Non-destructive Evaluation of Sustainable Pavement Technologies Using Artificial Neural Networks

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Abstract Evaluation and characterization of pavements that incorporate sustainable technologies and materials such as Warm Mix Asphalt (WMA) and Reclaimed Asphalt Pavements (RAP) becomes especially important for their future applicability. Artificial neural networks (ANN) have been recently used to forward-calculate pavement layer moduli from the falling weight deflectometer (FWD) test results. A full bond layer interface condition is commonly assumed to performed pavement layer moduli calculations, however, this condition is not guaranteed to happen in the field. The objective of this study was to develop ANN models capable of predicting pavement layer moduli rapidly and reliably for full bond and full slip layer interface conditions. ANN models were used to estimate the moduli of the National Center for asphalt Technology (NCAT) Test Track structural sustainable sections for the full bond (FB) condition and the full slip (FS) condition. The results indicated that WMA sections had lower moduli at all tested temperatures compared to a control section (7 to 10% lower), likely due to the reduced binder aging experienced by these sections. RAP sections had higher moduli (16 to 43% higher) and were less susceptible to changes in temperature due to the presence of stiffer aged binder. Overall, backcalculated layer moduli using the conventional iterative approach had the highest error, followed by a significant decrease in error by ANN predicted moduli under full bond condition. However, the consideration of the ANN with full slip condition yielded the best results (lowest error).

Keywords Warm Mix Asphalt, Reclaimed Asphalt Pavements, Neural Networks, FWD, Pavement Evaluation

1. Introduction

The asphalt industry has been developing sustainable paving technologies and practicing green-build techniques since the 1960's through the reduction in emissions from asphalt plants and through recycling (APAI, 2008). Since 1970, with the implementation of the Clean Air Act, total emissions from asphalt plants have dropped by more than 97% while annual production has increased by more than 250% (Cervarich, 2004).

The asphalt industry has been implementing the use of warm mix asphalt (WMA) as means of reducing greenhouse gas emissions. On the other hand, asphalt pavement is the most recycled material in the nation, with about 100 million tons of asphalt pavement being reclaimed every year and approximately 80% of it being recycled back into new asphalt mixes (Hansen & Newcomb, 2007). Evaluation and characterization of pavements that incorporate sustainable technologies and materials such as WMA and Reclaimed Asphalt Pavements (RAP) becomes especially important for their future applicability.

One of the most common field tests used to obtain pavement layer moduli is done with the falling weight deflectometer (FWD). Artificial neural networks (ANN) have also been used to calculate pavement layer moduli and critical pavement responses from FWD tests results (Meier et al,. 1995, 1997). An artificial neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use (Priddy and Keller, 2005). Consequently, knowledge is acquired by the network through a learning (training) process. The aim of the learning process is to map a given relation between inputs and outputs of the network.

One of the most common networks selected by pavement researchers uses a back-propagation algorithm (Meier et al, 1995, Ferregut et al.,1999, Ceylan et al, 2005). This learning algorithm is applied to multilayer feed-forward networks consisting of processing elements with continuous and differentiable activation functions. Such networks associated with the back-propagation learning algorithm are also called back-propagation networks (Priddy and Keller, 2005). Errors are calculated from outputs and targets and then used to update output weights by back propagating the error. The process continues until the performance of the network is optimized (i.e. minimum mean square error - MSE calculated between outputs and targets is obtained).

Even though, ANN models are excellent tools for pavement layer moduli estimation, these models depend on how the field conditions are being modeled. Romanoschi and Metcalf (2003) evaluated the potential error in pavement layer moduli backcalculation due to improper modeling of the layer interface condition. It was found that the condition of the wearing-binder layer interface leads to an error in backcalculated moduli for the granular base layers, for both flexible and the semirigid structures. Lenngren and Olsson (2003) studied the effect of performing conventional backcalculation on a four-layer system with full slip (air gap) condition between layers. Their results indicated that the backcalculated modulus of the unbound base was most affected by adding friction between layers. The effect on the unbound base is considerable and may explain a lot of underestimated modulus on base courses.

This document focuses on the evaluation and characterization of pavements that incorporate sustainable technologies and materials such as WMA and RAP. The methodology incorporates advanced modeling through the use of ANN models and full slip interaction between layers.

