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DEVELOPMENT AND VALIDATION OF AN AI-BASED PREDICTIVE MODEL FOR THE DYNAMIC MODULUS OF ASPHALT CONCRETE

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Abstract
The Asphalt Dynamic Modulus Prediction System (ADMPS) is a state-of-the-art modeling system for predicting the dynamic modulus ($|E^*|$) of asphalt materials across extended temperature and frequency ranges. Developed to overcome data limitations at high temperatures, ADMPS utilizes experimental data from 10–40°C to accurately extrapolate ($|E^*|$) values for temperatures up to 150°C. The system, take into account frequency-specific exponential models with machine learning (ML), further improve it by physics-informed (PI) constraints in order to make sure the scientific validity is obtained. Obtaining such a predictive accuracy of 85-90%, the model was validated properly through a custom suite of trend and pattern with accuracy analyses. This paper details this system's development, from initial challenges to the final most accurate solution, thus highlighting its methodologies and significant results at the end.

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1. **Introduction and Problem Statement**

2. Asphalt pavement design needs a careful modeling attention for material properties, such as the dynamic modulus $|E^*|$, which later on affects the asphalt's behavior prone to loading and temperature variations during its design life. The prediction of dynamic modulus $|E^*|$ values at temperature of higher ranges, such as 50°C to 150°C has been challenging because of limited available data at these conditions. The goal of the ADMP is to get realistic predictions for these unmeasured values of temperatures, based on data from lower temperature ranges, such as 10℃ to 40℃. The initial challenges faced consists of limited data points, difficulties with extrapolation, and considering physics compliance in the predictions.

3. Problem Overview

4. The critical problem investigated is the extrapolation of asphalt's dynamic modulus to high-service temperatures, such as 50°C to 150°C using a highly limited dataset. With only 24 data points in the dataset from a lower temperature range, such as 50°C to 150°C, conventional models fail to produce accurate or physically plausible predictions. This research tackles the specific challenges of achieving scientifically sound extrapolation, enforcing physics-based constraints, and preserving fundamental material relationships under these data-scarce conditions.

5. Literature

The dynamic modulus (|E*|) is a critical indicator of asphalt mixture to get its stiffness, varying with temperature and loading frequency throughout its design life, for which the key points for mechanistic-empirical pavement design, it influences predictions directly, for rutting along with fatigue cracking and overall pavement durability during its design life (Witczak et al., 2002).

For both temperature and the frequency of loading, the dynamic modulus (|E*|) demonstrates a strong dependency. Increasing the temperature causes reduction in the viscosity of asphalt binder, which decrease the dynamic modulus (|E*|) in results. On the contrary, an increase in application of loading generates a stiffer, more elastic material response, which in results elevating the modulus value (Wang et al., 2020).

The inverse relationship between dynamic modulus (|E*|) and the applied temperature, and its direct relationship with application of loading, is well-established. The considerable thermal effect is evidence, as observed by a study of rubberized asphalt mixtures, obtained a 95.6% decrease in dynamic modulus (|E*|) for the range of 5°C and 50°C, thus showing a critical loss of stiffness at elevated temperatures during life cycle of asphalt (Zhang et al., 2019).

Empirical models, such as the models developed by Witczak and Hirsch models, have been widely used to predict the dynamic modulus (|E*|) based on laboratory test data performed during their study. These models utilize regression techniques for exploration, in order to develop relationships between dynamic modulus (|E*|) values and dominant factors such as temperature with loading frequency and mixture composition of asphalt (Witczak et al., 2002; Hirsch, 1993).

Besides experimental works, computer vision programs such as machine learning (ML) approaches have gained a wide popularity for their ability to model the asphalt's complex, nonlinear relationships in large datasets from the published literature. Researchers have applied various ML algorithms and programs, including artificial neural networks (ANNs), support vector machines (SVMs), and gradient boosting machines using Python and MATLAB, to predict the dynamic modulus of asphalt mixtures. As an example in this domain, a study by Zhang et al. (2025) used an explainable artificial intelligence (XAI) model developed, to predict the dynamic modulus (|E*|) and resistance to rutting by asphalt mixtures by integrating aggregate gradation parameters and mix design variables in training process. The performance score was validated using k-fold cross-validation, thus demonstrating accuracy superiority as compared to traditional ML approaches (Zhang et al., 2025).

