Continuous Compaction Control Measurements for Quality Assurance in Conjunction with Light Weight Deflectometer Target Modulus Values

William J Baker[1], Christopher L Meehan[2]

[1] Graduate Student, University of Delaware, Dept. of Civil and Environmental Engineering, Newark, DE, USA

[2] Professor, University of Delaware, Dept. of Civil and Environmental Engineering

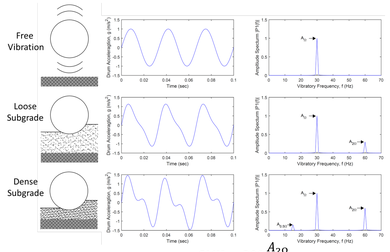
Introduction

AASHTO's mechanistic-empirical pavement design guide has caused a fundamental shift of wanting to measure a soil's mechanical properties (e.g. modulus) in situ during construction for Quality Assurance/Quality Control (QA/QC) purposes. Due to this fundamental shift, devices such as the Light Weight Deflectometer (LWD) have been developed in order to measure an elastic soil modulus in situ. AASHTO TP 123–17 has also been develop to indicate passing and failing LWD tests collected in the field. Other technologies such as Continuous Compaction Control (CCC) have also been developed where a compaction roller is instrumented with sensors that enable the compaction to provide real–time data and spatial maps of the compaction process. The goal of this study was to relate localized CCC measurements (e.g. Compactometer Value, CMV) to location specific LWD tests that were categorized as either 'passing' or 'failing' based on AASHTO TP 123-17. A machine learning technique, Support Vector Machine (SVM), was utilized to develop a decision–boundary to indicate 'passing' and 'failing' regions of localized CMV measurements with respect to field moisture content to determine if CCC can be a viable stand-alone QA/QC tool for earthwork construction.

Collection of Continuous Compaction Control & LWD Data During Active Construction

A Caterpillar CS56B compaction roller instrumented with an aftermarket CCC kit was utilized during this study to collect CMV data along four embankments during active construction of Section 3 of U.S. 301 located in Middletown, DE. 120 LWD tests, utilizing a 30 cm plate diameter LWD, were also conducted along the four earth embankments to obtain an estimate of the soil's elastic modulus. Representative moisture content samples were also collected at each of the specific LWD testing locations. It should be noted that the soil tested was generally classified as a silty sand (SM).

Figure 1. Caterpillar CS56B Compaction Roller CCC System



$$CMV = 300\frac{A_{2\Omega}}{A_{\Omega}}$$

Figure 2. Theory of Compactometer Value, CMV

Figure 3. Field Light Weight Deflectometer

Table 1. Calculation of Elastic Soil Modulus in the Field

Governing Equation

$$E_{Field} = \frac{2F_{peak}(1-\upsilon^2)}{A r_0 w_{peak}}$$

Parameters

E_{Field} – elastic soil modulus
F_{peak} – peak vertical applied force from field LWD
υ – Poisson's ratio
A – contact stress distribution of field LWD
r_0 – plate radius of field LWD
w_{peak} – peak vertical displacement of field LWD

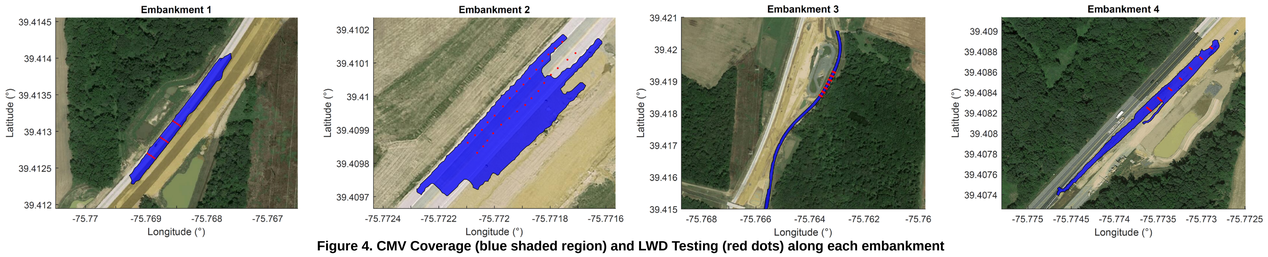


Figure 4. CMV Coverage (blue shaded region) and LWD Testing (red dots) along each embankment

Laboratory Analysis – AASHTO TP123–17

AASHTO TP 123–17 is an extension of traditional Proctor Analysis, where a each 'proctor point' the elastic soil modulus is measured utilizing a laboratory LWD at varying drop heights. Based on laboratory results a 'target' elastic soil modulus can be determined following this procedure:

Table 2. Calculation of Elastic Soil Modulus in the Laboratory

Governing Equation

$$E_{S_{OIL}} = \left(1-\frac{2\upsilon^2}{1-\upsilon}\right)\frac{4H}{\pi D^2}\frac{F}{\delta}$$

Parameters

$E_{S_{OIL}}$ – elastic soil modulus
υ – Poisson's ratio
F – peak applied force from laboratory LWD
H – height of Proctor mold
D – plate diameter of laboratory LWD
δ – peak vertical displacement of laboratory LWD

Figure 5. Laboratory Light Weight Deflectometer

Table 3. Procedure to determine 'Target' Soil Modulus for field LWD QA/QC Applications

Step	Procedure	Governing Equation	Parameters
1	Solve the following equation for $a_0 - a_4$	$E_{Soil} = a_0 + a_1 MC_{mold}^2 + a_2 MC_{Mold} + a_3 P_{Mold}^2 + a_4 P_{Mold}$	$E_{S_{OIL}}$ – elastic soil modulus measured with laboratory LWD; MC_{Mold}, P_{Mold} - Laboratory moisture content and applied LWD pressure
2	Utilize regression coefficients to determine 'target' elastic soil modulus in the field	$E_{Target} = a_0 + a_1 MC_{Field}^2 + a_2 MC_{Field} + a_3 P_{Field}^2 + a_4 P_{Field}$	E_{Target} – target elastic soil modulus for field QA/QC applications; MC_{Field}, P_{Field} - Field moisture content and applied LWD pressure
3	Determine if the elastic soil modulus in the field has 'passed'	$E_{Field} \geq E_{Target}$	E_{Field} – elastic soil modulus measured with field LWD

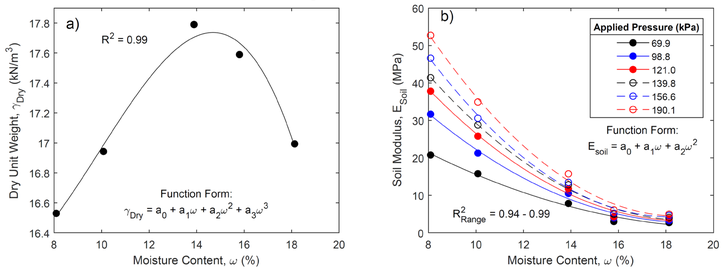


Figure 6. Laboratory results following AASHTO TP-123: a) Dry unit weight variation with moisture content, and b) Soil modulus variation with moisture content.

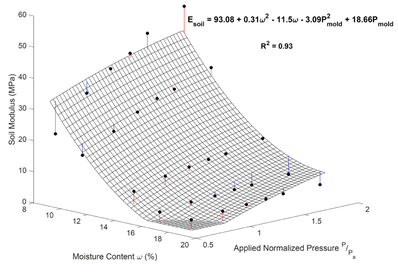


Figure 7. Multivariate Regression Analysis results following AASHTO TP-123

Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm that utilized categorical data (e.g. pass-fail in situ tests) in order to develop a decision-boundary between the two categories of data. The main idea behind SVM is to find the optimum decision-boundary or hyperplane by maximizing the distance between the two of categories of data (Goh and Goh 2007). In order to maximize the distance between the two sets of data, two parallel planes are constructed from support vectors, or points from both categories of data that are closest to the hyperplane. Therefore, in an intuitive sense, SVM tries to find the 'widest roadway' between the two of categories of data in order to develop the most optimum hyperplane.

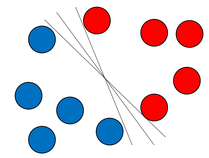


Figure 8. Multiple hyperplanes that separate the categorical data

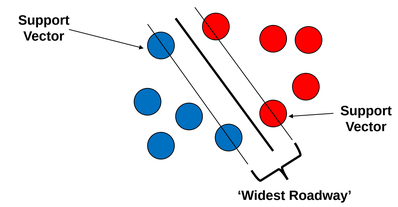


Figure 9. Optimal hyperplane that separates the categorical data

Results

Two SVM models were developed to create hyperplanes between 'Passing' and 'Failing' regions of localized CMV measurements from location specific LWD tests with respect to field moisture content values. Passing and failing localized CMV measured were based on associated passing and failing LWD tests per AASHTO TP123-17. Two SVM models were created, one utilizing a linear kernel function and the other utilizing a polynomial kernel function with a degree of 2 (e.g., quartic). The input variables to develop the SVM models were the averaged CMV values determined from the location specific LWD test locations along with the associated moisture content samples. The output variable was a binary vector consisting of either 1s or 0s, indicating a passing or failing LWD test, respectively. Results indicated that both SVM models had a 91% success rate of being able to properly classify a specific CMV and moisture content value combination either as passing or failing. Both models miss classifying passing points as failing points more often than miss classifying failing points as passing.

