

Exploring the Correlation Between Asphalt Pavement Friction and Texture Properties: An Application of Ensemble Empirical Mode Decomposition (EEMD)



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Abstract

The performance of asphalt pavement friction is primarily determined by its surface characteristics, mainly its micro texture and macrotexture properties. Therefore, understanding the relationship between surface texture and pavement skid resistance is crucial from a safety perspective. The aim of this research is to examine the relationship between the friction properties of asphalt pavement and its corresponding surface texture by applying the ensemble empirical mode decomposition (EEMD) method. The EEMD algorithm was utilized to optimize and extract the ensemble intrinsic mode function (eIMFs), which were subsequently combined to produce ensemble base intrinsic mode functions (eBIMFs). In addition, seven texture indicators were computed to characterize the original texture, eIMFs, and eBIMFs profiles. A correlation analysis revealed that eIMF3 exhibited the highest correlation with the original profile, achieving a correlation coefficient up to 0.69, followed by eIMF2 and eIMF4. The friction-texture correlation, initially weak for the original profile, showed significant improvement with the application of the EEMD method, particularly with eIMF6. A multilinear regression model was developed based on the texture characteristics of eIMF6, achieving an overall coefficient of determination (R²) of 0.878. Finally, a sensitivity analysis revealed that the importance of texture parameters, in descending order, was root-mean-square slope (Δq), root-mean-square deviation (Rq), root-mean-square wavelength of the profile (λq), mean difference of elevation (MDE), and kurtosis (Rku).

Keywords: Friction Properties; Surface Texture; Ensemble Empirical Mode Decomposition; Hilbert-Huang Transformation; Texture Indicators

Abbreviations: EEMD: Ensemble Empirical Mode Decomposition; eIMFs: Ensemble Intrinsic Mode Functions; eBIMFs: Ensemble Base Intrinsic Mode Functions; MDE: Mean Difference of Elevation; WT: Wavelet Transform; HHT: Hilbert-Huang Transform; IMFs: Intrinsic Mode Functions; MA: Mean Amplitude; MF: Mean Frequency; DFT: Dynamic Friction Tester; TR: Traprock; LS: Limestone; SMA: Stone Matrix Asphalt; DG: Dense-Graded; JMF: Job Mix Formula; MoDOT: Missouri Department of Transportation; CT: Circular Track; HHT: Hilbert-Huang Transform; HSA: Hilbert Spectral Analysis; MTD: Mean Texture Depth; MLR: Multilinear Regression

Introduction

Research has consistently shown a strong link between the skid resistance of pavement surfaces and overall road safety. Among the various attributes of pavement surfaces, skid resistance is the most essential. Tire-surface friction is influenced by multiple factors, including surface characteristics (texture, material composition properties), properties of vehicular tires (tread pattern and depth, rubber composition, and tire size and dimensions), the operational conditions, including (wheel speed, load, slip ratio, and pneumatic pressure), and finally the presence

of environmental contaminants (water, snow, ice, and dust) [1,2]. The texture of the pavement surface plays a vital role in influencing this friction. Therefore, gaining a deep understanding of how pavement texture impacts skid resistance is essential.

The pavement texture is categorized into four main groups based on texture wavelength (λ): micro-texture ($\lambda < 0.5\text{mm}$), macrotexture ($0.5\text{mm} \leq \lambda < 50\text{mm}$), mega-texture ($50\text{mm} \leq \lambda < 500\text{mm}$), and unevenness ($500\text{mm} \leq \lambda$) [2]. The skid resistance of pavement is significantly influenced by the summation of its

macro-texture and micro-texture. These textures, which exhibit random and non-stationary properties akin to natural signals, have led to the adoption of several signal processing methods in highway engineering to explore the friction-texture relationship of pavement surfaces. The Fourier and wavelet transforms are the primary analysis techniques utilized for this analysis. The FT is ideal for analyzing stationary signals with consistent frequencies over time, which is not the case with road textures. In contrast, one drawback of the Wavelet Transform (WT) analysis is its reliance on selecting the appropriate wavelet basis function since no single wavelet basis is applicable to all situations [3]. Thus, it is essential to investigate other signal processing techniques that are capable of effectively managing non-stationary signals and are flexible across different scenarios.

To overcome these limitations, the Hilbert-Huang Transform (HHT), an empirically derived method capable of analyzing non-linear and non-stationary data, has recently been employed to optimize and evaluate the texture profiles of pavement surfaces. Gagarin et al. [4] investigated the potential of using the HHT to analyze pavement surface texture, demonstrating that the pavement's physical characteristics can be discerned and interpreted through the combination of intrinsic mode functions (IMFs) derived from HHT. A comparative study was conducted by Ayenu-Prah et al. [5] to evaluate the accuracy of the HHT, FT, and WT methods in analyzing pavement profiles, noting HHT's superior adaptability in detailed profile analysis of pavement [5].

Cho [6] applied the Empirical Mode Decomposition (EMD) to extract the IMFs and then combined them into four Base Intrinsic Mode Functions (BIMFs): BIMF1 was the sum of the first four IMFs, BIMF2 was the sum of the following four IMFs, BIMF3 was the sum of the following four IMFs, and BIMF4 was the sum of the remaining IMFs. Subsequently, a mean amplitude (MA) and mean frequency (MF) were computed for each BIMF and correlated with the dynamic friction tester (DFT) values. Building on Cho's study, Rado & Kane [7] reported that the MA and MF indicators of the first two BIMFs (BIMF1 and BIMF2) were statistically significant and adequate for monitoring changes in measured DFT values, although the practical significance of the MF and MA indicators remains limited. Following the Cho study, Kane et al. [8] introduced two new texture indicators, density and sharpness, to characterize the obtained BIMFs. They observed that the friction-texture correlation at various speeds improved when considering density, sharpness, and the combination of density and sharpness. In addition, Yu et al. [9] found that the texture parameters of BIMF2, which is the sum of three IMFs (IMF3, IMF4, and IMF5), exhibited a strong correlation with the friction numbers compared to the main texture profile.

Research Significance

Noteworthy, research studies in the literature have focused on applying the EMD to optimize and extract the IMFs, although the EMD has some drawbacks, particularly mode mixing. Mode mixing occurs when the decomposition technique fails to group

signals of similar frequencies into individual IMFs. Consequently, various oscillation modes are mixed within a single IMF, causing them to lose their physical significance or inaccurately reflect the underlying physical processes [10,11]. To address this issue, the ensemble empirical mode decomposition (EEMD) was proposed, which improves the analysis by making the data more regular and less susceptible to mode mixing by incorporating noise assistance [11,12]. However, EEMD comes with the cost of increased computational complexity and the requirement for multiple iterations due to the ensemble process [11]. Overall, although EEMD provides improvements over EMD, the selection between these two methods would be based on the specific requirements and constraints of the application, such as signal purity, sensitivity to added noise, complexity level, and computational cost.

The main goal of this study is to explore the effectiveness of the EEMD method in modeling to better understand the correlation between pavement surface texture and friction properties, as indicated by the DFT values at 20km/hr (DFT20). The EEMD was used to extract the ensemble IMFs (eIMFs), which were then combined to produce ensemble BIMFs (eBIMFs). A comparative analysis of these developed eIMFs and the proposed eBIMFs against the original profile was conducted to identify which demonstrates the strongest correlation with pavement friction. Finally, by analyzing six texture indicators along with the mean profile depth (MPD) of the eIMF and eBIMF through the HHT, the texture parameter that exhibited the strongest correlation with surface friction was identified.

