PREDICTION OF SUBGRADE RESILIENT MODULUS USING GENETIC ALGORITHM AND CURVE SHIFTING METHODOLOGY AS AN ALTERNATIVE TO NONLINEAR CONSTITUTIVE MODELS

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ABSTRACT

This paper demonstrates the applicability of the genetic algorithm and curve shifting methodology to estimate resilient modulus at various stress states for subgrade soils using the results of triaxial resilient modulus tests. This innovative methodology is proposed as an alternative to conventional nonlinear constitutive relationships. Using the genetic algorithm, laboratory curves for different deviator stress levels at different confining pressures are horizontally shifted to form a final gamma distribution curve which can represent the stress-strain behavior of subgrade soils with the corresponding predicted shift factors. Resilient modulus values for a given stress state can be estimated based on this curve and another gamma function which represents the variation of shift values for different confining stresses. To compare the effectiveness of these two approaches, coefficients for the Uzan constitutive model are also determined for each laboratory test and compared with the approach described in this paper. Predicted resilient modulus values from each approach are separately compared with Artificial Neural Network (ANN) model predictions to evaluate their efficiency and reliability in terms of resilient response prediction. Results of the analysis indicated that curve shifting methodology gives superior estimates with a coefficient of determination 14% higher than the Uzan model predictions when the results are evaluated with the ANN model outputs. Thus, although it is not a constitutive model, use of the genetic algorithm and curve shifting methodology is proposed as a promising technique for the evaluation of subgrade soils' stress-strain dependency.

INTRODUCTION

Mechanistic-empirical pavement design requires successful determination of the material properties that produce calculated pavement responses to match those of real pavements. Dynamic nature of the traffic loads must be effectively simulated in laboratory tests to achieve realistic performance estimates for design. Since empirical design procedures are based on the static properties of pavement structures that are determined by using simple performance tests such as California bearing ratio and soil support value, a dynamic strength parameter needs to be determined in order to evaluate the performance under repeated loading.

Resilient modulus testing, developed by Seed et al. *(1)*, is one of the most common and reliable laboratory experiment for the estimation of unbound soils' response to dynamic traffic loads. It aims to determine stiffness values at different stress levels that describe the nonlinear stress-strain behavior of soils under cyclic loading. Resilient modulus is simply the ratio of the dynamic deviatoric stress to the recovered strain under a standardized haversine pulse loading. Mechanistic design procedures for pavements and overlays require resilient modulus of unbound pavement layers to design layer thicknesses and the overall system response to traffic loads. In AASHTO specification T-274 *(2)* based on the mechanistic methods, resilient modulus is considered as an important design input parameter. After this specification, AASHTO TP46 *(3)*, T292 *(4)*, T294 *(5)* and T307 *(6)* specifications were also published as improvements were made over the years in the test procedures, the equipment configurations and the loading stress levels.

The characteristics and behavior of subgrade, base and subbase soils have a major impact on the performance of flexible pavement systems. Pavement design based on field performance requires estimating realistic material properties that can simulate the in-situ behavior of unbound layers. Variation of resilient modulus at various critical in-situ stress states and loading conditions should be determined to evaluate the performance and reliability of empirical relations. Therefore, constitutive models were proposed to reflect the realistic behavior of the unbound pavement layers under repeated traffic loads. The relationship between the constitutive model coefficients and the index properties, such as particle size distribution, maximum dry- density, optimum water content levels and Atterberg properties, was also determined to evaluate resilient behavior of a specific soil type under a given stress state.

Many nonlinear constitutive models have been proposed to describe the phenomenon of stiffness variations of unbound layers under different traffic loads. These models can be used to estimate resilient modulus variations at different depths of the pavement structure related to traffic loading. Elastic theory can be used to estimate stress and strain levels at different subgrade levels. Accordingly, many equations were developed to define the resilient response of unbound layers as a function of various stress variables as shown in the following examples:

AASHTO Model *(5)*: $$M_R = k_1 (\theta)^{k2} \quad (1)$$

Hicks and Monismith *(7)*: $$\frac{M_R}{\sigma_{atm}} = k_1 \left(\frac{\theta}{\sigma_{atm}} \right)^{k2} \quad (2)$$

Uzan (Universal) *(8)*: $\frac{M_R}{\sigma_{atm}} = k_1\left(\frac{\theta}{\sigma_{atm}}\right)^{k2}\left(\frac{\sigma_d}{\sigma_{atm}}\right)^{k3}$ (3)

Johnson *(9)*: $M_R = k_1\left(\frac{J_2}{\tau_{oct}}\right)^{k2}$ (4)

Rafael Pezo *(10)*: $M_R = k_1 \sigma_d^{k2}\sigma_3^{k3}$ (5)

Louay *(11)*: $\frac{M_R}{\sigma_{atm}} = k_1\left(\frac{\sigma_{oct}}{\sigma_{atm}}\right)^{k2}\left(\frac{\tau_{oct}}{\sigma_{atm}}\right)^{k3}$ (6)

where:
M_R = resilient modulus
$\theta = \sigma_1+\sigma_2+\sigma_3$ (bulk stress)
k1, k2, k3 = regression coefficients
$\sigma_d = \sigma_1 - \sigma_3$ = deviator stress
σ_3 = confining pressure
σ_{atm} = atmospheric pressure
σ_{oct} = octahedral normal stress =1/3 ($\sigma_1 + 2\sigma_3$) = 1/3 ($\sigma_d + 3\sigma_3$)
$\tau_{oct} = (1/3)[(\sigma_1-\sigma_2)^2+(\sigma_1-\sigma_3)^2+(\sigma_2-\sigma_3)^2]$ (octahedral shear stress)
$J_2 = \sigma_1\sigma_2+\sigma_2\sigma_3+\sigma_1\sigma_3 = 2\sigma_3(\sigma_3+\sigma_d)+\sigma^2$ (second stress invariant)

In this study, application of genetic algorithm (GA) and curve shifting methodology as an alternative to nonlinear constitutive models is investigated. The Uzan (Universal) model is used for comparison purposes since it is determined to be the most effective nonlinear constitutive relationship for the measured data in this study. Tests were conducted on a wide range of materials from various regions of Turkey in order to develop reliable correlation functions for resilient modulus. Resilient modulus tests were conducted according to AASHTO T307 specification *(6)*. A total of 8 different soil types from different regions of Turkey were collected and 75 tests were conducted at four different compaction and water content couples which are: (1) W_{opt} – 100% compaction, (2) W_{opt} – 95% compaction, (3) (W_{opt} – 2), 100% compaction, (4) (W_{opt} + 2), 100% compaction. In addition, Atterberg limits, optimum water content, maximum dry-density and gradation characteristics of the specimens were determined. Soil types with different characteristics are chosen to obtain a prediction model with wide applicability. The experimental design for the laboratory resilient modulus tests is illustrated in Table 1.

