International Journal Of Engineering Research And Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 17, Issue 2 (February 2021), PP. 30-36

Comparison and sensitivity analysis of different back- calculation algorism for pavement layer moduli

Eng. Ayaat Ahmed Rabah, Prof. Dr. Ahmed Sabry El Hakim., Dr. Mohamed mahmoud Refaee, Dr. Mohamed El Gendy.

[1]*Lecture,*
[2]*Prof .At El Azhar University faculty of engineering,*
[3]*Associated Prof. El Azhar University faculty of engineering,*
[4]*Assistant Prof. El Azhar University faculty of engineering.*

ABSTRACT: *For a long time, the most important back-calculation method for determining elastic modulus in asphalt design has been recognised. Despite the fact that many back-calculation programmed use various back-calculation practices and algorithms, obtaining an accurate inverse of the pavement layer module remains a difficult task. In this study, all of the critical parameters and operators that affect both static modulus E and elastic modulus back-calculation using machine learning (ML) have been carefully investigated. Therefore, recommendations and findings regarding all the details needed to proceed the back- calculation process were identified. These indices were studied in order to determine typical module by climate, traffic, and age. This dissertation presents independent prediction modules were developed* ***Module*** *to predict dynamic elastic modulus by machine learning 149 sample were collected from LTPP database. Validation test sample system, 80% of data were used to validate the learning algorithm and 20% of data is tested. A back- calculation approach to determine pavement properties using the results from the Falling Weight Deflectometer (FWD) tests that were stored in Long-Term Pavement Performance (LTPP) database .The modulus of elasticity was obtained through previous models with a high accuracy of three method treatment in testing with R^2in random forest, tree algorism, lasso algorism is (89%, 88.7%, and 86.7%) The proposed module utilize the efficient and accurate and it can back-calculate the modulus simultaneously for any number of surface pavement layers.*

Date of Submission: 26-05-2021 Date of Acceptance: 09-06-2021

I. INTRODUCTION AND BACKGROUND

The failure of pavement before the end of its designed life generally results from loss of strength in one or more layers in the pavement's structure. One method of identifying the weakened layer is to evaluate the material properties of existing in-service pavements. There are two possible methods for evaluating the material properties. The first is to lead lab testing on either lab compacted samples or undisturbed samples taken from the asphalt. This technique is boring and annoying. And damaging to the asphalt structure. Likewise, coring regularly postpones traffic, which is normally unsuitable to people in general, Furthermore, The second method of evaluating the material properties is by means of nondestructive testing (NDT). NDT comprises of making nondestructive estimations on an asphalt's surface and deducing, from these estimations, in situ attributes identified with the basic sufficiency or stacking conduct. Such evaluation of highway pavements is of particular importance to those responsible for the operation and maintenance of these facilities. Giving a quantitative premise to assessing the asphalt's auxiliary condition at any phase of its life is one of the primary destinations of nondestructive testing of adaptable asphalt.[1]

Since its introduction in 1970's (Ullidtz 1987), Falling Weight Deflectometer (FWD) is one of the most commonly used for pavement property evaluation. During the FWD test, a mass is dropped to apply an impulse load on the pavement, (FWD) has been widely used as non- destructive tests, throughout the world [2]. FWD Involves applying impact loads to a loading plate while measuring the vertical displacement on the surface of the pavement at different locations. The measured deflections from the FWD test along the pavement surface are then utilized to back-calculate the modulus of elasticity in each layer ,While various methodologies were proposed for back-calculation of layer modulus and thickness.[1]

Due to the immense importance of stiffness in the analysis, design and performance evaluation of dynamic modulus and flexible pavement structures; researchers have been trying to develop accurate (modulus) laboratory test protocols as well as to develop accurate predictive models and equations. Over the last fifty years, numerous models and regression equations have been developed to predict the elastic modulus. Historically, the stiffness predictive models and equations were developed based on the conventional multivariate linear regression or non- linear regression analysis of laboratory test data and the established or anticipated basic engineering behavior.[3]