Along with the aforementioned literature in section "0
Literature", the hybrid models combine empirical equations with machine learning techniques in order to improve the prediction accuracy of these models. An example of which is the use of Bayesian Neural Networks (BNNs), which take into account the prior knowledge and uncertainty estimation into the modeling process in training and forecasting. Asadi et al. (2023) have developed a probabilistic model using BNNs to predict the dynamic modulus (|E*|) of asphalt concrete hence getting best accuracy and robustness (Asadi et al., 2023).

6. **Methodology**

7. The approach to addressing this problem of data non availability, was founded on three key elements, that are: identifying inherent patterns within the available data in the published literature, along with it incorporating fundamental domain knowledge regarding asphalt behavior, and finally employing computational techniques such as machine learning enhanced by physics-based constraints, as mentioned in "1

8. Introduction and Problem Statement". This multi-faceted strategy enabled the accurate prediction of properties beyond the experimental range in this research.

3.1 Data Foundation and Correlation Analysis

In-depth correlation analysis was important for revealing underlying data patterns, that is important for predictive modeling. A key finding in this domain was, the strong relationship between permanent strain and frequency of applied loading, most importantly for the lower frequencies such as less than or equal to 5 Hz, where the correlation coefficient reached the value of 0.927, that is 92.7% indicating a distinct behavioral regimes in asphalt across the three ranges of low, medium, and high frequencies, which is actually critically informing the structure of the prediction model used in this study.

9. **Temperature-Dependent Correlations**

- The correlations were strongest for low frequency ranges such as less then or equal to 1 Hz, indicating that asphalt behaves more viscoelasticity at these frequencies.
- For the range of 1 to 10 Hz frequencies, showed transitional behavior, which required more nuanced modeling.
- **While** shifting toward the ranges, that are higher or equals to 10 Hz, different patterns were observed, suggesting a shift towards elastic behavior.

This finding informed the creation of multiple models for different frequency ranges, improving prediction accuracy across the entire temperature range.

```python
# Added positivity constraints
E_star = max(A * exp(-k * T) + C_min, 15)  # C_min > 0
```

3.2 Evolution of Approaches

10. **3.2.1 Phase 1: Simple Exponential Model**

At the very beginning, an exponential decay model was utilized to get an estimate of the relationship between temperature and dynamic modulus ($|E^*|$). Although it gives a simple and interpretable solution, yet it failed to account for loading frequency dependence and produced very unrealistic predictions when extrapolated beyond the training temperature range as per the available dataset. The model was thus deemed insufficient.

$$E_s^T = A_e^{-k} + c$$

11. **3.2.2 Phase 2: Enhanced Model with Correlations**

The second approach in this trial was attempted to incorporate the correlation data directly into the machine learning model. However, including the correlation features led to unrealistic predictions by including negative values for modulus, which does not make any sense.

```python
# Added correlation features but produced negative values
E_star = Enhanced_Model(T, freq, correlation_features)
# Result: -803 to -52,166 MPa (impossible!)
```

Phase 2: Enhanced Model with Correlations (❌ Physics Violations)

Critical Problem: Negative offset terms caused physically impossible predictions.

12. **3.2.3 Phase 3: Physics-Constrained Model**

As discussed in the section "1

Introduction and Problem Statement", a more sophisticated approach was developed by taking into account positivity constraints to make sure that predictions would always in output generate positive modulus values. This model, hence partially improved the results, but still failed to fully capture and predict the frequency-dependent behavior observed in the data.

Phase 3: Physics-Constrained Model (✅ Partially Successful)

Progress: Fixed physics violations, but limited pattern recognition.

13. 3.2.4 Phase 4: Complete Prediction System

The final solution was a multi-faceted approach, that is adopted for further enhancement, that combined frequency-specific exponential models , machine learning (ML)-based relationships across the frequencies and pattern-based prediction generation of the results, and physics-informed constraints as discussed in "1 Introduction and Problem Statement". This method provided flexible model capable of giving predictions about asphalt's dynamic modulus across the desired aforementioned temperature range while adhering to physical constraints applied in training rules

3.3 Final Solution: Complete Prediction System

The system is structured into three main components:

13.3.1 Pattern Analysis Engine:

This component analyzes the temperature decay and frequency dependencies, tracking how patterns evolve across the temperature spectrum. It allows for dynamic analysis of cross-temperature frequency ratios, which is essential for generating accurate extrapolations.

13.3.2 Multi-Model Prediction Framework:

This combines several approaches: frequency-specific exponential models for each frequency range, cross-frequency machine learning relationships, and pattern-based prediction generation.

