

Article

An Optimized Approach for Predicting Asphalt Mixture Density Using L-R Dielectric Mixing Theory

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Abstract

Accurate prediction of asphalt mixture density is critical for quality control in pavement engineering. This study develops a novel dielectric-based predictive framework by applying the Lichtenecker–Rother (L-R) dielectric mixing theory to asphalt composites. The model's key microstructural parameter, the geometric arrangement factor c , was optimized to 0.3 using a combined experimental dataset: laboratory measurements on AC (asphalt concrete) mixtures produced in this study, supplemented with published data from open-graded friction course (OGFC), stone mastic asphalt (SMA), and asphalt mixture (AM) types reported in the literature. The resulting model, termed the Geometric Arrangement Optimization (GAO) model, was systematically compared against three established dielectric models: the complex refractive index method (CRIM), the Rayleigh mixing model, and the Bottcher-type model adapted by Leng et al. (denoted ALL). Validation on a total of 34 sets of laboratory specimens showed that GAO achieved the highest prediction accuracy, with a mean relative error of 1.83% and a coefficient of determination R^2 of 0.91. When tested on eight independent field cores, GAO maintained reliable performance, yielding a mean relative error of 3.01%. These results indicate that the GAO model provides a physically grounded and practically applicable approach for asphalt mixture density estimation, contributing a useful tool for pavement performance evaluation and quality assurance.

Keywords: asphalt pavement; asphalt mixture; density; relative permittivity; GAO model

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1. Introduction

During the construction of asphalt pavements, improper control of layer density, whether excessively high or low, can directly compromise the long-term performance of the pavement structure. Excessive compaction can lead to a reduction in designed air void content, potentially altering the mixture's volumetric structure and compromising its long-term durability [1,2]. In contrast, insufficient density raises the likelihood of moisture infiltration, which may trigger early-stage damage such as stripping and pothole formation. Additionally, low-density mixtures often exhibit reduced shear resistance, increasing their susceptibility to rutting under high temperatures and heavy traffic loads.

These issues not only significantly impair the functional serviceability and durability of the pavement but also substantially increase maintenance costs over its lifecycle [3,4].

Conventionally, the density of asphalt pavement is assessed by drilling core samples, typically four or five cores per kilometer, and measuring their bulk specific gravity using the saturated surface-dry (SSD) method [5]. Although this method provides accurate point measurements, it suffers from several limitations: high labor and time requirements, limited and discrete sampling that fails to represent spatial variability, and destructive nature that causes permanent damage to the pavement [6,7]. Therefore, developing an efficient, continuous, non-destructive, and accurate method for measuring the density of asphalt concrete is of great practical importance. Such an approach is essential for ensuring uniform compaction during construction, enhancing the overall quality of asphalt pavements, and extending their service life while reducing life-cycle costs.

Currently, electromagnetic techniques such as non-nuclear density gauges and Ground-Penetrating Radar (GPR) are widely used for the detection of asphalt pavement density [8,9], layer thickness [10,11], and distresses [12]. Both methods perform non-destructive detection based on differences in the dielectric properties of materials, with the relative permittivity being a key parameter characterizing these dielectric properties. Non-nuclear density gauges can rapidly estimate the density of asphalt pavement; however, they are limited to point-based measurements, resulting in low efficiency and a need for multi-point calibration via core drilling in advance [13–15]. In contrast, GPR enables high-speed, continuous, and full-cross-section measurement of the relative permittivity of asphalt pavement [16–18]. The relative permittivity obtained by GPR exhibits a strong correlation with volumetric properties of the asphalt mixture, such as density, air void content, and moisture content [19–22]. Therefore, the key to efficient and non-destructive detection of asphalt pavement density lies in establishing a reliable relationship between the density of asphalt mixtures and their dielectric characteristics.

Numerous researchers have conducted in-depth investigations into the dielectric properties of asphalt mixtures [23]. A primary focus of these studies has been to establish statistical functions or theoretical relationship models between the relative permittivity of asphalt mixtures and their bulk specific gravity. The fundamental objective behind this line of inquiry is to achieve accurate and non-destructive prediction of in-place asphalt pavement density.

In the realm of laboratory testing methods for the dielectric properties of asphalt mixtures, various techniques have been developed, each with inherent advantages and limitations. Fauchard et al. [24] employed a cylindrical resonant cavity to measure the complex permittivity of both asphalt mixtures and aggregate materials. While this method offers high measurement accuracy, it imposes stringent requirements on specimen dimensions; deviations can lead to significant measurement errors. Meng Meili [25] utilized a vector network analyzer equipped with a coaxial probe [26] to characterize the dielectric properties of asphalt mixtures. However, the contact surface of the coaxial probe is a mere 19 mm in diameter, resulting in a limited measurement area. This constraint introduces a degree of randomness when testing mixtures containing large-sized aggregates. Similarly, Yu Xiaohe et al. [27] measured the permittivity of asphalt mixture specimens with different compaction levels using an elevated temperature dielectric constant platform. The specimens used in their study were relatively small (26 mm in diameter $\times$ 12 mm in height), which may compromise the representativeness of the results for heterogeneous materials like asphalt mixtures.

In the field of density prediction models for asphalt mixtures, researchers have proposed various modeling approaches based on dielectric properties. Loizos et al. [28] used a Percometer device to measure the relative permittivity on the surface of Marshall specimens of both dense-graded and open-graded asphalt mixtures. They established linear

regression relationships between the mixture's air void content, stiffness modulus, and relative permittivity. Hoegh et al. [29] employed multi-channel GPR for rapid acquisition of the relative permittivity of asphalt pavement and applied a modified exponential relationship model to estimate the air void content effectively. For dense-graded asphalt concrete, Chang et al. [30] developed a multiple linear regression model that predicts mixture density using relative permittivity, air void content, and asphalt content as independent variables, thereby improving the model's adaptability to material composition. In a series of studies, Chen et al. [31,32] statistically analyzed data from numerous pavement cores and identified a strong exponential correlation between air void content and relative permittivity. Based on this relationship, they proposed a method for calculating air void content, offering a new approach for evaluating pavement compaction quality. Fernandes et al. [33] further considered the influence of moisture by establishing a linear relationship between air void content and relative permittivity in asphalt mixtures under wet conditions, thereby extending the model's applicability to real-world scenarios.