Research Methodology

This research study adopted the EEMD to analyze the surface texture profile of asphalt mixture slabs and investigate the friction-texture relationship. The EEMD decomposes the measured profile into a set of eIMFs and often a residue, ordered from the highest to the lowest frequency component. Height-, spacing- and shape-related texture indicators were computed for the original and each eIMF to determine which eIMF correlates best with the friction properties. Consequently, a circular track meter (CT-Meter) was utilized to measure the macrotexture profile of the fabricated slabs, while the DFT was employed to monitor the friction properties of asphalt mixtures. Figure 1 illustrates the research methodology.

Materials

Seven asphalt mixtures were fabricated using different aggregate sources-traprock (TR) and limestone (LS)-and mix designs, including stone matrix asphalt (SMA) and dense-graded (DG) mixtures. The details of these asphalt mixtures are presented in Table 1. Additionally, Figure 2 shows the typical job mix formula (JMF) of the investigated mixtures alongside the specification limits. Notably, the SMA mixtures were designed to meet the Missouri Department of Transportation (MoDOT) specifications, incorporating 0.3% cellulose fibers and 50% by volume of traprock [13,14].

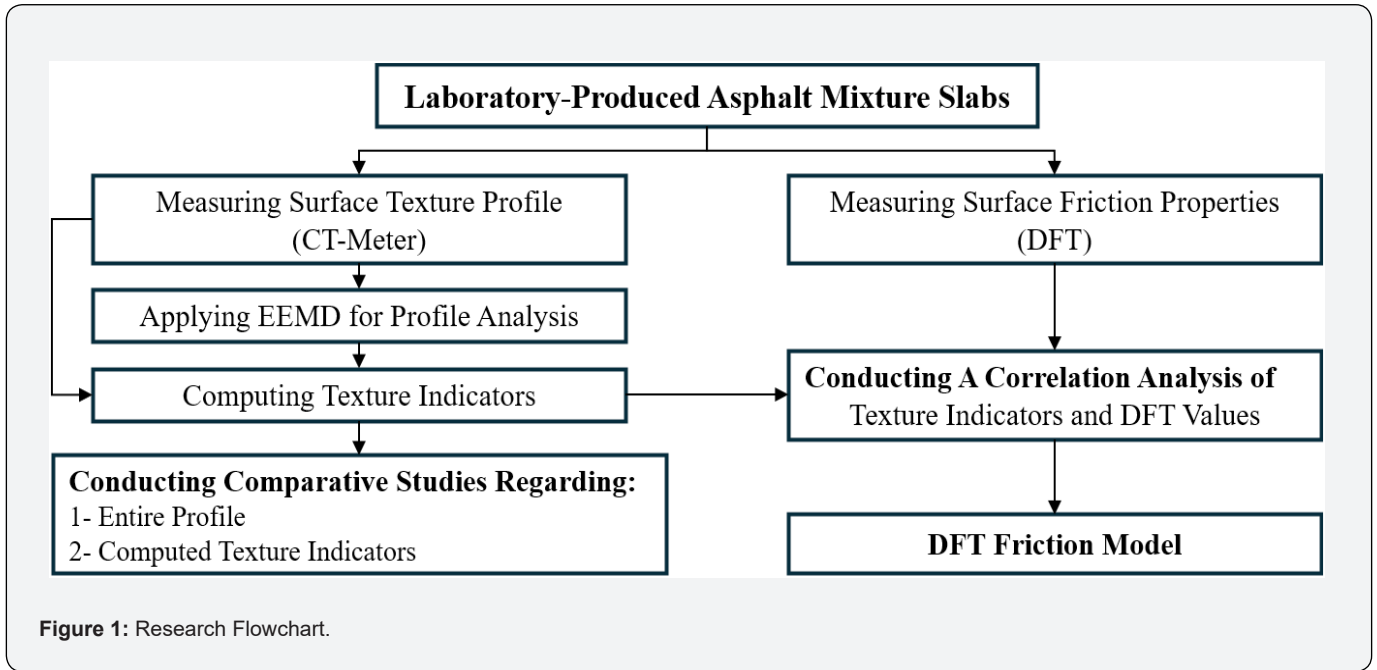


Figure 1: Research Flowchart.

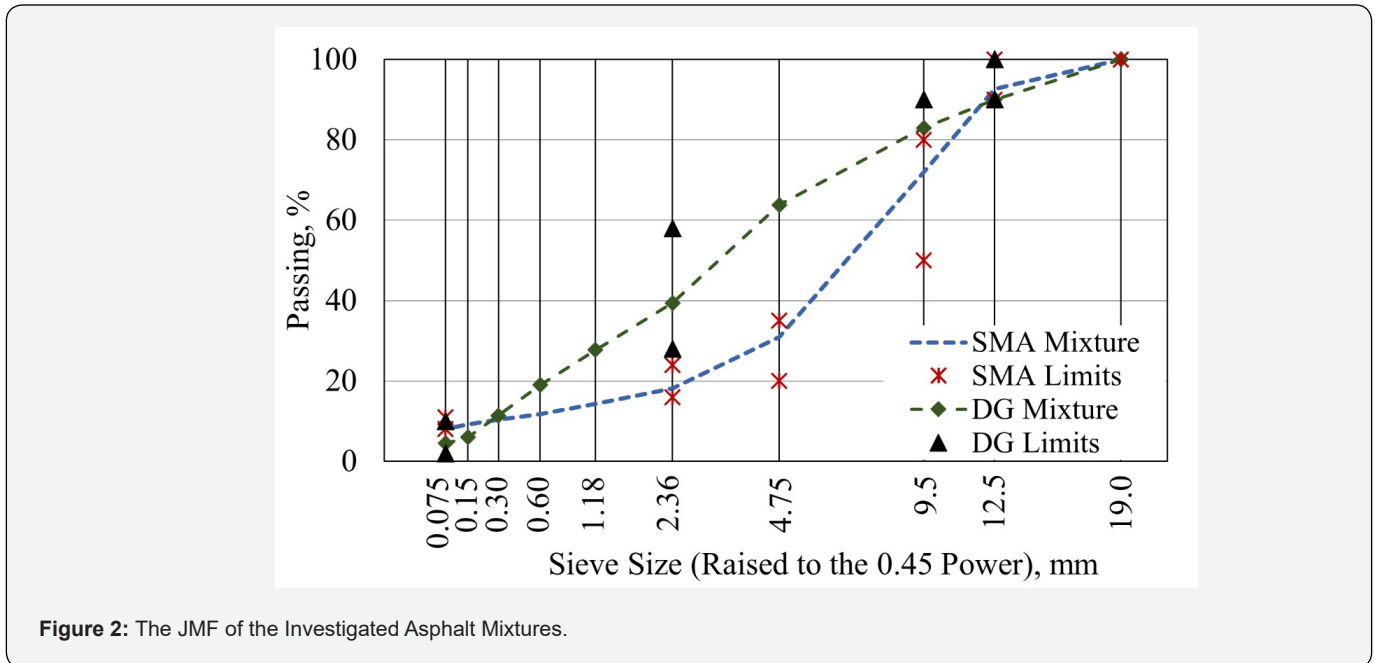


Figure 2: The JMF of the Investigated Asphalt Mixtures.

