Prediction of Asphalt Pavement Surface Layer Modulus using the Long-Term Pavement Performance (LTPP) Falling Weight Deflectometer Data

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Introduction

- Accurate estimation of asphalt surface layer modulus is essential for structural evaluation and network-level pavement management.
- FWD testing offers non-destructive pavement characterization.
- Conventional modulus backcalculation software is sensitive to material property assumptions, temperature, and structural configuration.
- Data-driven methods can bypass backcalculation sensitivities by learning directly from FWD response - yet have not been comprehensively benchmarked for surface modulus prediction using LTPP data.

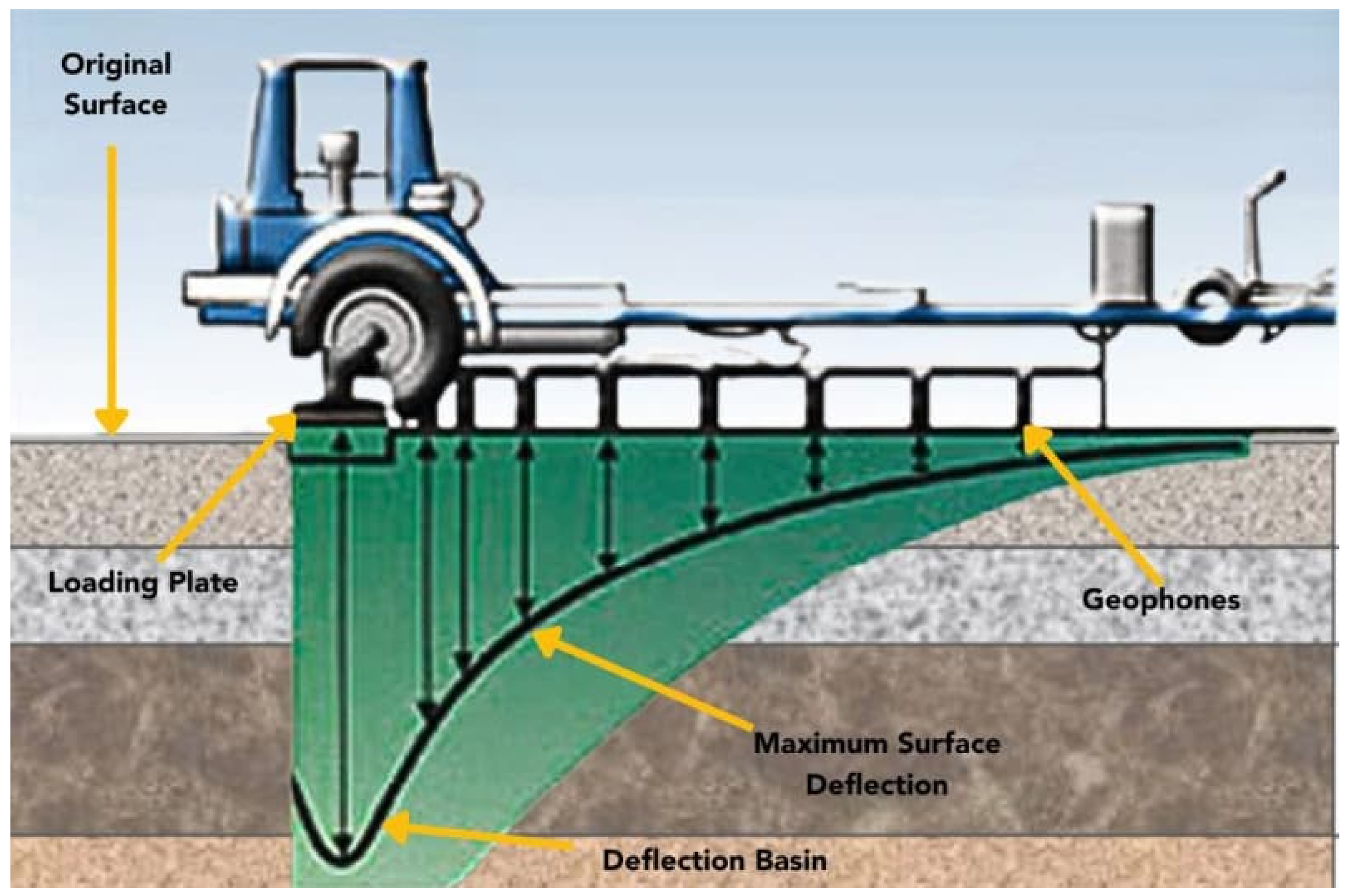

Figure 1. Falling Weight Deflectometer Test Setup

Objectives

- To develop a prediction model for evaluating the asphalt surface layer modulus.
- To integrate key influential parameters such as surface layer thickness, drop load, air and base temperatures, peak deflections, surface curvature index (SCI), and lane type.
- To capture complex interactions among the key influential parameters.

Dataset Description

- Data sourced from Long Term Pavement Performance Program (LTPP).
- All General Pavement Study (GPS) and Specific Pavement Study (SPS) sections from Texas.