The model development process greatly depends on the statistical analysis and linear or non- linear optimization process followed. The statistical analysis is aimed at reducing the error from prediction by comparing the predicted values with the observed values for the same values of the input variables in different ways. Model optimization is aimed at finding out the values of the fitting parameters used in a model that typically lead to the lowest prediction ever possible. When these values are used, the model is supposed to provide its best prediction. [1]

MEPDG, one of these |E*| predictive models, employs one of three techniques to calculate E* through the construction of a master curve, the method depending on the level of complexity in design chosen. The model represented in Equation 1 was chosen due to the very high coefficients of determination and importance of each regression coefficient.[4]

$$E^* = ab^T f^c \qquad \text{(Eq.1)}$$

where:
E* = dynamic modulus of HMA (psi)
T = Temperature (°F)
f = loading frequency (Hz)
a, b, c = regression coefficients

II. MACHINE LEARNING

Machine Learning is the process of enabling a computer algorithm to perform a given task without being specifically instructed to do it. The algorithm learns from its mistakes or errors and builds upon that learned behavior based on statistical information. Arthur Samuel coined the word machine learning when he worked at IBM in 1959. Today, machine learning is ever present in our daily lives and is extensively used in a wide range of applications for image recognition, speech recognition, internet search, online advertising, Fraud detection by credit card, medical testing and any other prediction based on data.[5]

In the context of machine learning, the input variables are called features, often noted as $x^{(i)}$. The output variables are referred to as targets and are characterized by the letters y. (i). The success of a machine learning algorithm is heavily dependent on the proper selection of independent and influential features. Not all features carry the same weight or impact on the prediction. For a problem with n features, there will be a total of 2^n different combinations of features as every single feature can be either included in or excluded from a subset of features. In addition to using the original features, it is common also to use some kind of transformation to modify the originals in order to gain a fast-converging or a more accurate algorithm. For example, one may use logarithmic transformations, trigonometric functions, or any polynomial combinations of the raw inputs so they can fit a desired curve such as the Gaussian curve.[5]

Machine learning algorithms are divided into two main categories: supervised learning and unsupervised learning algorithms. This study focuses on supervised learning, which is explained in the next section.

Machine Learning algorithms are developed based on (i) a dataset generated through numerical simulations, (ii) a dataset of experimental data generated surveys. Given the limited size of the numerical simulations-based dataset, the former algorithm was used only to evaluate the experimental data for a validation. The latter algorithm was validated using both the validation slab, and another data set[5]

III. OBJECTIVES OF STUDY

The primary objective of this research is:

- To develop a new solution that could be used for back-calculation in time domain. In order to overcome some of the drawbacks related to the discrete transforms, the new solution will utilize continuous integral transforms that are more appropriate for transient, no periodic such as the FWD time histories.
- Furthermore, the resulting algorithm must be tested against some current E modelling solutions. In order to explain the actions of generated modules, sensitivity tests would be performed.
- Because of the calculation made, the exploration will also investigate back calculation.

IV. RESEARCH METHODOLOGY

The research methodology is presented in flowchart figure(1) investigate that the current practice of the back-calculated elasticity moduli based on a basic value between the measured deflections on united state database (LTPP database).This database can be effectively used for developing accurate stiffness models for binders. The LTPP database (149 sample will be collected) provides faster and flexible way to collect the data records for any local area in the United States from the online database. And verification.

1. Direct calculation modulus elasticity (E) pavement performance indices from condition surveys Represented in (traffic, age, temperature, another parameters).
2. Back- calculation of pavement structural properties from nondestructive test (NDT) devices, including the falling weight deflectometer (FWD).