Table 1: Details of the Investigated Asphalt Mixtures.

Code	Description
SMA-1	The mixture has 43% TR, 50% LS-1, and 6% filler with warm-mix additive and cellulose fibers.
SMA-2	The control SMA mixture has 43% TR, 50% LS-2 source, and 7% filler with warm-mix additive.
SMA-3	The control mixture is redesigned to consider a PG 64-22 binder with 10% rubber (dry process), a warm-mix additive.
SMA-4	The JMF of the control mixture was adjusted to incorporate 19% RAP material by cutting 19% from the fine limestone stockpiles, achieving 15% asphalt binder replacement (ABR).
SMA-5	The SMA mixture has 43% TR, 50% LS-3 source, and 7% filler with warm-mix.
DG-1	Dense-graded mixture with LS-4 source with 16.9% MD abrasion loss.
DG-2	A dense-graded mixture with 44% TR, 19% RAP material (18% ABR), and 32% LS-5 source is similar to the 19% RAP SMA mixture.

*LS is the limestone, TR is the traprock, RC is the recycled components, RAP is the reclaimed asphalt pavement, and ECR is the engineering crumb rubber.

Asphalt Mixture Slabs Preparation

Fourteen asphalt mixture slabs, each measuring 20 by 20 inches, were fabricated using a vibratory compactor following AASHTO PP104-21 [15]. To ensure homogeneity, aggregates from all sources were screened, and precise weights for each type and size were meticulously collected. These aggregates were then uniformly mixed with asphalt binder to create four equal batches. The subsequent process involved filling the mold, leveling the

mixture, and compacting till the target density was achieved.

Testing Methods

Firstly, the fabricated asphalt mixture slabs were marked, using a white marker, to designate the DFT spot to ensure that the friction and texture measurements were taken consistently at the same point. Figure 3 illustrates the test setup for assessing friction and texture properties.

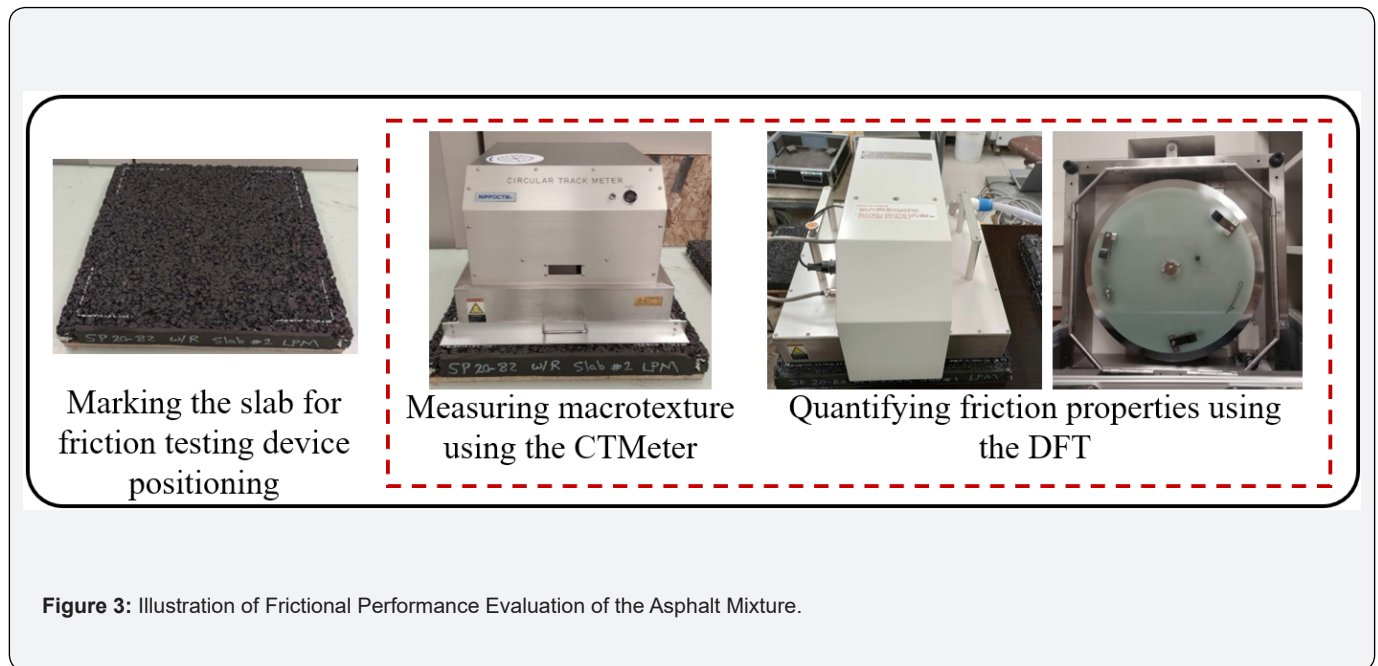


Figure 3: Illustration of Frictional Performance Evaluation of the Asphalt Mixture.

Circular Track Meter (CT-Meter)

The CT-Meter was used to measure the surface characteristics of pavements according to ASTM E2157 [16]. It features an arm that holds sensors, commonly laser-displacement sensors, which capture the macrotexture texture of the pavement surface. This arm rotates around a circular track with a radius of typically 5.6 in, allowing the sensor to record deviations in surface texture from a reference plane. Notably, the CT-Meter provides high-resolution measurements with a vertical resolution as fine as $3\mu\text{m}$, a horizontal resolution of around $50\mu\text{m}$, and a sampling rate of $870\mu\text{m}$.

Dynamic Friction Tester (DFT)

The DFT was used to measure the friction properties of pavement surfaces under wet conditions, as specified by ASTM E1911 [17]. It operates by rotating a circular disk equipped with three rubber pads against the pavement surface at specified speeds, up to 90 km/hr. As the disk contacts the surface, it measures the resistance caused by friction, thereby recording the torque. The friction coefficient is then calculated by dividing this computed torque force by the weight of the disk. Notably, the friction coefficient obtained at 20 km/hr (DFT_{20}) is indicative of the surface's micro texture properties [2,18].

Hilbert-Huang Transform (HHT)

The HHT is an adaptive method to analyze non-linear and non-stationary signals, composed of two main parts:

1) Empirical Mode Decomposition (EMD) or its variant, such as ensemble empirical mode decomposition (EEMD), which decomposes a signal into its ensemble intrinsic mode functions (eIMFs).

2) Hilbert Spectral Analysis (HSA) on these eIMFs. The HSA applies the Hilbert Transform to each eIMF to obtain instantaneous frequency data, creating a time-frequency-energy distribution known as the Hilbert spectrum.