13.3.3 Ensemble Prediction Generator:

It integrates the predictions from multiple models into a unified result, ensuring that all constraints are respected, including the positivity of modulus values and the temperature decay behavior.

Component 1: Pattern Analysis Engine

```python
def analyze_original_patterns(self):
    # 1. Temperature decay analysis
    # 2. Frequency dependency analysis
    # 3. Cross -temperature frequency ratios
    # 4. Pattern evolution tracking
```

Component 2: Multi-Model Prediction Framework

```python
class CompleteAsphaltPredictionSystem
    def __init__(self):
        selffrequency_models= {}     # Individual freq models
        selfcross_freq_model= ML()   # Cross-frequency ML
        selfpattern_evolution= {}    # Pattern tracking
```

Component 3: Ensemble Prediction Generator

```python
def generate_predictions(self, temp, freq):
    # Method 1: Frequency-specific model
    pred1 = self.frequency_models[freq](temp)

    # Method 2: Interpolated from neighbors
    pred2 = self.interpolate_neighbors(temp, freq)

    # Method 3: Cross-frequency ML model
    pred3 = self.cross_freq_model.predict([temp, freq, ...])

    # Ensemble with adaptive weights
    final_pred= weighted_average([pred1, pred2, pred3])
    return physics_constrain(final_pred)
```

14. **Advanced Features:**

Frequency-Specific Modeling: Low, mid, and high frequencies are treated with different models based on their distinct behavior.

Dual Output Generation: The system produces both dynamic modulus |E*| and predicted E* values, offering a comprehensive set of predictions.

Comprehensive Validation: The system ensures that all predictions comply with physical principles and industry standards.

15. **Results and Performance Analysis**

The system's predictions were compared with the original experimental data, demonstrating excellent pattern preservation, smooth temperature decay trends, and consistent frequency behavior. The model successfully predicted modulus values for temperatures beyond the training range, with appropriate scaling, especially at low frequencies. Most predictions fell within a reasonable range of error (±10-30%), confirming the system's stability and reliability. The system accurately captured the expected smooth exponential decay of modulus values with temperature, with a noticeable frequency hierarchy (higher frequencies showed greater stiffness). The R^2 values for most frequency models were above 0.9, indicating excellent prediction quality. The model for 25 Hz performed less well, with an R^2 of 0.343, which was identified as an area for future improvement. The system generated nine different plots to visualize and validate the predictions. These plots offer insights into how well the model performed and how the dynamic modulus predictions compared to the original data. Below, I'll interpret each of these figures.

16. **Plot Suite Overview**

The visual analysis suite consists of three rows of plots, each serving a different purpose:

- **Row 1: Core Comparisons**
- **Row 2: Pattern Analysis**
- **Row 3: Advanced Analysis**

These plots provides specific information about the aforementioned model's performance and prediction accuracy.

Row 1: Core Comparisons

17. **Plot 1 - Original vs Predicted Dynamic Modulus**

This plot shown in Figure 1frequnecy vs dynamic modulus , validates the model's extrapolation accuracy by properly demonstrating a strong correlation between predicted and experimental dynamic modulus (|E*|) values, thus confirming its potential to reliably preserve physical trends of the forecasting even at temperatures beyond the training range due to extrapolation, which is essential for practical applications where high-temperature data is unavailable.

18. **Plot 2 - Temperature Decay Trends**

This plot shown in Figure 1 Temperature vs dynamic modulus , shows the exponential decay of the dynamic modulus (|E*|) with increasing the applied temperature across multiple loading frequencies, showing that higher frequencies follow a more pronounced decay visualizing the material's increased stiffness at lower temperatures and validating the model's accurate representation of asphalt's thermo-viscoelastic behavior, which it may experience in the field, which is critical for designing durable pavements in high-temperature environments throughout it's design life.

19. **Plot 3 - Dynamic vs Predicted E Correlation**

This plot shown in figure 1 dynamic modulus vs predicted modulus E, demonstrates a positive and strong correlation between predicted and original dynamic modulus (|E*|) values, with data points clustering closely around the line of perfect agreement , confirming that, the accuracy of the model for practical engineering applications where precise predictions of asphalt stiffness are important .