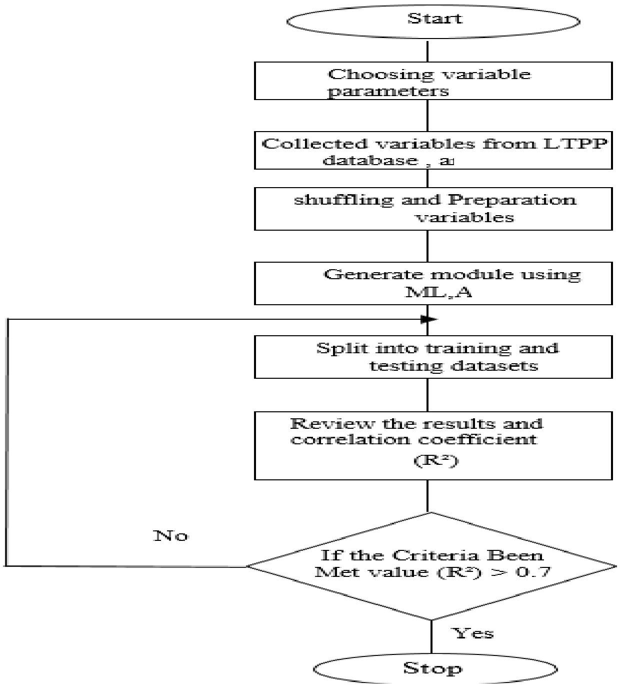

Figure 1: Flow chart all steps to reach a perfect module

V. NEW (E) MODULES OF NUMEROUS NEURAL NETWORKS

5. 1 New model (dynamic E) by machine learning (ML) (module 1)

The effective utilization of ML approaches on the displaying of material properties requires the determination of a fitting arrangement of demonstrating factors or, in particular, the descriptors for the property of interest, In general, the descriptors are expected to be capable of both sufficiently distinguishing each of the modeled compounds/materials and determining the targeted property [6]

5.2. Data Preparation and Processing for Evaluation of the E*Performance (by machine learning)

Table 1: apart of data preparation of (124) sample collected from LTPP database

Temperature (ºF)	sample age (year)	K_ESAL(kip)	E _star (Mpa)
40	5	318	1778433
70	3	235	182005
14	2	278	3084771
70	2	73	251661
40	13	80	1995557

5.2.1 Dataset Statistics of (module E*)

Table 2: dataset statistics (124 sample of LTPP data) (module 1)

	temperature	sample age	K_ESAL	E_star
count	124.000000	124.000000	124.000000	1.240000e+02
mean	44.741935	5.798387	249.919355	1.945876e+06
std	28.938362	5.094202	159.196182	1.309816e+06
min	14.000000	0.000000	57.000000	3.739600e+04
25%	14.000000	2.000000	138.250000	6.226865e+05
50%	40.000000	5.000000	213.500000	2.015776e+06
75%	70.000000	12.000000	315.750000	3.084059e+06
max	100.000000	15.000000	699.000000	4.686146e+06

5.2.2 Looking for Correlations

Can easily compute the standard correlation coefficient (also called Pearson's r) between every pair of attributes

Table 3: correlation coefficient for model of M.L (module 1)

	temperature	Sample age	K_ESAL(kip)	E*
Temperature(F°)	**1.00**	**-0.21**	**-0.03**	**-0.91**
sample age (years)	**-0.21**	**1.00**	**-0.01**	**0.37**
K_ESAL(kip)	**-0.03**	**-0.01**	**1.00**	**0.07**
E*	**-0.91**	**0.37**	**0.07**	**1.00**

Correlations to E*

Table 4: correlation coefficients of M.L (module 1)

temperature	-0.913478
K_ESAL(kip)	0.074623
Sample age(years)	0.372429
E*	1.000000
Name: E*,	dtype: float64

5.3 dividing the data collection into training and testing

Table 5: 10 sample part from 99 sample training data set (module*)

Temperature (°F)	sample age (year)	K_ESAL(kip)	E _star (Mpa)
14	15	57	3870344
14	0	324	2754982
14	14	160	3638355
40	3	135	1954581
40	5	491	2425280
40	14	360	1841633
40	3	285	1534435
70	7	640	344903
70	0	189	696731