Ensemble Empirical Model Decomposition (EEMD)

The EEMD is an enhancement of the EMD method, designed to overcome the issue of mode mixing that can occur due to signal intermittency or noise. The EEMD method adds white noise to the original signal multiple times, computes the EMD for each noisy version of the signal, and then averages the results [11,12], as illustrated in Figure 4. Notably, over sifting can reduce the amplitudes of eIMFs, making them less meaningful in a physical context. To avoid over sifting, the sum of the differences (SD_k) is computed between two consecutive sifting results and is kept within 0.2 to 0.3 [19], as illustrated in Figure 4.

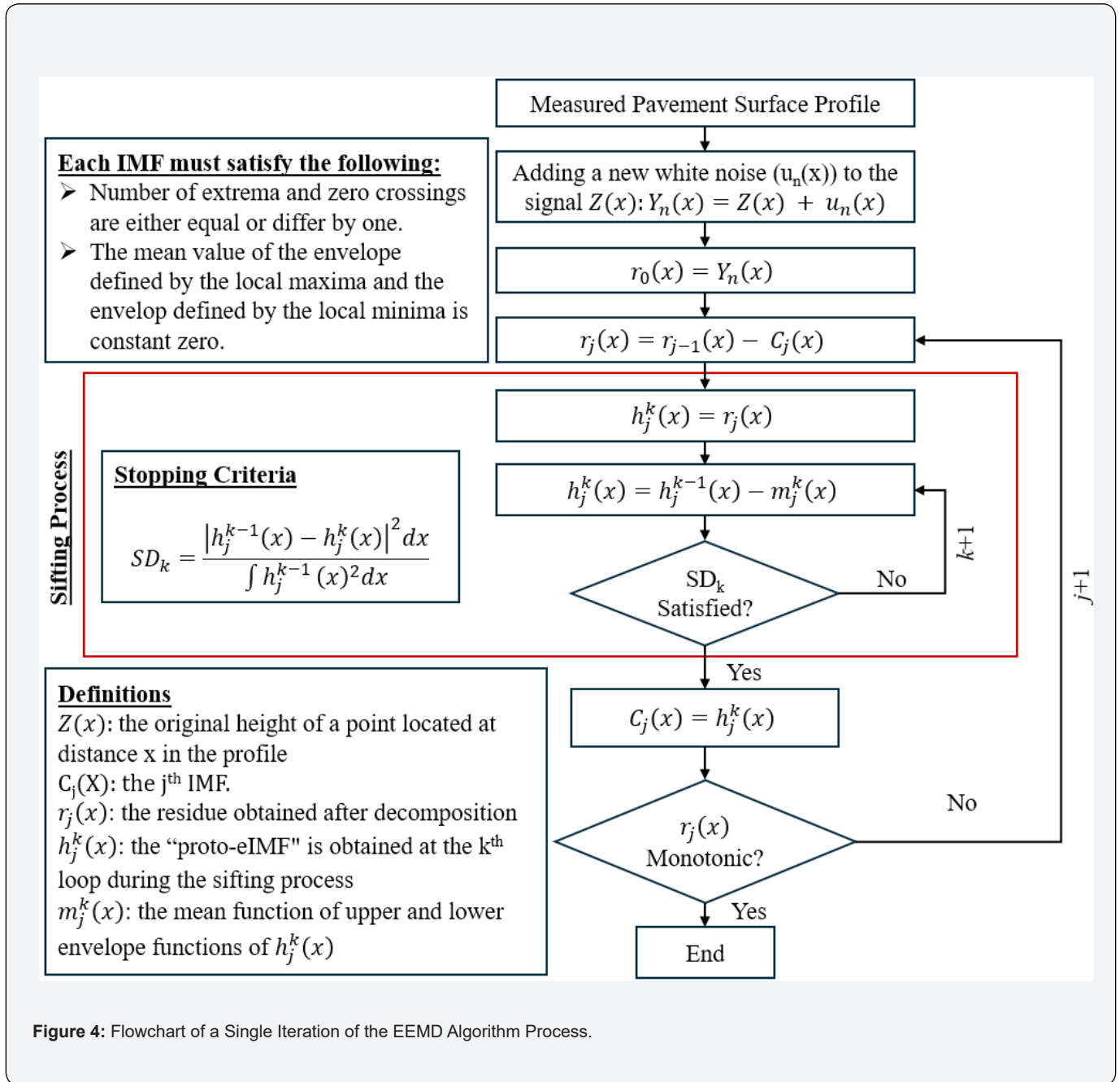
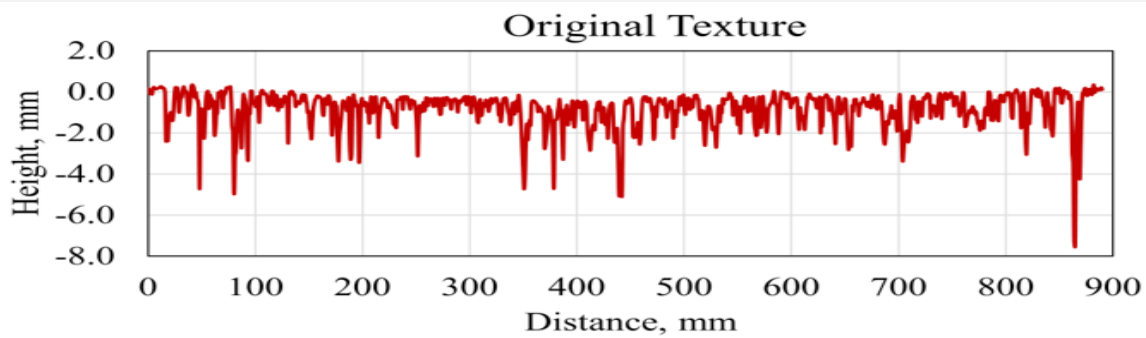


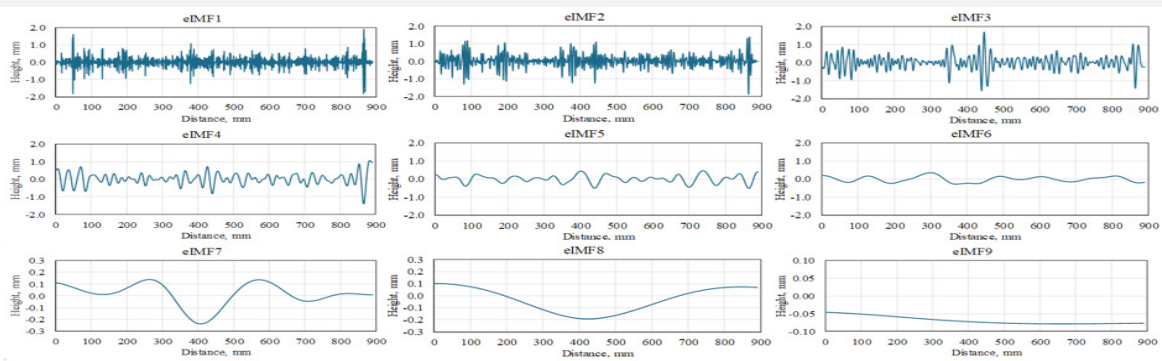
Figure 4: Flowchart of a Single Iteration of the EEMD Algorithm Process.