Based on the dielectric relationships between composite materials and their constituent phases, Al-Qadi et al. [34] derived theoretical density prediction models for asphalt mixtures, including the Rayleigh model, the Böttcher model, and the Complex Refractive Index Model (CRIM). By employing the ground-penetrating radar (GPR) amplitude reflection method, they calculated the relative permittivity of a specific type of asphalt pavement and preliminarily validated the feasibility of the Rayleigh model for density estimation. Both the Rayleigh and Böttcher dielectric mixing models are derived from electromagnetic mixture theory, which conceptualizes composite materials as consisting of a background medium and embedded scatterers [35,36]. The Rayleigh model assumes that the scatterers are spherical and significantly smaller than the wavelength of the electromagnetic wave, while also neglecting mutual polarization interactions between scatterers. In contrast, the Böttcher model extends the Rayleigh formulation by incorporating a fixed polarization term to account for interactions among scatterers [37,38]. The CRIM originates from the Lichtenecker–Root (L-R) [39] equation with the geometric arrangement factor c set to 0.5 [40]. When $c = 1$, the model reduces to the Brown model (also referred to as the linear model) [41], while when $c = 1/3$, it becomes the Looyenga model (or the cubic root model) [42], which is suitable for simulating the dielectric behavior of spherical and randomly distributed ellipsoidal materials. This demonstrates that the L-R equation serves as a fundamental theoretical basis for dielectric modeling of composite media, wherein the value of the parameter c plays a critical role in accurately characterizing the dielectric properties of multiphase composite materials.

In practical engineering applications, the morphological complexity of scatterers within asphalt mixtures presents a significant challenge for dielectric modeling. To address this, researchers have conducted a series of studies aimed at refining existing models. Leng et al. [43,44] introduced an enhanced Böttcher model (referred to as the ALL model) by incorporating an aggregate shape factor. They further developed the CP dielectric mixing model by optimizing scatterer shape parameters. In subsequent work, considering the compaction characteristics and complex interlocking state of pavement layer materials, they optimized the Böttcher model to determine the optimal polarization influence coefficient for component scatterers. Xiong Xuetao et al. [45–47] established an ISO dielectric mixing model based on the Rayleigh model, which simultaneously accounts for the effects of particle shape and polarization interactions. Meanwhile, Ling Tianqing et al. [48–50] proposed a PM model capable of accurately predicting the density of large-porosity asphalt mixtures. Despite these advancements, existing models still exhibit notable limitations in parameter determination. For instance, the relative permittivity of different types of asphalt is often assigned an empirical value of 3, while the relative permittivity of aggregates is typically back-calculated from calibrated core samples—a process that tends

to yield inconsistent results in practice. These uncertainties highlight the need for more robust and reliable parameter acquisition methods to improve the applicability and accuracy of dielectric-based density prediction models.

In summary, statistical models for asphalt mixture density prediction are typically derived from regression analysis of limited sample data from specific pavement types. While these models may take linear or exponential forms, they often lack generalizability due to their data-driven nature. In contrast, theoretical models for density estimation incorporate the dielectric and volumetric parameters of mixture components into a unified mathematical formulation, offering broader applicability across different asphalt pavements. Prominent theoretical models include the Complex Refractive Index Model (CRIM), the Rayleigh model, the Bottcher model, and the ALL model. Among these, the Looyenga–Raleigh (L-R) equation exhibits distinct theoretical advantages. Unlike the Rayleigh model, which assumes spherical scatterers, or the Bottcher model, which incorporates a fixed polarization term, the L-R equation introduces a flexible geometric arrangement factor c . This parameter enables the model to adapt to a wide range of composite structures—from series to parallel configurations—making it particularly suitable for representing the complex morphology and spatial distribution of aggregates in actual asphalt mixtures. Notably, several established models such as CRIM ($c = 0.5$), the Brown model ($c = 1$), and the Looyenga model ($c = 3$) can be regarded as special cases of the L-R equation, further underscoring its potential as a unified theoretical framework.

Despite its theoretical soundness, the application of the Lichtenecker–Rother (L-R) dielectric mixing model to asphalt mixtures remains hindered by a fundamental knowledge gap: the geometric arrangement factor c , a parameter that governs the dielectric–density relationship, has typically been assigned either default values or empirical constants derived from other material systems. No systematic, experimentally grounded methodology currently exists to determine c specifically for asphalt composites, nor has its physical significance been interpreted in relation to mixture microstructure. This study addresses this gap by making the following original contributions:

- (1) A unified density prediction framework based on the L-R equation is established, and the geometric arrangement factor c is optimized exclusively using asphalt mixture data, yielding a mixture-specific value of $c = 0.3$ that differs from generic assumptions adopted in prior work.
- (2) The optimized c value is physically interpreted as representing an intermediate phase arrangement characteristic of densely compacted asphalt mixtures, bridging the theoretical extremes of series and parallel mixing models.
- (3) The proposed GAO (Geometric Arrangement Optimization) model is systematically validated against both laboratory-fabricated and field-cored specimens encompassing multiple mixture types, demonstrating superior predictive accuracy and practical generalizability.

By integrating dielectric mixing theory with mixture-specific experimental calibration, this study provides a physically grounded, generalizable, and readily implementable approach for asphalt mixture density prediction. The findings contribute not only to advancing the application of dielectric methods in pavement engineering but also to a deeper understanding of how microstructural characteristics influence the electromagnetic response of composite materials.

2. L-R Dielectric Mixing Theory

2.1. Dielectric Mixing Model

The dielectric properties of a composite multiphase material are fundamentally determined by the dielectric constants and volume fractions of its constituent phases. This

structure–property relationship is quantitatively captured by dielectric mixing models, which are pivotal for predicting the effective permittivity of heterogeneous media. These models are broadly classified into two categories: semi-empirical mixtures models and theoretical electromagnetic models. Semi-empirical models, a prominent example of which originates from the foundational work of Lichtenecker and Rother, are often derived from effective media approximations. The seminal L-R equation [39], which operates on a power-law principle as given in Equation (1), serves as a cornerstone for many subsequent semi-empirical approaches.

$$(\epsilon_m)^c = \sum_{i=1}^n V_i (\epsilon_i)^c \quad (1)$$

where ϵ_m denotes the dielectric constant of the composite multiphase medium. ϵ_i represents the dielectric constant of the i -th constituent phase. V_i is the volume fraction of the i -th phase. c is the geometric arrangement factor, a parameter reflecting the influence of microstructural configuration on the dielectric behavior. n denotes the number of constituent phases.

