TECHBRIEF

Macrotexture Model Development for Asphalt Mixtures Aimed at Safety Analysis

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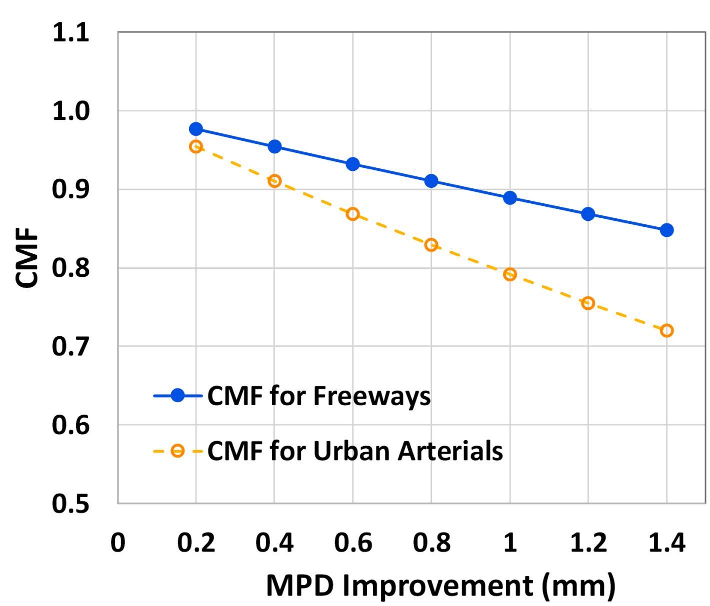
The Safe System Approach,[1] the guiding paradigm of the United States Department of Transportation National Road Safety Strategy,[2] recognizes that system redundancy is crucial to reducing deaths and serious injuries on our Nation's roads. Where pavements are concerned, this paradigm involves providing adequate levels of friction supply to meet the friction demand (i.e., the level of friction needed to perform braking, steering, and acceleration maneuvers safely) of a given road type and context.[3] Two pavement surface characteristics, microtexture and macrotexture, are the primary factors that influence the pavement friction. Microtexture contributes to traction at the pavement–tire interface at all traffic speeds. While also contributing to traction at all traffic speeds, macrotexture is more critical at high speeds. Macrotexture influences the hysteresis, or energy lost due to the rubber deformation component of friction and facilitates drainage at the pavement–tire interface, so macrotexture is particularly critical during conditions when water is present on the pavement, such as during adverse weather.

Several international studies have reported that increasing macrotexture levels on a pavement surface reduces crash risk.[4,5] Consequently, highway agencies in several countries, including the United Kingdom, Australia, and New Zealand, have established minimum macrotexture levels for new and in-service pavements. A recent study in the United States has confirmed this relationship between macrotexture and safety performance (figure 1).[6] An investigation in North Carolina also found a statistical association between macrotexture and crashes and proposed a macrotexture investigatory level of mean profile depth (MPD) = 0.80 mm.[7]

Figure 1. Graph. Crash modification factors for various macrotexture levels.[6]



Source: FHWA.
CMF = crash modification factor.

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Although research on the influence of pavement macrotexture levels on crash risk in the United States is limited, highway agencies are increasingly recognizing the importance of macrotexture. Equipment for measuring macrotexture in the laboratory and field has been available for years. High-speed laser equipment (HSLE) for characterizing macrotexture at the network level has made possible the inclusion of macrotexture as a data item for pavement management and safety analysis. Similarly, portable macrotexture analyzers also enable measuring macrotexture on hot-mix asphalt (HMA) laboratory compacted specimens. However, because the recognition of the safety implications of macrotexture is relatively recent and thus the use of macrotexture data is also increasing, several gaps in the current state of the practice exist. These gaps include validated quality standards to ensure macrotexture measurements are accurate and repeatable, in addition to how to use these measurements to assess the impact on safety of the HMA mix design by ensuring adequate levels of macrotexture.

STUDY OBJECTIVE AND SCOPE

This TechBrief documents the results of a study to:

- Develop models for predicting the as-constructed macrotexture of asphalt-surfaced pavements based on aggregate and mix properties.
- Provide a framework for agencies and construction contractors to use these models in designing asphalt mixes to meet agency macrotexture requirements for pavement safety.

The effort included assembling and reviewing literature on macrotexture and safety, testing and characterizing macrotexture, and establishing a relationship between mix properties and macrotexture. Although macrotexture changes with time after construction because of the polishing and wear produced by traffic, this effort is aimed at predicting the macrotexture shortly after construction.