1.1 Objective

The objective of this study was to develop ANN models capable of predicting pavement layer moduli rapidly and reliably for the sustainable pavement structures placed at the NCAT Test Track.

2. Development Of ANNs For Sustainable Sections At The 2009 Test Track

Table 1 contains pertinent as-built information for each lift in all the studied sections. The primary difference between S9 (control) and sections S10 and S11 was the technology used to create the mixture at the plant. S10 was produced with a foam-based warm mix asphalt (WMA) technology and S11 was produced as an additive-based WMA. The primary difference between S9 (control) and sections N10 and N11 was the inclusion of reclaimed asphalt pavement (RAP), the asphalt modifier and the technology used to create the mixture at the plant. Mixes in N10 and N11 were used without asphalt modifiers but each lift was designed to incorporate 50% RAP in the mixture. In addition, N11 was produced as a WMA mixture. The effect of the aged binder contained in the RAP resulted in the highest Superpave performance grade for the intermediate and bottom lifts of N10 (PG 94-10). Overall, all sections and lifts met or exceeded 92% of maximum theoretical density (less than 8.0% in-place air voids).

A synthetic database was generated using layered-elastic analysis (LEA) for a three-layered flexible pavement structure. For each ANN, a total of 100,000 data points were generated using multiple load levels ranging from 5,000 lb to 20,000 lb. To create each ANN, the variables deflections (nine total), layer thicknesses and load were selected as input signals and the moduli of the AC layer (E1), the granular base (E2) and the subgrade (E3) were selected as the target signals.

Table 1 Asphalt Concrete Layer Properties – As Built

Lift	1-Surface				
Section	S9	S10	S11	N10	N11
%Modifier	2.8	2.8	2.8	0.0	0.0
PG Grade[a]	76-22	76-22	76-22	82-10	80-16
RAP[b], %	0.0	0.0	0.0	50	50
Asphalt, %	6.1	6.1	6.4	6.0	6.1
Air Voids, %	6.9	7.5	6.4	7.4	8.0
Thickness, in	1.2	1.3	1.5	1.4	1.2
Lift	2-Intermediate				
Section	S9	S10	S11	N10	N11
%Modifier	2.8	2.8	2.8	0.0	0.0
PG Grade[a]	76-22	76-22	76-22	94-10	88-10
RAP[b], %	0.0	0.0	0.0	50	50
Asphalt, %	4.4	4.7	4.6	4.4	4.7
Air Voids, %	7.2	7.0	7.2	7.1	6.8
Thickness, in	2.8	2.7	2.8	2.7	3.0
Lift	3-Base				
Section	S9	S10	S11	N10	N11
%Modifier	0.0	0.0	0.0	0.0	0.0
PG Grade[a]	67-22	67-22	67-22	94-10	88-10
RAP[b], %	0.0	0.0	0.0	50	50
Asphalt, %	4.7	4.7	5.0	4.7	4.6
Air Voids, %	7.4	7.9	6.2	5.0	5.8
Thickness, in	3.0	3.0	2.6	3.0	2.9

[a]Superpave Asphalt Performance Grade
[b]Reclaimed asphalt pavement

The learning method used to develop these ANN models was a feed-forward back propagation with the sigmoid function, Equation 1, as the transfer function. It was found that the three-layer network with twenty nodes in the two hidden layers was the most appropriate for this dataset. The basic form of the ANN is given by Equations 1 through 4. For these equations, a single index indicates an array; dual indices represent a matrix with the first letter indicating the values in the row and the second letter indicating the values in the column. The index i represents the input parameters, the index k represents the first hidden layer, and the j subscript represents the second hidden layer. An illustration of the model and the training process are shown in Figure 1.

$$f(T) = \frac{2}{1+e^{-2T}} - 1 \qquad (1)$$

$$H_k^1 = B_k^1 + \sum_{i=1}^{m} W_{ik}^1 P_i \quad (2)$$

$$H_j^2 = f\left(B_j^2 + \sum_{k=1}^{n} H_k^1 W_{kj}^2\right) \quad (3)$$

$$Output = Ln(E_1, E_2, E_3) = f\left(B_O + \sum_{j=1}^{n} H_j^2 W_j^3\right) \quad (4)$$