The geometric arrangement factor c , in the Lichtenecker–Rother (L-R) equation signifies distinct mixing geometries. A value of $c = -1$ corresponds to a layered composite with phases arranged in parallel or alternating strata, where the electrodes are aligned parallel to the layers. This configuration is analogous to a series mixing rule. Conversely, $c = +1$ represents the same layered structure but with electrodes perpendicular to the layers, equivalent to a parallel mixing rule. Physically, these two extremes represent the theoretical bounds for the geometrical combination of two materials. In most practical scenarios, the parameter c varies between -1 and $+1$, describing an intermediate microstructure.

- (1) When the parameter $c = 1$, the L-R equation reduces to a linear dielectric mixing model, known as the Brown model [41], as given in Equation (2).

$$\epsilon_m = \sum_{i=1}^n v_i \epsilon_i \quad (2)$$

- (2) When the parameter $c = 0.5$, the model is termed the Complex Refractive Index Method (CRIM) model [40], also referred to as the root mean square model, as given in Equation (3).

$$\sqrt{\epsilon_m} = \sum_{i=1}^n v_i \sqrt{\epsilon_i} \quad (3)$$

- (3) A parameter value of $c = 1/3$ corresponds to the Looyenga model [42], also known as the cubic root model, as expressed in Equation (4).

$$(\epsilon_m)^{1/3} = \sum_{i=1}^n v_i (\epsilon_i)^{1/3} \quad (4)$$

2.2. Density Prediction Model for Asphalt Mixture

Asphalt mixture is a non-homogeneous, three-phase composite material composed of asphalt binder, mineral aggregates, and air voids. Its mass and volume composition is illustrated in Figure 1. Based on the L-R equation (Equation (1)), the asphalt mixture is postulated as a three-phase composite comprising asphalt, aggregates, and air. Consequently, the dielectric mixing model for the asphalt mixture, given by Equation (5), is derived.

$$(\epsilon_{AC})^c = V_a (\epsilon_a)^c + V_b (\epsilon_b)^c + V_{se} (\epsilon_s)^c \quad (5)$$

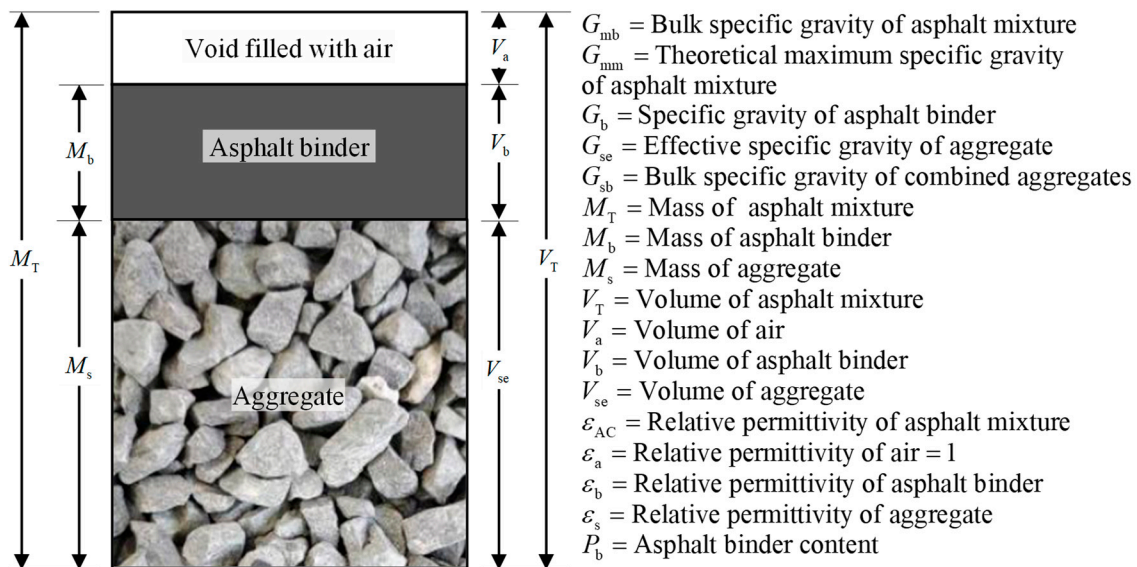


Figure 1. Volumes and masses of the components in asphalt mixture.

With the total bulk volume V_T normalized to 1, the volume fractions for the air voids, asphalt binder, and aggregates are derived as follows (Equations (6)–(8)).

$$V_a = 1 - \frac{G_{mb}}{G_{mm}} \quad (6)$$

$$V_b = \frac{M_b}{G_b} = \frac{M_T P_b}{G_b} = \frac{G_{mb} P_b}{G_b} \quad (7)$$

$$V_{se} = \frac{M_s}{G_{se}} = \frac{G_{mb} (1 - P_b)}{G_{se}} \quad (8)$$

Given the conventional value of $\epsilon_a = 1$ for the relative permittivity of air, the substitution of the component volume fractions (Equations (6)–(8)) into the dielectric mixing model (Equation (5)) leads to the general density prediction model formulated in Equation (9), thereby establishing an L-R-based model applicable to different asphalt mixture types.

$$G_{mb} = \frac{\epsilon_{AC}^c - 1}{\frac{P_b}{G_b} \epsilon_b^c + \frac{1 - P_b}{G_{se}} \epsilon_s^c - \frac{1}{G_{mm}}} \quad (9)$$

When the parameter c takes values of 1, 1/2, and 1/3, Equation (5) simplifies to the Brown, CRIM, and Looyenga dielectric mixing models for asphalt mixture, respectively. The corresponding density prediction models are given by Equations (10)–(12). The geometric arrangement factor c , which ranges from -1 to 1 , embodies the composition and spatial arrangement of the constituent particles. Therefore, a critical research endeavor is to investigate and determine the optimal value of c that renders the L-R-based optimized model most suitable for predicting asphalt mixture density.