MACROTEXTURE MEASUREMENT

Over the past decade, innovative macrotexture measuring technologies have been developed, and researchers and private vendors are producing new systems to address gaps in current technology. Thus, a wide range of macrotexture measurement devices is available for the laboratory and the field. These technologies allow for macrotexture measurements using volumetric, two-dimensional line profiles, and three-dimensional area measurements. The measured macrotexture from these devices is reported using several metrics, including MPD, mean texture depth, and root mean square. However, no definitive research has been conducted on which macrotexture metrics are best correlated with highway safety.[8]

A careful evaluation of available devices, such as those presented in figure 2, showed that different technologies are used for measuring macrotexture

Figure 2. Photos. Examples of macrotexture measuring equipment.

A. Laser Texture Scanner.

B. HSLE.

in the laboratory and in the field. The research team selected the Laser Texture Scanner for laboratory testing because of its portability, availability, proven repeatability and accuracy, level of automation (which reduces reliance on an operator), and its small imprint that allows for testing field cores and laboratory-prepared specimens. HSLE is more appropriate for field testing because it efficiently measures macrotexture at traffic speed. Such equipment is already available at many agencies.

AGGREGATE AND ASPHALT MIX PROPERTIES THAT INFLUENCE PAVEMENT SURFACE MACROTEXTURE

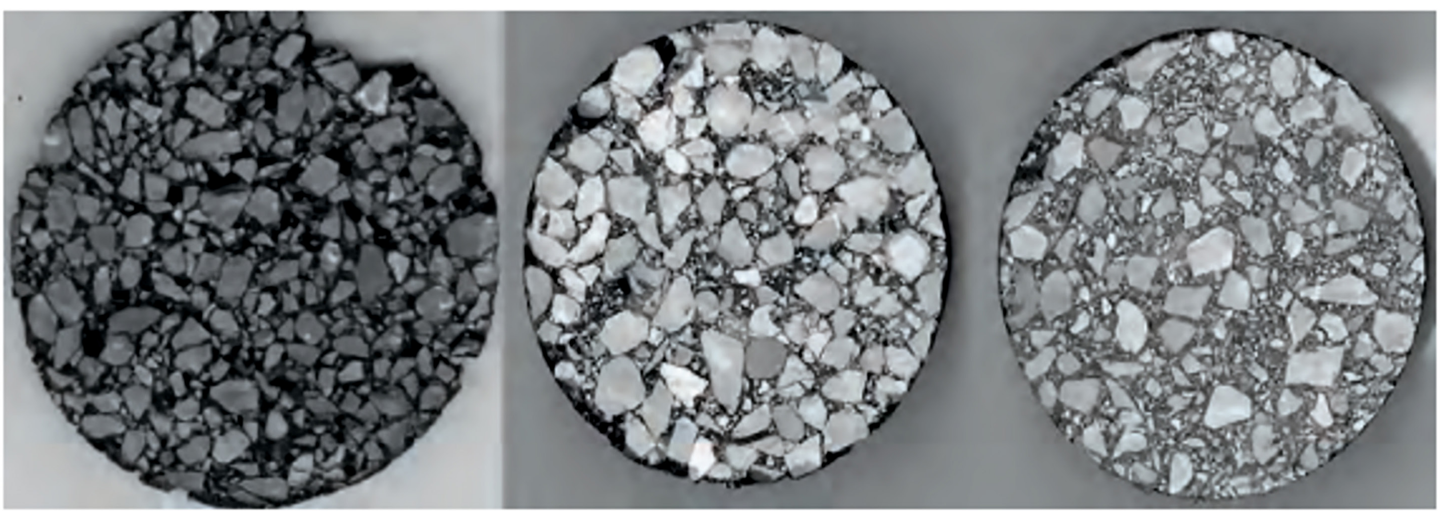
Published literature has reported on how aggregate, asphalt mix properties, and laboratory and construction activities influence laboratory and as-constructed macrotexture. However, most past research was limited in the number of mix types evaluated, national coverage, and range of design properties and macrotextures investigated. This study identified the percentage passing sieve No. 8 and passing sieve No. 200, and the coefficient of uniformity (Cu) as key parameters that impact macrotexture. Also, mix type and asphalt mix volumetrics parameters, such as voids filled with asphalt (VFA), impact macrotexture.[7,9]

NATIONALLY REPRESENTATIVE MIX TYPES

This study investigated the asphalt surface mixture types commonly used across the U.S. transportation network, as shown in figure 3.[10] Researchers compared mixes used in several States to identify the most common mixes. The review found that the following surface mixes are commonly used:

- Dense-graded mixes—The most commonly used nominal maximum aggregate size (NMAS) are 12.5 mm and 9.5 mm, but some States have used larger top-size aggregate 19-mm mixes. Smaller top-size aggregate mixes (4.75 mm) are also becoming more popular for thin preservation treatments.
- Gap-graded mixes (e.g., stone matrix asphalt (SMA)) with NMAS of 9.5 mm and 12.5 mm. Some agencies also use 19-mm SMA, but they are not common.
- Open-graded friction courses with NMAS of 9.5 mm and 12.5 mm.

