \frac{(1-\nu^2)a\sigma_0}{d} \cdot f \tag{4}$$

where ν is Poisson's ratio, a is the radius of the plate = 100 mm (4 in.), σ_0 is the applied stress under the plate = 212 kPa (30 psi), and d is the displacement (which in this study is obtained from the FE model). Parameter f is the shape factor depending on stress distribution, assumed as π/2 for a rigid plate that creates an inverse parabolic shape for stress distribution under the plate (simulating clay, subgrade, and lime stabilized subgrade materials), 2.0 for flexible plates that create a uniform stress distribution (for two layer soil systems including granular base and clayey subgrade), and 8/3 for flexible plates forming a parabolic stress distribution (simulating cohesionless sand, Terzaghi and Peck, 1967; Fang, 1991). A value of π/2 was assumed for the shape factor in this study.

Figure 3 shows the vertical displacement and stress contours under the LWD impact for a cohesive single-layer geomaterial (subgrade only) with k'_1 = 420, k'_2 = 1.75, and k'_3 = -3.65. The maximum vertical displacement appears at the surface under the center of the LWD plate (Figure 3a); while the maximum vertical stress occurs close to the geomaterial surface as demonstrated in Figure 3b. In case of cohesive soils, the maximum vertical stress appears under the plate edge. However, for cohesionless soils (with a higher k'_2 and lower k'_3 values), the maximum stress occurs under the plate center.

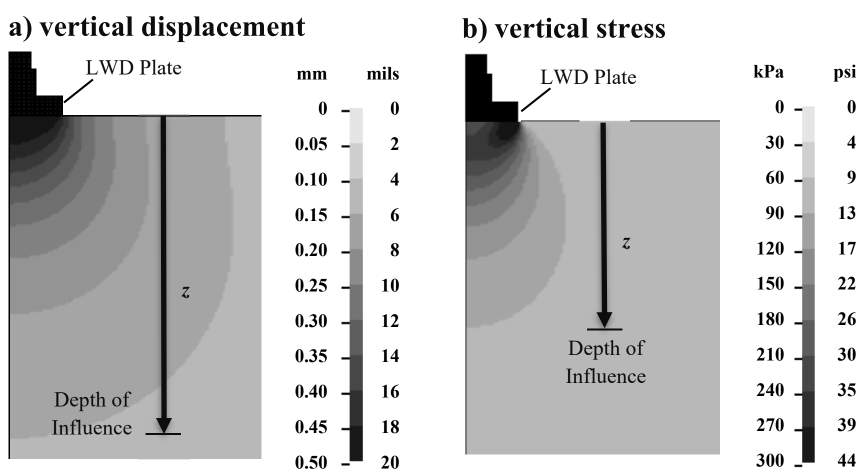

Figure 3. Contour plots for a single-layer soil system under LWD impact.

Figure 3 also indicates that the depth of influence with respect to displacement criterion is deeper compared to the scenario considering stress criterion, if the depth of influence is defined as the depth at which the pavement response (being displacement, stress, or strain) attenuates to 10% of the maximum corresponding response. Tirado et al. (2017 and 2018) found that the depth of influence (z) varied between 2 to 5 times the plate diameter (D) based on the displacement criterion. They reported that z/D varied between 2.1 and 2.8 when considering the stress criterion.

MODELS FOR PREDICTING MODULUS OF UNBOUND GEOMATERIALS

In this study, ANN modeling was used to develop models for estimating the moduli of single- and two-layer geosystems under the LWD load. A multi-layer perceptron (MLP) model was deployed. MLP is one of the most popular neural networks that includes several layers including an input layer, a hidden layer, and an output layer. In each layer, there are several variables which are interconnected with several weighted links. Specific processes such as forward feeding the initial solutions, back-propagating the errors throughout the entire network and adjusting the connection weights can assist the network to find the best solution (Hertz et al., 1991). The root mean squared error (*RMSE*), was used to evaluate the robustness of the prediction models. *RMSE* is expressed as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{n}} \tag{5}$$

where x_i is the measured value, y_i is the predicted value, and n is the number of samples.