$$G_{mb} = \frac{\varepsilon_{AC} - 1}{\frac{P_b}{G_b} \varepsilon_b + \frac{1 - P_b}{G_{se}} \varepsilon_s - \frac{1}{G_{mm}}} \quad (10)$$

$$G_{mb} = \frac{\sqrt{\varepsilon_{AC}} - 1}{\frac{P_b}{G_b} \sqrt{\varepsilon_b} + \frac{1 - P_b}{G_{se}} \sqrt{\varepsilon_s} - \frac{1}{G_{mm}}} \quad (11)$$

$$G_{mb} = \frac{\sqrt[3]{\varepsilon_{AC}} - 1}{\frac{P_b}{G_b} \sqrt[3]{\varepsilon_b} + \frac{1 - P_b}{G_{se}} \sqrt[3]{\varepsilon_s} - \frac{1}{G_{mm}}} \quad (12)$$

Furthermore, based on electromagnetic mixing theory, the Rayleigh model [51] assumes spherical scatterers and considers only one-dimensional scattering. In contrast, the ALL model [52], building upon the Bottcher model [53], employed least squares regression analysis and determined that a parameter value of $u = -0.3$ minimized the total sum of squared errors (SSE) for density prediction across five asphalt mixtures. Consequently, the Rayleigh model and the ALL model for predicting the bulk specific gravity of asphalt mixtures are given by Equations (13) and (14), respectively. These two models are subsequently compared with the optimized model in the following analysis.

$$G_{mb} = \frac{\frac{\varepsilon_{AC} - \varepsilon_b}{\varepsilon_{AC} + 2\varepsilon_b} - \frac{1 - \varepsilon_b}{1 + 2\varepsilon_b}}{\frac{\varepsilon_s - \varepsilon_b}{\varepsilon_s + 2\varepsilon_b} \frac{1 - P_b}{G_{se}} - \frac{1 - \varepsilon_b}{1 + 2\varepsilon_b} \frac{1}{G_{mm}}} \quad (13)$$

$$G_{mb} = \frac{\frac{\varepsilon_{AC} - \varepsilon_b}{3\varepsilon_{AC} - 2.3\varepsilon_b} - \frac{1 - \varepsilon_b}{1 - 2.3\varepsilon_b + 2\varepsilon_{AC}}}{\frac{\varepsilon_s - \varepsilon_b}{\varepsilon_s - 2.3\varepsilon_b + 2\varepsilon_{AC}} \frac{1 - P_b}{G_{se}} - \frac{1 - \varepsilon_b}{1 - 2.3\varepsilon_b + 2\varepsilon_{AC}} \frac{1}{G_{mm}}} \quad (14)$$

3. Experimental Design

3.1. Experimental Setup

The relative permittivity of the materials was measured using a Percometer dielectric constant tester, which operates within a frequency range of 40–50 MHz, as shown in Figure 2. The system consists of a main unit connected to an SF sensor probe with an outer ring diameter of 6 cm. The probe features concentric metal rings that function as electrodes. During testing, the probe is placed on a flat surface of the material, and the sensor detects the capacitance between the electrodes. This capacitance value is then converted into the relative permittivity of the material using the calculation formula given in Equation (15). The resulting value is displayed on the main unit's screen. The Percometer has a measurement range of 1 to 32 and an effective measurement depth of approximately 3 cm.



Figure 2. Percometer instrument.

$$\varepsilon_r = \frac{C_m}{C_v} \quad (15)$$

where ε_r is the relative permittivity of the medium. C_m represents the capacitance measured between the electrodes with the medium present. C_v denotes the capacitance between the electrodes in a vacuum, which is generally approximated by the capacitance in air and is set as a default value in the instrument.

3.2. Experimental Materials

In this experiment, the aggregate gradation adopted the median value of the AC-25 grading curve, as shown in Figure 3. All aggregates were limestone, a lithology widely used in Chinese asphalt pavements due to its availability and consistent engineering properties. The binder used was Liaohe 90# base asphalt, a conventional medium-grade binder commonly employed in temperate-region pavement construction. Its key technical parameters were as follows: penetration of 86.5 mm/10 at 25 °C (100 g, 5 s), softening point of 46.8 °C, and ductility exceeding 100 cm at 25 °C. This binder was selected not for exceptional high- or low-temperature performance, but rather as a representative baseline material to ensure the generalizability of the dielectric–density relationship established in this study.

To accurately determine the dielectric properties of the constituent materials, a Percometer dielectric constant tester was employed. Direct in-situ measurements were performed on the surface of un-crushed quarry stones and on asphalt binder samples obtained from storage tanks. This approach yields the relative permittivity of both aggregates and binder directly, avoiding the uncertainty and indirect calibration procedures associated with conventional estimation methods.

The AC-25 mixture used in this study follows a standard job-mix formula widely applied in Chinese highway engineering. Since the primary objective of this work is to establish and validate a dielectric-based density prediction model rather than to optimize mixture proportioning, a full detailed mixture design is not reiterated here.

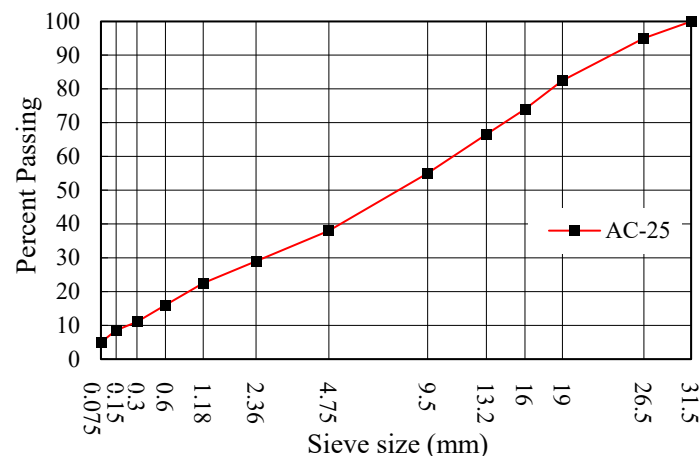


Figure 3. Aggregate gradations used for the asphalt mixture.

3.3. Experimental Data

To fabricate asphalt mixture specimens with targeted air void contents, a gyratory compactor was operated in height-controlled mode. Specimens were compacted to a fixed final dimension of 100 mm in diameter and 84 mm in height. The mass of the mixture placed in the mold was pre-calculated based on the theoretical maximum specific gravity (G_{mm}), the target specimen volume, and the designed air void level. By varying the mass of the mixture while maintaining the same final compacted volume, specimens covering a range of porosity levels were produced under consistent geometrical conditions.