Figure 3. Photos. Asphalt mixtures with different types of aggregate blends.



Open-graded aggregate blend (air voids≈18%). | Dense gap-graded blend (air voids≈6%). | Dense well-graded blend (air voids≈6%).

MACROTEXTURE PREDICTION MODEL DEVELOPMENT

The macrotexture prediction model development consisted of the following:

- Identifying a limited number of highway agencies with projects from which macrotexture, aggregate and asphalt mix properties, and construction practices data are available and can be used for model development.
- Assembling identified data in a database and reviewing for quality and rectifying anomalies as needed.
- Identifying mathematical formulations appropriate for model development.
- Fitting assembled data to identified formulations to develop a preliminary model.
- Reviewing and revising the preliminary model as needed.

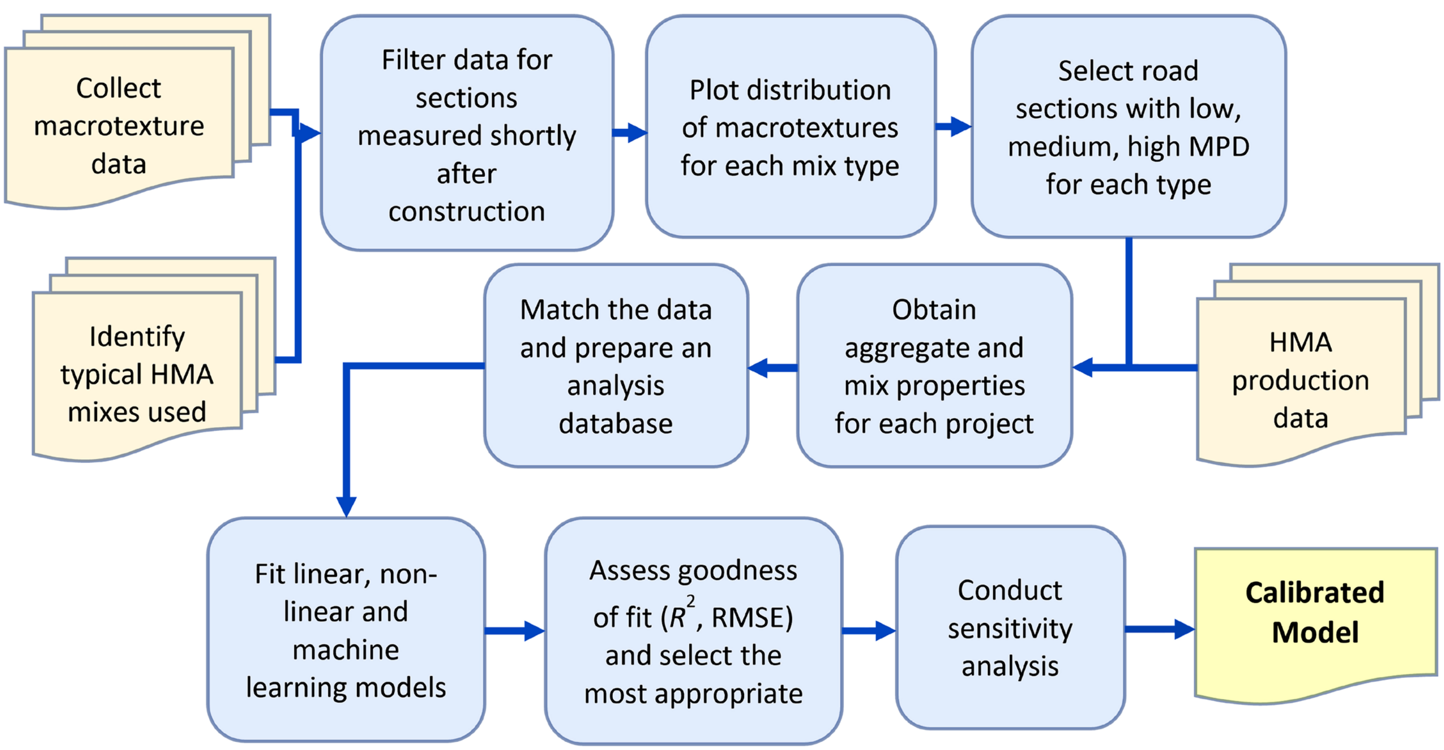
Figure 4 shows a flowchart describing the preliminary model development process.