The general procedure followed to investigate the application and compare the efficiency of the curve shifting methodology is given below:

1. Determine Uzan constitutive model coefficients (k_1, k_2, k_3) *(8)*.
2. Using the GA, shift laboratory deviator stress vs. resilient modulus curves with respect to confining pressures by minimizing the residual sum of squares between the shifted curves and a gamma distribution function *(12)*.
3. Fit a gamma distribution function to the confining pressure levels vs. shift factor

data points *(12)*.
4. Develop Artificial Neural Network (ANN) models to determine resilient modulus at various stress levels for different soil types.
5. Determine the critical stresses at subgrade level using the software KENLAYER *(13)*.
6. Determine critical resilient modulus values using the developed models (Uzan, curve shifting and ANN).
7. Compare the prediction results for Uzan model and curve shifting with respect to ANN predictions. Predictions of the methodology with better fit to the data will be similar to ANN outputs.

UZAN (UNIVERSAL) NONLINEAR CONSTITUTIVE MODEL

Nonlinear stress-strain characteristics of subgrade soils can be effectively determined using resilient modulus tests. Performance prediction models directly rely on the parameters developed from constitutive models for each laboratory test. Constitutive relationships which represent the effects of stress-strain on subgrade soils are therefore extremely important in achieving effective results from calculation of pavement response under traffic loading *(14)*. Inadequate constitutive models will decrease the predictive capability of performance prediction models. Although the Uzan constitutive model is capable of developing parameters which can effectively represent the stress-strain characteristics of coarse grained gravels with coefficient of determination values ranging from 0.97 to 0.99, parameter prediction for coarse grained sand and fine-grained soil test results is inadequate with coefficient of determination values ranging from 0.68 to 0.78 *(15)*. Since these coefficients are used as inputs for the performance prediction models, estimations with large standard errors at the initial stages will cause error accumulation throughout the performance prediction process. In this study, an innovative methodology, curve shifting, is proposed as an alternative to constitutive relationships to reduce the effect of this type of problem.

For a typical resilient modulus test, the Uzan model (Equation 3) can be used to model the effects of stress on subgrade soils. The general nonlinear equation can be normalized as follows to perform linear regression to determine the model coefficients for each test:

$$\log\left(\frac{M_R}{\sigma_{atm}}\right) = \log(k_1) + k_2 \cdot \left(\log\left(\frac{\theta}{\sigma_{atm}}\right)\right) + k_3 \cdot \left(\log\left(\frac{\sigma_d}{\sigma_{atm}}\right)\right)$$

After estimation of the nonlinear model coefficients, resilient modulus values at different stress states can be estimated. The deviator stress, confining pressure and bulk stress parameters at the top of the subgrade layer are determined based on the example pavement section characteristics, the elastic modulus values and the axle configurations using the layered-elastic program KENLAYER *(13)*. The example pavement section and the representative axle configurations with the estimated critical stresses are given in Figure 1. A representative resilient modulus for a given test can be determined using this example pavement section's characteristics, corresponding stress states and the constitutive model coefficients. Confining pressure, σ_3, and deviator stress, σ_d, at the top of the subgrade are determined to be 18.28 kPa and 38.21 kPa, respectively. Since these stress values are in the range of the stresses applied during the laboratory tests, resilient modulus predictions will not require any extrapolation errors. These stress values are going to be used throughout this study as representative values. However, analysis can also be conducted for different pavement structures and axle configurations. Resilient modulus for a given test can be determined using these stress values and the Uzan model coefficients determined from a certain laboratory test following AASHTO T307 specification *(6)* for one of the soils in Table 1(Kayseri 6/2, compaction at optimum water content) as follows:

$$M_R = 101.325 \times 693.05 \left(\frac{(3 \times 18.28 + 38.21)}{101.325} \right)^{0.2360} \left(\frac{38.21}{101.325} \right)^{-0.1440} = 79{,}202 \text{ kPa}$$

APPLICATION OF GA AND CURVE SHIFTING METHODOLOGY

The GA is a method originally developed to evaluate the fitness of a population at the end of a number of trials *(16)*. The method is based on the generation of new genes with the goal of improving the solution each time in order to achieve the best results at the end of each application. The GA is a computer simulation of function evaluations where the analyst creates the environment in which the population must evolve.

Planning and scheduling of construction projects, life cycle cost analysis, back-calculation of asphalt layer moduli and pavement design are the primary applications of GA in pavement engineering. The GA has been used to predict the fatigue performance of asphalt pavements in recent studies *(12, 17, 18)*. In addition, Liu-Wang *(19)* used GA for the design of asphalt pavements. Kameyama et al. *(20)* also developed a methodology which uses the GA to backcalculate pavement layer moduli from falling weight deflectometer (FWD) measurements. In addition to these studies, Shekharan *(21)* used the GA to develop pavement deterioration models and Attoh-Okine *(22)* applied the GA for the prediction of the roughness progression in flexible pavements.

Potential limitation of applying GA lies in the prediction of initial parameters and the population size. The length of the input interval range, the number of iterations and the number of discarded genes will have considerable influence on the computational time and precision of the results. A novice can increase the length of the input interval range while increasing the number of the iterations to avoid divergence from the actual solution, which will consequently increase the computational time. Thus, optimum number of iterations which will conserve the accuracy by keeping the computational time at reasonable levels should be determined before starting the model implementation.

In this study, the GA and curve shifting methodology is proposed as an alternative to conventional constitutive nonlinear models. Since these models present results that leave room for improvement for coarse-grained (sandy) and fine-grained soils, the application of the GA and curve shifting methodology is recommended for consideration for better estimation of the resilient modulus. The deviator stress vs. resilient modulus curves obtained from the laboratory resilient modulus tests were used to characterize the elastic response of unbound layers under repeated loads. Resilient modulus tests were conducted at three different confining pressure levels, 13.8, 27.6 and 41.4 kPa, which constitute three different curves. Figure 2*a* presents these curves for a single test conducted for a fine-grained subgrade soil. In this study, a GA code written in software FORTRAN is used to determine feasible horizontal shift amounts for the deviator stress – resilient modulus curves in order to obtain a final gamma distribution curve which describes the resilient response as a function of deviator stress. The main purpose in conducting the nonlinear fitting of data is to find a suitable function that can describe the relationship between the resilient modulus and the deviator stress at various confining pressures.