5.3.1Training Data Statistics of module 1

Table 6: data statistics training (99 samples from 124 samples of LTPP database)

	temperature	sample age	K_ESAL
count	99.000000	99.000000	99.000000
mean	44.363636	5.676768	253.878788
std	28.378439	4.981247	157.044662
min	14.000000	0.000000	57.000000
25%	14.000000	2.000000	141.500000
50%	40.000000	5.000000	223.000000
75%	70.000000	12.000000	324.000000
max	100.000000	15.000000	699.000000

5.4 Evaluating Decision Tree Algorithm with Data Cross-Validation[7]

Parameters being tested (by python program screen):

```
GridSearchCV(cv=10, estimator=DecisionTreeRegressor(),
             param_grid={'min_samples_split': [5, 10, 20]}, scoring='r2')
```

Results Best score of average 10-cross validation process: 0.8825006026068181

Best tested parameters

Running model on the testing dataset to get testing R^2-Score: 0.8876492179935588

5.5 Get tree visualized

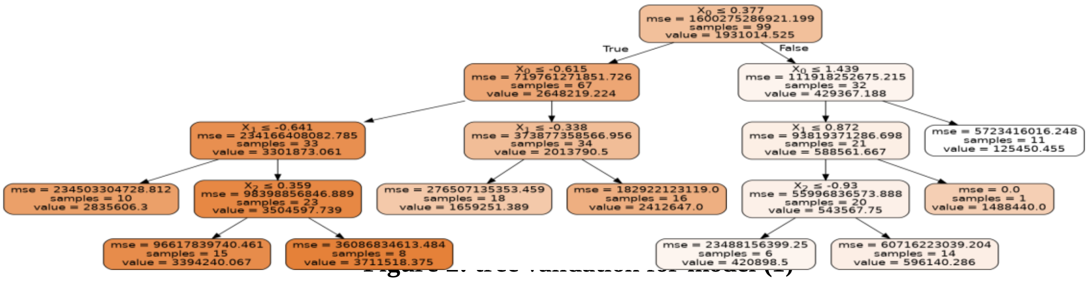

Figure 2: tree validation for model (1)

5.6 Evaluating Random Forest Algorithm with DataCross-Validation[7, 8]

Parameters being tested:

Results Best score of average 10-cross validation process: 0.879217305340938

```
GridSearchCV(cv=10, estimator=RandomForestRegressor(),
             param_grid=[{'min_samples_split': [5, 10],
                          'n_estimators': [10, 20, 30, 50, 70]},
                         {'bootstrap': [False, True],
                          'min_samples_split': [10, 15],
                          'n_estimators': [10, 20, 30, 50, 70]}],
             scoring='r2')
```

Best tested parameters

Running model on the testing dataset to get testing R^2-Score: 0.8932545470039163

5.7 Evaluating LASSO Regression[9, 10]

Parameters being tested:

Results Best score of average 10-cross validation process: 0.8480824429150694

Running model on the testing dataset to get testing R2-Score**:** 0.867738908500274

5.8 Final Coefficients of LASSO Regression:

Intercept coef.

(1931014.53 (***β*0**), 1120394.68 (***β*1**), 264231.04 (***β*2**), 69420.03 (***β*3**) **the equation will be:**

E *(MPa) = β0 + (β1 ∗ temp (F°). std) + (β2 ∗ age (year) std) + (β3 ∗ KESAL (kip). std)

$$E_{star} = 1931014.53 + (-1120394.68) * \frac{temp. - 44.36}{28.38} + (264231.04) * \frac{age - 5.68}{4.98} + (69420.03) * \frac{k_{esal} - 253.88}{157.04}$$

5.9 Final Prediction on Testing Dataset

Table 7: the predict and test dataset (9 from 25 samples LTPP database) in M.L

Observations	3549530	1789076	23059159	3310217	43387627	51382833	6167640	739416	854684
Final predictions	3660000	850000	3410000	732000	3550000	2550000	537000	-558000	-396000