The models were developed using a representative sample of as-constructed highway speed collected macrotexture (MPD) data from seven States and complemented with limited MPD data obtained by using cores from two additional States and the National Center for Asphalt Technology. The data collected included project location, macrotexture, mix gradation, asphalt content, and mix volumetrics.

The model was developed and evaluated in terms of fit and bias in estimating macrotexture, beginning with key parameters and variables, including the following:

- Aggregate properties: NMAS, gradation, and sieve analysis (used to compute gradation characterization parameters).
- Mix volumetrics: Binder content, air voids, voids in mineral aggregate, voids in total mix, and bulk density.

Figure 4. Flowchart. Initial model development flowchart.



Source: FHWA.
RMSE = root mean square error.

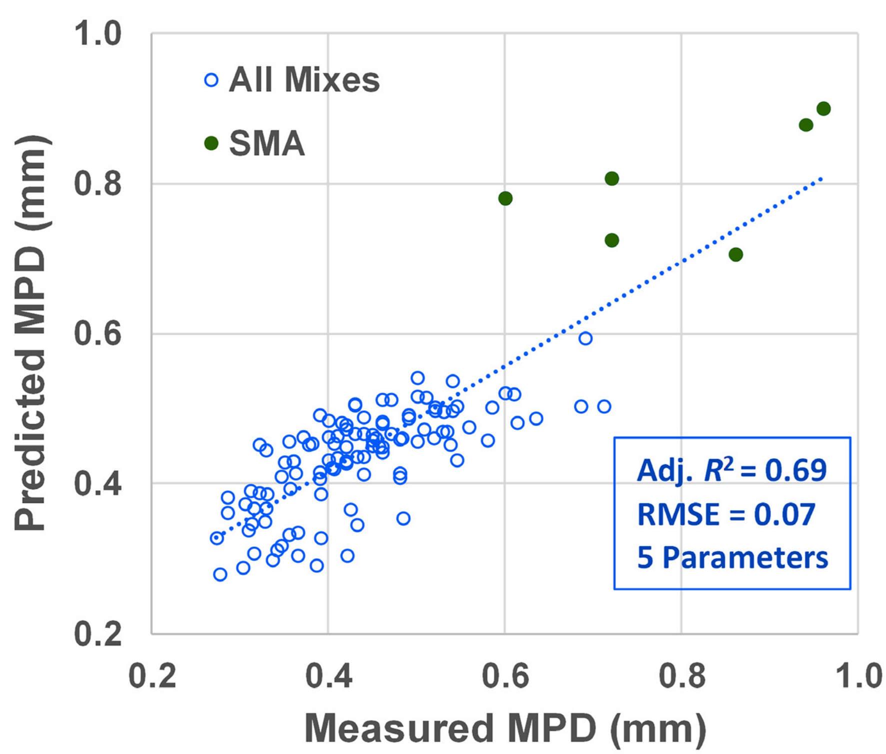
Researchers reviewed the assembled data to identify outliers and potentially erroneous entries using bivariate plots and to identify highly correlated variables that provided the same information and, thus, should not be included in the initial macrotexture model. A correlation analysis showed that many of the variables considered are correlated, which needs to be considered during the modeling process.

The initial macrotexture prediction model included asphalt mix and aggregate test results and metrics. The research team evaluated various linear and multiplicative regression models, as well as Random Forest (RF) and Extreme Gradient Boosting (XGBoost) models, which are machine-learning (ML) techniques. Researchers considered other artificial intelligence tools, such as artificial neural networks. Still, RF and XGBoost were preferred due to their lower computational requirements and data needs, making them more appropriate for the relatively small dataset used in this project. Researchers conducted a sensitivity analysis to validate the reasonableness of all trends for the most promising models. The most appropriate model was selected following an iterative process to balance prediction accuracy, robustness, reliability, and simplicity.

RESULTS

The approach presented in the previous sections enabled the team to iteratively select the most appropriate model that resulted in appropriate goodness-of-fit statistics and coefficient signs that align with engineering expectations. After several iterations, the best model for the data collected in the study consisted of a linear model including the Cu percent passing sieves No. 8 (2.38 mm) and No. 200 (75 µm) and VFA as predictors, as well as a dummy variable to account for the type of mix. Figure 5 presents predictions for this model, represented by equation 1. SMA mixes are indicated separately to illustrate the impact of including them in the modeling.