For each target air-void level, three replicate specimens of AC-25 mixture were fabricated, resulting in a total of 36 specimens across 12 designed porosity levels, as shown in Figure 4. All dielectric and density results presented in this study are based on the average of three replicate measurements, thereby improving statistical reliability and mitigating the effect of specimen-to-specimen variation.

The air void content of each AC-25 specimen was calculated based on the measured bulk specific gravity (presented in Figure 5) and the theoretical maximum specific gravity (G_{mm}) provided in Table 1. The calculated air void contents ranged from approximately 2% to 9%, covering a typical spectrum of low to high porosity levels commonly encountered in asphalt pavement construction and quality control. This range was selected to comprehensively evaluate the dielectric–density relationship under various compaction conditions.

Prior to testing, approximately 7 mm was sawn off from both the top and bottom surfaces of each specimen. This sawing process served two key purposes: it created smooth and flat testing surfaces that ensured consistent contact with the Percometer probe, thereby minimizing the influence of surface texture; and it resulted in a final specimen height of 70 mm, promoting a more uniform and stable distribution of air voids along the vertical direction. The relative permittivity of each specimen was determined by taking the average of five measurements taken at different locations on both the top and bottom surfaces. Finally, the bulk specific gravity of the sawn specimens was measured using the saturated surface-dry (SSD) method.

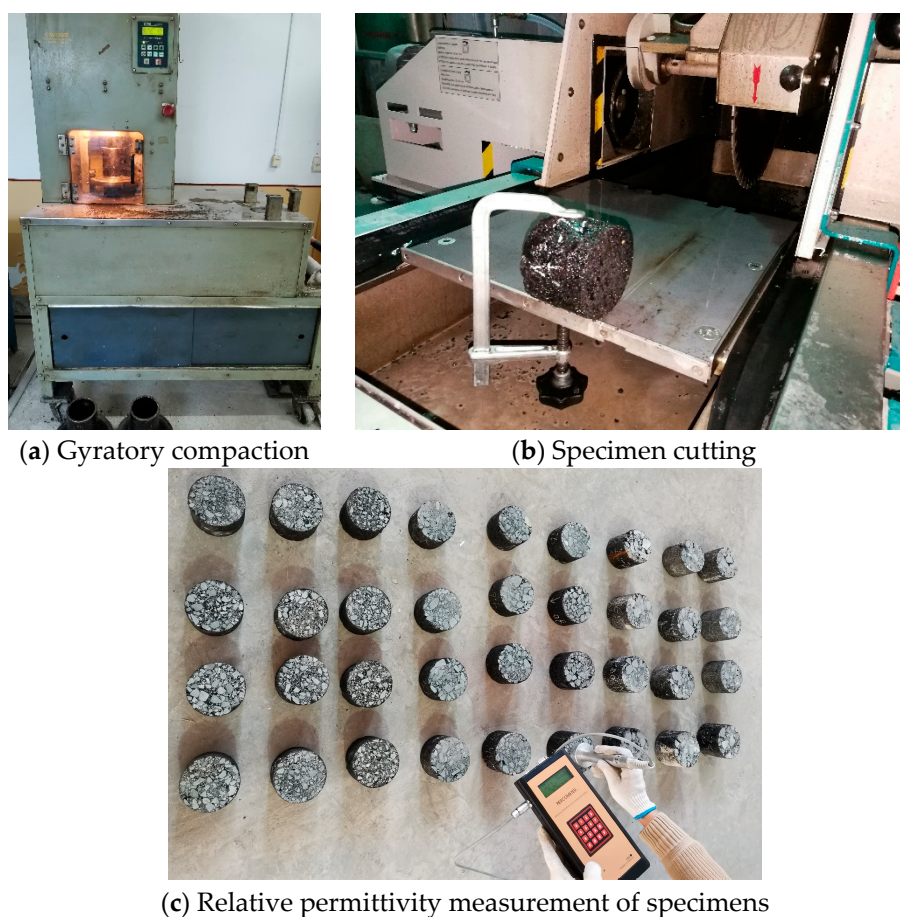


Figure 4. Fabrication and relative permittivity measurement of asphalt mixture specimens.

It is recognized that gyratory-compacted specimens may exhibit non-uniform air-void distribution across the cross-section due to mold confinement. To minimize the influence of such heterogeneity on dielectric measurements, the Percometer probe (6 cm in diameter) was consistently placed at the center of each specimen (10 cm in diameter), where void distribution is generally more uniform. Additionally, trimming the top and bottom surfaces further reduced potential edge effects and ensured consistent probe contact.

The bulk specific gravity and relative permittivity of AC-25 asphalt mixture specimens were measured in the laboratory. These data were combined with 22 sets of relevant data from Cui et al.'s [18] study on other asphalt mixtures (OGFC-13, SMA-13, and AM-13), as illustrated in Figure 5, along with other measured parameters required by the density prediction model listed in Table 1. As shown in Figure 5, the bulk specific gravity of the asphalt mixture exhibits a positive correlation with its relative permittivity. This relationship can be attributed to the fact that an increase in mixture density implies a reduction in the volume fraction of air voids, which have a relative permittivity of 1. Consequently, the proportion of other components with higher relative permittivity, such as asphalt binder and mineral aggregates, increases, leading naturally to a higher overall relative permittivity of the mixture.

Statistical models for asphalt mixture density prediction are typically derived from regression analysis of limited sample data from specific pavement types. While these models may exhibit reasonable accuracy within their original dataset, their generalizability is often constrained by their data-driven nature. In contrast, theoretical models grounded in dielectric mixing theory, such as the following proposed model, incorporate the dielectric constants and volume fractions of mixture components into a unified

physical formulation. This approach not only supports density estimation but also provides insight into the role of material composition, enhancing applicability across different asphalt pavement types and mixture designs.

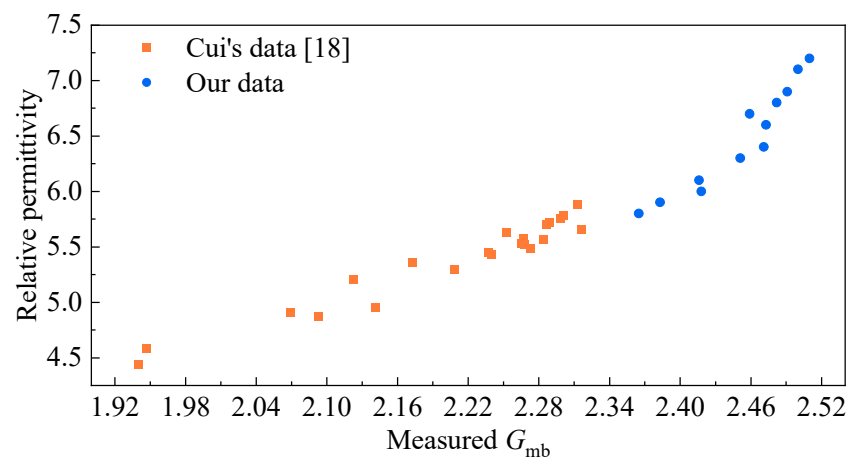


Figure 5. Measured results of bulk specific gravity and relative permittivity for asphalt mixtures.