The general procedure for the application of the GA is as follows:

1. **Interval Prediction:** Potential shift amounts (S_1 and S_2) are determined by the analyst using the plots of deviator stress vs. resilient modulus. As the uncertainty about the possible shift amounts increases, the length of the intervals should be extended while increasing the number of iterations in order to decrease the estimation error.
2. **Gene Pool Generation:** Gene pools are obtained by generating uniformly distributed random variables within the estimated shift intervals (80 numbers are generated for the S_1 and S_2 prediction intervals).
3. **Fitting:** For each gene in a gene pool, the derivative quantities S_1 and S_2 are determined and then the deviations of the predicted values from the measured data are evaluated using the fitness function. Fitted resilient modulus values are estimated based on the gamma distribution functions. The fitness function of the GA for the estimation of the shift amounts is basically the residual sum of squares (RSS) function which expresses the goodness of fit between the measured (test results) and predicted (fitting function) data points *(12)*.

   $$\mathrm{RSS} = (y_i - \hat{y}_i)^2 \qquad (7)$$

   where y_i is the measured resilient modulus and $\hat{y}_i$ is the predicted resilient modulus.

4. **Ranking:** The genes in the gene pool are ranked according to their RSS values.
5. **Mating and Discarding:** The ranked genes are mated in order to decrease the effects of bad genes. The last half of the genes with higher RSS is discarded. These discarded genes are then replaced with the new genes by returning to Step 2. The required number of iterations depends on the level of uncertainty about the possible shifting amounts in the data set and the required accuracy of the test parameters.

After the most effective shift values are determined using the GA by minimizing the RSS between the actual test results and the fitting function, the parameters of the fitting function are determined by using the "nls" function available in the software S-PLUS *(23)*. The final structure of the shifted curves and the application of curve fitting are illustrated in Figure 2*b*. The following gamma distribution function is used for the correction of the deviator stress and confining pressure effects for unbound materials:

$$M_R = \exp\left(C + A\left(1 - \exp\left(-\frac{(x)}{B}\right)\sum_{m=0}^{n-1}\frac{(x)^m}{B^m m!}\right)\right) \qquad (8)$$

where A, B and C are the function parameters, m is an index number and x is the modified deviator stress.

Shift amounts determined from the GA application are also modeled using gamma distribution function following the development of the shifted deviator stress vs. resilient modulus curves. The final gamma distribution function developed to model the confining pressure vs. confining pressure shift factor curves is given in Figure 2*c*. The confining pressure shift relationship for the fitting functions is given as follows:

$$a_T = D.\left(1 - \exp\left(-\frac{\left(\sigma_3 - \sigma_{3(ref)}\right)}{E}\right)\right) \tag{9}$$

where $\sigma_{3(ref.)}$ = 27.6 kPa (reference), D and E are function parameters and a_T is the confining pressure shift factor in kPa.

$$x = \sigma_d + a_T \tag{10}$$

where x is the modified deviator stress.

For a given test, resilient modulus values at different stress states can be determined by using Equations 8-10 with the coefficients estimated as described above. Resilient modulus values are only associated with the deviator stress where the effect of confining pressure is also considered during the analysis. The procedure for the estimation of the resilient modulus related to confining pressure and deviator stress is quite promising since the effects of other parameters on the resilient modulus variation are relatively small when compared with the confining pressure and deviator stress effect for a single test.

Demonstration Example

The deviator stress and confining pressure at the top of the subgrade of an example pavement section is determined in the previous section (Figure 1). At the top of the subgrade, the deviator stress is estimated to be 38.21 kPa when the confining pressure is 18.28 kPa. Deviator stress and confining pressure effects are corrected by the application of the following procedure for a typical test result and the resilient modulus at the top of the subgrade is determined by using the coefficients of the gamma distribution functions. Backward estimation of the resilient modulus is performed as follows:

1. Determine the difference between the reference (27.6 kPa) and the test confining pressures.

   $\sigma_3 - \sigma_{3(ref.)} = 18.28 - 27.579 = -9.299$

2. Obtain the confining pressure shift factor.(Equation 9) (Figure 2*c*)

$$a_T = D.\left(1-\exp\left(-\frac{\left(\sigma_3-\sigma_{3(ref)}\right)}{E}\right)\right) = -52.3952.\left(1-\exp\left(-\frac{\left(-9.299\right)}{20.8955}\right)\right) = 29.369$$

3. Determine the modified deviator stress. (Equation 10)

$x = \sigma_d + a_T = 38.21 + 29.369 = 67.579$ kPa

4. Determine the resilient modulus at a given confining pressure and deviator stress using the calculated modified deviator stress (Equations 8).

$$M_R = \exp\left(11.18780 - 0.39782.\left(1-\exp\left(-\frac{(67.579)}{13.9146}\right).\sum_{m=0}^{2}\frac{(67.579)^m}{(13.9146)^m.m!}\right)\right) = 51{,}256 \text{ kPa}$$

The final estimation results are shown in Figures 2*a* and 2*b*.