As the decomposition process produces eIMFs sorted from highest to lowest frequency, the merging principle requires combining components of similar frequencies. This approach ensures that the frequency characteristics of the merged Base eIMFs (eBIMFs) remain consistent throughout the analysis. Consequently, the developed eIMFs were combined to produce three combinations of eBIMFs, as presented in Table 2, to analyze

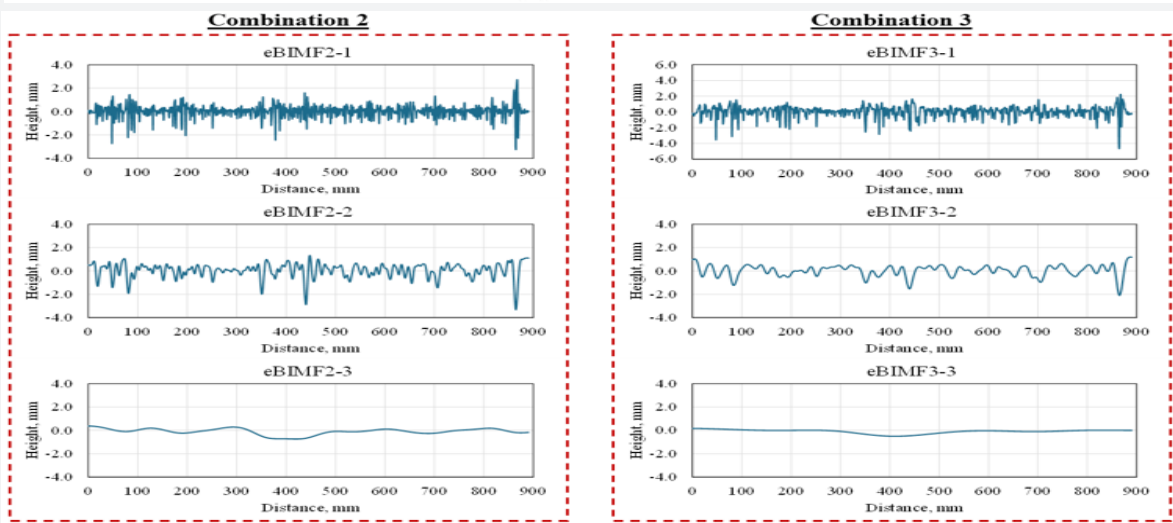
the pavement friction-texture relationship. For each eBIMF combination, three eBIMFs were computed, designated as eBIMF1, eBIMF2, and eBIMF3. As the number of eIMFs is unpredictable, for all combinations, eBIMF3 consistently represents the cumulative sum of the remaining eIMFs that were not included in eBIMF1 and eBIMF2. Figure 5 presents an example of the decomposed eIMFs by the EEMD and two eBIMFs combinations.



(a) Original Surface Texture



(b) eIMFs



(c) eBIMFs

Figure 5: Example of the EEMD Results.

Hilbert Spectral Analysis (HSA)

This study performed the HSA on the eBIMFs to compute both instantaneous amplitude and frequency. Subsequently, the means of the instantaneous amplitude and frequency, MA and MF, respectively, of the eBIMFs were computed and utilized to analyze the friction-texture relationship. Equation (1) defines the

analytical signal used to compute the instantaneous frequency. This equation consists of two parts: the real component, $x(t)$, and the imaginary component, $\hat{x}(t)$. The real part represents the original signal ($eBIMF_i(n)$), while the imaginary part is the result of the Hilbert Transform (Equation (2)). Finally, the instantaneous amplitude and frequency were computed using Equations (3) and (4).

$$v(n)=x(n)+j\hat{x}(n) = a(n) \exp(j\theta(n)) \quad (1)$$

$$\hat{x}(n) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{n-\tau} d\tau \quad (2)$$

$$a(n) = (x^2(n) + \hat{x}^2(n))^{1/2} \quad (3)$$

$$f(n) = \frac{\omega(n)}{2\pi} = \frac{1}{2\pi} \cdot \frac{d\theta(n)}{dn}, \theta(n) = \tan^{-1} \left(\frac{\hat{x}(n)}{x(n)} \right) \quad (4)$$

where $\theta(n)$ is the phase function of original signal $(v(n))$.

Parameters Selection for Characterizing Surface Texture

It is recognized that the MPD is strongly associated with

the mean texture depth (MTD) for portraying friction in asphalt pavements [20,21]. Both MTD and MPD serve as critical parameters for measuring pavement macrotexture. However, these parameters may not adequately represent the distribution of pavement texture characteristics when analyzing tire-pavement friction. Consequently, to enhance the evaluation of asphalt pavement texture properties, six additional parameters along with the MPD were introduced. These texture parameters are categorized based on their characteristics: height-related parameters include MDE (Mean Difference of Elevation), Rsk (Skewness), Rku (Kurtosis), and Rq (Root-Mean-Square Deviation); spacing-related parameters include λ_q (Root-mean square wavelength of the profile); and shape-related indicators include Δ_q (Root-mean square slope), as detailed in Table 3. Furthermore, these parameters were computed for five combinations, the original profile, the first seven eIMFs, and three eBIMFs, to promote a comparative analysis with the original texture profiles.

Table 2: The Details of the Base eIMFs Combinations.

Combination	eBIMF1	eBIMF2	eBIMF3
Combination 1	eIMF1 + eIMF2	eIMF3 + eIMF4	Summation of the remaining eIMFs
Combination 2	eIMF1 + eIMF2 + eIMF3	eIMF4 + eIMF5 + eIMF6	
Combination 3	eIMF1 + eIMF2 + eIMF3 + eIMF4	eIMF5 + eIMF6 + eIMF7	

Table 3: The Texture Indicators for Pavement Surface Characterization.

Model	Description
$MPD = \frac{h_1 - h_2}{2} = \bar{h}$	A strong linear relationship was found between the MPD and MTD [20,21].
$MDE = \frac{\sum_{i=1}^N DE_i }{n-1}$	A higher MDE value indicates better macrotexture properties [22].
$Rq = \sqrt{\frac{1}{N} \sum_{i=1}^N h_i^2}$	Rq indicates the deviation of the profile about the reference plan (mean plan), offering a way to assess texture uniformity [23].

$R_{sk} = \frac{1}{RMS^3} \sqrt{\frac{1}{N} \sum_{i=1}^N h_i^3}$	<p>R_{sk} represents the symmetry level of the profile about the mean plane [23].</p> $R_{sk} = \begin{cases} +ve, & \text{indicates valleys dominant} \\ Zero, & \text{indicates normally distributed profiles} \\ -ve, & \text{indicates peaks are dominant} \end{cases}$
$R_{ku} = \frac{1}{RMS^4} \sqrt{\frac{1}{N} \sum_{i=1}^N h_i^4}$	<p>R_{ku} indicates the presence of peaks and valleys [23,24].</p> $R_{ku} = \begin{cases} > 3, & \text{indicates presence of peaks} \\ = 3, & \text{indicates normally distributed profiles} \\ < 3, & \text{indicates lack of peaks} \end{cases}$
$\lambda_q = 2\pi \frac{R_q}{\Delta_q}$	<p>λ_q measures the wavelength variability within the pavement texture profile [23].</p>
$\Delta_q = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{\Delta h_i}{\Delta x} \right)^2}$	<p>A higher Δ_q value indicates a rougher texture with potentially more effective water dispersion capabilities [23].</p>

R_q is the root mean square, MDE is the mean difference of elevation, R_{sk} is the skewness, R_{ku} is the kurtosis, λ_q is the root mean square wavelength, and Δ_q is the root mean square slope.