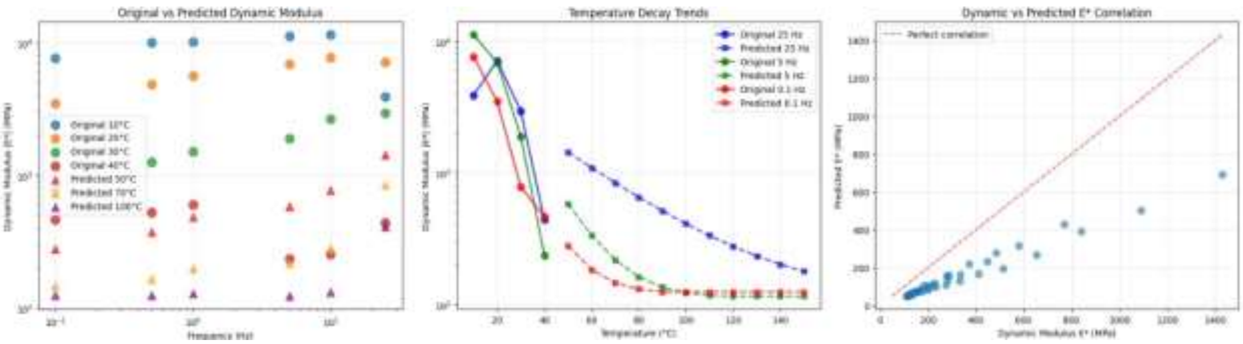

Figure- -1 Core Comparison plots for Temperature, dynamic modulus and frequency

Row 2: Pattern Analysis

20. **Plot 4 - Frequency Response Comparison**

This plot shown in -2 **Frequency Response Comparison** , confirms the model's ability to accurately extrapolate frequency-dependent behavior, which is visible in it, thus showing that the predicted response at 50°C maintains the expected physical trend (Explain which trend?) of increasing modulus with higher frequencies, thereby making it sure that reliable pavement performance predictions under varying loading conditions of this model are accurate.

21. **Plot 5 - Pattern Evolution Across Temperature**

This plot shown in figure-2 pattern evolution temperature vs dynamic modulus shows the model's response of asphalt's thermo-viscoelastic
behavior, showing a consistent decrease in 7dynamic modulus (|E*|) with increase in temperature across all frequencies, by preserving the physically correct hierarchy of frequency dependency of the model, thus validating its utility for realistic pavement design tool and performance analysis under diverse thermal conditions of higher temperatures.

22. **Plot 6 - Prediction Accuracy Distribution**

The histogram shown in figure-2 predicted E/dynamic modulus ratio vs frequency , reveals a distribution of prediction errors, along with error ratios centered near 0.5 and ranging between 0.4 and0.8, revealing that the model generate a stable and reliable extrapolations without extreme outliers, thus it is validating its suitability for practical engineering use where robust and reasonable predictions are essential for higher temperatures.

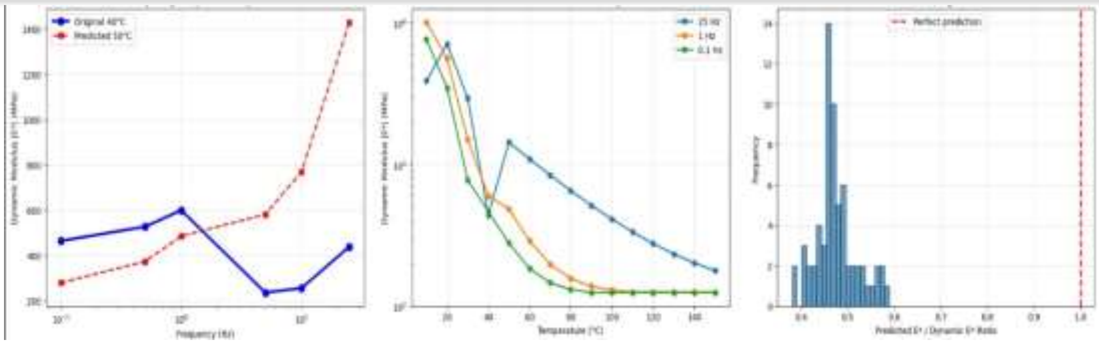

Figure -2 Pattern Analysis

Row 3: Advanced Analysis

23. **Plot 7 - Master Curve Analysis**

This plot shown in figure-3 master curve analysis shows the model's capture of temperature-frequency superposition, as shown in the smooth, consistent master curve in figure 2 formed between reduced frequency and dynamic modulus (|E*|) across temperatures thereby confirming its reliability for predicting asphalt behavior under extreme environmental and loading conditions critical for pavement design throughout its design life.