- Dataset include:

✓ *Peak deflections in microns (PEAK_DEFL_1 to PEAK_DEFL_3)*
✓ *Lane number and drop load in kPa*
✓ *Surface and base temperatures in °F*
✓ *Surface Curvature Index (SCI)*
✓ *Thickness of asphalt surface layer in inches (Thickness_L1)*

- To ensure uniformity, only records with complete deflection basins and valid modulus records were retained.

Methodology

- Developed a predictive modeling framework to determine asphalt pavement surface layer modulus (Modulus_L1).
- Implemented and compared the following models:

a) *Multiple Linear Regression* b) *Random forest*
c) *Extreme Gradient Boosting* d) *Artificial Neural Network*

➢ Correlation Analysis

- To understand if the selected features are non-redundant and improve model stability.
- SCI highly correlated with D1 & D2 - redundant variable.
- Raw deflections (D1–D3) retained for mechanistic relevance.
- Surface & base temperature are highly correlated but physically distinct.
- Thickness_L1 shows negative correlation with modulus.

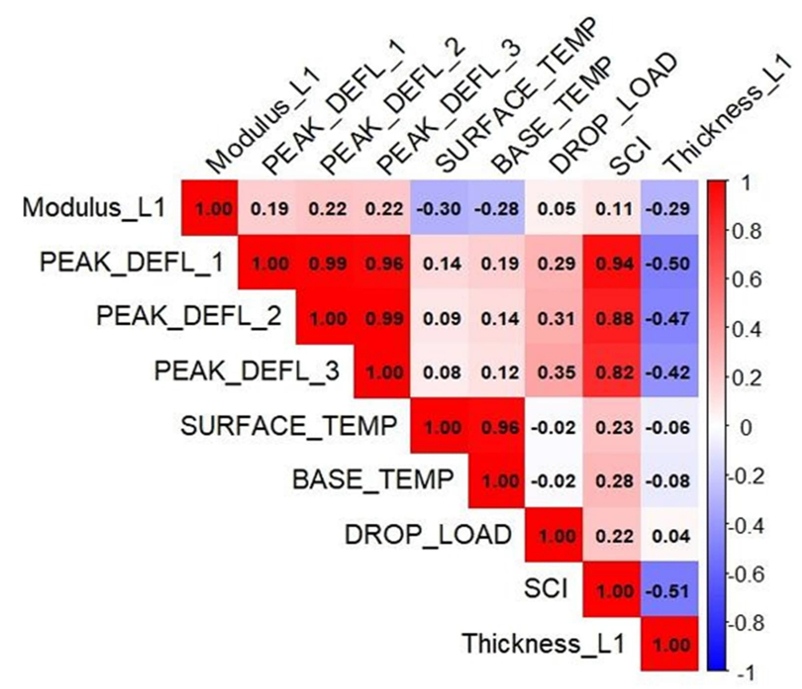

Figure 2. Correlation matrix

➢ Model implementation

a) Multiple Linear Regression

- To establish an interpretable relationship between asphalt surface layer modulus and various predictor variables derived from FWD test.