Results, Analysis, and Discussion

Correlation Analysis of Original Vs. Decomposed Texture Profiles

A correlation analysis was conducted to compare the original profile with its decomposed counterparts, using the entire profile and the proposed texture parameters detailed in Table 3. Figure 6(a) illustrates the results of the correlation analysis between the original texture profiles and the developed eIMFs, with error bars representing the range of maximum and minimum values of the correlation coefficient across the investigated mixtures. A prominent peak in correlation occurred at eIMF3, followed by eIMF4 and eIMF2, indicating that these eIMFs correlate most robustly with the original texture profile. After this peak, a progressive decrease in the correlation coefficients was observed, extending from eIMF4 to eIMF9. Therefore, eBIMFs that incorporate eIMF3, eIMF4, and/or eIMF2 are likely to show the highest correlation with the original profile, as depicted in Figure 6(b). The variation in correlation levels across different eBIMF combinations indicates that the method of combining eIMFs into eBIMFs significantly impacts their correlation with the original texture profile.

Furthermore, a correlation analysis of the texture indicators showed that, among the eIMFs, the eIMF2 and eIMF3 demonstrated the strongest correlation with the parameters computed for the

original profile, yielding convergent results. The eIMF3 exhibited the strongest correlation with the original profile in terms of the MPD, R_q , and R_{sk} , while the eIMF2 showed superior correlation with respect to the MDE, R_{ku} , λ_q , and Δ_q , as illustrated in Figure 7. However, while the eBIMFs exhibited a higher correlation with the original texture profile, as shown in Figure 6(b), they exhibited a lower correlation coefficient than eIMFs regarding the texture parameters.

Correlation Analysis of the Friction and Texture Properties

A correlation analysis was also performed to evaluate the relationship between the friction properties, as indicated by DFT_{20} values, and the texture characteristics, as defined by the computed texture indicators, with the results presented in Figure 8. As illustrated in Figure 8(a), the correlation between the texture characteristics and the friction properties was initially weak; however, it improved with the application of EEMD. Furthermore, the correlation varied across the eIMFs and combinations of eBIMFs. Generally, the computed texture indicators, particularly Δ_q , R_q , and MDE, of the eIMF6 exhibited the strongest correlation with the DFT_{20} , achieving a correlation coefficient (r) exceeding 0.65. Additionally, the R_q and R_{sk} parameters of the eBIMFs exhibited a good correlation with the DFT_{20} values, as illustrated in Figure 8(b). Therefore, the eIMF6 was adopted to examine the friction-texture relationship.

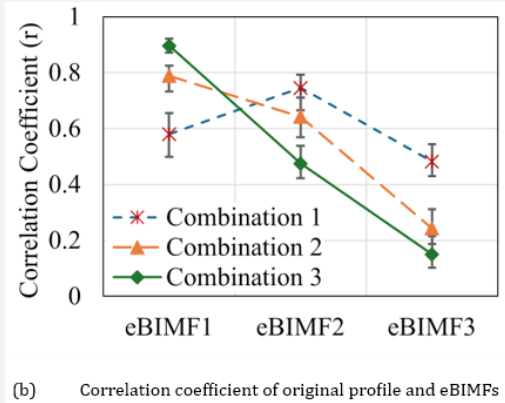
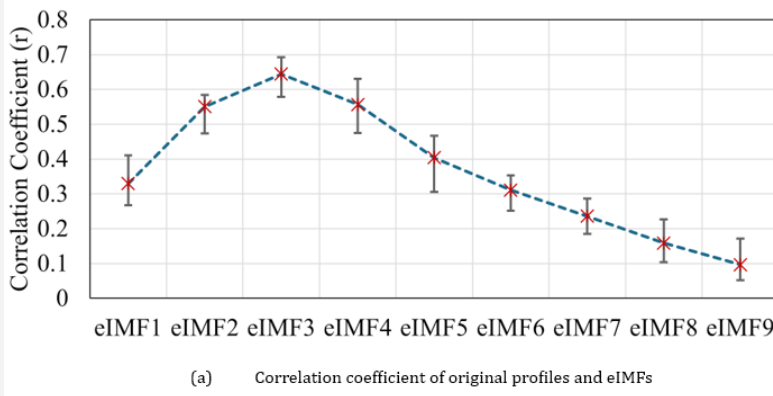


Figure 6: Correlation Analysis between the Original and Decomposed Profiles.

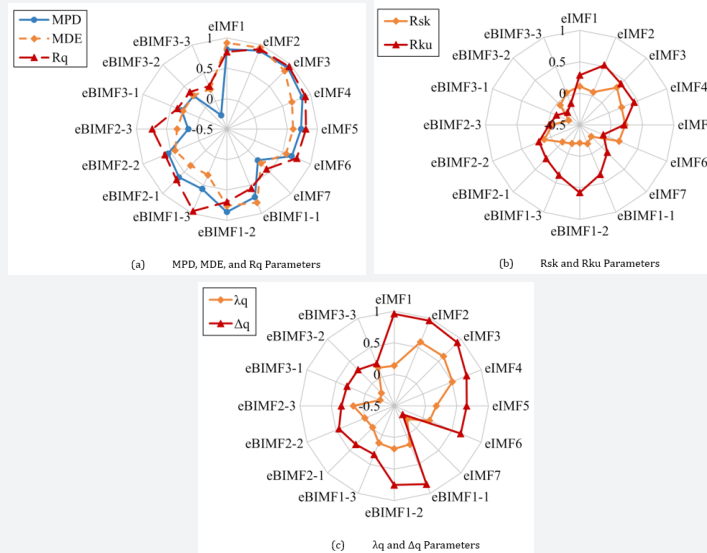


Figure 7: Correlation Analysis of the Texture Parameters of the Original and Decomposed Profiles.

Impact of EEMD on the Friction-Texture Relationship

The friction-texture relationship was explored based on the texture characteristics of both the original and eIMF6 profiles, as shown in Figure 9. As depicted in Figure 9, the relationship based on the characteristics of the original profile was very weak for all proposed texture indicators. However, an improvement was observed with the application of EEMD. It was found that the Δq , Rq , and MDE parameters demonstrated relatively good correlations with the DFT_{20} . In contrast, Rsk , Rku , and λq showed very weak correlation with the DFT_{20} values.

Multilinear Regression (MLR) Analysis

A backward stepwise multilinear regression (MLR) analysis was conducted to identify the most significant texture indicators affecting pavement friction, aiming to develop an accurate friction-texture prediction model. Equation (5) expresses the general MLR model. Initially, a full model including all texture indicators of

the eIMF6 was constructed. It systematically removed the least significant predictors, one at a time, those with a p-value greater than 0.05, until no further predictors could be removed without a significant loss of fit. The results of the MLR analysis are presented in Table 4. It was noted that λq , Rq , Δq , Rku , and MDE were statistically significant for predicting pavement friction (p-value < 0.01). In addition, MDE , Rq , and Rku positively influenced the friction values, while λq and Δq had a negative impact due to their respective positive and negative coefficients.

$$DFT_{20} = c + \sum_{i=1}^N a_i \times x_i \quad (5)$$

where DFT_{20} is the dynamic friction value at 20 km/hr, c is the error term, a_i is the coefficient representing the respective independent variables' effects on the dependent variable, and x_i is the independent texture indicator.