Where;
T = placeholder variable,
H_k^1 = transferred value of nodes at first hidden layer,
H_j^2 = transferred value of nodes at second hidden layer,
P_i = input variables,
W_{ik}^1 = weight factors for first hidden layer,
W_{kj}^2 = weight factors for the second hidden layer,
W_j^3 = weight factors for the output layer,
B_k^1 = bias factors for first layer,
B_j^2 = bias factors for second layer,
$B0$ = bias factor for outer layer,
m = number of nodes in first hidden layer
n = number of nodes in second hidden layer
$Ln(E_1, E_2, E_3)$ = natural logarithm of the AC, base and subgrade modulus, respectively.

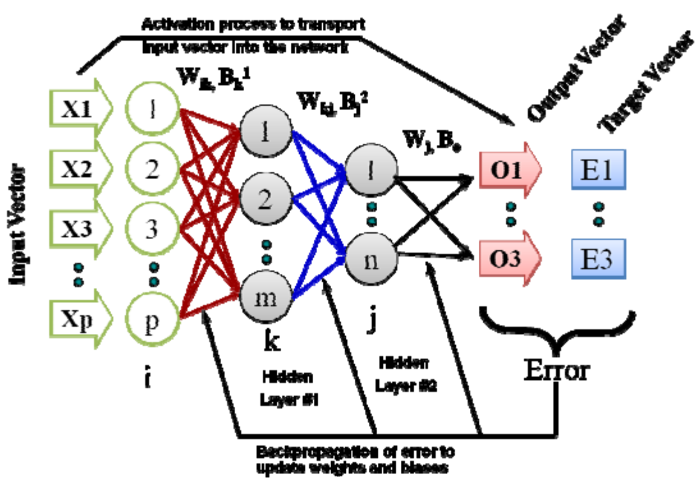

Fig. 1 Schematic of ANN model and training process

Checking the adequacy of the trained ANN's was performed by the use of goodness of fit regression parameters. Since the dataset used for this exercise was synthetic, it was expected to have estimated moduli highly correlated to the actual values and with minimum errors as shown in Table 2.

Table 2 Goodness of Fit for the Synthetic Database ANN models

Parameter	ANN Predicted – Full Bond		ANN Predicted – Full Slip	
	R^2	Se/Sy	R^2	Se/Sy
E1	0.99	0.069	0.99	0.057
E2	0.99	0.083	0.99	0.071
E3	1.00	0.009	1.00	0.010

3. Application of ANN Models on Measured Deflection Basins

ANNs were used to estimate the moduli of seven structural sections built in 2009 for the full bond (FB) condition and the full slip (FS) condition. Figure 2 illustrates the measured relationship between backcalculated AC modulus and mid-depth temperature. For each test section, the AC modulus was estimated at the outside wheelpath, where greater damage is expected to occur.

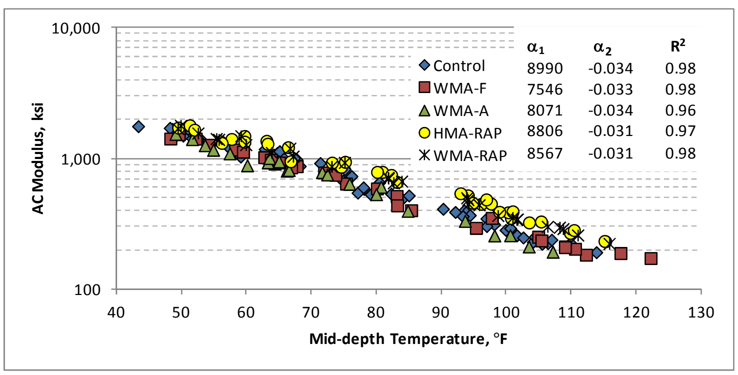

Fig. 2 Relationship Between Estimated AC Modulus and Mid-depth Temperature

To determine if the stiffness-temperature relationship was statistically similar among the sections, 95% confidence intervals were obtained for the intercepts and slopes of all the plotted relationships (Figure 3). If the intervals overlapped, it could be concluded that the differences in the regression coefficients were not statistically significant. At 95% confidence level, there was no evidence that the intercepts of high RAP sections were statistically different from the control. However, the intercepts of the WMA sections were significantly lower than the control, indicating that the modulus tended to be lower at all temperatures. The slopes of the high RAP sections were lower than that of the control section and virgin

WMA sections, which means they were less influenced by temperature presumably due to the presence of aged binder.