COMPARISON OF CURVE SHIFTING METHODOLOGY AND UZAN CONSTITUTIVE MODEL USING ANN PREDICTIONS

ANN is a special type of computational model which was inspired by the information processing in biological systems. The power of ANN applications is a result of the hidden layer neurons that are used for processing and transferring information between the model inputs and outputs. Links between the layers carries different weights which indicate the strength of connection between the layers. In this study, one hidden layer is used for ANN model development since the number of input parameters and the complexity of the problem do not require the use of many hidden layers *(24)*. The most successful ANN modeling approach for the pattern recognition is accepted to be the feed-forward neural network which is also the one used in this study *(25)*. In addition, an error backpropagation algorithm which is based on the evaluation of the error function by sending information forwards and backwards in the network is also used to improve the predictive capability of the ANN models. In this study, the logistic sigmoid function type is selected as the activation function because of its superiority to other function types, such as linear and threshold functions *(26)*. Linear combinations of fixed nonlinear basis functions are used to develop the ANN frameworks which can be explained by the following relationship *(25)*:

$$y(x,w) = f\left(\sum_{j=1}^{M} w_j \phi_j(x)\right) \tag{11}$$

where $f(\cdot)$: identity function

$\phi_j(x)$: basis function

w_j: model coefficients

M: total number of parameters in the model

Basis functions are the nonlinear functions which are formed by using linear combinations of the model input variables. The basis function in the model, $\phi_j(x)$, depends on different parameters which are simultaneously adjusted using model coefficients. This adjustment process is called "training". Different types of activation functions can be used based on the characteristics of the problem. In this study, the following logistics sigmoid function is used to scale continuous arguments:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

In this study, ANN model predictions are used to compare the performance of the Uzan model and the curve shifting methodology. Although ANN models are highly effective in predicting resilient modulus for different stress states and different soil types, they cannot be used to determine the stress-strain dependency (constitutive relationship) of a test specimen for a single test. Model parameters, such as the Uzan and curve shifting method model coefficients, which represent the effects of stress on a single test specimen, should be determined to develop performance prediction models. In addition, ANN models do not provide insight into resilient behavior nor help understand values for soils other than those actually tested. Therefore, in this study, ANN models are only used for the prediction of resilient modulus, without extrapolations, at different deviatoric and confining stresses. ANN model cannot be generalized to estimate resilient modulus of coarse-grained (sandy) and fine-grained soils which are out of the range of the empirical training set.

In this study, different soil index parameters and stress variables were used to develop ANN models to evaluate the resilient response of subgrade soils (Table 2). Input variables used for the analysis were determined by performing different types of soil index tests. In addition, 5 deviator stress levels and 3 different confining pressures are applied during a certain resilient modulus test to evaluate resilient response of the material. As a result, the complete dataset for the ANN application is composed of 1,125 data points (75 tests $\times$ 15 stress couples). It was observed that $\pm$ 2% variation in the compaction water content (Wcc) has a considerable effect on the resilient response of the material. In addition, optimum water content (W_{opt}), maximum dry-density (γ_{dmax}), plasticity index (PI) and percent passing number 200 sieve (PP200) were determined to be effective parameters for ANN model development.

Despite its superior prediction capability within the original dataset, ANN models have certain disadvantages which need attention during the analysis. Overfitting, low extrapolation capability and their nonparametric nature are accepted to be the most important problems *(25)*. In this study, these concerns are minimized by applying different methods. The overfitting problem is minimized by performing analysis to determine the optimum number of hidden nodes which can effectively represent the input-output relationships without causing any generalization problems. Models with different number of hidden nodes are developed and variation of the error is monitored for each application. Twenty percent of the data points are randomly selected and not used for the ANN model development. The ANN model is developed using the remaining eighty percent and the predictive capability of the final model is tested using the validation dataset which includes twenty percent of the data points. The accumulated error for the ANN development will always decrease by increasing the number of hidden nodes in the network. However, the accumulated error for the validation dataset predictions will increase after a certain level. In this study, the optimum number of hidden nodes was determined to be 6 since the most effective predictions for the validation dataset can only be achieved at that level. The number of nodes vs. error ($1-R^2$) plot which is used during the decision process is given in Figure 3.

The extrapolation capability of the ANN model is monitored by using the prediction profiles for each input variable. The 95% confidence intervals for the mean response, resilient modulus, and the variations in intervals by changing the input variables are determined by using prediction profiles (Figure 4). The effect of overfit penalty on the prediction capability of the ANN model is illustrated in Figure 4. Increasing the overfit penalty value from 0.001 to 0.016 decreases the size of confidence intervals without causing important effects on the accumulated model error. Thus, the ANN model developed using the 0.016 overfit penalty and 6 hidden nodes is selected as the final model for resilient modulus prediction. The architecture of the ANN used for prediction of resilient modulus is given in Figure 5. It is noteworthy that changing the levels of the input variables can affect the size of the confidence intervals. However, the shape of the model curve for each input variable does not change by varying the levels of the input variables. In addition, the size of the confidence interval for the response variable does not exceed certain levels at the extremum values of the input variables, which avoids the extrapolation problems for the ANN model. The effect of each parameter on the variation of the resilient modulus is also monitored by using the prediction profiles which avoids the possible problems arising from the nonparametric nature of the ANN models. Comparison of the measured and ANN predicted resilient modulus values show that the ANN model for resilient modulus prediction is quite satisfactory with a coefficient of determination of 0.89. The coefficient of determination for the linear regression model developed by using the same input parameters is only 0.71 which emphasizes the power of ANN applications.

COMPARISON OF UZAN CONSTITUTIVE MODEL AND CURVE SHIFTING METHODOLOGY USING NEURAL NETWORK PREDICTIONS

This part of the paper focuses on comparison of the Uzan model and the curve shifting methodology for resilient modulus prediction of subgrade soils at different stress levels. Resilient modulus values for each test were determined based on the stress levels estimated for the example pavement section (σ_3 =18.28 kPa, σ_d = 38.21 kPa) illustrated in Figure 1. Since these stress values are in the range of the stresses applied during the laboratory tests, interpolations will not cause any problems. Results of the analysis indicate that the resilient modulus values predicted from the curve shifting methodology are nearly identical to the ANN model predictions with a coefficient of determination of 0.96. However, predictions performed by using the Uzan model present higher deviation from the ANN model predictions with a coefficient of determination of 0.82 (Figure 6). Coefficient of determination values for the Uzan and curve shifting methodology predictions are separately calculated based on the regression fits with respect to ANN predictions without an intercept parameter. Based on the results of the analysis, it is concluded that curve shifting methodology is superior to the Uzan model in terms of the representation of the stress-strain dependency of subgrade soils.

SUMMARY AND CONCLUSIONS

In this paper, the application of a novel approach, the GA and curve shifting methodology, as an alternative to nonlinear constitutive models was investigated. A total of 8 different soil types from different regions of Turkey were collected and 75 triaxial tests were performed under various conditions. Specimens were compacted at 3 different water content and 2 different compaction levels. Laboratory tests were conducted at 5 deviator stress levels and 3 different confining pressures to evaluate resilient response of the material. Coefficients for the Uzan constitutive model, which is accepted to be the most effective model, were determined for each test to evaluate the stress-strain dependency of the specimens. In addition, parameters for the curve shifting methodology were determined to compare its effectiveness with the Uzan model. A representative pavement section similar to existing highway structures in Turkey was analyzed and the critical stresses at the top of the subgrade for a typical axle configuration were determined. These critical stresses were integrated with the Uzan and curve shifting models to determine resilient modulus values for different subgrade soil types. Predicted resilient modulus values from each method were separately compared with ANN model predictions to compare their efficiency and reliability in terms of resilient response prediction.