It should be noted that the dielectric measurements in this study were performed using a Percometer tester operating at 40–50 MHz, while the literature data from Cui et al. were obtained with a GPR system centered at 2 GHz. Although the operating frequencies differ, both fall within the high-frequency range where the relative permittivity of asphalt mixtures shows limited frequency dispersion for density-related applications. Therefore, the influence of measurement frequency on the results is considered negligible in the present context.

In addition to the relative permittivity of the asphalt mixture, several other parameters are required for the density prediction model. The relative permittivity of the aggregates (ϵ_s) and asphalt binder (ϵ_b) were directly measured using the Percometer dielectric constant tester on the raw materials. The specific gravity of the asphalt binder (G_b), the effective specific gravity of the aggregate (G_{se}), and the theoretical maximum specific gravity of the asphalt mixture (G_{mm}) were determined experimentally in accordance with the Standard Test Methods of Bitumen and Bituminous Mixtures for Highway Engineering (JTG 3410-2025) [54]. The binder content by weight (P_b) was derived from the mix design documentation. Detailed procedures for these tests can be found in the aforementioned standard and are therefore not reiterated here.

Table 1. Parameters of the density prediction model for asphalt mixtures.

Mixture Source	ϵ_s	ϵ_b	P_b	G_b	G_{se}	G_{mm}
AC-25 (Our)	7.7	2.7	3.8%	1.011	2.746	2.580
Cui's [18]	6.838	3	5.7%	1.015	2.694	2.462

A total of 34 sets of volumetric and dielectric parameters from different types of asphalt mixtures were thus compiled. A complete dataset of specimen specific properties, including gradation, binder content, and volumetric details, is provided in References [18,47]. This comprehensive dataset provides a solid and extensive foundation for optimizing the parameter c in the unified form of the L-R equation (Equation (5)) for the density prediction of asphalt mixtures.

4. Optimizing the Density Prediction Model

4.1. GAO Model

To determine the optimal geometric arrangement factor (c) applicable to asphalt mixtures, values of c were sampled at intervals of 0.1 across the range $[-1, 1]$. For each value of c , the bulk specific gravity of the 34 asphalt mixture specimens was predicted using the general density prediction model derived from the L-R equation (Equation (9)), in conjunction with the volumetric and dielectric parameters listed in Figure 5 and Table 1. The predicted densities were compared with the measured values, and the mean relative error (MRE) for each c was calculated. The resulting relationship between the geometric arrangement factor c and the MRE of density prediction is presented in Figure 6.

As shown in Figure 6, the MRE of the density prediction first decreases and then increases with the rise of the c value. The minimum MRE of 1.83% is achieved at $c = 0.3$. Therefore, setting c to 0.3 yields the optimized density prediction model based on the L-R equation, designated as the Geometric Arrangement Factor Optimization (GAO) model, given by Equation (16).

The optimized value $c = 0.3$ can be interpreted physically as representing a microstructure in which the three phases (aggregate, asphalt binder, and air) are arranged in an intermediate geometric configuration between the idealized series ($c = -1$) and parallel ($c = +1$) extremes. This reflects the typical state of a well-compacted asphalt mixture, where aggregates are partially coated, binder forms a continuous matrix, and air voids are dispersed within the composite. The consistent performance of $c = 0.3$ across different mixture types suggests that it effectively captures the characteristic dielectric response resulting from realistic phase arrangement in asphalt pavements.

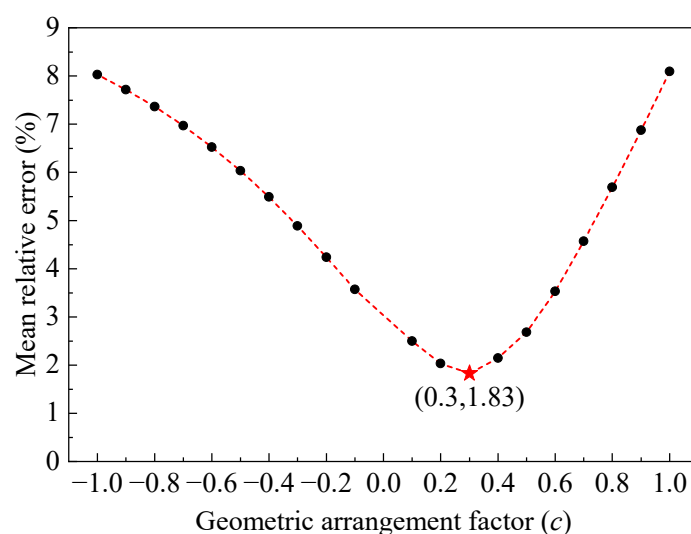


Figure 6. Relationship between MRE and Geometric Arrangement Factor c .

$$G_{mb} = \frac{\epsilon_{AC}^{0.3} - 1}{\frac{P_b}{G_b} \epsilon_b^{0.3} + \frac{1 - P_b}{G_{se}} \epsilon_s^{0.3} - \frac{1}{G_{mm}}} \quad (16)$$

Based on the GAO model, the density prediction errors and the mean relative error for the 34 asphalt mixture specimens are shown in Figures 7 and 8, respectively. The density prediction errors range from -0.12 to 0.1 , with a maximum mean relative error not exceeding 5%. No clear correlation is observed between the prediction error and the density of the asphalt mixtures.

Furthermore, a comparison of density prediction errors among the Complex Refractive Index Model (CRIM), Rayleigh model, ALL model, and GAO model for these 34 specimens is presented in Figure 9. The coefficients of determination (R^2) for the CRIM, Rayleigh, ALL, and GAO models are 0.85, 0.88, 0.83, and 0.91, respectively, while their corresponding mean relative errors are 2.96%, 2.11%, 3.13%, and 1.83%. These results clearly demonstrate that the GAO model achieves the highest predictive accuracy, exhibiting not only the best goodness-of-fit but also the smallest average deviation, thereby confirming its superior reliability for density prediction in asphalt mixtures.