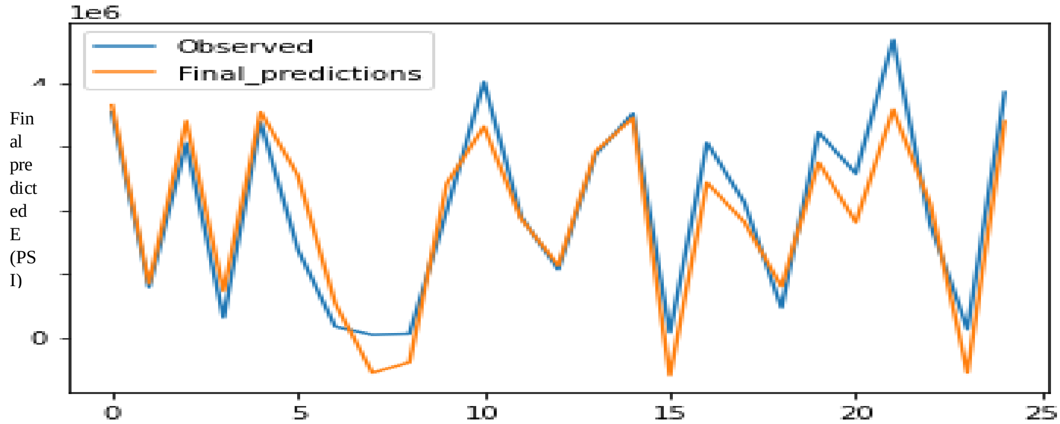

Figure 3: curve predict dynamic E (from module 1) vs observed

5.10. Conclusion (first module of LTPP database):

Calculated E*is almost the same as Predicted E* with small difference due to the existence of a lot of fractions with many mathematic operations.

6. Comparison between obtained modules

An M.L model was presented as an alternative to regression models for predicting elastic modulus on flexible pavements containing no samples for assessing future rehabilitation needs FWD study results were used in the study. Age, traffic, and temperature three input variables are fixed parameter in all model. The results of the machine learning model and multi regression models were compared. The R^2 values of M.L model were consistently higher than regression models as shown in Table (8)[11]

Table 8: Comparison of M.L, MLR (Multiple Linear Regression) models

Data set type	Model type	R^2 value	No. of samples
Training data set	MLR	N/A	30
	ML	0.88	124
Testing data set	MLR	N/A	30
	ML	0.89	25

As indicated by the aftereffects of the examinations, presumed that the neural network approach in adaptable asphalts was exact enough in anticipating versatile modulus list giving data about the presentation and state of the asphalt. Moreover, it was underlined that the versatile neural network approach can be utilized as an affectability investigation device to distinguish the main factors expected to foresee flexible modulus.

Affectability investigation is a significant advance in model assess A model with excellent goodness of fit (high R^2 and small Se/Sy) may not pass the sensitivity tests. Models based on a narrow range of input parameters may result in unrealistic predictions. Errors in the model structure can also lead to unrealistic prediction even though the model is based on a very wide range of input parameters.

Hence, it is very important to conduct a sensitivity analysis of any new model and evaluate the full range of each predictor variables upon the model rationality. Sensitivity to a specific variable can be accomplished by varying that variable within its full range, while keeping all other input variables constant.