Results of the analysis indicated that curve shifting methodology gives superior estimates with a coefficient of determination 14% higher than the Uzan model predictions when the results were compared with the ANN model outputs. Thus, application of GA and curve shifting methodology is proposed as a promising technique for the evaluation of subgrade soils' stress-strain dependency.

Results of the analysis further indicated that a 2 % variation in the water content during compaction highly affected the resilient moduli. In addition, plasticity index (PI), percent passing number 200 sieve (PP200), maximum dry-density (γ_{dmax}) and optimum water content (W_{opt}) parameters were observed to be effective variables for resilient modulus predictions. ANN models developed by using these important index properties and the stress levels appear to be effective tools for the prediction of the subgrade soils' stress-strain dependency within the range of the empirical training set. The predictive capability of the ANN models can be improved by selecting the effective overfit penalty values and monitoring the results on a randomly generated validation dataset. However, since ANN models do not provide insight into resilient behavior nor help understand values for soils other than those actually tested, they are not recommended as effective resilient modulus prediction tools for the subgrade soils which are out of the range of the empirical training set.

Computational time is accepted to be an important problem for the GA applications. However, for this particular case, it is observed that model run times are considerably low since no serious calculation is involved in determining the curve shift amounts. Therefore, a novice can intuitively select a wide initial interval range in order to optimize the shift amounts by increasing the number of iterations. Because computational time does not appear to be an obstructive issue, this simple algorithm can be integrated with layered elastic programs. Deficiencies in layered elastic approach to determine the nonlinear stress-strain dependency of unbound pavement materials can be minimized by calibrating their outputs with the curve shifting methodology. In addition, models proposed in this study can be integrated with mechanistic empirical design programs after the model parameters for each representative case are calculated with GA and curve shifting methodology. Thus, the computational inefficiency of GA will not be an issue with the available model parameters.

Although the results obtained from this study are impressive, further study is required to develop prediction models for each coefficient of the curve shifting model to determine their variation related to soil index parameters. Resilient response of different subgrade soil types can be predicted based on these model coefficients and curve shifting methodology. In addition, the effect of confining stresses on resilient response can be evaluated based on the curve shift amounts.

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TABLE 1 Experimental Design for Laboratory Resilient Modulus Testing

City	Region	Unified	AASHTO	Number of Tests				PP200 (%)	PI (%)	W_{opt} (%)	$\gamma_{d\,max}$ (gr/cm^3)
				C 100%			C 95%				
				opt-2	opt	opt+2	opt				
Kayseri	6/2	SM	A-7-5	2	3	2	2	48.3	13.8	19.2	1.702
	6/5	SM-SC	A-2-4	2	4	3	2	33.0	NP	15.8	1.780
	6/6	SM	A-2-7	3	3	2	2	18.3	21.2	28.4	1.436
	6/7	SM	A-5	2	3	2	2	48.5	9.7	24.8	1.478
Diyarbakir-Bismil	9/17	CH	A-7-6	2	3	3	2	83.7	37.3	22.5	1.599
Diyarbakir-Silvan	9/3	MH	A-7-6	2	3	2	2	76.1	24.9	22.8	1.590
Diyarbakir Kiziltepe Viransehir	9/6	CH	A-7-6	2	3	2	2	94.2	28.8	25.8	1.527
Ankara -Cankiri	-	SC	A-6	2	2	2	2	41.3	21.6	14.8	1.844

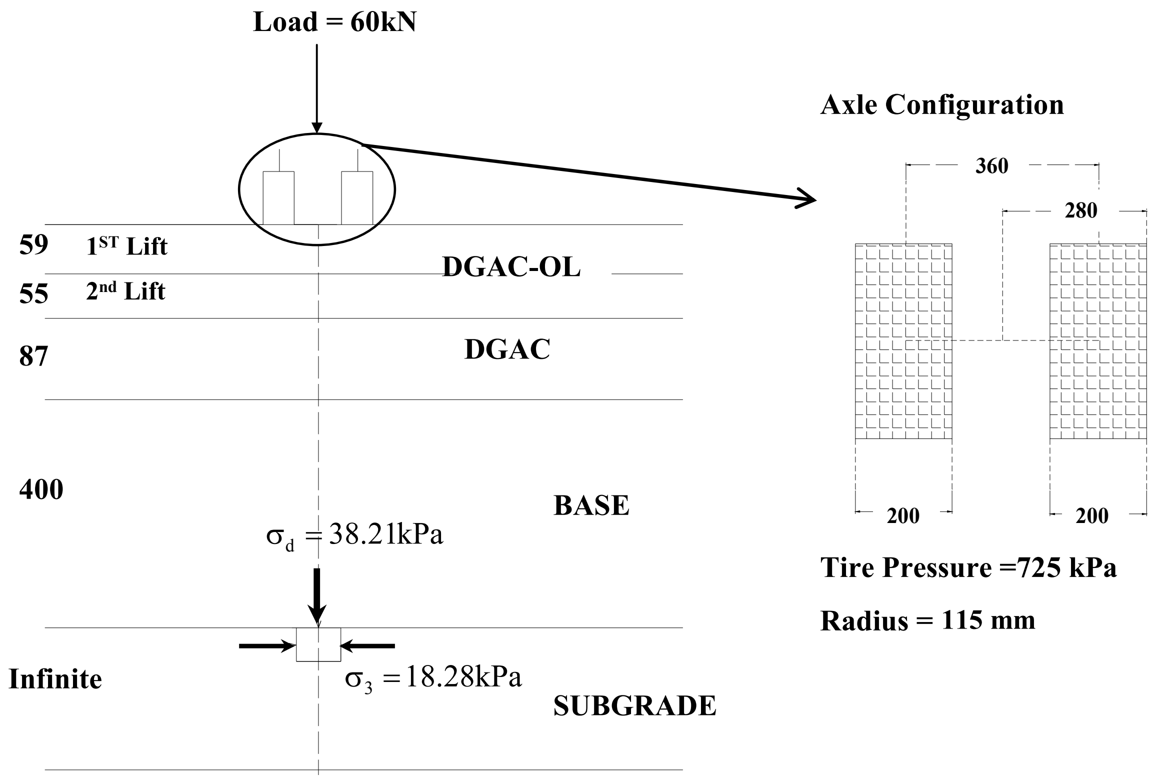
- : data not applicable

Note: PP200: Percent passing No. 200 sieve
PI: Plastic Index
W_{opt}: Optimum Water Content
γ_{dmax}: Maximum dry-density
NP: Non-plastic