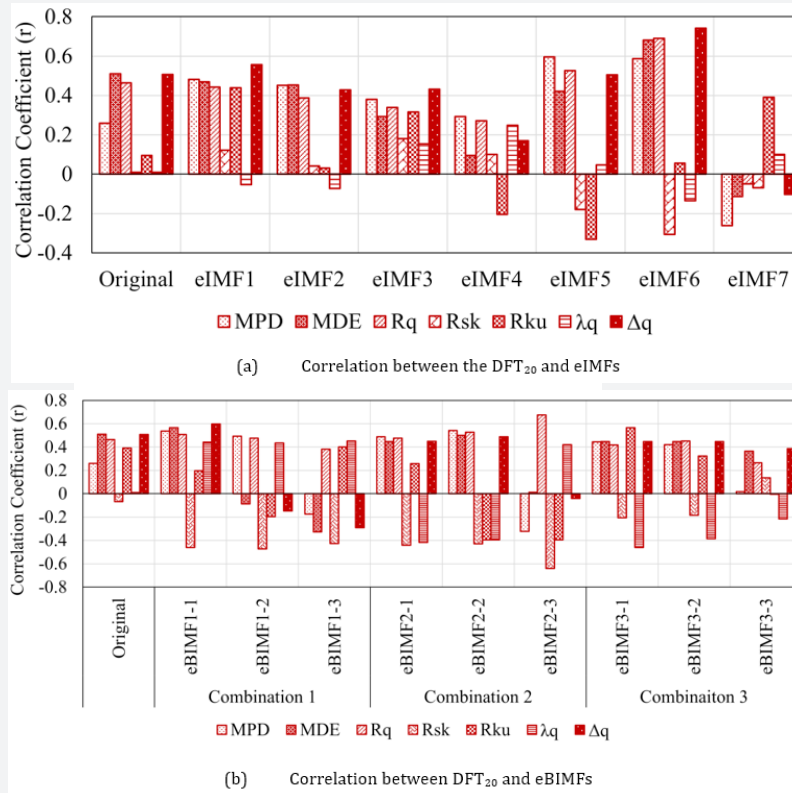


Figure 8: A Correlation Analysis of the Friction and Texture Properties.

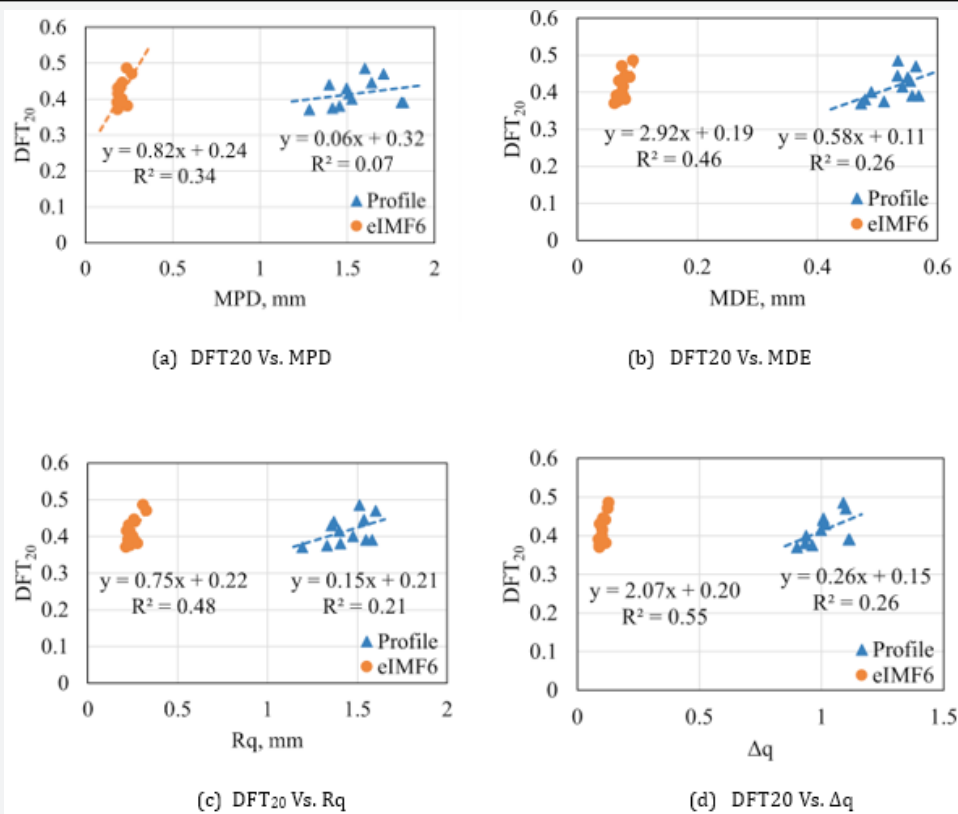


Figure 9: Relationships Between DFT₂₀ and the Significant Texture Indicators of eIMF6..

Table 4: The Backward Stepwise MLR Analysis Results of the Friction-Texture Relationship.

	Coefficients	t Stat	P-value	Standard Error	p-value	R ²
Intercept	0.805	7.00948	0.00011	0.01645	< 1.0E-05	0.878
MDE	70.044	3.80485	0.0052			
Rq	5.598	6.61088	0.00017			
Rku	0.175	5.51409	0.00056			
λq	-0.0068	-7.28061	0.00009			
Δq	-156.13	-5.81387	0.0004			

The accuracy of the MLR model was assessed by analyzing the bias of the data points, which reflects their rotation or shift around the line of equality, and the precision, which measures the degree of scatter around the equality line [25,26]. Figure 10(a) displays the non-constrained regression lines comparing measured versus predicted DFT₂₀ values, accompanied by goodness-of-fit statistics. A sensitivity analysis was also conducted to identify

the most influential texture indicators in predicting pavement friction, as illustrated in Figure 10(b). The analysis was conducted using the range of computed data; the minimum, mean, and maximum values of the computed texture parameters were used. It was observed that the importance of the parameters ranked in descending order as follows: Δq, Rq, λq, MDE, and Rku.