As the first step of the sensitivity analysis, the maximum, minimum and average values of each predictor variables at specific combinations of temperature, age and traffic were summarized

Next, the range of a target variable was divided into five to six subdivisions. Then the observed E values were averaged over each subdivision as the subdivision provided average values of the specific predictor variable. Now, the new E model was used to predict the E stiffness of the mix for all those average subdivision values of the target variable by the use of constant average values of other variables for that specific combination of temperature and age average subdivision. This allowed an avenue for the rational comparison of the observed versus predicted E values while only one specific predictor variable is varied over its full range. The model sensitivity analysis is presented in the following sub sections.[1]

VI. Conclusions

- Running model on the testing (using tree algorism) dataset to get testing R^2-Score: 0.887.
- Running model on the testing (with random forest) dataset to get testing R^2-Score: 0.893.
- Running model (by lasso regression) on the testing dataset to get testing R^2-Score: 0.867.
- The R^2 values of machine learning model were consistently higher than linear regression models.
- By developing a learning algorithm based on lasso algorism, random forest, tree algorism, it was demonstrated that machine learning works very well for numerical data Methods for identifying characteristics and determining targets were also explained. Building upon the numerical simulation experience, the same process was used to train a new algorithm for the experimental data.

BIBLIOGRAPHY

[1] J. Bari, "Development Of A New Revised Version Of The Witczak E* Predictive Models For Hot Mix Asphalt Mixtures," Doctor of Philosophy, Arizona State University, 2005.
[2] T. T. Gary E. Elkins, Barbara Ostrom, and Beth and Visintine, "Long-Term Pavement Performance Information Management System User Guide," FHWA-RD-03-088 (revision), June 2018 2018.
[3] A. S. Ernian Pan, Amirhossein Molavi, Yanfei Zhao, and Ping Yi, "An Efficient And Accurate Genetic Algorithm For Backcalculation Of Flexible Pavement Layer Moduli," Prepared in cooperation with The Ohio Department of Transportation and the U.S. Department of Transportation, Federal Highway Administration, Final Report FHWA/OH-2012/18, December 2012 2012.
[4] M. M. Robbins, "An Investigation Into Dynamic Modulus Of Hot-Mix Asphalt And Its Contributing Factor," Masters of Science, Auburn University, May 9, 2009.
[5] F. S. IMANI, "Comprehensive Full-Depth Condition Assessment Of Reinforced Concrete Bridge Decks Using Ground Penetrating Radar," Doctor of Philosophy, Graduate Program in Civil and Environmental Engineering, Graduate Program in Civil and Environmental Engineering, 13813597, 2019.
[6] G. Z. Yong-Jie Hu1, Mingfei Zhang1, Bin Bin1, Tyler Del Rose1, Qian Zhao3, Qun Zu3, Yang Chen3, Xuekun Sun4, Maarten de Jong5,6 and Liang Qi1*, "Predicting densities and elastic moduli of SiO2-based glasses by machine learning," Department of Materials Science and Engineering, University of Michigan, Ann Arbor, Michigan, 48109, USA 2Department of Statistics, Pennsylvania State University, State College, Pennsylvania,16802, USA 3Sinoma Science & Technology Co., Ltd., Nanjing, Jiangsu, 210012, China 4Continental Technology LLC, Indianapolis, Indiana, 46033, USA 5Department of Materials Science and Engineering, University of California, Berkeley, California, 94720, USA 6Space Exploration Technologies (SpaceX), Hawthorne, California, 90250, USA.
[7] R. K. Jehad Ali1, Nasir Ahmad3, Imran Maqsood4, "Random Forests and Decision Trees," *International Journal of Computer Science,* vol. 9, no. 5 p. 8, septemper 2012 2012, Art. no. 5.
[8] L. Breiman, "Random Forests," p. 33, January 2001 2001.
[9] j. b. lee, "How to Develop LASSO Regression Models in Python," 12 october 2020.
[10] r. tibshirani, "regression shirnkage and selection via the lasso," *journal of the royal statical society,* vol. 58, 2003.
[11] M. B. Bayrak, "Analysis of jointed plain concrete pavement systems with nondestructive test results using artificial neural networks," Doctor Of Philosophy, Civil Engineering (Geotechnical Engineering), Iowa State University, 3337379, 2008.

Eng. Ayaat Ahmed Rabah, et. al. “Comparison and sensitivity analysis of different back-calculation algorism for pavement layer moduli." *International Journal of Engineering Research and Development*, vol. 17(02), 2021, pp 30-36.