C 95% : 95 % compaction
C 100% : 100 % compaction
opt-2: compaction performed at (W_{opt} -2)% water content level
opt: compaction performed at (W_{opt})% water content level
opt+2: compaction performed at (W_{opt}+2)% water content level

TABLE 2 Ranges of Soil Index Parameters and Test Stress Levels

Variable Type	Symbols	Description	Range
Dependent	M_R	Laboratory resilient modulus for varying stress states	12823 – 198640 (kPa)
Independent	σ_3	Confining pressure	13.790 - 41.369 (kPa)
	θ	Bulk stress	53.964 - 199.631 (kPa)
	σ_d	Deviator Stress	13.790 - 68.948 (kPa)
	W_{opt}	Optimum water content	14.80 - 29.60 (%)
	γ_{dmax}	Maximum dry - density	1.404 - 1.844 (Mg/m^3)
	PP200	Percent passing #200 sieve	18.3 – 94.2 (%)
	PI	Plasticity index	0 – 37.3 (%)
	Wcc	Category covariate for compaction level	Compaction at opt-2 %, opt, opt+2%



Notes: DGAC-OL: Dense graded asphalt concrete overlay
Not to Scale – Dimensions in mm

FIGURE 1 Example pavement section characteristics.

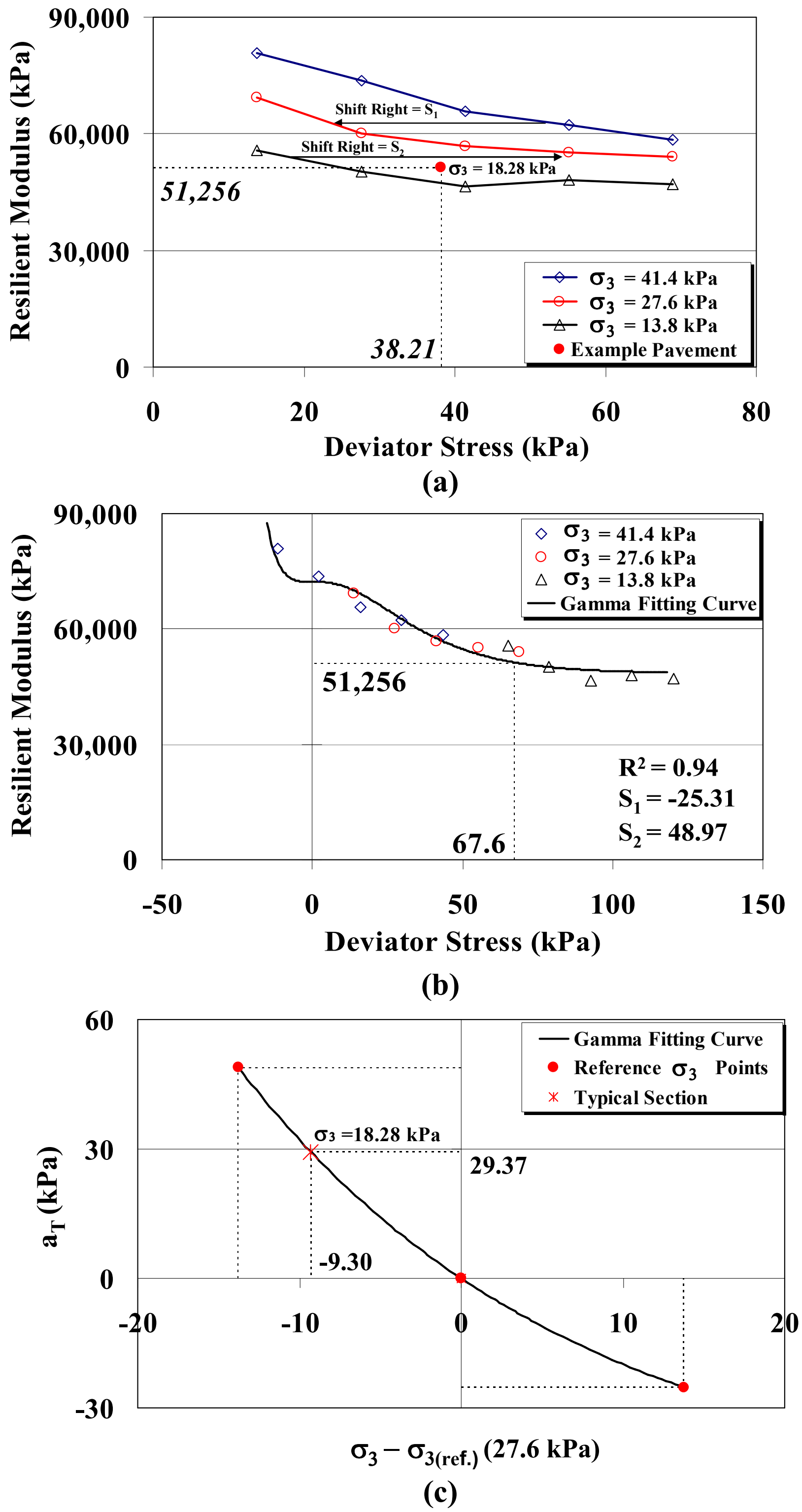


FIGURE 2 (a) Deviator stress vs. resilient modulus curves at three different confining pressures (b) Final gamma fitting curve for the representation of the shifted test results (A = -0.3978, B = 13.9146, C = 11.1878 (Eqn. 8)) (c) The relationship between confining pressure and confining pressure shift factor (Eqn. 9).