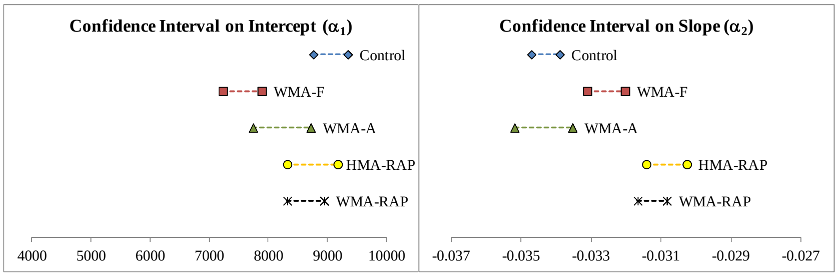

Fig. 3 95% Confidence Intervals for Regression Coefficients

Table 3 shows the backcalculated and ANN-predicted layer moduli range for all sections. In general, the predicted moduli from ANN-FB were not statistically different to backcalculated for all three layers (95% confidence level). The same trend was observed between ANN-FS predicted moduli and backcalculated for E1 and E3. In the case of E2, the results showed that ANN-FS predicted moduli were statistically different (95% confidence level) from more than double the backcalculated ones. These results suggested that the moduli of the granular base were underestimated for considering a full bond condition when applying conventional backcalculation or when predicting moduli with ANN-FB.

Table 3 Ranges of Predicted Layer Moduli for All Sections

Technique	**Section**	**E1, ksi**	**E2, ksi**	**E3, ksi**
Conventional Backcalculation	S9 (Control)	134 - 2357	1.0 - 11.2	14 – 42
	S10 (WMA-F)	122 - 1946	1.0 - 8.1	17 - 38.8
	S11 (WMA-A)	124 - 2060	1.0 - 7.8	13 - 43.9
	N10 (HMA-RAP)	172 - 2440	1.0 - 9.8	26.1 - 64.2
	N11 (WMA-RAP)	161 - 2173	1.6 - 13.1	28.5 - 52.6
ANN Full Bond	S9	129 - 2519	1.0 - 12.5	12.2 - 38.8
	S10	108 - 2073	1.0 - 7.0	13 - 35.1
	S11	115 - 2190	1.0 - 6.4	10.2 - 41.5
	N10	230 - 2536	1.0 - 11.2	17.1 - 54.8
	N11	185 - 2336	1.3 - 13.4	25.1 - 46.6
ANN Full Slip	S9	151- 2231	1.1 - 26.2	12.1 – 39
	S10	129 - 1817	1.3 - 15.8	14.1 - 36.6
	S11	135 - 1941	1.1 - 13.1	9.1 - 41.7
	N10	117 - 2313	1.1 - 35.3	14.9 - 55.7
	N11	159 - 2169	2.6 - 48.6	27.3 - 48.7

Figure 4 shows the relationship between the moduli obtained from conventional backcalculation and predicted moduli using ANN-FS. The slope of a linear trend-line plotted between backcalculated moduli and ANN moduli was used to quantify the expected difference. For this case, the slope indicated that an overall decrease of 6.0% in the modulus of the AC layer was obtained when using ANN-FS. In this case an R2 value close to 1.0 indicates that the relationship between variables can be expressed with a linear function.

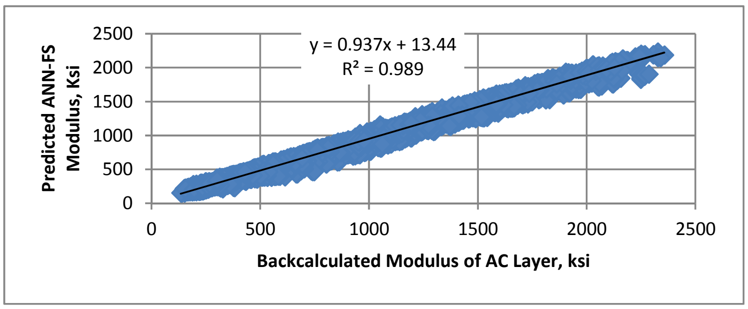

Fig. 4 Backcalculated vs. ANN Predicted E1 of the Control Section (S9)

