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“A New Revised Version Predictive Model of Elastic Modulus Using Artificial Neural Network”

Eng. Ayaat Ahmed Rabah, Prof. Dr. Ahmed Sabry El Hakim., Dr. Mohamed mahmoud Refaee, Dr. Mohamed El Gendy,
Lecture, Prof .At El Azhar University faculty of engineering, Associated prof. at El Azhar University faculty of engineering, Assistant prof. at El Azhar University faculty of engineering,

الملخص العربى :

في العديد من البلدان غير الصناعية ، يؤدي الافتقار إلى الأجهزة الدقيقة بالإضافة إلى الخبرة حول كيفية استخدام هذه المعدات المحددة إلى إجبار مصممي الأسفلت على المعالجة والأداء في التجارب العلمية التي لا تعكس الوجود المعقد لأحمال المرور المتكررة أو تكرار الظروف الحقيقية لنظام رصف تحت التحميل. تم تقييم المعامل المرن لطبقات الأسفلت لتكون من بين أكثر الخصائص الفعلية إثارة للجدل في تصميم الأسفلت. عادة ما يتم إجراء الاختبارات غير المدمرة على الأرصفة الحالية لقياس انحرافات السطح ، والتي تستخدم لإعادة حساب المعاملات الديناميكية المرنة لطبقات الرصيف. على الرغم من ذلك ، فإن دقة النموذج المحسوبة بأثر رجعي تعتمد على عملية الحساب الخلفي .تطور هذه الدراسة طرق الحساب الرجعي الكلاسيكية الحالية طريقة لتقدير المعامل المرن لنظام رصف مرن من ملء بيانات انحراف مقياس انحراف الوزن. من السهل الحصول على نموذج التنبؤ بمعامل المرن للرصف من خلال برمجة البيانات. في هذا البحث ، يمكن أن تكون وحدات البحث بمثابة مساعدة أولية في تقييم هياكل الرصف المرنة. تم تحليل استخدام الشبكة العصبية الاصطناعية مع R^2 بين معاملات بنسبة 99 بالمائة على نطاق واسع من أجل ضبط جميع المعاملات المهمة مثل (درجة الحرارة ، وعمر العينة ، وحجم حركة المرور) والمشغلين الذين يؤثرون على آلية الحساب الخلفي التي كان رمزا مميزا من FWD. أيضا ، تم تمييز الاكتشافات المتعلقة بجميع التفاصيل الدقيقة المتوقعة للقيام بدورة الحساب الخلفي وتحدث عنها تماما. تم تطوير طرق جديدة لدراسة التفاعل بين المتغيرات وتأثيرها على معامل المرونة الاستاتيكية.

Abstract:

In many non-industrial countries, the lack of superior hardware as well as expertise about how to use this particular equipment forces asphalt designers to process and performance on scientific experiments that do not reflect the complex existence of repetitive traffic loads or replicate the real conditions of a pavement system under loading in the region. The elastic module of asphalt layers assessed to be among the most disputable actual properties in asphalt designing. What's more, asphalt examination utilizing the flexible module of the establishing layers is generally known and acknowledged by engineering and professionals because of its straightforwardness. Non-destructive tests are commonly performed on existing pavements to measure the surface deflections, which used to back-calculate the elastic dynamic module of the pavement layers. Notwithstanding, the accuracy of the back- calculated module is dependent on the back-calculation operation and the associated seed module. None of the existing classical back-calculation methods can this study developed a method to estimate the elastic module of a flexible pavement system from fulling Weight Deflectometer deflection data. It's simple to program into the forecasting model. In this research modules can be of a primary Initial help the evaluation of the flexible pavement structures. The use of an artificial neural network with R^2 between parameters of 99 percent has been extensively analyzed in order to fine-tune all of the significant parameters such as (temperature, sample age, traffic volume) and operators that influence the back-calculation mechanism that was token from FWD. Also, discoveries with respect to all the subtleties expected to do the back-calculation cycle were distinguished and talked about altogether. New novel methods to study the interaction between parameters and their effect on the static elastic modulus were developed.

Keywords: elastic modulus, non-destructive tests, back-calculation, Fulling Weight Deflectomere (FWD), Artificial Neural Network (ANN).