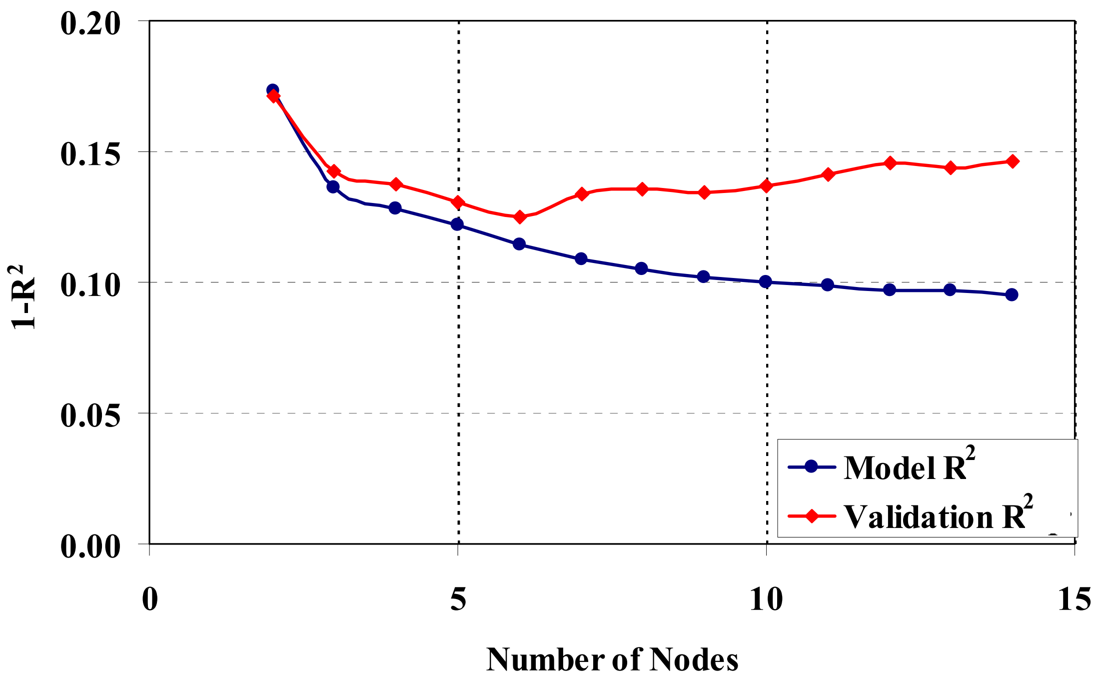
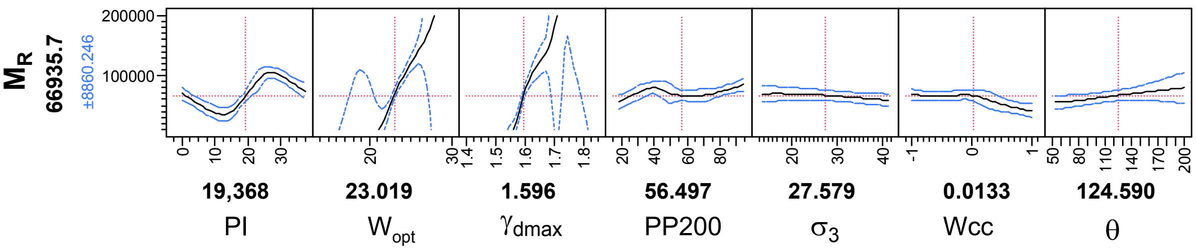
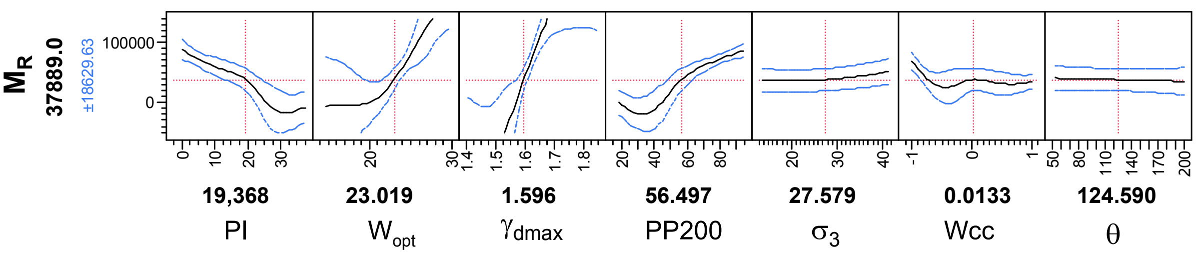


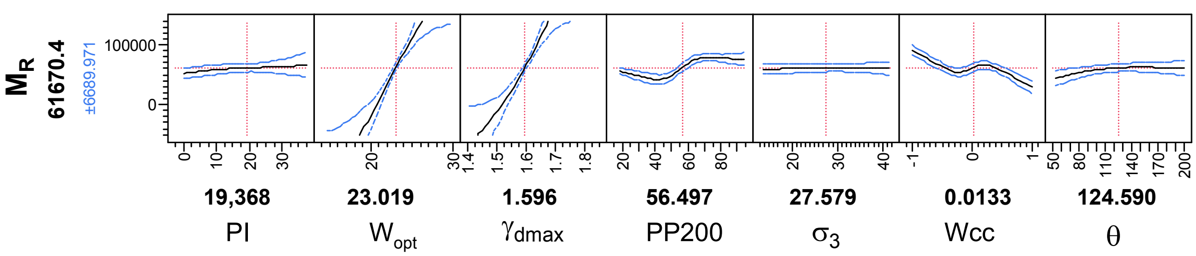
FIGURE 3 Variation of ANN model error ($1 - R^2$) by increasing number of hidden nodes (R^2: coefficient of determination for the ANN model).



(a)



(b)



(c)

FIGURE 4 Effect of overfit penalty on ANN models predictions:
(a) Prediction for model with overfit penalty = 0.001, number of nodes = 6, R^2_{model}=0.889, $R^2_{validation}$=0.867
(b) Prediction for model with overfit penalty = 0.008, number of nodes = 6, R^2_{model}=0.890, $R^2_{validation}$=0.870
(c) Prediction for model with overfit penalty = 0.016, number of nodes = 6, R^2_{model}=0.886, $R^2_{validation}$=0.869.