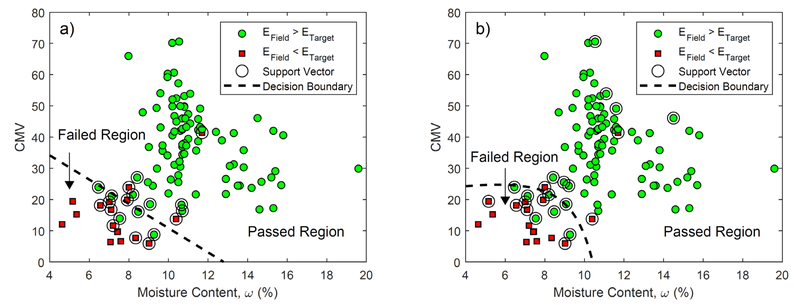


Figure 10. Passing and failing regions developed utilizing Support Vector Machine: a) Linear kernel function, and b) Quadratic kernel function.

Discussion and Potential Implications for QA/QC

It should be noted that the majority of the data points utilized to develop the SVM models were passing LWD tests. In essence, the decision boundaries developed by using SVM are influenced by the data that is used to develop these type of models; e.g. the addition of failing points that have a higher moisture content beyond 12% can affect the shape of the decision boundaries. Therefore the addition of more failing points is necessary to better understand the sensitivity of these type of decision boundaries. As a QA/QC tool, the use of SVM may have the ability for integrating CCC measurements such as CMV as stand alone quality assurance tool to help stream line the QA/QC process during earthwork construction.

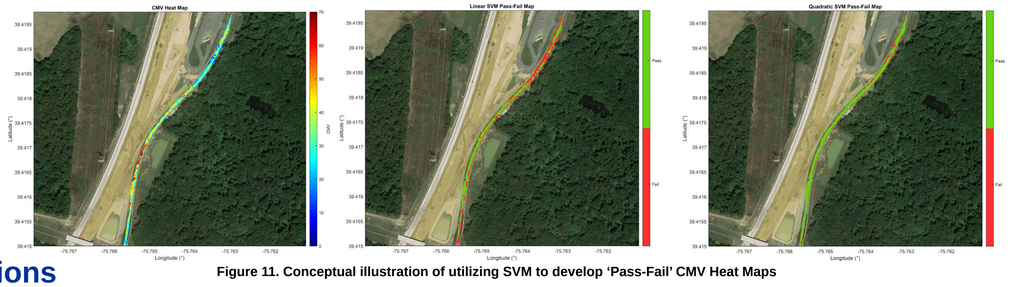


Figure 11. Conceptual illustration of utilizing SVM to develop 'Pass-Fail' CMV Heat Maps

Conclusions

The two SVM models developed had over 90% accuracy rate when classifying points as either passing or failing based on the decision boundaries developed by the models. The use of SVM in this context may be a viable option for enhancing the use of CCC technology as a decision making QA/QC tool. Though promising, the current data set is limited to a small percentage of failing points (e.g. 16%). More data in needed in future studies of this type, in order to validate these initial findings and to better understand the general trends that are present when using SVM in the context of earthwork QA/QC.

Acknowledgements

This material is based upon work supported by the Mid–Atlantic Transportation Sustainability Transportation Center under Grant No. DTRT13–G–UTC33. The authors would also like to thank the Delaware Department of Transportation (especially James Pappas) and Greggo & Ferrara, Inc. (especially Nicholas Ferrara III, Dana Felming and R. David Charles) for facilitating access to the project site during the duration of this study.

References

AASHTO TP123-17 (2017). "Laboratory Determination of Target Modulus Using Light-Weight Deflectometer (LWD) Drops on Compacted Proctor Mold." American Association of State and Highway Transportation Officials, Washington, D.C.

Goh, A. T. C. and Goh, S. H. (2007). "Support Vector Machines: Their Use in Geotechnical Engineering As Illustrated Using Seismic Liquefaction Data." Computers and Geotechnics, 34(5), 410-421..