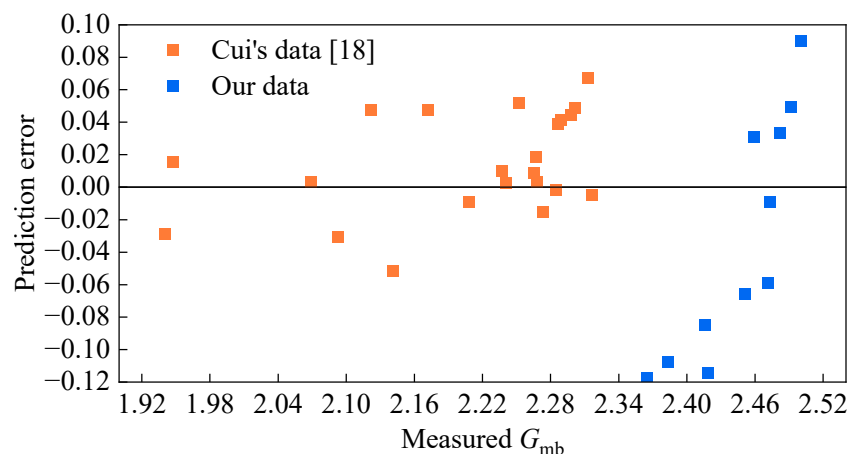


Figure 7. G_{mb} prediction errors of GAO model for asphalt mixtures.

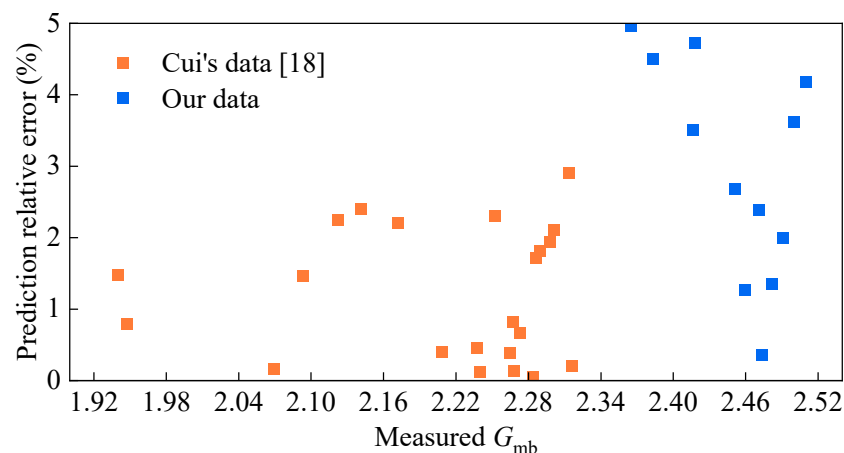


Figure 8. G_{mb} prediction relative errors of GAO model for asphalt mixtures.

It is noted in Figure 9 that the predicted G_{mb} shows an abrupt variation near $\varepsilon_{AC} = 5.8$. This corresponds to the transition between the two data sources integrated in this study: laboratory-produced AC-25 specimens and literature data from Cui et al. (OGFC-13, SMA-13, and AM-13). The discontinuity arises from differences in mixture composition and does not imply a physical discontinuity in the dielectric–density relationship. Rather, it highlights the dataset diversity and reinforces the need for a unified predictive model.

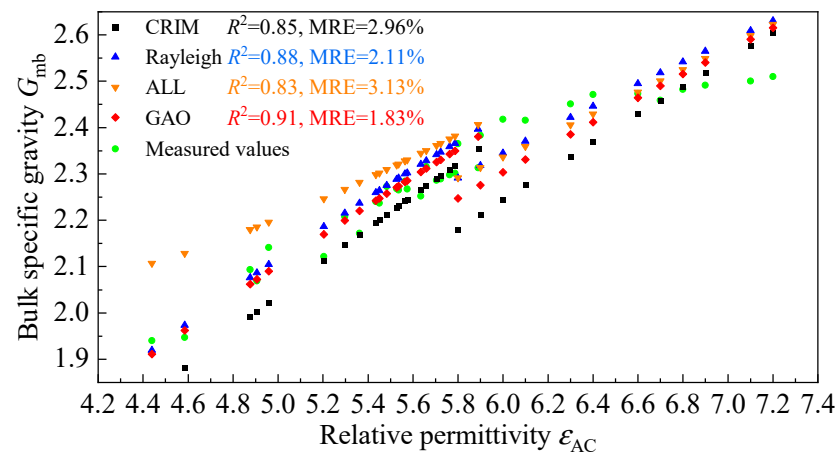


Figure 9. Measured and predicted G_{mb} variation as a function of ϵ_{AC} based different models.

4.2. Model Comparison and Validation

To further validate the effectiveness and reliability of the GAO model, data on the volumetric and dielectric parameters of Limestone binder mix from Leng et al.'s study [54], obtained from eight field core samples, were introduced. The density prediction accuracy of the Complex Refractive Index Model (CRIM), Rayleigh model, ALL model, and GAO model for these asphalt mixture cores was compared, as summarized in Tables 2 and 3 and illustrated in Figure 10.

The results indicate that the density prediction errors of all models tend to be larger when the core samples have lower density, which corresponds to higher air void content. Specifically, the mean relative errors for the eight core samples predicted by the CRIM, Rayleigh, ALL, and GAO models are 3.34%, 3.87%, 3.76%, and 3.01%, respectively. This confirms that the GAO model still achieves the highest prediction accuracy. It is worth noting that the GAO model shows relatively lower accuracy for the two least dense cores (Samples #7 and #8), whereas its predictions for the other, denser cores are highly accurate, with errors not exceeding 1.85%.

In Figure 10, special attention is drawn to the region near $G_{mb} \approx 2.15$, which corresponds to two low-density cores (Samples #7 and #8) with high air void contents (14.13% and 14.05%). For these specimens, the ALL model achieved the lowest mean relative error (1.73%), outperforming the CRIM (9.83%), Rayleigh (4.24%), and GAO (8.57%) models. This suggests that empirical models like ALL may be better calibrated for high-void conditions. The slightly reduced accuracy of GAO in this range is likely due to increased microstructural complexity and deviations from the idealized phase distribution assumed in the L-R framework. Future work could focus on extending the model to better accommodate highly porous mixtures, for instance by introducing a void-shape factor or refining the geometric arrangement parameter c for such cases.