1) Introduction And Background

The determination of the paving layer module is a major phase in the evaluation and study of the efficiency of current pavements on roads. Over the years, several methodologies involving static, dynamic, and adaptive processes developed obtaining in-situ pavement layer moduli from Falling Weight Deflectometer (FWD) test deflection data through inverse analysis and parameter identification routines[1]

Historically, various types of material parameters have been used for presenting the stiffness characteristics of asphalt mixtures that include flexural stiffness, creep compliance, relaxation modulus, resilient modulus, dynamic modulus etc. At present, one of the most universally used methodologies to characterize the modulus of asphalt mixtures is the dynamic (complex) modulus (E*). (Research, led by Dr. M. W. Witczak, conducted at ASU, under the NCHRP 9-19) project demonstrated that the complex (dynamic) modulus (E*) can be used as a good performance indicator for the HMA design stage .[2] [3] As compared to other rigidity parameters (e.g. resilient module, Mr), Witczak and other colleagues working on NCHRP 9-19 have outlined a range of benefits of using the E* in the HMA pavement research and design.

1. E data allows a hierarchical HMA mixture characterization approach to be used.
2. aging can be taken into account,
3. vehicle speed (time of load) can be taken into account, E can be linked to the SHRP Performance Graded binder specifications,

There are various modules described, with one of the most important being the discovery that the AASHTO's effective modulus (Ep) is an outstanding transfer variable for evaluating E1. Using Eq. (1) equation, E1 can now be calculated. The equation expressed is the relation between the Ep product and the thickness (HT) of the pavement and the three pavement layer modules yield a high R-square value.[4]

$$E_p H_T = -4467.933 + 0.490 E_1 H_1 + 1.229 E_2 H_2 + 0.653 E_3 H_3 \qquad \text{Eq. (1)}$$

$R^2 = 0.918$

Where,

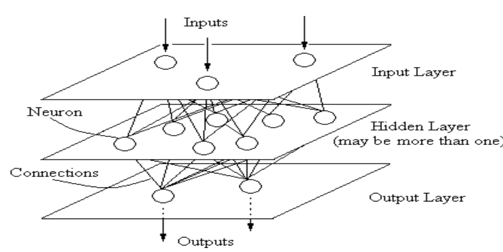
E_p = Equivalent modulus of the pavement, (MPa)

H_T = Total Thickness of layers # 1, 2, and 3, (cm)

2) Artificial neural network

Artificial neural networks are computer processing techniques that simulate biological nervous systems that can overcome nonlinear relations in a particular challenge. ANNs are also capable of learning from examples by highly linked processing systems, called neurons, like the human brain. Neural network architectures, arranged in layers, involve synaptic connections amid neurons which receive signals and transmit them to the other neurons via activation functions. Each connection has its own connection weight and learning is the process of adjusting the connection weights between neurons to minimize the error between the predicted and given values. In the learning process, addition to the relation weights, node biases are also balanced. As interconnected neurons are flexible in adjusting weight, neural networks can analyse difficult problems with powerful capacity. ANNs, inspired by the neuronal architecture and operation of the human brain, contribute to our understanding of several complex, non-linear pavement engineering problems with various pavement materials and pavement foundation variables. Figure 1 displays a typical structure of ANNs that consists of a number of neurons that are usually arranged in layers: an input layer, hidden layers, and an output layer.[5]

Figure 1. A general schematic view of the artificial neural networks



3) Problem Statement and Objectives

- Pavement efficiency under traffic loading is predicted by using pavement solution models that use artificial neural networks to assess the mechanical behaviour of the various layers in a multi-layered pavement structure.
- The implementation of the material model and the pavement response model provides a more realistic, reliable, and low-cost approach for the design and analysis of pavements.
- Given the significance of the proposed technique for developed countries, its applicability extends beyond the regional limits of the Mechanistic development knowledge is given to transportation agencies in developing countries with very different design cultures.[6]