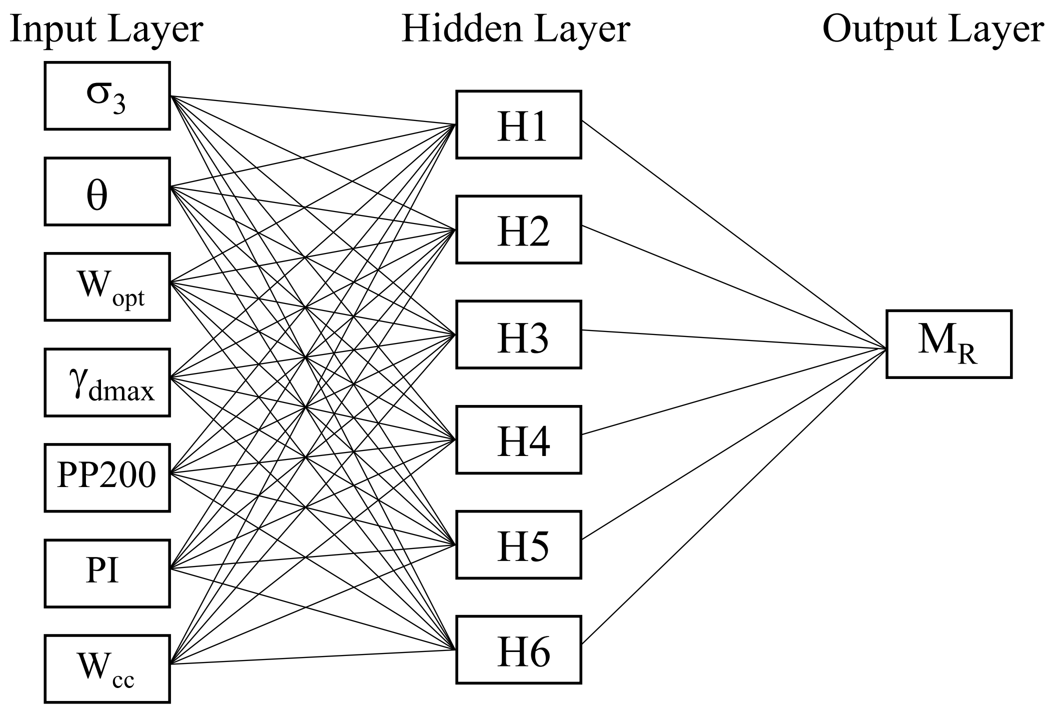
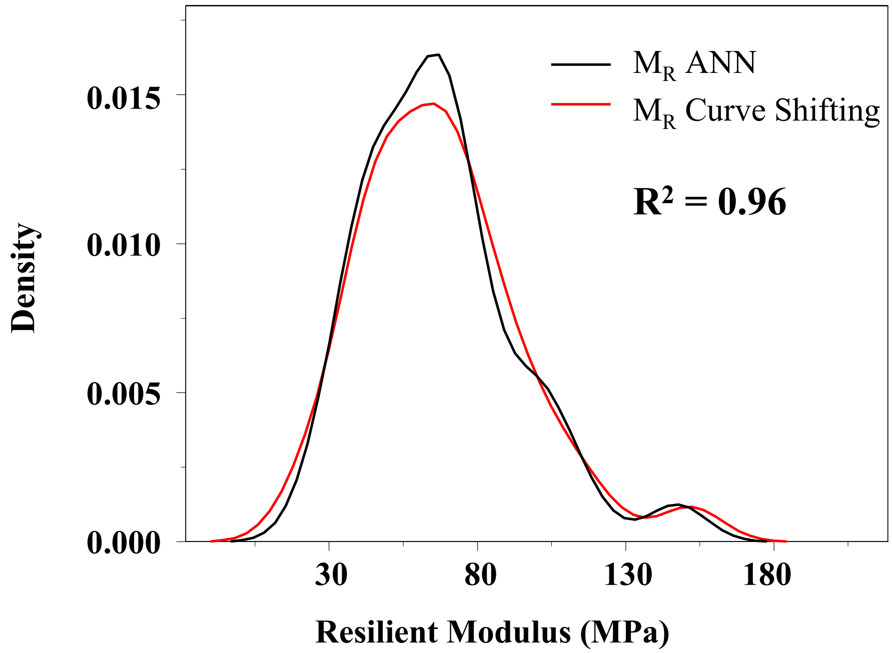
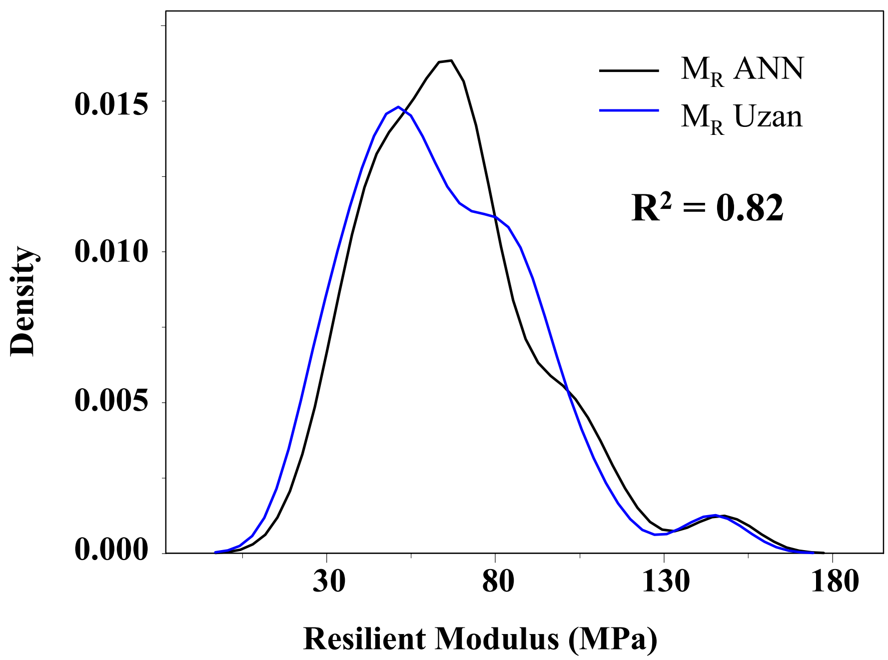


FIGURE 5 One layer ANN architecture for prediction of resilient modulus.



(a)



(b)

FIGURE 6 Comparison of Uzan model and curve shifting methodology predictions using ANN model predictions (a) Comparison of curve shifting methodology with ANN model predictions (R^2 = 0.96) (b) Comparison of Uzan model with ANN model predictions (R^2 = 0.82).