The LWD modulus (E_{LWD}) was defined as a function of different input parameters for single- and two-layer geosystems as listed in Eq. (6) and (7), respectively:

$$E_{LWD\ (single-layer\ system)} = f\left(k_1^{'s}, k_2^{'s}, k_3^{'s}\right) \tag{6}$$

$$E_{LWD\ (two-layer\ system)} = f\left(k_1^{'b}, k_2^{'b}, k_3^{'b}, k_1^{'s}, k_2^{'s}, k_3^{'s}, h_b\right) \tag{7}$$

where h_b is the thickness of the base, and k_i^b and k_i^s are the nonlinear parameters of the base and subgrade, respectively. The target dataset, i.e., E_{LWD}, was trained using the predictor variables shown in Eq. 6. In this study, the ANN model was built using an input layer containing the independent variables, hidden layers containing four neurons, and an output layer comprised of the target values. The Levenberg-Marquardt training algorithm (Moré 1978) with multilayer feed-forward neural network and error backpropagation were employed.

The database was randomly divided into the training and testing datasets. For this purpose, 80% of the database (1600 data samples) was assigned to the training set and the rest (400 scenarios) to the testing set. Figure 4 demonstrates the comparison of the moduli estimated by using the ANN model with expected moduli used as input for the single-layer systems for both the training and testing datasets. The ANN model can predict the simulated LWD modulus with a coefficient of determination, R^2, of 0.99 and root mean square error (RMSE) of 3.3 MPa for the training set, and R^2 of 0.99, RMSE of 3.9 MPa for the testing dataset.

Similarly, the prediction power of the ANN model for moduli of the two-layer geosystems is shown in Figure 5. For two-layer systems, the target dataset (E_{LWD}) was trained using the seven input parameters listed in Eq. 7. Again, for two-layer systems, 80% of the database (13,200 data samples) was assigned to the training set and the rest (3300 scenarios) to the testing set. Due to the level of complexity for the two-layer geosystems, the optimized number of neurons was increased to seven for the training data set to avoid overfitting. The predicted values are in good agreement with the corresponding moduli obtained from FE models as judged by the number of cases within the ±10% uncertainty limits (see Figures 5a and 5b).

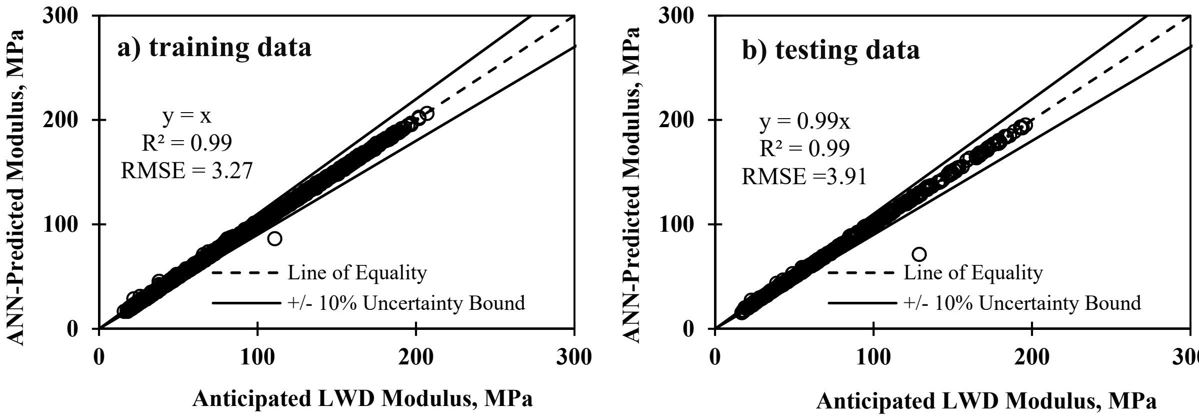

Figure 4. Comparison of ANN-predicted and FE estimated moduli of single-layer geosystems