Table 4 shows the slope of a linear function calculated between backcalculated moduli and ANN moduli and its associated R^2 value for each section. These results were used to quantify the expected difference and overall trend. When considering the observed difference for all the sections and for all the layer moduli, the results indicated that an overall decrease in the estimated moduli was obtained for the three layers (from 5.0% to 10.0%) when comparing backcalculated and ANN-FB methods. The largest decrease in modulus was obtained for section S10 followed by S11 in the case of E1. The results also indicated that an overall decrease in the estimated moduli was obtained for E1 and E3 when comparing backcalculated and ANN-FS methods. However, a significant increase (overall 234%) was observed in the case of E2. Section N10 was the most affected with an increase in 327%. Although the use of ANNs in full slip condition indicated that the moduli of the granular base can be more than twice the estimated by conventional backcalculation, the results provided lower RMSE values and more realistic moduli for the base. The modulus of the granular base obtained from conventional backcalculation ranged from 1.0 psi to 15.7 psi. The modulus of the granular base obtained from ANN-FS ranged from 1.1 psi to 48 psi which can be considered as more realistic moduli range for the base.

Table 4 Overall Changes in Moduli for All Sections

ANN	Section	Slope of Back. Mod. Vs ANN Mod.			R^2 of Back. Mod. Vs ANN Mod.		
		E1	E2	E3	E1	E2	E3
Full Bond	S9 (Control)	0.95	0.88	0.93	0.98	0.85	0.85
	S10 (WMA-F)	0.84	0.97	0.89	0.96	0.65	0.7
	S11 (WMA-A)	0.85	0.97	0.94	0.97	0.78	0.84
	N10 (HMA-RAP)	0.91	0.88	0.94	0.97	0.9	0.81
	N11 (WMA-RAP)	1.01	1.11	0.89	0.99	0.89	0.88
Average		0.93	0.91	0.96	0.92	0.97	0.81
Full Slip	S9	0.94	2.16	0.94	0.99	0.96	0.94
	S10	0.90	1.90	0.96	0.98	0.93	0.91
	S11	0.91	1.91	0.95	0.98	0.94	0.93
	N10	0.98	2.36	1.07	0.99	0.94	0.86
	N11	0.99	3.27	0.84	1.00	0.90	0.89
Average		0.95	0.94	2.32	0.95	0.99	0.93

Figure 5 shows the cumulative distribution plot (CDP) of the Root Mean Square (RMS) error for three different scenarios. CDPs for ANN-FB and ANN-FS showed a significant decrease in the level of error from backcalculated values. In addition, the consideration of a full slip condition yielded even better results. A maximum RMS error of 3.0% was set to determine the amount of data to be used for all the analyses regarding the 2009 Test Track research cycle. Approximately 84% of the backcalculation solutions generated by conventional backcalculation had RMS errors below 3.0%. In the case of ANN-FB method, 88% of the results had RMS errors below 3.0%. Finally, for ANN-FS method, 92% had RMS errors below 3.0%. When the amount of data below 1.0% were considered as an "excellent match" between measured and calculated deflections (Everseries User's Guide, 2005), only 20% were found below 1.0% for backcalculated values, 73% for ANN-FB and 88% for ANN-FS. These results demonstrated the significant advantage of using ANNs over conventional backcalculation that does not consider a full-slip condition.