Figure 5. Graph. Plot of predicted versus measured macrotexture for the "best" linear regression model.



Source: FHWA.

- $$\text{MPD} = 1.03 + 0.224 * \text{Type} + 0.0034 * C_u - 0.0050 * P_8 - 0.0105 * P_{200} - 0.0049 * \text{VFA} \quad (1)$$

Where:

MPD = estimated MPD (mm).

Type = mix type, 0 for dense-graded and 1 for SMA.

P8 = percentage passing sieve No. 8.

P200 = percentage passing sieve No. 200.

The application of ML techniques proved to be even slightly more effective, with lower standard error and marginally better coefficients of determination for the testing set. The XGBoost model produced the "best" models with the highest R^2 and RMSE (figure 6). However, the two ML techniques investigated showed similar performance and almost perfect fit for the training set.

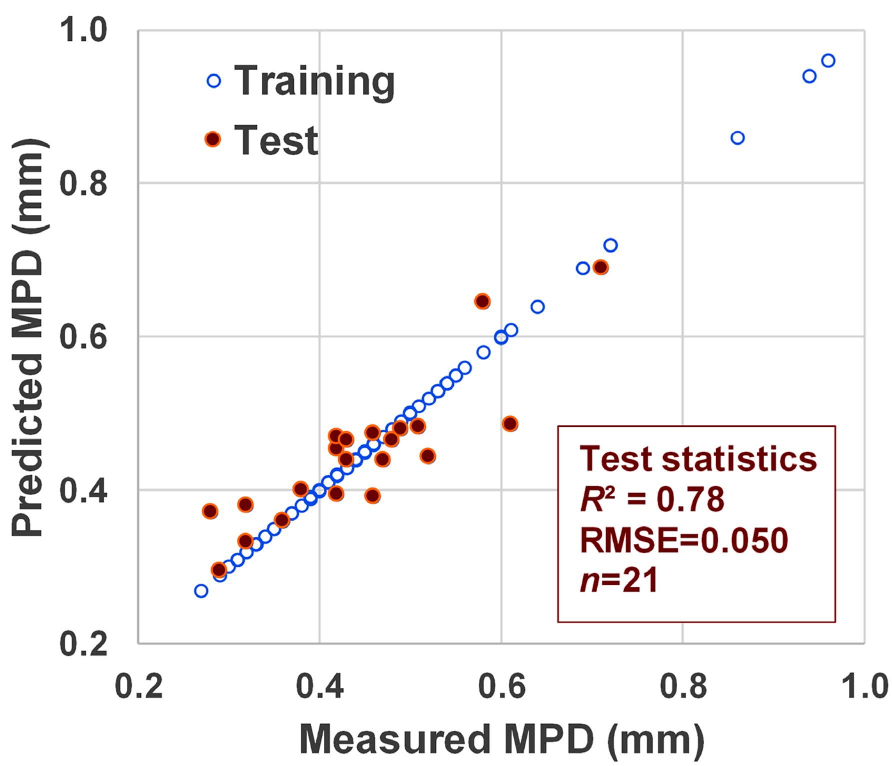
CONCLUSIONS

Researchers selected the most appropriate models in an iterative process that resulted in appropriate goodness-of-fit statistics. From a purely statistical point of view, the XGBoost model can be recommended for developing models for predicting pavement macrotexture based on asphalt mix and aggregate gradation properties, due to its ability to effectively capture the complex relationships between macrotexture and mix and aggregate properties. However, the complexity of the algorithm may be an issue in some cases, and the linear regression models may be more appropriate when ease of use and the ability of estimating the contribution of each variable is more important than the prediction abilities.

The proposed approach provides a framework that agencies can use for incorporating macrotexture predictions into HMA design. Agencies adopting the approach can follow this template to collect additional data and verify the models with these data. Once the approach is implemented, the impact on pavement safety can be investigated comparing crash rates before and after its application.

Mixes with high macrotexture (e.g., SMA) and laboratory measurements on cores are underrepresented in the current dataset, and additional data collection and model recalibration may produce even more robust models.

Figure 6. Graph. Plot of predicted versus measured macrotexture for the XGBoost ML model.



Source: FHWA.

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Researchers—This study was conducted by Gerardo Flintsch, Edgar de León Izeppi, Alejandra Medina, Behrokh Bazmara, Ilker Boz, Andy Mergenmeier and Amir Golalipour, contract No. 693JJ319D000015.

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