ABSTRACT

Resilient Modulus (M_R) is a fundamental parameter in the Mechanistic-Empirical Pavement Design Guide (MEPDG) that characterizes the stiffness of subgrade soils under repeated traffic loads. Traditionally, M_R determination involves direct laboratory testing, which can be labor-intensive, costly, and impractical for large-scale pavement projects or rehabilitation efforts. To address these challenges, the current research has explored non-destructive testing methods, such as Falling Weight Deflectometer (FWD) and Ground Penetrating Radar (GPR), as well as the use of predictive models to estimate M_R based on soil properties. This study aimed to enhance the understanding of M_R testing and improve predictive models, contributing to more reliable and efficient M_R estimation techniques.

The research involved an extensive experimental program, which began with the collection of subgrade soil samples from various road construction projects across Indiana. The collected soils were characterized through standard geotechnical tests, including gradation analysis, Atterberg limits, and compaction tests. Resilient modulus testing followed the AASHTO T 307 protocol, performed on both untreated and treated soil samples to simulate field conditions. Post-construction, the test sites were revisited to conduct FWD and GPR tests, ensuring a comprehensive dataset for correlating M_R with field test results. The use of GPR for pavement thickness estimation proved effective in identifying discrepancies between as-built and design thicknesses in both flexible and rigid pavements. For flexible pavements, a strong correlation was observed between laboratory M_R values and FWD backcalculated moduli, indicating that FWD testing can reliably estimate M_R for untreated subgrade soils.

The study also explored the use of machine learning algorithms, such as random forest and gradient boosting, to predict M_R based on soil properties, offering an alternative to traditional regression analysis. The research found that stress-independent models failed to yield statistically significant correlations between M_R and basic soil properties such as moisture content, dry density, and Atterberg limits. In contrast, stress-dependent models, particularly the Uzan and octahedral models, revealed weak dependencies on confinement and deviatoric stresses, leading to significant variability in M_R values across tested samples. The results highlight the limitations of current soil- and stress-based models, suggesting that while they may work well for specific cases, they cannot be generalized across a wide range of conditions.

An effort to compare soil performance during the different stages of resilient modulus testing and a numerical method that included a stress-dependent soil model confirmed the empirical finding of a weak dependency between M_R and confinement and deviatoric stress. This was the case not only for the standard AASHTO T 307 protocol, but also for other protocols where the loading sequence was reversed compared to the standard test.

The research demonstrated the potential of machine learning for M_R prediction and the complexity of the soil behavior during resilient modulus testing. Thus, models to accurately predict M_R results should be able to follow the stress path that the soil is subjected to during the test.