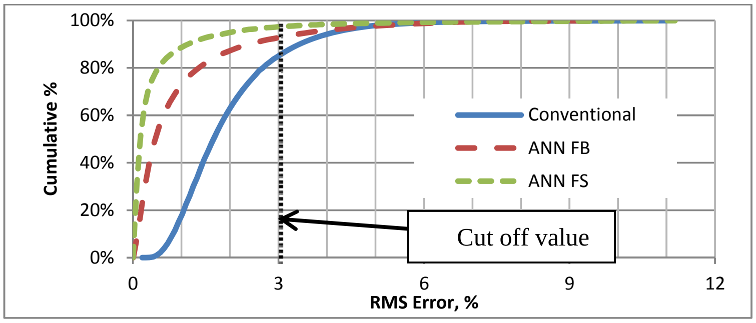

Fig. 5 Cumulative Distribution Plot For Estimated Moduli

Table 5 shows an extension of the previous analysis applied to all sections. A significant increase in the amount of data that was considered "excellent match" between measured and calculated deflections was obtained when using ANNs compared to conventional backcalculation for all sections. The largest increase was observed from conventional backcalculation to ANN-FS for all the sections. Section S10 had the lowest overall increment followed by S11 and N10. These results were attributed to the higher variability observed in the layers moduli due to the higher permanent deformation (rutting) for sections S10 and S11. These sections had rut depths 35% to 54% higher than the control section (West et al, 2012). Rutting is a type of distress that changes the shape of the pavement surface increasing the variability in terms of thickness and density.

Table 5 Analysis of RMS errors for all sections

RMSE	Section	Percent data below cutoff value		
		Conv. Back.	ANN FB	ANN FS
Below 1%	S9 (Control)	21.5	76.2	93.2
	S10 (WMA-F)	22.9	40.9	78.3
	S11 (WMA-A)	21.9	54.5	79.8
	N10 (HMA-RAP)	8.28	53.8	65.1
	N11 (WMA-RAP)	8.2	92.9	99.9
Below 3%	S9	85.8	94.8	99.2
	S10	89.9	81.3	97.2
	S11	74.7	83.2	95
	N10	86.1	86.2	87.6
	N11	92.8	100	100

The amount of data below 3.0% was also increased when using ANN-FB for all sections but S10. However, the increment was significant when using ANN-FS for all sections. In general, the quality of the layer moduli prediction (RMSE <

1.0%) was significantly increased by the use of ANNs and the amount of usable data (RMSE < 3.0%) was also significantly increased by the consideration of full slip condition between layers (ANN-FS).

4. Summary

The increasing use of sustainable pavement technologies and the transition of many state agencies from an empirical pavement design method to a mechanistic-empirical approach have prompted the need to evaluate the physical and structural characteristics of these sustainable pavements. By doing so, performance prediction can be improved, thus allowing for more efficient designs. In this study, four sustainable pavement test sections were included: two warm mix asphalt sections (one foam-based and one additive-based) and two high RAP sections (one produced as a hot mix and one produced as a warm mix). All of these were compared to a control section of the same thickness consisting of dense-graded materials and produced as a hot mix.

Customized ANN models were created based on structural sections built in 2009 at the NCAT Test Track. ANN-predicted layer moduli from synthetic results were comparable to backcalculated layer moduli in terms of R2 regression parameters and consequently adequate to predict layer moduli.

An analysis of the potential errors in pavement layer moduli backcalculation due to improper modeling of the layer interface condition was performed using synthetic data. The results indicated that the tendency was to significantly overestimate the AC modulus (by 30%) and also the tendency was to underestimate the modulus of the granular base (by 74%).

ANNs were used to estimate the moduli of the NCAT Test Track structural sections for the full bond (FB) condition and the full slip (FS) condition. Backcalculated layer moduli had the highest overall error followed by a significant decrease in error by ANN predicted moduli under full bond condition. However, the consideration of the ANN with full slip condition yielded the best results (lowest error).

5. Conclusions

Based upon the research conducted in this study, the following conclusions can be made concerning the application of ANNs used to characterize material properties.

1. Contrary to backcalculation, ANNs do not depend on seed values and the ANN-predicted layer moduli can be estimated at lower RMS errors.

2. Significant differences in layer moduli can be obtained due to the improper modeling of the layer interface condition. The modulus of the granular base can potentially be the most affected.
3. The capability for ANNs to predict pavement layer moduli was validated using multiple load levels and full slip condition as a layer interaction. This presented a clear advantage over previous studies that have been focused on one load level and full bond conditions.
4. Virgin WMA sections had lower AC moduli than the control. Although the differences were statistically significant due to low variability in the sections, the magnitudes of the moduli of all sections produced with virgin aggregates were within 10%, which may not be considered to have a practical impact. High RAP mixes exhibited the highest AC moduli overall.

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