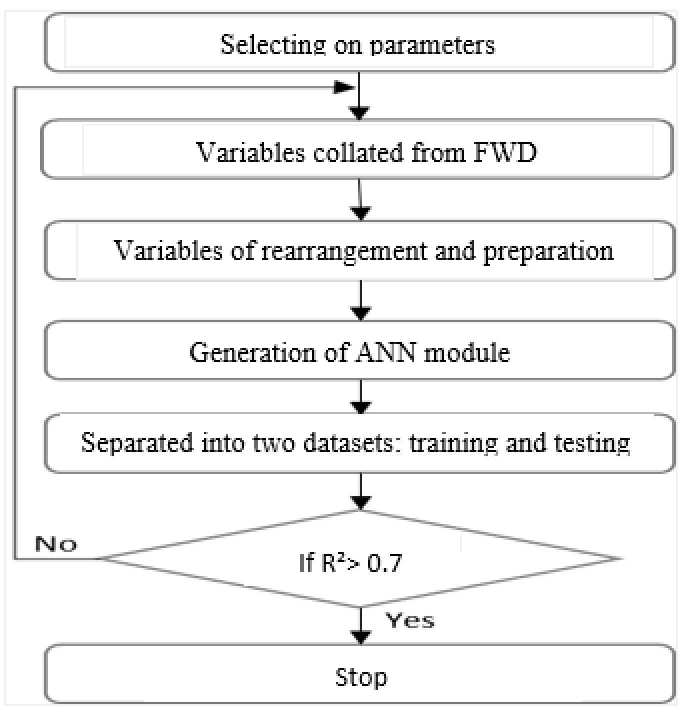
The goal of the study to presented an enhanced version of elastic modulus predictive model for flexible pavement of estimating changes in modulus as a function of changes in traffic volumetric, age, temperature and other parameter for the data.

4) Research Methodology

The analysis technique is represented in the flowchart figure (2). The current practice of the back-calculated elasticity moduli was studied in this analysis based on a simple value between the measured deflections on the FWD (from 581 sample).This data can be used successfully to establish detailed stiffness models for binders. The database collected is a quicker and more flexible way to gather value of E. There are two key streams of studies that take advantage of feature approximation capacities to minimize gathered pavement condition information to usable information. The reported results can be screened and confirmed

1. Direct calculation by condition surveys of Elastic Module (E) pavement quality indices (ESAL, age, temperature, and other parameter)
2. Modularizing of pavement structural properties using non-destructive testing (NDT) instruments such as the falling weight deflectometer (FWD)

Figure 2: Flowchart all steps to achieving a perfect module.



5) Current neural network innovative module

After collected data that mention in table (1), with using of python programme a critical investigation of the quality of E database; of E were eventually obtained in the final modelling [2]

5.1 Static elastic modules from data field using ANN (by python programmed) (module E)

Collected dataset in table (1) The test data for the evaluation of the ANN performance are divided into testing, validation training stops when any of the following conditions is satisfied: the maximum number of iterations is reached and testing functions and in typical ANNs most of the data are used to train the network. The performance gradient falls below a minimum value; or the performance is minimized to the target value. Throw FWD parameter, traffic, age, and temperature surface.[6]

5.1.1 Dataset of module E

Table 1: Part of (464 samples) of dataset rearrangement into python program for a table extension head

Out[2]:	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	w	surface temp	current life	AADTT	E-Asphalt
0	384.861503	281.535328	255.552997	220.225553	191.714513	144.839710	106.723834	78.966255	60.675312	45.777709	24	40	4	487	1321.488890
1	213.610276	119.833278	92.139036	67.514768	51.718941	35.115801	23.640480	16.867276	13.189980	10.012790	24	40	4	487	2380.925728
2	268.000000	221.000000	194.000000	162.000000	141.000000	108.000000	81.000000	62.000000	51.000000	42.000000	20	8	4	808	1876.871724
3	179.000000	163.000000	152.000000	136.000000	123.000000	101.000000	79.000000	64.000000	53.000000	44.000000	20	8	4	808	2810.064928
4	209.000000	187.000000	172.000000	148.000000	131.000000	101.000000	75.000000	56.000000	46.000000	37.000000	20	8	4	808	2406.706326