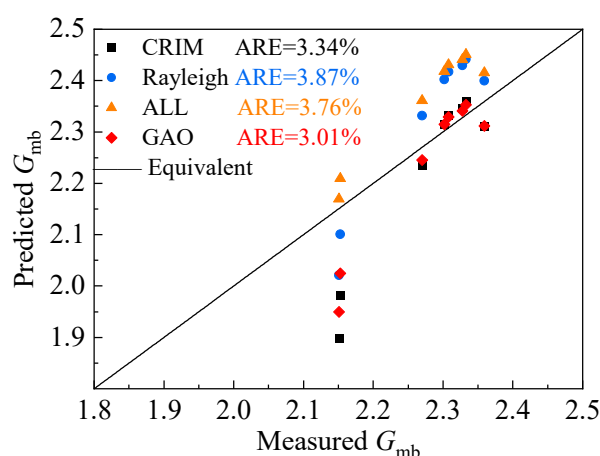
These findings collectively verify the accuracy and feasibility of the GAO model for density prediction in asphalt layer core samples, particularly under typical density conditions.

Table 2. Measured parameter values for limestone binder mix.

Mix Type	ϵ_s	ϵ_b	P_b	G_b	G_{se}	G_{mm}
Limestone binder mix	6.62	2.668	4.3%	1.015	2.668	2.505

Table 3. Measured and predicted G_{mb} of cores in asphalt pavement.

Core No.	Measured G_{mb}	ϵ_{AC}	CRIM Model		Rayleigh Model		ALL Model		GAO Model	
			Predicted G_{mb}	Relative Error (%)	Predicted G_{mb}	Relative Error (%)	Predicted G_{mb}	Relative Error (%)	Predicted G_{mb}	Relative Error (%)
1	2.359	5.73	2.311	2.02	2.399	1.71	2.312	2.38	2.415	1.85
2	2.333	5.87	2.359	1.13	2.441	4.63	2.353	5.05	2.450	1.16
3	2.328	5.83	2.346	0.76	2.429	4.35	2.341	4.83	2.440	0.83
4	2.308	5.79	2.332	1.04	2.417	4.73	2.329	5.31	2.430	1.15
5	2.302	5.74	2.315	0.55	2.402	4.35	2.315	5.03	2.417	0.72
6	2.270	5.51	2.234	1.57	2.331	2.71	2.245	4.01	2.361	1.15
7	2.151	4.6	1.898	11.74	2.021	6.05	1.950	0.84	2.169	10.37
8	2.153	4.82	1.982	7.92	2.101	2.43	2.025	2.61	2.209	6.76

**Figure 10.** Measured G_{mb} compared with predicted G_{mb} using different models.

5. Conclusions

This study proposed a density prediction framework for asphalt mixtures based on the L-R dielectric mixing theory, with the geometric arrangement factor (c) optimized using a combined dataset of laboratory-tested AC-25 mixtures and literature-reported data from OGFC-13, SMA-13, and AM-13 mixtures. The following conclusions can be drawn within the scope of the materials and methods investigated:

- (1) The Percometer dielectric constant tester enables rapid and direct measurement of the relative permittivity of asphalt binder, aggregates, and asphalt mixture specimens. This approach reduces the uncertainty associated with empirically estimated permittivity values and provides a reliable technique for dielectric characterization of the specific materials tested in this study.
- (2) By applying the L-R dielectric mixing model to asphalt mixtures, a general density prediction formulation was established. Based on the volumetric and dielectric parameters of the four mixture types examined, the optimal geometric arrangement factor was determined to be $c = 0.3$. The resulting GAO (Geometric Arrangement Optimization) model demonstrated improved prediction accuracy for the datasets considered.
- (3) Comparative evaluation against the CRIM, Rayleigh, and ALL models showed that the GAO model achieved the lowest mean relative error (1.83%) and highest R^2 (0.91) for the 34 sets of laboratory specimens analyzed. For the eight field core samples evaluated, the GAO model yielded a mean relative error of 3.01%. These findings indicate that, for the mixture types and test conditions considered in this study, the GAO model offers a promising and physically grounded approach for asphalt

mixture density estimation.

It should be emphasized that the validity of the GAO model has been established only for the materials, mixture designs, and experimental conditions investigated. Further validation using a wider range of aggregate lithologies, binder grades, gradations, and compaction methods is recommended to assess the generalizability of the optimized c value and the broader applicability of the proposed framework.

6. Future Work and Limitations

While the proposed GAO model demonstrates superior accuracy in density prediction under the tested conditions, certain limitations warrant attention. The model's performance was observed to decrease for core samples with higher air void contents (exceeding 14%), suggesting that the relationship between dielectric properties and density may be influenced by extreme porosity levels. Furthermore, the current model was developed and validated using specific mixture types; its applicability to a wider range of materials, such as those incorporating recycled components or novel modifiers, remains to be verified. The optimization of the geometric arrangement factor (c) was also based on a discrete sampling approach, which, while effective, may not have captured its most precise continuous value.

Future research should focus on enhancing the model's robustness across a broader spectrum of material conditions. This includes investigating the incorporation of additional microstructural parameters, such as aggregate orientation or void distribution, to improve predictions for high-porosity mixtures. Expanding the validation dataset to encompass recycled asphalt pavement (RAP), rubber-modified mixes, and other non-conventional materials is essential to generalize the model's applicability. Finally, exploring the potential for in situ implementation, perhaps through the development of a portable, non-destructive testing protocol based on this dielectric approach, represents a critical step toward practical field application and could significantly impact pavement quality control practices.

Although the GAO model has promising accuracy in this study, further validation with larger and more diverse datasets is recommended to statistically confirm its generalizability. In particular, a comprehensive uncertainty analysis should be conducted to quantify the effects of measurement errors, material variability, and model parameter sensitivity on density predictions. Future work will focus on collecting additional laboratory and field data, including mixtures with recycled materials, modified binders, and a wider range of air void contents, to support probabilistic modeling and uncertainty quantification. Such analysis will not only enhance the reliability of the GAO model but also provide clearer guidance for its practical application in pavement evaluation.

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