Asphalt surface layer modulus = $\beta_0 + \beta_1 \cdot PEAK\_DEFL\_1 + \beta_2 \cdot PEAK\_DEFL\_2 + \beta_3 \cdot PEAK\_DEFL\_3 + \beta_4 \cdot Lane + \beta_5 \cdot Drop\ load + \beta_6 \cdot Surface\_temp + \beta_7 \cdot Base\_temp + \beta_8 \cdot Thickness\_L1 + \varepsilon$

b) Random Forest Model

- Captures nonlinear relationships between FWD variables and modulus.
- Resistant to multicollinearity and noise in data.

c) Extreme Gradient Boosting (XGBoost)

- XGBoost was used to capture complex non-linear relationships beyond the limitations of the regression model.
- Target variable: Asphalt surface layer modulus

$Objective\ function{:}\ L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k)$,

$Regularization\ term{:}\ \Omega(f) = \Upsilon T + \frac{1}{2}\lambda\, ||w||^2$

- The predicted value is updated iteratively as: $\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i)$ where (x_i) represents the input features.

d) Artificial Neural Network

- A feedforward neural network model was developed with 7 input neurons, 20 hidden neurons, and 1 output neuron as shown in Figure 3.

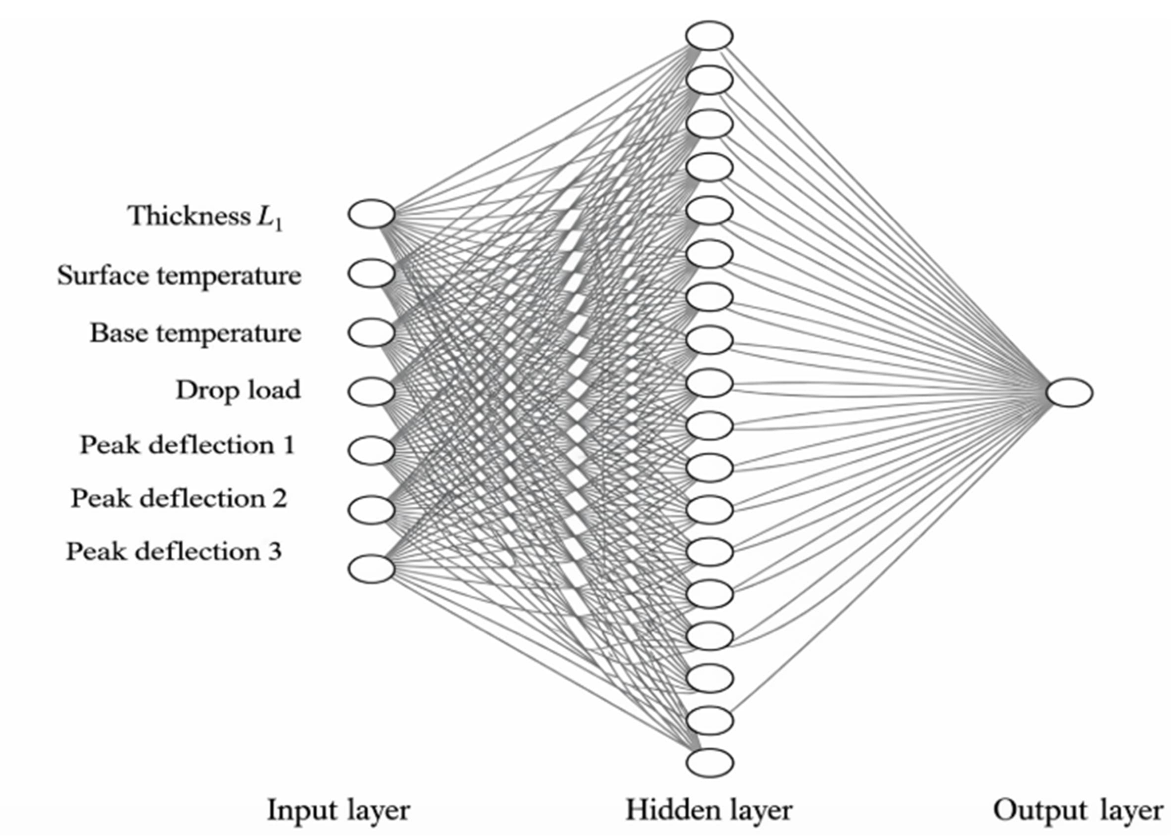

Figure 3. Architecture of Neural Network

Results & Discussion

a) Multiple Linear Regression

Accuracy: 23.9%

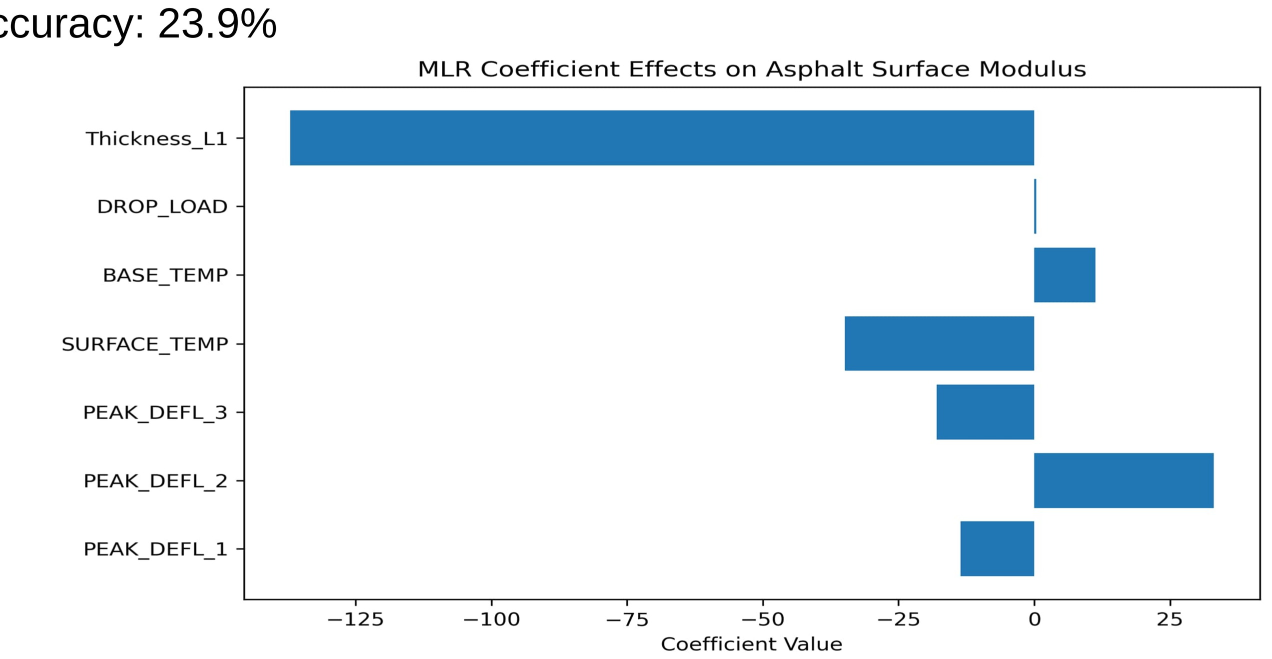

Figure 4. MLR Coefficient Plot

b) Random Forest Model

- Training accuracy: 98.6% and testing accuracy: 94.9%.