Dataset Statistics of module of E

Table 2: Part of dataset from python program for a table extension

Out[4]:	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	w	surface temp	current life	AADTT	E-Asphalt
count	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000
mean	217.847861	183.072589	165.499471	142.231911	125.758076	99.350482	75.723681	58.664265	48.818701	39.950156	21.211704	10.120482	4.349398	700.640275	2399.665524
std	83.026174	56.083836	45.725503	36.709639	30.890874	23.675100	18.832504	14.380895	12.256392	9.951036	2.925206	9.542244	0.477191	125.875361	713.454417
min	106.909044	96.081518	85.812629	52.796954	34.834898	15.610433	5.202572	0.830289	0.000115	0.108683	20.000000	0.000000	4.000000	487.000000	473.222987
25%	177.000000	154.000000	141.000000	123.000000	110.000000	89.000000	68.000000	53.000000	45.000000	37.000000	20.000000	8.000000	4.000000	586.000000	2122.369714
50%	197.904031	172.000000	157.000000	137.000000	122.000000	97.000000	74.000000	58.000000	48.000000	40.000000	20.000000	8.000000	4.000000	731.000000	2515.008111
75%	229.000000	196.000000	179.000000	154.000000	137.000000	106.158736	80.000000	63.000000	52.000000	43.000000	20.000000	8.000000	5.000000	808.000000	2825.851810
max	892.778934	601.000000	570.000000	520.000000	464.000000	365.000000	265.000000	168.942191	140.782203	113.593845	30.000000	40.000000	5.000000	808.000000	4451.341789

5.1.2 Looking for Correlations

Computing the standard correlation coefficient (also called Pearson's r) between every pair of attributes.

Table 3: Correlation values of the ANN parameter models of static E (module)

Out[5]:

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	w	surface temp	current life	AADTT	E-Asphalt
d1	1.00	0.94	0.85	0.73	0.60	0.39	0.25	0.10	0.04	-0.01	0.32	0.64	-0.20	-0.38	-0.74
d2	0.94	1.00	0.96	0.87	0.77	0.58	0.42	0.23	0.17	0.12	0.22	0.52	-0.17	-0.24	-0.70
d3	0.85	0.96	1.00	0.97	0.90	0.74	0.59	0.39	0.34	0.27	0.25	0.39	-0.17	-0.20	-0.70
d4	0.73	0.87	0.97	1.00	0.98	0.87	0.75	0.56	0.51	0.45	0.27	0.22	-0.14	-0.15	-0.67
d5	0.60	0.77	0.90	0.98	1.00	0.95	0.86	0.69	0.65	0.59	0.25	0.07	-0.11	-0.09	-0.60
d6	0.39	0.58	0.74	0.87	0.95	1.00	0.97	0.84	0.83	0.78	0.21	-0.17	-0.03	-0.01	-0.47
d7	0.25	0.42	0.59	0.75	0.86	0.97	1.00	0.93	0.92	0.89	0.22	-0.31	0.01	0.01	-0.38
d8	0.10	0.23	0.39	0.56	0.69	0.84	0.93	1.00	0.99	0.97	0.26	-0.43	0.02	0.01	-0.30
d9	0.04	0.17	0.34	0.51	0.65	0.83	0.92	0.99	1.00	0.99	0.24	-0.49	0.05	0.02	-0.25
d10	-0.01	0.12	0.27	0.45	0.59	0.78	0.89	0.97	0.99	1.00	0.22	-0.54	0.04	0.05	-0.21
w	0.32	0.22	0.25	0.27	0.25	0.21	0.22	0.26	0.24	0.22	1.00	0.06	-0.30	-0.70	-0.72
surface temp	0.64	0.52	0.39	0.22	0.07	-0.17	-0.31	-0.43	-0.49	-0.54	0.06	1.00	-0.15	-0.37	-0.28
current life	-0.20	-0.17	-0.17	-0.14	-0.11	-0.03	0.01	0.02	0.05	0.04	-0.30	-0.15	1.00	-0.24	0.34
AADTT	-0.38	-0.24	-0.20	-0.15	-0.09	-0.01	0.01	0.01	0.02	0.05	-0.70	-0.37	-0.24	1.00	0.51
E-Asphalt	-0.74	-0.70	-0.70	-0.67	-0.60	-0.47	-0.38	-0.30	-0.25	-0.21	-0.72	-0.28	0.34	0.51	1.00

It seems that there are a lot of correlations between dataset features which may cause calculations instability during building model as features must be independent. (Relation between features and targets is a dependency relationship). So applied the Principle Component Analysis (PCA) algorithm to remove these dependencies between features each other.