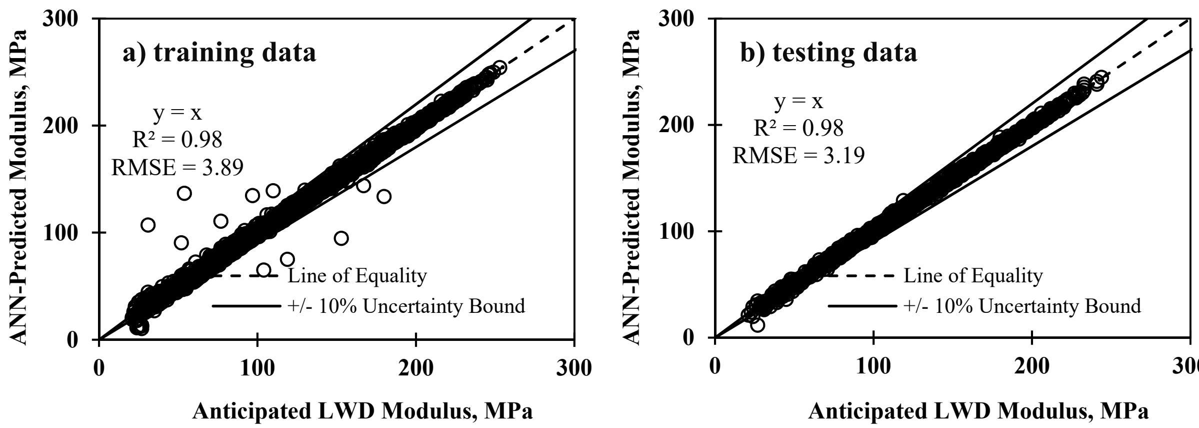

Figure 5. Comparison of ANN-predicted and FE estimated moduli of two-layer geosystems

The ratio of the moduli predicted by ANN to the corresponding moduli anticipated for the single- and two-layer soil systems was calculated as an estimate of model accuracy. As presented in Figure 6, the ratio for 98% of the dataset is within 0.95 and 1.05 for the single-layer system. The same ratio for the two-layer systems is 97% of the ratios are within 0.9 and 1.1.

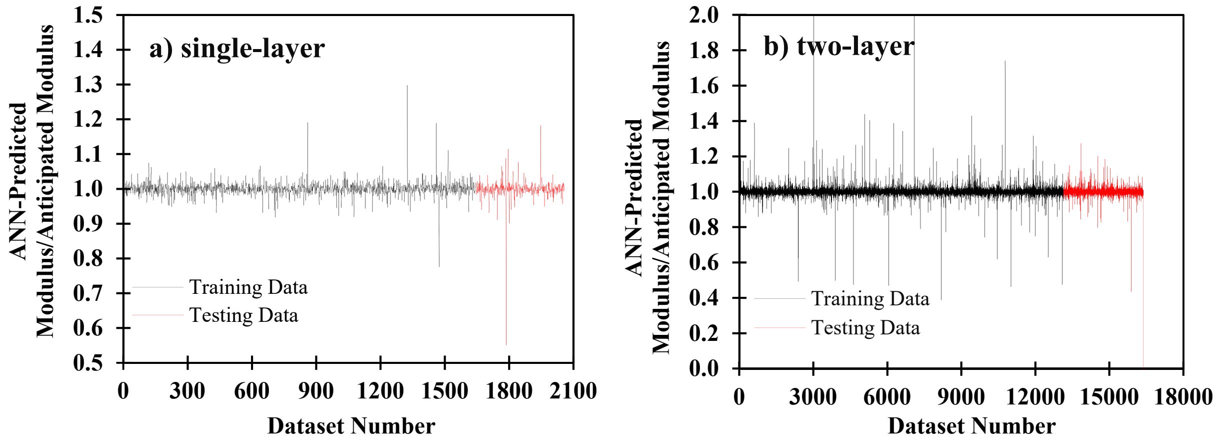

Figure 6. Ratio of predicted to measured moduli.

SUMMARY AND CONCLUSIONS

Lightweight deflectometer is a practical modulus-based device that has attracted the attention of several DOTs and highway agencies for quality management of roadwork. LWD can be utilized for a quick estimation of the modulus of compacted geomaterials. A homogeneous linear-elastic half-space and a uniform stress distribution under the plate are typically assumed to assess the LWD modulus. To estimate the LWD modulus more realistically, a dynamic finite element (FE) model for the estimation of the nonlinear LWD modulus was used to develop a comprehensive database.

The effort in this study was mainly focused on developing predictive models to estimate target moduli of unbound materials for single and two-layer systems. For this purpose, a database containing more than 18,500 scenarios, including a wide range of single- and two-layer geosystems with different nonlinear layer properties and base thickness, was generated. ANN modeling was employed to develop models for estimating the target moduli of single- and two-layer geosystems under the LWD induced impact. The predictor variables used for the training purpose included the thickness of the base and nonlinear parameters of the base and subgrade. The ANN model can reasonably predict the LWD target moduli of single- and two-layer systems of unbound materials as judged by the number of cases lying inside the ±10% uncertainty bounds, and the small *RMSE.*

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