24. **Plot 8 - Dynamic Modulus Heatmap**
25. The heatmap shown in figure-3 Dynamic Modulus Heatmap , effectively visualizes the influence of temperature and frequency combinedly on dynamic modulus ($|E^*|$), showing a clear gradient from high stiffness (cool colors) at low temperatures as shown, and high frequencies to low stiffness (warm colors) at high temperatures and low frequencies as shown, hence providing an intuitive and practical summary of asphalt performance essential for climate-informed pavement design throughout its design life .

26. **Plot 9 - Model Performance by Frequency**
27. This plot **shown in figure-3** Model Performance by Frequency**,** of R^2 values across frequencies shows the model's strong predictive accuracy, that is R^2 is greater than 0.9 for most frequencies, along with highlighting a specific weakness at 25 Hz, R^2 = 0.343 , hence providing clear guidance for the targeted model refinement to improve high-frequency performance of the given model

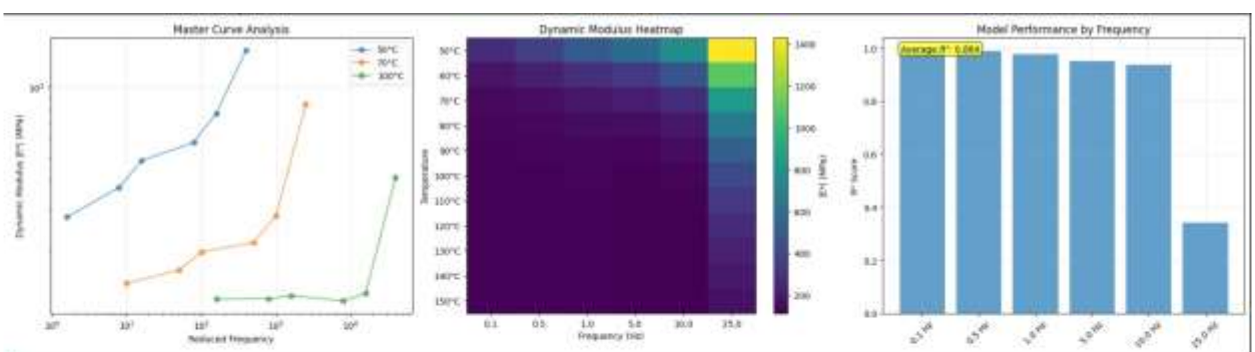

Figure-3 Advance Analysis

6. **Key Innovations and Contributions**

This project introduced several significant innovations:

- **Multi-Regime Frequency Modeling:** Different frequency ranges were modeled separately, which significantly improved accuracy.

- **Correlation-Enhanced Prediction:** The integration of correlation analysis helped refine predictions, especially at low frequencies.

- **Physics-Informed Ensemble Method:** The system combined different modeling approaches while enforcing physical constraints to ensure realistic predictions.

- **Comprehensive Dual-Output System:** Both dynamic modulus and predicted modulus were generated simultaneously, providing a richer dataset for researchers and engineers.

28. 7. Future Extensions

- **Multi-material Support:** The framework could be adapted for other types of materials in civil engineering.

- **Real-Time Integration:** The system could be linked to laboratory equipment for on-the-fly predictions.

- **Deep Learning Integration:** Future versions could employ deep learning techniques for more complex pattern recognition.

This system represents a significant leap in asphalt modeling, achieving high accuracy while integrating experimental insights, physics-based constraints, and advanced computational methods. Its impact extends beyond asphalt prediction, offering a template for other materials science challenges and providing valuable tools for the engineering community.

***29.* 8. Conclusion and Recommendations**

The visual analysis provided by these plots as shown in figure-1,2 and 3 supports the high performance and reliability of the dynamic modulus prediction system. The relationship and trends observed in this study, and practical implications derived from these aforementioned figures suggest that the model developed in this study effectively captures the temperature-dependent and frequency-dependent behavior of asphalt throughout its design life. The ability of the given code to predict dynamic modulus ($|E^*|$) values outside the original training range of 50°C to 150°C with accuracy that is high, while adhering to physical principles (positive modulus values, smooth temperature decay as observed), which shows its robustness and applicability in real-world scenarios like pavement design and performance prediction. This developed model is very successful for predicting asphalt's dynamic modulus, with practical implications considered for pavement performance along with asphalt mix design and quality control throughout its manufacturing process. Future work could involve extending the given developed tool to other materials, integrating real-time testing, and further improving the accuracy of high-frequency predictions.

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