Correlations to static (E) asphalt

Table 4: correlation of (E) (module) by ANN

d1	-0.735842
w	-0.723745
d2	-0.700038
d3	-0.696460
d4	-0.666932
d5	-0.603659
d6	-0.465148
d7	-0.375806
d8	-0.303385
surface temp	-0.275199
d9	-0.251132
d10	-0.211780
current life	0.336095
AADTT	0.508262
E-Asphalt	1.000000
Name: E-Asphalt, dtype: float64	

5.2Splitting Dataset into Training and Testing for module E
5.2.1Training Data Statistics

Table 5: training data statistics for module E

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	w	surface temp	current life	AADTT
count	464	464	464	464	464	464	464	464	464	464	464	464	464	464
mean	217.923	182.296	164.806	141.429	125.009	98.7859	75.3404	58.3316	48.6053	39.8024	21.1983	10.3793	4.35776	698.166
std	84.8829	56.5475	45.666	36.5569	31.018	24.1347	19.2608	14.4432	12.3855	10.0629	2.87904	9.8434	0.47986	126.208
min	113	96.0815	85.8126	52.797	34.8349	15.6104	5.20257	0.83029	0.00012	0.10868	20	0	4	487
25%	177	154	141	122	110	89	68	53	45	37	20	8	4	586
50%	198	172	157	136	121	97	74	58	48	40	20	8	4	731
75%	228.237	194.25	177.25	153.25	135	105.25	80	63	52	43	20	8	5	808
max	892.779	601	570	520	464	365	265	150.782	126.082	100.773	30	40	5	808

5.2.2. Testing dataset statistics

Table 6: testing data statistics for module E

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	w	surface temp	current life	AADTT
count	117	117	117	117	117	117	117	117	117	117	117	117	117	117
mean	217.54998	186.15337	168.25047	145.41753	128.72814	101.58963	77.243865	59.983577	49.665098	40.536102	21.26496	9.09402	4.31624	710.453
std	75.553093	54.332911	46.054379	37.296996	30.329989	21.709779	17.020257	14.11489	11.743387	9.513381	3.11391	8.19796	0.46701	124.599
min	106.90904	98.323971	95.013226	86	81	73	47.712473	26.153752	17.347025	12.624344	20	0	4	487
25%	175	154	141	124	111	90	69	54	45	37	20	8	4	586
50%	196	173	158	137	124	98	74	58	48.746805	40	20	8	4	808
75%	231	199	185.80752	160	140	108	81	63	52	43	20	8	5	808
max	536.58529	418.68865	364.14209	315.30296	291.16519	245.11139	203.56115	168.94219	140.7822	113.59385	30	40	5	808

5.3 Data Transformation with (PCA) Principle Component Analysis Algorithm

Data being transformed to get the principle components of dataset's features to overcome the multi-coo linearity between features.

5.4 Evaluating ANN

5.4.1 Neural Network Summary:

Table 7: hidden layer& parameter value in ANN archituire (module E)

Model: "sequential"		
Layer (type)	**Output Shape**	**Param #**
Hidden_0 (Dense)	(None, 256)	3840
Hidden_1 (Dense)	(None, 128)	32896
Hidden_2 (Dense)	(None, 64)	8256
Hidden_3 (Dense)	(None, 32)	2080
Output (Dense)	(None, 1)	33
Total params: 47,105		
Trainable params: 47,105		
Non-trainable params: 0		