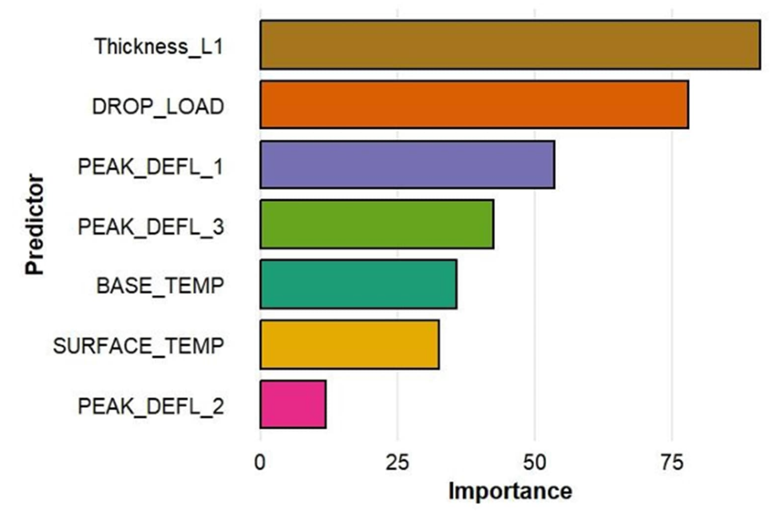

Figure 5. Random Forest Variable Importance

c) XGBoost Model

- Training accuracy: 95.9% and testing accuracy: 92.9%.

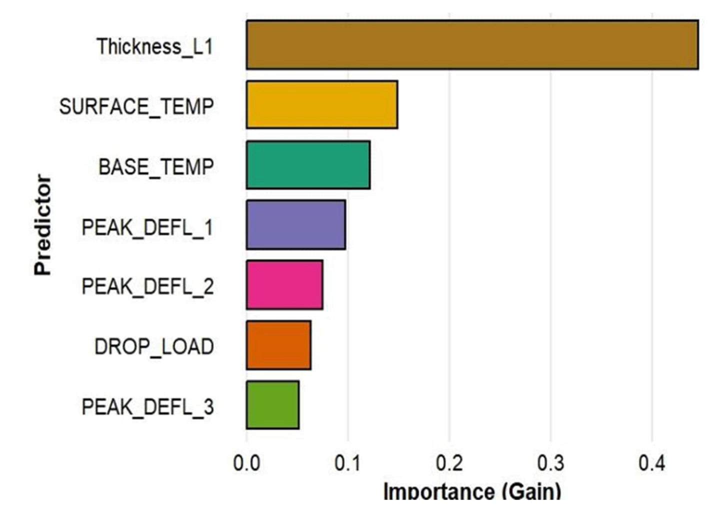

Figure 6. XGBoost Variable Importance

d) Artificial Neural Network

- Training accuracy: 85.7% and testing accuracy: 85.3%

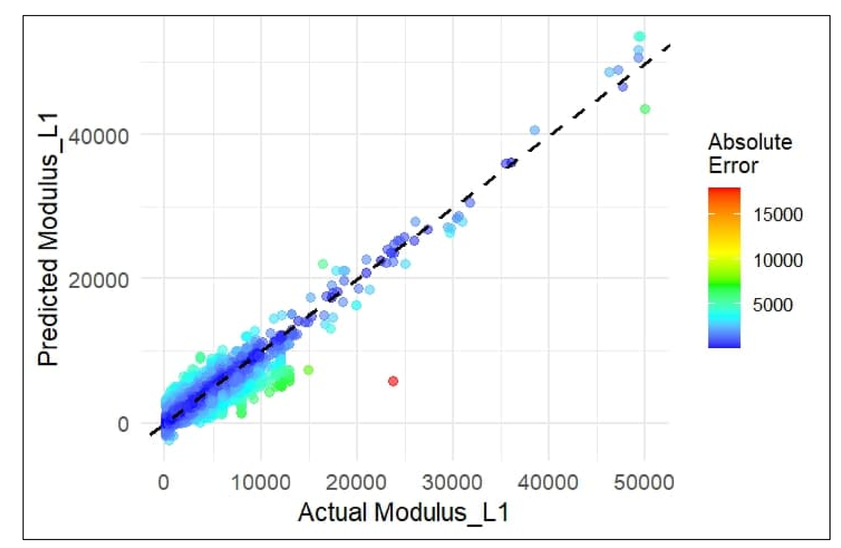

Figure 7. ANN model (Predicted vs Actual)

Conclusions

- The ML-based models for predicting the modulus of asphalt surface layers give high accuracy and provide a fast, efficient alternative to traditional backcalculation methods.
- Asphalt layer thickness, surface temperature, followed by deflections were the strongest predictors.
- The developed models would be evaluated using additional FWD datasets outside the LTPP database.

Acknowledgements

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