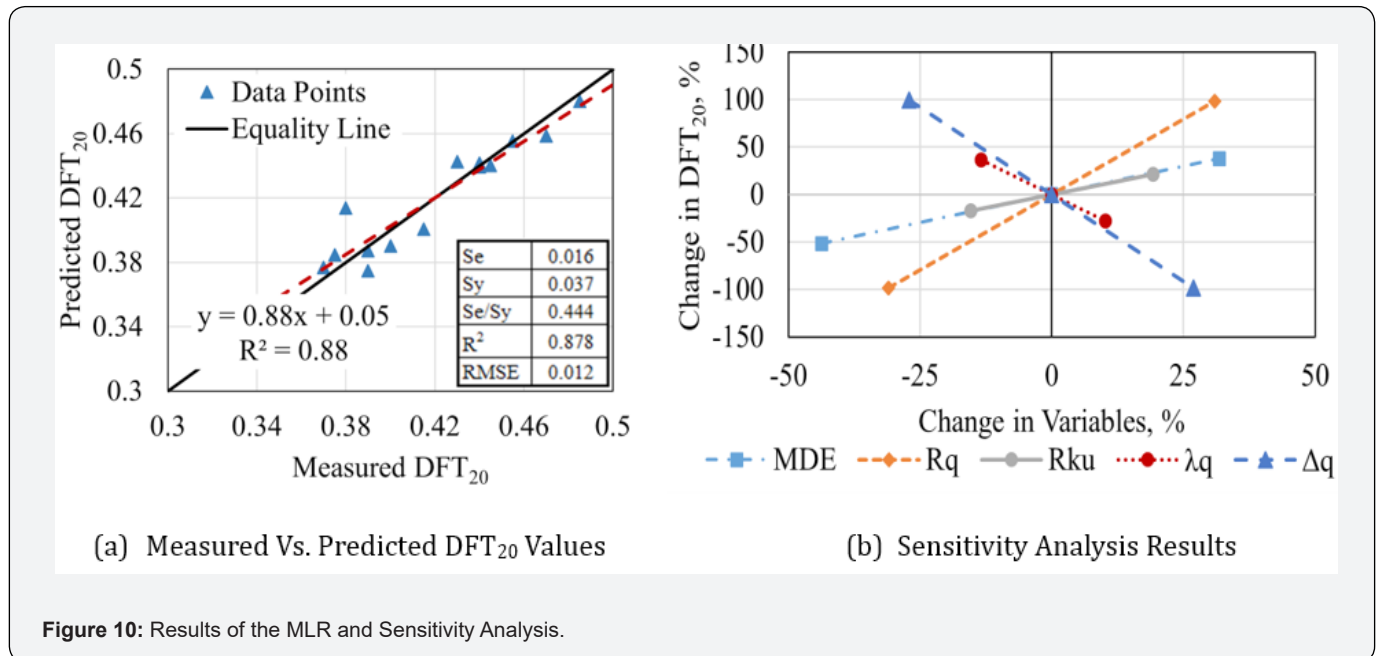


Figure 10: Results of the MLR and Sensitivity Analysis.

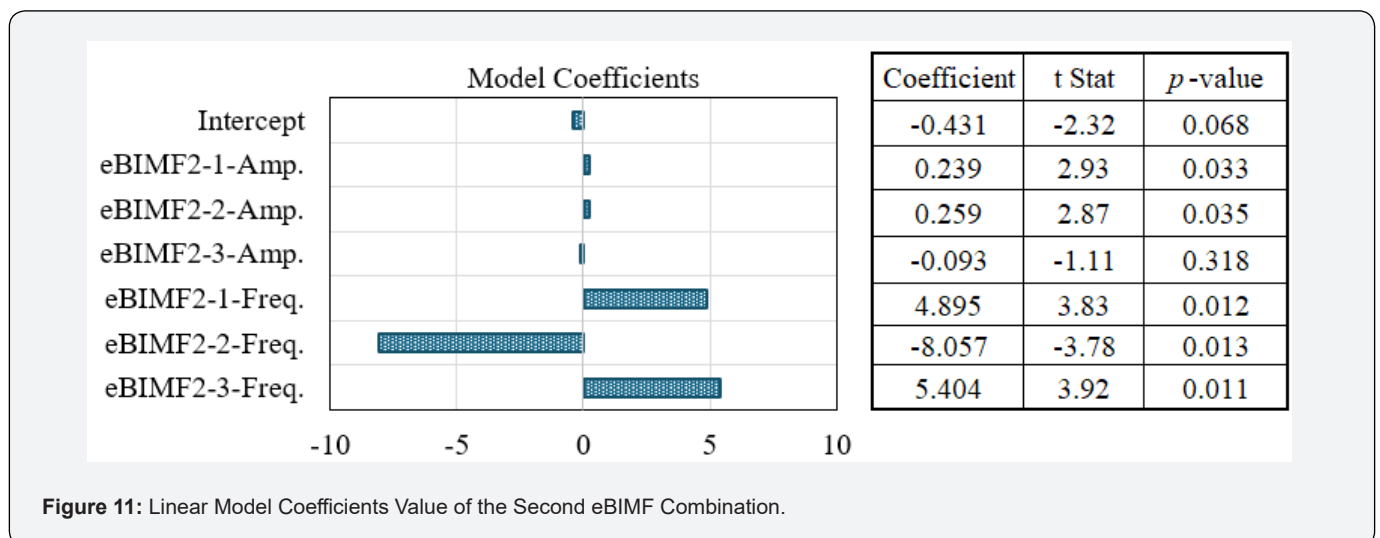


Figure 11: Linear Model Coefficients Value of the Second eBIMF Combination.

Correlation Analysis Based on HSA Results

The friction-texture relationship was further explored using the MA and MF parameters obtained through the HSA. Therefore, HSA was performed on eBIMF combinations to obtain instantaneous amplitudes and frequencies, and the MA and MF were computed. Among the computed eBIMF combinations, the second combination exhibited a statistically significant correlation with the friction properties. Specifically, the MF of eBIMF2-1, eBIMF2-2, and eBIMF2-3 and MA of eBIMF2-1 and eBIMF2-3 were statistically significant parameters, as shown in Figure 11.

Summary, Conclusion, and Recommendation

This research explores the relationship between pavement friction and texture using the EEMD algorithm. Fourteen asphalt mixture slabs were fabricated, and their friction and texture properties were evaluated using a dynamic friction tester (DFT) and a circular track meter (CT-Meter). The EEMD method was adopted to optimize and extract the eIMFs to better characterize the surface texture profile. Subsequently, three eBIMF combinations were proposed to investigate the friction-texture relationship further. Additionally, seven texture parameters were computed for the original and developed eIMF and eBIMF profiles. The key findings are outlined as follows:

- i. The characteristics of the original texture profile exhibited relatively weak correlations with the DFT results, as indicated by a low correlation coefficient (r) and coefficient of determination (R^2).
- ii. Applying EEMD enhanced the friction-texture correlation, indicating the effectiveness and applicability of the EEMD method in optimizing the friction-texture relationship.
- iii. Among the eIMFs and eBIMFs, the texture characteristics of eIMF6 exhibited the strongest correlation with the DFT results.
- iv. The correlation analysis revealed that the λ_q , R_q , Δ_q , and MDE were statistically significant in predicting pavement friction.
- v. Two friction-texture models were developed using backward stepwise multilinear regression analysis: (1) based on the HSA of the eBIMF2; and (2) based on the characteristics of eIMF6, with an overall R^2 of 0.878, an r of 0.937, and p -value of less than $1.0E-05$.
- vi. Based on the sensitivity analysis, the importance of texture parameters, in descending order, was Δ_q , R_q , λ_q , MDE, and R_{ku} .

Finally, adopting the HHT analysis would enhance the friction-texture prediction model. However, a comparative analysis of various empirical mode decomposition methods is essential to determine the most effective decomposition approach. Additionally, future research should expand to include a broader range of asphalt mixtures and additional texture indicators to further validate and refine the models.

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