5.4.2 Learning Curves

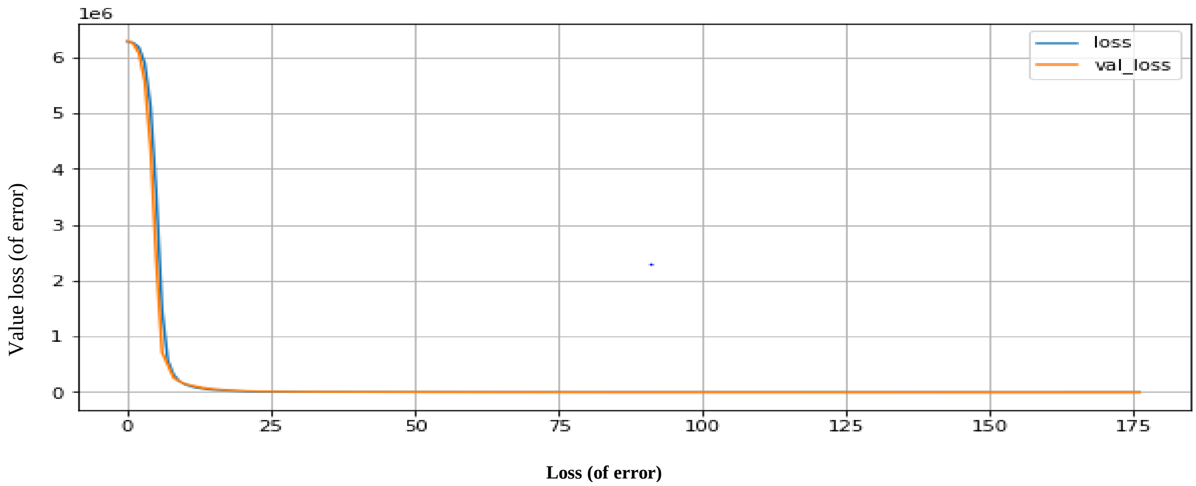


Figure 3: Training progress curve loss vs Val-loss

5.5 Predictions of Testing Dataset

Table 8: part of 117 samples final predict & observed values of static E

	Observations	Final predictions
0	2307.34689	2311.895508
1	1349.426007	1325.880249
2	2158.805245	2169.602295
3	1617.753651	1622.436768
4	2958.833071	2993.508789
...	...	...
112	2018.298167	1894.334229
113	1849.27067	1832.266357
114	2245.542956	2264.593262
115	3030.130254	3077.576904
116	1934.621624	1932.9104

5.6 Calculating R^2 Score

Table 9: Part of final predict, observed, Mean of Observed Values of E

	Observations	Final predictions	$(y - y)2$	$(y - \bar{y})2$
0	2307.34689	2311.895508	20.68992008	4788.085568
1	1349.426007	1325.880249	554.4027109	1054969.08
2	2158.805245	2169.602295	116.5762843	47409.67952
3	1617.753651	1622.436768	21.93157892	575761.1003
4	2958.833071	2993.508789	1202.405405	339061.8618

R^2 Score Equation:

R^2 = $1 - (\Sigma\,(y - y)^2 / \Sigma\,(y - \bar{y})^2)$ Eq. (2)

Where:

- **У :** Observed value
- **y:** Predicted Value
- **ỳ :** Mean of Observed Values

Observations mean-value = 2376.542884307223

R^2 = 0.99303628909910361

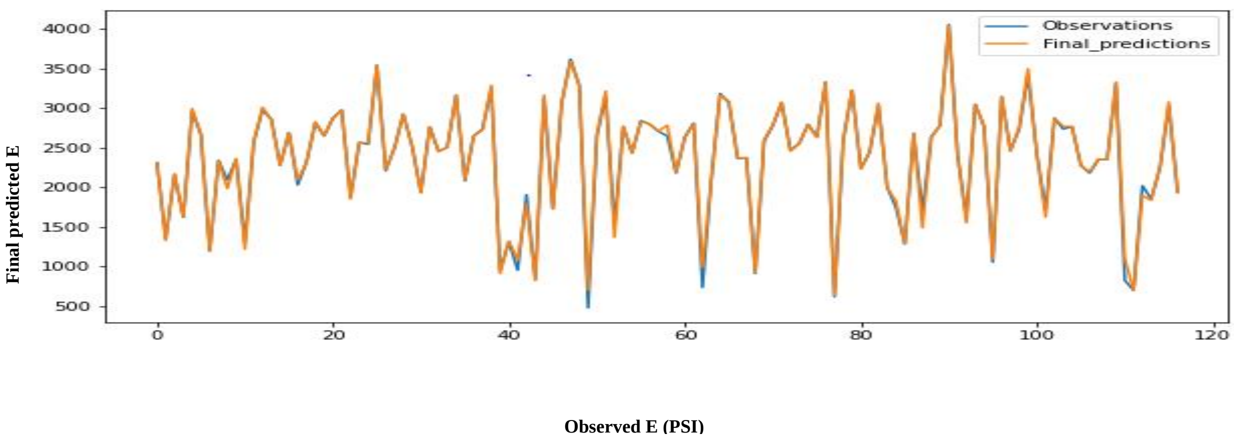


Figure 4: final prediction of static (E) VS observed static (E) curve (module 2)

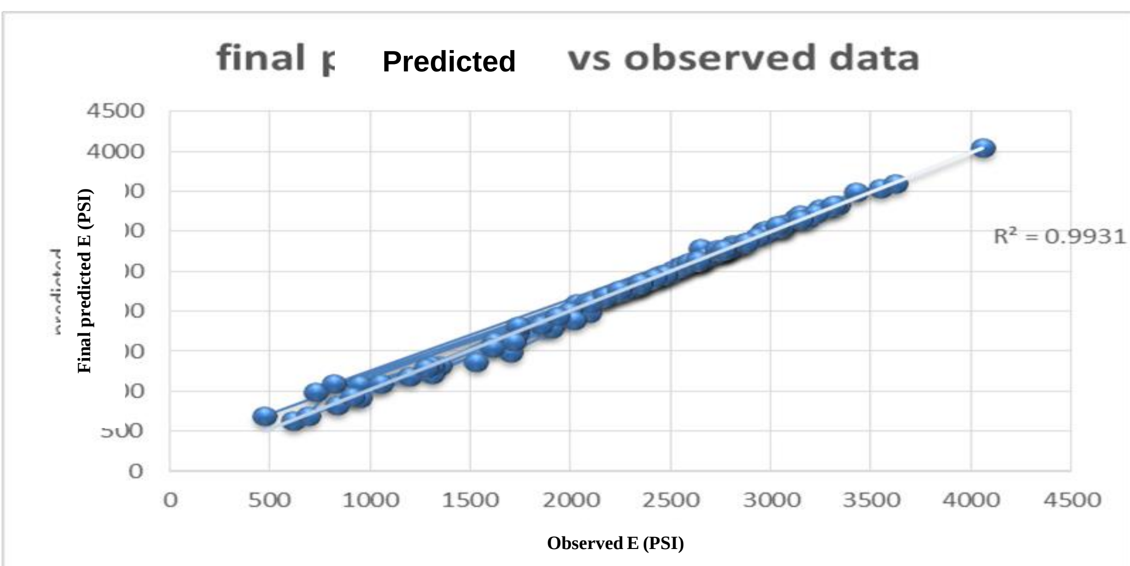


Figure 5: Correlation Plot model between observed data of 464 sample collected and final predicted of ANN model

6. Comparison of modules gained

In order to determine potential recovery needs, an ANN model was proposed as an alternative to regression models for estimating elastic modulus on flexible pavements with no tests. Results of the FWD analysis were included. Three input variables of age, traffic and temperature are set in both models. Comparisons were performed with ANN, and multi-regulation models. ANN's R^2 values were still higher than regression models as shown in Table (10)[5]

Table 10: Comparison of N.N, MLR (Multiple Linear Regression) models

Data set type	Model type	R^2 value	No. of samples
Training data set	AAN	0.99	464
	MLR	N/A	30
Testing data set	AAN	0.99	117
	MLR	N/A	30

As the after results of the exams have shown, the neural network methodology is thought to be effective enough in the expectation of a diverse modular list of data on asphalts. Furthermore, the multidisciplinary approach to the neural network may be used to determine the key variables that are required to be elastic module as an efficacy evaluation

Affectability analysis is a major step forward in model assessment. The sensitivity tests can fail a model with excellent goodness of fit (high R and small Se/Sy). Models with a limited set of input parameters which produce unrealistic predictions. Even if the model is based on a broad variety of input parameters, errors in the model structure will lead to unrealistic predictions.

As a result, it is critical to perform a sensitivity analysis on every new model and test the maximum spectrum of each predictor variable on the model's rationality. Sensitivity to a given variable can be achieved by varying it across the entire spectrum while holding all other input variables unchanged.

The high, minimum, and average values of each predictor variable at specific combinations of temperature, age, and traffic were summarized as the first step in the sensitivity analysis.

Following that, a target variable's distribution was subdivided into five or six subdivisions. The observed E values were then averaged across each subdivision depending on the average values of the particular predictor variable given by the subdivision. The new E model was then used to estimate the E stiffness of the blend for all of the target variable's average subdivision values using constant average values of other variables for that particular combination of temperature and age average subdivision. This provided a fair comparison of observed versus expected E values while only one particular predictor variable was varied across the complete spectrum.[2]

6) Conclusions

- This study developed a new module to calculate the pavement surface layers elastic moduli directly from fulling Weight Deflectometers (FWD) deflection data.
- The statistical analysis suggests that the developed module have a reasonable goodness-of-fit.
- The average R^2 for the ANN used for static elastic module is 0.99

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